Mérnöki Kar
Rendszermérnöki Intézeti Tanszék
Pannon Egyetem

Habilitációs tézisek

Ember-központú gyártási rendszerek

Pannon Egyetem
University of Pannonia

A Pannon Egyetem habilitációs címének megszerzésére.

írta
Ruppert Tamás
Veszprém, Magyarország

Veszprém, 2025. szeptember 30.

Tartalomjegyzék

Kérelem

Dr. Hartung Ferenc

Vezető

Informatikai Tudományok Doktori Iskola

Tisztelt Professzor Úr!

Dr. Ruppert Tamás, mint a Pannon Egyetem Mérnöki Kar Rendszermérnöki Intézeti Tanszék egyetemi docense kérem az Informatikai Tudományok Doktori Iskola vezetőjét, hogy Mesterséges intelligencia tudományterületen részemre habilitációs eljárás folytasson le a 2025. április 24-től hatályos habilitációs szabályzat alapján.

Veszprém, 2025. 09. 30.

Dr. Ruppert Tamás

Befogadó nyilatkozat

Dr. Ruppert Tamás habilitációs kérelmet nyújtott be az Informatikai Tudományok Doktori Iskolához, hogy Mesterséges Intelligencia tudományterületen részére habilitációs eljárás folytassunk le a 2025. április 24-től hatályos habilitációs szabályzat alapján. A pályázatot az Informatikai Tudományok Doktori és Habilitációs Tanácsa befogadja és illetékességi körében el is bírálja.

Veszprém, 2025.

Prof. Dr. Hartung Ferenc
Vezető
Informatikai Tudományok Doktori Iskola

3 Önéletrajz

Ruppert Tamás a Pannon Egyetem Mérnöki Karán a Rendszermérnöki Intézeti Tanszék vezetője, egyetemi docens. PhD fokozatát 2020 júniusában szerezte. Eddigi kutatásaiban az emberi munkaerő kihívásaira fókuszált a negyedik ipari forradalom módszertanainak fejlesztése során. Az Operátor 4.0 koncepció alapján célzottan kutatja azokat a Mesterséges Intelligencia alapú eszközöket, amelyekkel segíthetők és támogathatók az emberi tevékenységek a gyártási környezetben. Ezen kutatások kapcsán létrehozta a Pannon Egyetemen az Ipar 5.0 laboratóriumot, ahol olyan szenzor-, eszköz- és algoritmus-fejlesztési kutató munkákat végeznek, amelyek megalapozzák az általa kidolgozott Intelligens Kollaboratív Gyártási Tér koncepciót. Több hazai és nemzetközi kutatás-fejlesztési projektnek is volt a szakmai vezetője. Az Ipar 4.0 megoldásokat fejlesztő adat- és rendszertudományi szakmérnök és a Mechatronikai Mérnök Mesterszak képzések szakfelelőse. Jelenleg kilenc PhD hallgató témavezetője Kutatási eredményeit eddig összesen 44 tudományos folyóiratcikkben publikálta, ebből 10 db D1-es, 16 db Q1-es és 11 db Q2-es. Összesen 1631 hivatkozás érkezett a google scholar szerint, ebből az MTMT adatbázisban 1199 db független hivatkozás található meg. Az eddigi publikációi teljes impakt faktor értéke 185, relatív impakt faktor 49. A Tud-O-Méter alapján az MTA doktora tudományos cím kritériumait minden szempontból eléri. A scientometrics.org lekérdezés alapján D1-es kutatónak minősül a saját szakterületén és nyolc “High impact papers” tartozik hozzá. 2023 szeptemberétől Bolyai János kutatói ösztöndíjjal végzi a kutatásait. A 2022-es évben az MTA Veszprémi Területi Bizottság az év Kiemelkedő Ifjú Kutatója díját ítélte meg számára a Műszaki tudományok területén. DAAD ösztöndíjjal négy, ill. Magyar Állami Eötvös Ösztöndíjjal egy hónapot töltött a Stuttgarti Egyetem Ipari automatizálási és szoftvermérnöki intézetnél, akikkel azóta nemzetközi projektet vezet. 2024-ben további három hónapot töltött a bécsi műszaki egyetemen (TU-Wien) az ember-gép kapcsolatok kutatócsoportnál szintén egy nyertes Magyar Állami Eötvös Ösztöndíjjal. Köztestületi tagja az MTA Műszaki Tudományok Osztályának Automatizálási és Számítástechnikai Tudományos Bizottságának. Vezetőségi tagja az MTA Fiatal Kutatók Akadémiájának. Egyedüli magyarként meghívásos alapon tagja az IFAC TC 5.1 és az IFIP 5.7-es nemzetközi szervezetek munkacsoportjainak. Alapító elnöke a GTE Operátor szakosztálynak és számos nemzetközi konferencia szervezőbizottsági tagja. Az elmúlt három évben megalkotta az Operátor 4.0 kutatói hálózatot, amelyet a kutatási téma megalkotójával Prof. David Romeroval vezetnek és szervezik a nemzetközi csapat szakmai munkáját, amelyhez kapcsolódóan 2023-ban Veszprémben, a Pannon Egyetemen szervezték meg az első Operátor 4.0 szimpóziumot, amelyre összesen kilenc országból hívtak meg kutatókat. Ehhez kapcsolódóan társelnökként alapította meg a Human-Centered Systems Special Interesting Group-ot az IFIP nemzetközi szervezetnél.

Ruppert Tamás publikációs jegyzéke

2025
MTMT független hivatkozások száma: **1200**
MTMT Hirsch index (független): **18**

Google tudós i10-index: **30**
Google tudós h-index: **22**
Google tudós hivatkozások száma: **1630**

1 Könyv, monográfia

1. J. Abonyi, L. Nagy, and T. Ruppert, *Ontology-Based Development of Industry 4.0 and 5.0 Solutions for Smart Manufacturing and Production: Knowledge Graph and Semantic Based Modeling and Optimization of Complex Systems*. Springer Nature, 2024

2 Külföldi kiadású szakfolyóiratban idegen nyelven megjelent cikkek

2. M. Gugolya, T. Medvegy, J. Abonyi, and T. Ruppert, "Assessing the learning curve of human operators under verbal distraction," *IET Collaborative Intelligent Manufacturing*, vol. 7, no. 1, p. e70038, 2025
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3. A. K. Eesee, V. Varga, G. Eigner, and T. Ruppert, "Impact of work instruction difficulty on cognitive load and operational efficiency," *Scientific Reports*, vol. 15, no. 1, p. 11028, 2025
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40. J. Hegedűs-Kuti, J. Szőlősi, D. Varga, G. Farkas, T. Ruppert, J. Abonyi, and M. Andó, "3d scanning and model error distribution-based characterisation of welding defects," *Hungarian Journal of Industry and Chemistry*, vol. 49, no. 2, pp. 3–7, 2021
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41. T. Ruppert and J. Abonyi, “Worker movement diagram based stochastic model of open paced conveyors,” *Hungarian Journal of Industry and Chemistry*, vol. 46, no. 2, pp. 55–62, 2018
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4 Külföldi szakmai koferencia kiadvány

42. A. K. Eesee, D. Kostolani, V. Varga, T. Kang, S. Schlund, and T. Ruppert, “Studying dual-task awareness in industrial settings through reaction times and physiological signals,” in *2025 IEEE Conference on Cognitive and Computational Aspects of Situation Management (CogSIMA)*, pp. 151–156, IEEE, 2025
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44. A. Nadaffard, N. Karimi, and T. Ruppert, “Integration of human learning and complexity effects in production ramp-up cost,” in *IFIP International Conference on Advances in Production Management Systems*, pp. 163–177, Springer, 2025
45. M. Gugolya, V. Varga, T. Medvegy, and T. Ruppert, “The impact of work instruction simplification on operator performance and learning curve efficiency,” in *IFIP International Conference on Advances in Production Management Systems*, pp. 148–162, Springer, 2025
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53. A. Racz-Szabo, T. Ruppert, and J. Abonyi, “Improving micro-logistics processes by indoor positioning system and the tools of data science,” *Editorial Board*, p. 10, 2024
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56. L. Nagy, T. Ruppert, and J. Abonyi, “Towards an ontology-based fault detection and diagnosis framework-a semantic approach,” in *2023 9th International Conference on Control, Decision and Information Technologies (CoDIT)*, pp. 1267–1272, IEEE, 2023
57. J. Grimstad, T. Ruppert, J. Abonyi, and A. Morozov, “Preventive risk-based maintenance scheduling using discrete-time markov chain models,” 2023
58. L. Nagy, T. Ruppert, and J. Abonyi, “Human-centered knowledge graph-based design concept for collaborative manufacturing,” in *2022 IEEE 27th International Conference on Emerging Technologies and Factory Automation (ETFA)*, pp. 1–8, IEEE, 2022
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62. T.-a. Tran, T. Ruppert, G. Eigner, and J. Abonyi, “Real-time locating system and digital twin in lean 4.0,” in *2021 IEEE 15th International Symposium on Applied Computational Intelligence and Informatics (SACI)*, pp. 000369–000374, IEEE, 2021
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5 Hazai szakmai koferencia kiadvány

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6 Egyéb szakmai oldalon való megjelenés

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Nyilatkozat

Dr. Hartung Ferenc

Vezető

Informatikai Tudományok Doktori Iskola

Tisztelt Professzor Úr!

Dr. Ruppert Tamás, mint a Pannon Egyetem Mérnöki Kar Rendszermérnöki Intézeti Tanszék egyetemi docense habilitációs eljárás lefolytatását kezdeményezem az Informatikai Tudományok Doktori Iskolánál Mesterséges Intelligencia tudományterületen. Ehhez kapcsolódóan nyilatkozom, hogy nincs folyamatban habilitációs eljárásom, továbbá az elmúlt két éven belül nem utasították el habilitációs kérelmemet. Továbbá nyilatkozom, hogy többéves egyetemi oktatói gyakorlattal rendelkezem. Javaslat a habilitációs eljárás nyilvános szakaszában tartandó tanórai előadások témájára:

1) Digitális iker és a folyamatmodellek
2) Folyamatbányászat beltéri pozícionáló rendszer adatain
3) Digitális ikerpár az ötödik ipari forradalomban

Az eljárás során tartandó tudományos kollokvium témájának címe:

Human-centered systems in manufacturing

Veszprém, 2025.09.30. Dr. Ruppert Tamás

Nyilatkozat többéves egyetemi oktatói gyakorlatról

Alulírott Dr. Ruppert Tamás nyilatkozom, hogy a Pannon Egyetemen 2017 óta oktatóként veszek részt az egyetemi hallgatók oktatásában. Az oktatási feladatokat 2017-től PhD hallgatóként, 2020-tól adjunktusként, 2022-től egyetemi docensként látom el.

Az egyetemi oktatásban aktívan oktatott féléveim száma (a PhD képzés során végzett oktatást is figyelembe véve): 17.

Az oktatói munkám során mechatronikai mérnök (BSc, MSc), adattudomány MSc, üzleti adattudomány BSc és posztgraduális hallgatók számára tartottam előadásokat és gyakorlatokat. A Pannon Egyetem Vegyészmérnöki és Anyagtudományok Doktori Iskolában, a Gazdálkodás- és Szervezéstudományok Doktori Iskolában, Informatikai Tudományok Doktori Iskolában, továbbá a Budapesti Corvinus Egyetem Közgazdasági és Gazdaságinformatikai Doktori Iskolájában vagyok aktív PhD témavezető.

Oktatói munkám során a következő tantárgyakat oktattam:

- Irányítástechnika I. és II.
- Biztonságkritikus rendszerek és intelligens karbantartás
- Folyamatmenedzsment
- Adatfeldolgozás és programozás
- Digitális iker és folyamat szimuláció
- Folyamatinformatika
- Folyamatmodellezés és folyamatbányászat
- Termelési intelligencia
- Termelési intelligencia és folyamatinformatika
- Digitális Iker
- Ipar 4.0 megoldások fejlesztése

Szak- és diplomadolgozatok vezetése

Szak- és diplomadolgozatok száma: 51

7 Önértékelési adatlap

Pályázó neve:	Ruppert Tamás	
A habilitáció támogatásához szükséges minimális pontszám:	**120**	
A pályázó összpontszáma	**185**	

	Érték	Pontszám
I. Felsőoktatási tevékenység (összesen adható pontok száma) 100		
1a.1. Oktatási tapasztalat		
Kontakt órák száma a pályázat benyújtását megelőző tíz évben	4500	
Ebből előadás	4038	
1a.2. Hallgatók tanulmányi, tudományos munkájának vezetése		
Diplomamunka, szakdolgozat. TDK témavezetések száma	63	
Összesen (1a.1.+1a.2.)		**60**
1a.3. Graduális és/vagy posztgraduális, illetve a Bologna-rendszer megfelelő képzési szintjeinek bármelyikén szervezett előadás, gyakorlat, szeminárium tartása idegen nyelven.		
Kontakt órák száma a pályázat benyújtásának időpontjáig (beleértve a külföldi vendégtanári meghívást).	0	
Összesen (1a.3.)		**0**
1b. Oktatásfejlesztési tevékenység, eredményesség		
Tárgyfelelősség – kötelező tárgy, db	14	
Tárgyfelelősség – fakultatív tárgy, db	1	
Érdemi részvétel tantárgy fejlesztésében, db	5	
jegyzet, tankönyv, legalább 100 oldalas oktatási segédlet vagy digitális tananyag (első vagy egyedüli vagy legalább 50%-ban szerzője), db	1	
Összesen (1b.1.+1b.2.)		**25**
I. Felsőoktatási tevékenység összesen		**85**

	Érték	Pontszám
II. Tudományos tevékenység (összesen adható pontok száma) 100		
2a.1. Kiemelkedő tudományos, kutatói munkásság (a pályázat benyújtásáig		
Rendelkezik-e MTA doktora címmel? (igen/nem)	nem	
MTA követelmények teljesülése: Q érték	51.596	
MTA követelmények teljesülése: I érték	1145	
Összesen (2a.1.)		**50**
2a.2. Fiatal oktatók tudományos munkájának vezetése, témavezetői részvétel doktori képzésben		
Fokozatot szerzett PhD-hallgató, fő (társtémavezetés 0,5 fő)	2.5	
Jelenlegi doktoranduszok, doktorjelöltek, fő (társtémavezetés 0,5 fő)	5.5	

2a.3. Műhelyteremtő képesség		
Műhelyteremtő tevékenység (pl.: kutatócsoport vezetője és/vagy alapítója), db	1	
2a.4. Szakmai közéleti tevékenység		
Szakmai közéleti tevékenység (pl.: egyetemi szakmai bizottság vezetője vagy tagja, más egyetem valamely bizottságának külső tagja, egyetemen kívüli szakmai testület tagja, egyetemi szenátus, kari tanács tagja, egyetemi szakmai bizottság elnöke vagy tagja), db	2	
Összesen (2a.2.+2a.3.+2a.4.)		**30**
2b.1. Kutatásszervezési tapasztalat, eredményesség		
Elnyert országos vagy nemzetközi kutatási/fejlesztési/innovációs pályázat témavezetése, db	2	
Érdemi részvétel országos vagy nemzetközi kutatási/fejlesztési/innovációs pályázat megvalósításában, db	10	
Intézményi pályázat témavezetése, db	3	
Összesen (2b.1.)		**10**
2b.2. Hazai és nemzetközi elismertség		
Hazai vagy nemzetközi tudományos szervezet elnöke, db	1	
Hazai vagy nemzetközi tudományos szervezet elnökségi tag, konferencia elnök, db	2	
Társelnök, szekciószervező elnök, felkért plenáris előadó,db	10	
Összesen (2b.2.)		**10**
II. Tudományos tevékenység összesen		**100**

Ruppert Tamás (Mérnöki)

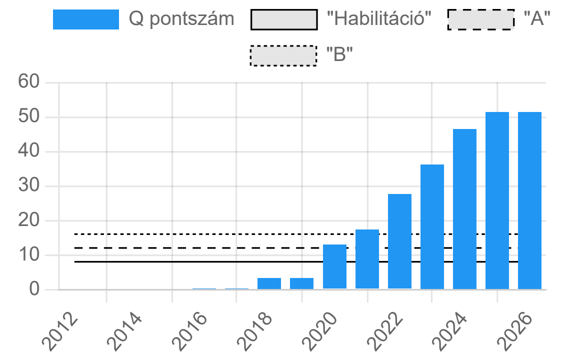
 PhD 2020

Lekérdezés dátuma: 2025. 08. 25. 9:57:20

Összefoglaló táblázat

	Pontszám	BME VIK Habilitáció	MTA-MTO Követelmény A	MTA-MTO Követelmény B
Q szám összesen:	51.339	8	12	16
Q szám cikkekből:	51.289		min. 6	min. 8
Q szám könyvből:	0.050		max. 3	max. 3
I szám:	1109	40	90	200
I szám WoS idézetekből:	524	20	45	100
Impakt faktor:	185.329			
Relatív impakt faktor:	49.662	2	3	4
IF-es cikkek száma:	37	4	6	8
Egyszerzős IF-es cikkek:	0		2	2
H index:	18	4	5	7
Összes idéző:	1259			
Összes publikáció:	87			

Figyelem! A Tud-O-Méter csak az 1993-ban, vagy később megjelent publikációk impakt faktorát ismeri, az ennél korábbi impakt faktoros folyóiratokat kézzel kell hozzávenni a pontozáshoz!


Q pontszám
"Habilitáció"
"A"
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2012
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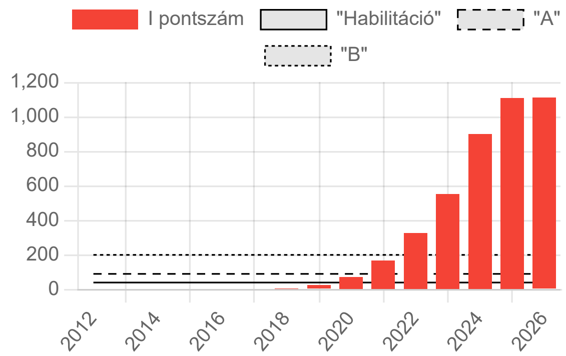
I pontszám
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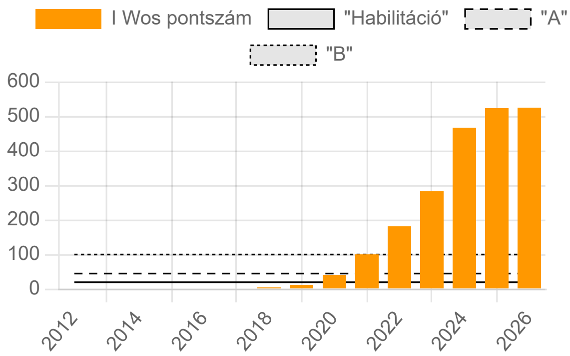
I Wos pontszám
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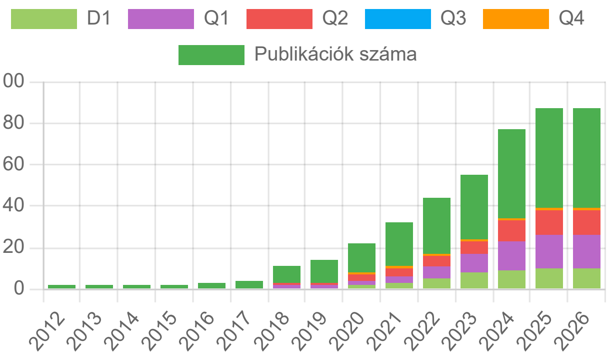
D1
Q1
Q2
Q3
Q4
Publikációk száma
100
80
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2012
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17

A kérelmező publikációs és alkotási teljesítménye (Q-szám)

Publikációk	Külföldön	Magyarországon		
		idegen nyelven	magyarul	
	megjelent közlemények száma			pontszám
Tudományos folyóiratcikk				
-lektorált	43	2	1	50.529
-lektorált, WoS Q1 rangú	15	0	0	
-lektorált, IF-ral	37	0	0	
-ebből egyszerzős	0	0	0	
Konferenciacikk (min. 4 oldal) konferenciakötetben, folyóiratban, könyvrészletben	12	2	0	0.760
Tudományos cikk összesen				51.289
Tudományos könyv, könyvrészlet szerzőként				
-könyv	0	0	0	0.000
-könyvrészlet	1	0	0	0.050
Tudományos könyv összesen				0.050
Internetes adatbázisban megtalálható	54	2	0	
Teljes szöveggel elérhető a Weben	55 (?)	2 (?)	1 (?)	

A kérelmező idézettsége (I-szám)

Hivatkozások darabszáma	könyvben, fejezetben	folyó-iratban	konf. cikkben	érteke-zésben	eddig összesen	oltalmi formában	további köz-leményben
csak külföldi szerző, külföldi kiadás	142	543	18	0	703	0	1
csak külföldi szerző, hazai kiadás vagy nincs megjelölve	45	0	2	10	57	0	5
hazai szerző (is) itthon (vagy nincs megjelölve hol)							
-idegen nyelven	2	15	0	0	17	0	0
-magyarul	0	1	0	0	1	0	0
nincs megadva, hogy van-e hazai szerző az idézők között	64	268	9	6	347	0	27
Összesen	253	827	29	16	1125	0	33

Független WoS (SCI) hivatkozásai: 524
Független Scopus hivatkozásai: 455
Független Google Scholar hivatkozásai: 51

Megjegyzés: A Tud-O-Méter a disszertációkban megjelent idézeteket nem számolja bele az "I" számba, mivel a szabályzat nem minden típusú értekezést fogad el idézőként.

Pontozás részletező

Publikáció	Q pont	I pont
Impact of work instruction difficulty on cognitive load and operational efficiency 2025, 4 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) WoS: Q1 SJR: Q1	0.975	0
Studying Dual-Task Awareness in Industrial Settings Through Reaction Times and Physiological Signals 2025, 6 szerző, Könyvrészlet/Szaktanulmány (Könyvrészlet) (Túl rövid, 6 oldal!!!)	0.000	0
Assessing the Learning Curve of Human Operators Under Verbal Distraction 2025, 4 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) WoS: Q3 SJR: Q2	0.775	0
Digital Shadow Implementation for Intelligent Maintenance Application - A Case Study 2025, 4 szerző, Könyvrészlet/Szaktanulmány (Könyvrészlet) (Túl rövid, 6 oldal!!!)	0.000	0
A kutatói életpálya kihívásai és a pályaelhagyás lehetséges okai a fiatal kutatók akadémiai életútján 2025, 5 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk)	0.060	0
Risk-Based Maintenance Optimization of Production Tools in a Dynamic Environment 2025, 3 szerző, Könyvrészlet/Szaktanulmány (Könyvrészlet) (Túl rövid, 6 oldal!!!)	0.000	0
The Future of Manufacturing and Industry 4.0 2025, 2 szerző, Folyóiratcikk/Összefoglaló cikk (Folyóiratcikk) WoS: Q2 SJR: Q2	1.250	1
Nagy nyelvi modell alapú tevékenységfelismerés és munkautasítások validálása = Large lenguage model based activity recognition and validation of work instructions 2025, 2 szerző, Egyéb konferenciaközlemény/Absztrakt / Kivonat (Egyéb konferenciaközlemény)	0.000	0
Clustering and Network Analysis of Mobility Patterns as an Analysis Tool for Lean Project 2025, 3 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) SJR: Q1	0.133	0
WEBA dataset as the Reflection of Work content effect on Workload perception in Real life Working conditions 2025, 4 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) WoS: Q1 SJR: D1	1.725	0
Utilizing Biosensor Technologies to Improve Industrial Efficiency and Promote Worker Well-being 2024, 3 szerző, Egyéb/Nem besorolt (Egyéb)	0.000	0
Utilizing Biosensor Technologies to Improve Industrial Efficiency and Promote Worker Well-being 2024, 3 szerző, Könyvrészlet/Absztrakt / Kivonat (Könyvrészlet)	0.000	0
Designing Augmented Reality Assistance Systems for Operator 5.0 Solutions in Assembly 2024, 5 szerző, Könyvrészlet/Konferenciaközlemény (Könyvrészlet)	0.040	0
Extending factory digital Twins through human characterisation in Asset Administration Shell 2024, 6 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) WoS: Q2 SJR: Q1	0.667	18
Particle filtering supported probability density estimation of mobility patterns 2024, 3 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) WoS: Q1 SJR: Q1	1.200	2
Human-Centered Task Allocation: A Simulation-Based Case Study 2024, 4 szerző, Folyóiratcikk/Konferenciaközlemény (Folyóiratcikk)	0.100	0
Extension of HAAS for the management of cognitive load 2024, 5 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) WoS: Q2 SJR: Q1	0.720	5
May I Have Your Attention?! Exploring Multitasking in Human-Robot Collaboration 2024, 7 szerző, Folyóiratcikk/Konferenciaközlemény (Folyóiratcikk)	0.057	1
Az emberi operátorok tanulási görbéjének értékelése a kognitív terhelés során 2024, 3 szerző, Könyvrészlet/Absztrakt / Kivonat (Könyvrészlet)	0.000	0
Game-Based Design of a Human-Machine Collaboration Monitoring System 2024, 4 szerző, Könyvrészlet/Konferenciaközlemény (Könyvrészlet)	0.050	0
Digitális Ikerpárral támogatott kockázat alapú karbantartás 2024, 4 szerző, Könyvrészlet/Absztrakt / Kivonat (Könyvrészlet)	0.000	0
Embermodell alapú tevékenység felismerés 2024, 2 szerző, Könyvrészlet/Absztrakt / Kivonat (Könyvrészlet)	0.000	0
Enriching Scene-Graph Generation with Prior Knowledge from Work Instruction 2024, 5 szerző, Könyvrészlet/Konferenciaközlemény (Könyvrészlet)	0.040	0
Self-improving situation awareness for human–robot-collaboration using intelligent Digital Twin 2024, 4 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) WoS: Q1 SJR: D1	1.850	31
Knowledge Graph-Based Framework to Support Human-Centered Collaborative Manufacturing in Industry 5.0 2024, 3 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) WoS: Q2 SJR: Q2	0.833	4
Goal-oriented clustering algorithm to monitor the efficiency of logistic processes through real-time locating systems 2024, 4 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) WoS: Q2 SJR: Q1	1.000	2
Enhancing material supply for an automated production line by implementing a Markov Decision Process model for AGV-based material handling 2024, 3 szerző, Könyvrészlet/Konferenciaközlemény (Könyvrészlet)	0.067	2

Publikáció	Q pont	I pont
Data reconciliation of indoor positioning data: Improve position data accuracy in warehouse environment 2024, 3 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) WoS: Q2 SJR: Q2	0.633	1
Multilayer Network-Based Evaluation of the Efficiency and Resilience of Network Flows 2024, 3 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) WoS: Q2 SJR: Q1	0.567	1
Ontology-Based Development of Industry 4.0 and 5.0 Solutions for Smart Manufacturing and Production 2024, 3 szerző, Könyv/Szakkönyv (Könyv) (Nincs terjedelem megadva!!!)	0.000	3
Technology-enabled cognitive resilience: what can we learn from military operation to develop Operator 5.0 solutions? 2024, 3 szerző, Folyóiratcikk/Összefoglaló cikk (Folyóiratcikk) WoS: Q2 SJR: Q2	1.067	3
The Use of eXplainable Artificial Intelligence and Machine Learning Operation Principles to Support the Continuous Development of Machine Learning-Based Solutions in Fault Detection and Identification 2024, 3 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) WoS: Q2 SJR: Q2	1.400	2
IMPROVING MICRO-LOGISTICS PROCESSES BY INDOOR POSITIONING SYSTEM AND THE TOOLS OF DATA SCIENCE 2023, 3 szerző, Egyéb konferenciakötet	0.000	0
Multi-objective hierarchical clustering for tool assignment 2023, 5 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) WoS: Q2 SJR: Q1	0.920	5
Current development on the Operator 4.0 and transition towards the Operator 5.0: A systematic literature review in light of Industry 5.0 2023, 6 szerző, Folyóiratcikk/Összefoglaló cikk (Folyóiratcikk) WoS: Q1 SJR: D1	2.050	126
Indoor Positioning-based Occupational Exposures Mapping and Operator Well-being Assessment in Manufacturing Environment 2023, 4 szerző, Könyvrészlet/Könyvfejezet (Könyvrészlet)	0.050	0
3D Scanner-Based Identification of Welding Defects—Clustering the Results of Point Cloud Alignment 2023, 6 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) WoS: Q2 SJR: Q1	0.567	7
Logisztikai és termelési folyamatok optimálása reinforcement learning algoritmussal = Optimizing logistics and production processes with reinforcement learning algorithm 2023, 3 szerző, Könyvrészlet/Absztrakt / Kivonat (Könyvrészlet)	0.000	0
Demonstration Laboratory of Industry 4.0 Retrofitting and Operator 4.0 Solutions: Education towards Industry 5.0 2023, 5 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) WoS: Q2 SJR: Q1	0.680	28
Ipar 4.0 -Beltéri pozícionálás – a barnamezős ipari digitalizáció alapja 2023, 1 szerző, Egyéb konferenciaközlemény/Absztrakt / Kivonat (Egyéb konferenciaközlemény)	0.000	0
The human-centric Industry 5.0 collaboration architecture 2023, 6 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) WoS: Q2 SJR: Q2	0.283	54
Assessing human worker performance by pattern mining of Kinect sensor skeleton data 2023, 4 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) WoS: Q1 SJR: D1	3.075	14
Heart Rate Variability Measurement to Assess Acute Work-Content-Related Stress of Workers in Industrial Manufacturing Environment—A Systematic Scoping Review 2023, 9 szerző, Folyóiratcikk/Összefoglaló cikk (Folyóiratcikk) WoS: Q1 SJR: D1	0.956	8
Data-driven business process management-based development of Industry 4.0 solutions 2022, 4 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) WoS: Q2 SJR: Q1	1.200	56
Processing indoor positioning data by goal-oriented supervised fuzzy clustering for tool management 2022, 4 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) WoS: Q1 SJR: D1	3.025	12
PATRICLE FILTER ALKALMAZÁSA MOBILITÁSI MINTÁZATOK ELEMZÉSÉRE (PARTICLE FILTER FOR MOBILITY PATTERN ANALYSIS) 2022, 3 szerző, Könyvrészlet/Absztrakt / Kivonat (Könyvrészlet)	0.000	0
Machine learning-based software sensors for machine state monitoring - The role of SMOTE-based data augmentation 2022, 4 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) SJR: Q2	1.250	22
Trajectory Prediction of Moving Workers for Autonomous Mobile Robots on the Shop Floor 2022, 6 szerző, Könyvrészlet/Konferenciaközlemény (Könyvrészlet)	0.033	6
Goal-oriented possibilistic fuzzy C-Medoid clustering of human mobility patterns—Illustrative application for the Taxicab trips-based enrichment of public transport services 2022, 6 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) WoS: Q2 SJR: Q1	0.617	1
Hypergraph-based analysis and design of intelligent collaborative manufacturing space 2022, 4 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) WoS: Q1 SJR: D1	3.025	17
Human-centered knowledge graph-based design concept for collaborative manufacturing 2022, 3 szerző, Könyvrészlet/Konferenciaközlemény (Könyvrészlet)	0.067	11
Folyamatok többrétegű hálózatokban 2022, 3 szerző, Könyvrészlet/Absztrakt / Kivonat (Könyvrészlet)	0.000	0
Intelligent Collaborative Manufacturing Space for Augmenting Human Workers in Semi-Automated Manufacturing Systems 2022, 4 szerző, Könyvrészlet/Konferenciaközlemény (Könyvrészlet)	0.050	4

Publikáció	Q pont	I pont
Retrofitting-based development of brownfield Industry 4.0 and Industry 5.0 solutions 2022, 4 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) WoS: Q2 SJR: Q1	0.975	53
Heart Rate Variability measurement to assess Work-Related Stress of physical workers in manufacturing industries - Protocol for a Systematic Literature Review 2022, 5 szerző, Könyvrészlet/Konferenciaközlemény (Könyvrészlet)	0.040	3
Data administration shell for data-science-driven development 2021, 6 szerző, Folyóiratcikk/Konferenciaközlemény (Folyóiratcikk)	0.067	11
Szerszám menedzsment támogatás beltéri pozíció adatok Gauss keverék modell alapú csoportosításával 2021, 3 szerző, Egyéb konferenciaközlemény/Absztrakt / Kivonat (Egyéb konferenciaközlemény)	0.000	0
3D Scanning and Model Error Distribution-Based Characterisation of Welding Defects 2021, 7 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk)	0.043	0
Tailored digitization with real-time locating systems 2021, 7 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk)	0.057	4
Architecture of a Human-Digital Twin as Common Interface for Operator 4.0 Applications 2021, 5 szerző, Egyéb konferenciaközlemény/Konferenciaközlemény (Egyéb konferenciaközlemény)	0.040	44
Ontology-Based Analysis of Manufacturing Processes: Lessons Learned from the Case Study of Wire Harness Production 2021, 3 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) WoS: Q2 SJR: Q1	0.707	18
Folyamatfejlesztési módszertanok alkalmazása közlekedési hálózatokban - New York taxi esettanulmány 2021, 3 szerző, Egyéb konferenciaközlemény/Absztrakt / Kivonat (Egyéb konferenciaközlemény)	0.000	0
Estimation of machine setup and changeover times by survival analysis 2021, 3 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) WoS: Q1 SJR: D1	2.393	15
Real-time locating system and digital twin in Lean 4.0 2021, 4 szerző, Könyvrészlet/Konferenciaközlemény (Könyvrészlet)	0.050	24
Indoor Positioning Systems Can Revolutionise Digital Lean 2021, 3 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) WoS: Q2 SJR: Q2	0.946	27
Real-Time Locating System in Production Management 2020, 6 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) WoS: Q1 SJR: Q2	0.596	58
Pozícióadatokon alapuló automatizált folyamatmodellépítés 2020, 3 szerző, Könyvrészlet/Absztrakt / Kivonat (Könyvrészlet)	0.000	0
Monitoring Activity During Wire Harness Assembly 2020, 2 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) SJR: Q4	0.200	0
Trajectory Prediction of Humans in Factories and Warehouses with Real-Time Locating Systems 2020, 6 szerző, Könyvrészlet/Konferenciaközlemény (Könyvrészlet)	0.033	14
Analytic Hierarchy Process and Multilayer Network-Based Method for Assembly Line Balancing 2020, 3 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) WoS: Q2 SJR: Q2	0.893	18
Fuzzy activity time-based model predictive control of open-station assembly lines 2020, 3 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) WoS: Q1 SJR: D1	2.878	20
Integration of real-time locating systems into digital twins 2020, 2 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) WoS: Q1 SJR: D1	5.032	79
Új eszköztár az operátorok munkáját támogató Ipar 4.0 megoldások fejlesztésére 2020, 1 szerző, Disszertáció/PhD (Disszertáció)	0.000	0
Digitális iker a gyártási folyamat optimalizációban 2019, 3 szerző, Könyvrészlet/Konferenciaközlemény (Könyvrészlet) (Túl rövid, 1 oldal!!!)	0.000	0
OPTIMIZING RESOURCES ASSIGNMENT FOR BALANCING MODULAR PRODUCTION LINE 2019, 4 szerző, Könyvrészlet/Konferenciaközlemény (Könyvrészlet)	0.050	0
OPTIMIZING RESOURCES ASSIGNMENT FOR BALANCING KSK PRODUCTION LINE 2019, 4 szerző, Könyvrészlet/Absztrakt / Kivonat (Könyvrészlet)	0.000	0
Multiobjective optimal sensor placement for data reconciliation 2018, 3 szerző, Egyéb/Nem besorolt (Egyéb)	0.000	0
Enabling Technologies for Operator 4.0: A Survey 2018, 4 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) WoS: Q2 SJR: Q1	0.554	227
„Digitális Iker” a jövő termelésmenedzsmentjében 2018, 3 szerző, Könyvrészlet/Absztrakt / Kivonat (Könyvrészlet)	0.000	0
Worker movement diagram based stochastic model of open paced conveyors 2018, 2 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk)	0.150	2
Industrial Internet of Things based cycle time control of assembly lines 2018, 2 szerző, Könyvrészlet/Konferenciaközlemény (Könyvrészlet)	0.100	20
Software Sensor for Activity-Time Monitoring and Fault Detection in Production Lines 2018, 2 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) WoS: Q1 SJR: Q2	1.516	22
Multilayer Network-Based Production Flow Analysis 2018, 3 szerző, Folyóiratcikk/Szakcikk (Folyóiratcikk) WoS: Q1 SJR: Q1	0.864	2

Publikáció	Q pont	I pont
Assembly line balancing with conveyor stoppages in wire harness industry 2017, 2 szerző, Könyvrészlet/Absztrakt / Kivonat (Könyvrészlet)	0.000	0
CYCLE TIME ADAPTATION OF STOCHASTIC ASSEMBLY LINE 2016, 2 szerző, Könyvrészlet/Konferenciaközlemény (Könyvrészlet)	0.100	0
Interactive Balanced Scorecard based on Simulation of Production and Services Systems 2012, 5 szerző, Egyéb konferenciaközlemény/Konferenciaközlemény (Egyéb konferenciaközlemény) (Nincs terjedelem megadva!!!)(Nincs ISBN/ISSN szám megadva!!!)	0.000	0
Monte-Carlo sensitivity analysis of discrete event simulation – applications to the development of production and services processes 2012, 5 szerző, Egyéb konferenciaközlemény/Konferenciaközlemény (Egyéb konferenciaközlemény) (Nincs terjedelem megadva!!!)(Nincs ISBN/ISSN szám megadva!!!)	0.000	1

9 Habilitációs tézisek magyarul

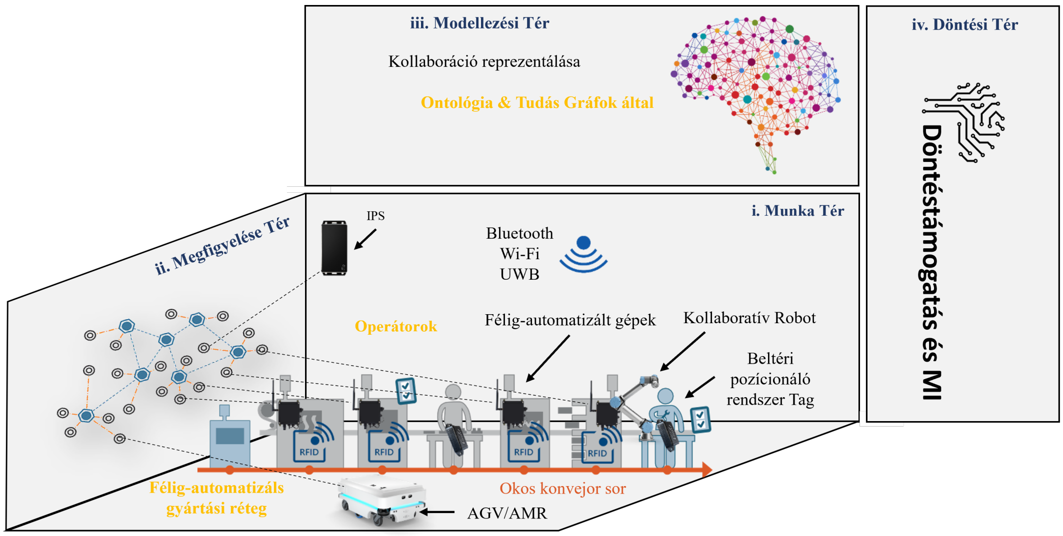
Az elmúlt öt évben az emberközpontú gyártási kihívásokra és azok megoldásaira koncentráltam. Miután megszereztem a doktori fokozatom egy kapcsolódó területen, elkezdtem kidolgozni az Ipar 5.0 laboratóriumot és összeállítani egy kutatás-fejlesztései csapatot.

A magyarországi és az európai iparágak munkaerő-kitettsége miatt erősödő probléma a társadalom elöregedése és a humánerőforrás-változás szükségessége. Az üzleti területen mindig a teljesítmény és a befektetés megtérülése (ROI) a legfontosabb szempont. Mivel Európa munkaerőhiánnyal küzd, ezek a szempontok az utóbbi években még fontosabbá váltak. A munkaerő teljesítményének csökkenésének fő okainak megértése egyre fontosabb, ezáltal a piac egyre inkább emberközpontú és motivált munkahelyeket teremt és igényel.

Az emberi tevékenységek megértése az első lépés egy támogató rendszer létrehozásában. Ennek érdekében különböző módszereket fejlesztettünk ki az emberközpontú teljesítményértékeléshez, ötvözve a hagyományos Lean módszertanokat a legújabb technológiákkal. Jelentős tapasztalatokkal rendelkezem a valós idejű helymeghatározó rendszerek (RTLS), más néven beltéri helymeghatározó rendszerek (IPS) terén. Emellett különböző megoldásokon dolgozunk a vizuális alapú tevékenységfelismerés területén.

Ahhoz, hogy a munkavállalóinkra vonatkozó információkat integráljuk a jelenlegi rendszerünkbe, emberközpontú modellekre és adatstruktúrákra van szükségünk. Kidolgoztunk egy Human-Asset Administration Shell (HAAS) modellt, amely fiziológiai paramétereket és számított emberközpontú tényezőket, például kognitív terhelést és stresszszintet tartalmaz. Bizonyítottuk azt is, hogy az emberközpontú tudásgráfok hasznosak az emberi viselkedés modellezéséhez. Összességében az Intelligens Kollaboratív Gyártási Tért (Intelligent Collaborative Manufacturing Space - ICMS) keretrendszert fejlesztettem ki. A kifejlesztett ICMS keretrendszer alapján megteremtettem az emberközpontú rendszerek alapjait. Számos laboratóriumi kísérletet végeztünk, hogy bemutassuk a fiziológiai jelek alkalmazhatóságát a gyártásban hordható érzékelők segítségével. Mivel a munkavégzésre vonatkozó utasítások jelentős szerepet játszanak az iparban, kidolgoztunk egy értékelési módszert azok hatékonyságának felmérésére is.

A következőkben röviden bemutatom az ICMS keretrendszert, amely az elmúlt öt évnyi kutatásaim eredményeként alakult ki. Az ICMS célja egy új szintű együttműködési környezet létrehozása, ahol az emberi munkavállalók és az automatizált és félig automatizált termelési eszközök ugyanazon a területen dolgozhatnak együtt, hogy olyan termelékenységi és rugalmassági szintet érjenek el, amelyet egyikük sem tudna egyedül elérni. Ennek megvalósításához intelligens automatizálási rendszerekre van szükség a „ember-automatizálás szimbiózis" eléréséhez. Az ICMS célja egy keretrendszer létrehozása az intelligens érzékelőhálózatok és az adattudományi technikák alapján történő együttműködések támogatására. A 10.1 ábra a javasolt ICMS elemeit mutatja be, amelynek célja az automatizált és félig automatizált termelési eszközök valós idejű, megfigyelésen alapuló vezérlésének bemutatása, hogy az emberi munkavállalók és a gépek közötti együttműködés biztonságosabbá és pontosabbá váljon. Négy fő elem vagy altere jellemzi ezt az „intelligens munkaterületet": (i) a munkaterület, (ii) a megfigyelési terület, (iii) a modellezési terület és (iv) a döntési terület.



9.1. ábra: Az intelligens együttműködésen alapuló gyártási rendszer négy tere

Az ICMS egy olyan keretrendszer, amelynek célja az emberek és az automatizált és félig automatizált termelési eszközök közötti hatékony együttműködés támogatása, tevékenységfelismerés és -előrejelzés, valamint gépi tanulási optimalizáló algoritmusok alapján.

9.1 A dolgozat áttekintése és összefoglalása

9.1.1 I. Téziscsoport

Kifejlesztettem egy algoritmus csomagot és módszertani rendszert, amely a valós idejű helymeghatározó rendszer (RTLS) információi és a vizuális megfigyelésen alapú tevékenységfelismerés alapján értékeli ki az emberközpontú teljesítménymutatókat. Ezeket a digitális megoldásokat összekapcsoltuk a hagyományos Lean technikákkal, hogy valós idejű és adatalapú folyamatfejlesztést biztosítsunk.

Bebizonyítottuk, hogy az RTLS nem csak a teljesítményértékeléshez használható, hanem a valós gyártási környezetben dolgozó munkavállalók körülményeinek felméréséhez is. Az eredmények azt mutatják, hogy a beltéri helymeghatározási adatok nemcsak a munkavállalók mozgásának és tevékenységének nyomon követéséhez hasznosak, hanem a tényleges környezeti információkról (pl. zaj, hőmérséklet) is információt nyújtanak, amelyek alapján értékelhető az ember térbeli és időbeli komfort szint változása is.

A hagyományos csontvázadatokon alapuló elemzéseket alkalmaztuk a gyártósoron végzett emberi teljesítmény értékelésére, hogy értékes információkat nyújtsunk a feladatok jobb elosztásához. Az MS Kinect adatokat a hagyományos Lean technikával párosítottuk, hogy értékeljük az emberi teljesítményt egy valós gyártási adatkészleten. Az eredmények megmutatták a csontvázadatok alkalmazhatóságát, és bizonyították azok hasznosságát az emberközpontú teljesítményértékelés esetében.

Összefoglalva, a téziscsoport értékes eszközkészletet biztosít a valós gyártási helyzetekben az operátorok teljesítményének és komfort szintjének felmérésére és kiértékelésére, valamint ezeknek a vizuális és érzékelőalapú információknak a hagyományos Lean technikákkal való összekapcsolására a hatékonyabb folyamatok létrehozása érdekében.

9.1.2 II. Téziscsoport

A valós idejű teljesítménymérések kezelése érdekében kifejlesztettem egy emberi Asset Administration Shell (HAAS) modellt, amely az emberi digitális iker alapját képezi, és támogatja az emberi tényezők (úgy, mint fiziológiai jelek, képességek, stb.) integrációját. Emellett bizonyítottam a tudásgráf használhatóságát, és kifejlesztettem egy emberközpontú tudásgráfot a gyártási komplex rendszerek modellezésére kifejezetten az emberi munkaerőt előtérbe helyezve.

Kifejlesztettünk egy kiterjesztett HAAS modelt a feladatkiosztással és operátorral kapcsolatos információk kezelésére. Egyrészt a modell képes kezelni a valós idejű fiziológiai mutatók alapján ténylegesen érzékelt kognitív terhelést, másrészt a modell kezeli a feladat követelményeit is, mint például a környezeti feltételeket, a munkavállaló jellemzőit és a feladatspecifikus információkat (például rutin vagy nem rutin, kognitív vagy fizikai igénybevételt jelentő, egyéni vagy csapatmunkát igénylő), hogy a kijelölt feladatokat az operátor képességeihez illessze. A modell a kognitív terheléskezelés alapját képezi, értékes adatsémával a feladatkiosztáshoz.

Mindezen információk a termelési rendszerekkel való hatékony integrálására egy emberközpontú tudásgráfot (HCKG) fejlesztettünk ki, hogy standard ontológiák, adatkinyerési módszerek és lehetséges alkalmazások segítségével tudásgráfot hozva létre az emberrel kapcsolatos folyamatok kezeléséhez. A kifejlesztett gráf értékes megoldás a termelésirányítás számára, ahol különböző eszközöket/szereplőket (robotokat, operátorokat, érzékelőket és aktuátorokat) kell kezelni egy rendszerben.

9.1.3 III. Téziscsoport

A fizikai aktivitás teljesítményének mérését kiegészítve az emberközpontú információkkal, elkezdtem dolgozni a gyártási környezetben végzett fiziológiai információk mérhetőségén, hogy a teljesítmény megfigyelése, a feladatkiosztás és a folyamatfejlesztés alapján emberközpontúbb és személyre szabottabb megoldásokat tudjunk kidolgozni. Egyszerű, viselhető szenzorokkal bizonyítottam a fiziológiai jelek használhatóságát és alkalmazhatóságát a gyártási folyamatokban, integrálva a valós idejű emberi állapotokat és viselkedéseket a gyártási rendszerekbe.

Elkezdtem a gyártással kapcsolatos kísérleteket, hogy szubjektív és objektív módon mérjem a kognitív terhelést "multitasking" környezetben, ahol a résztvevőknek egy adott másodlagos feladatot kellett elvégezniük az elsődleges feladat végrehajtása közben. Mindkét esetben az eredmények ígéretes összefüggést mutattak az észlelt kognitív terhelés és a tudatosság szintje, valamint az iparban használható hordható érzékelőkkel mért fiziológiai adatok között. Ezek az "open source" kísérleti adatkészletek értékes információkat nyújtanak a további kutatásokhoz ezeken a területeken, mivel alapul szolgálnak az iparban használható érzékelők alkalmazhatóságához a gyártási folyamatokban az emberi munkavállalók kognitív terhelésének értékelése céljából.

A munkautasítások az egyik leggyakrabban használt felület az emberi munkavállalók támogatására, mivel minden szükséges információt megadnak a tényleges feladatok végrehajtásához. Objektíven mértük a különböző típusú munkavégzési utasítások (például kód- és vizuális alapúak) használhatóságát és hatékonyságát egy laboratóriumi környezetben végzett összeszereléshez hasonló feladat során. A teljesítményt és a minőséget a fiziológiai méréseken és a résztvevők szubjektív értékelésén keresztül mértük. Az eredmények értékes információkat szolgáltattak a kód- és vizuális alapú munkavégzési utasítások helyes használatáról, valamint a hordható érzékelők alkalmazhatóságáról.

9.2 I. téziscsoport: Emberközpontú teljesítményértékelés

Az emberközpontú gyártásban egyre nagyobb jelentőséget kap az operátorok teljesítményének figyelemmel kísérése. Ezt a tendenciát a képzett munkaerő egyre növekvő hiánya, a valós idejű helymeghatározó rendszerek integrálása és a vizuális alapú tevékenységkövető technológiák egyre szélesebbkörű használhatósága ösztönzi. Ezek a fejlesztések pontosabb, rugalmasabb és munkavállaló-orientáltabb megközelítést tesznek lehetővé az ipari folyamatok irányításában, biztosítva mind a működési hatékonyságot, mind az emberek komfort szintjét. Ebben a téziscsoportban bebizonyítom a valós idejű helymeghatározó rendszerek és a vizuális megfigyelési eszközök alkalmazhatóságát az emberi tevékenységek felismerésében.

9.2.1 Valós idejű helymeghatározó rendszerek használhatósága

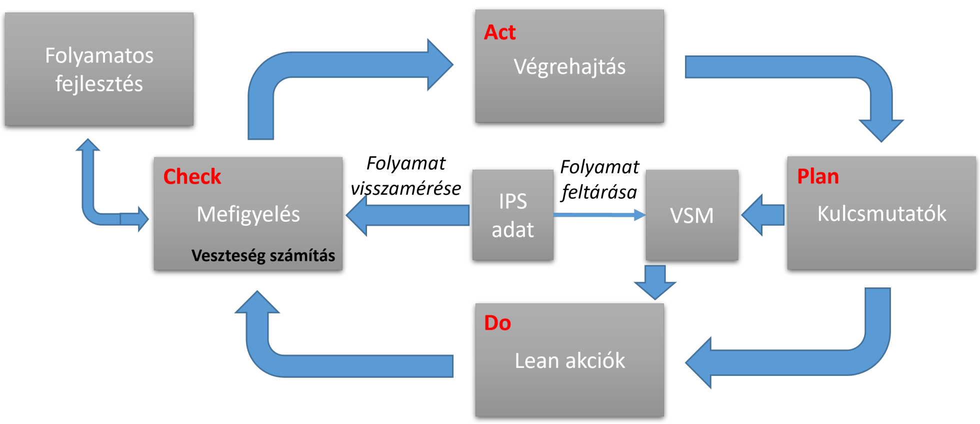
A kutatás háttere

Az emberi munkavállalók értékelése nehéz feladat, mivel mindannyian különbözőek vagyunk, különösen egy komplex gyártási folyamatban. Emberközpontú megoldásként emberorientált és személyre szabott értékelési rendszerre van szükség. Ebből a célból különböző algoritmusokat fejlesztettem ki, hogy az úgynevezett beltéri helymeghatározó rendszer (IPS, más néven valós idejű helymeghatározó rendszer – RTLS) információiból értékes, emberközpontú információkat nyerjek ki, a hagyományos Lean technikákkal párosítva.

A Lean elvek és a digitális technológiák hatékony kombinációja gyorsabbá teszi a veszteségek azonosítását és csökkentését, mint a hagyományos Lean módszerek. Az új Digital Lean (más néven Lean 4.0) megoldások szenzorokat és digitális berendezéseket tartalmaznak, így innovatív megoldásokat kínálnak, amelyek kiterjesztik a hagyományos Lean eszközök hatékonyságát. A kifejlesztett algoritmusok és módszerek nemcsak a teljesítménymutatókat, hanem a munkavállalók tényleges komfort szintjét is képesek értékelni.

A kidolgozott módszerek

A beltéri pozícióadatok és a Plan–Do–Check–Act (PDCA) ciklus alapján egy keretrendszert dolgoztunk ki (lásd a 10.2 ábrát) a beltéri környezetben dolgozó operátorok komfort szintjének és teljesítményének értékelésére, ahol az operátorok kényelmi szintje mérhető mutatóként szolgál. Ez egy részletes útmutató arról, hogyan lehet az IPS által nyújtott információkat felhasználni a Lean menedzsmentben. A javasolt módszer a folyamatos fejlesztés koncepciójába ágyazódik. A Six Sigma módszertanban alkalmazott strukturált DMAIC (Define-Measure-Analyze-Improve-Control) megközelítés szintén követi a PD-CA ciklus koncepcióját, amely hatékonynak bizonyult a nem értéknövelő tevékenységek csökkentésében az ellátási láncokban és a szerelősorokon.

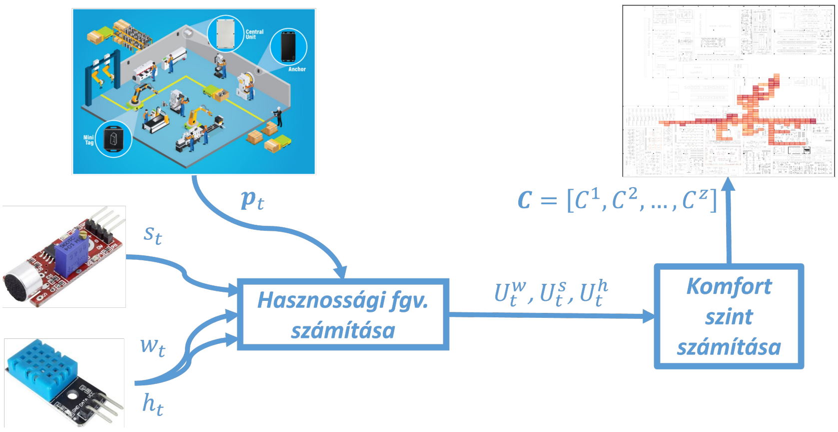


9.2. ábra: Az IPS-adatok a javasolt PDCA-alapú módszertan kulcsfontosságú elemeivel.

A módszer központi eleme a folyamatmodell (a 10.2 ábrán VSM-ként ábrázolva), amely a gyártási folyamatra vonatkozó összes lényeges információt tartalmazza. A javasolt fejlesztési ciklus az IPS-adatok segítségével folyamatosan frissíti a modellt. A cél a gyártás folyamatos és automatikus figyelemmel kísérése. A kifejlesztett keretrendszer a folyamatbányászat eszköztárával az IPS-adatok alapján folyamatosan feltárja a valós folyamatmodellt. Az így kapott modelleket a VSM-ek frissítésére, valamint a folyamat teljesítményének értékelésére használjuk a Lean KPI-k kiszámításával. Gantt-diagramokat alkalmaztunk a műveletek időtartamának elemzésére. A pozíció adatok elemzése alapján a gyártási folyamat további állapotaiban lehet meghatározni és hozzárendelni a termék- és anyagáramlásokat, valamint az erőforrások állapotait (pl. meghatározhatók az időbeli készletek). Az IPS folyamatbányászati algoritmusok által feltárt állapotok és további időbélyegek felhasználhatók a VSM-ek frissítésére. A folyamatáramok valós idejű pozíciójának köszönhetően mozgásalapú anomáliák is felismerhetők.

Fontos megérteni azokat a konkrét területeket és körülményeket, ahol a munkavállalók különböző környezeti tényezőknek vannak kitéve. Az elosztott információk elengedhetetlenek a foglalkozási expozíciók (zajok, hőmérsékleti kitettség, fényviszonyok, stb.) térbeli és kontextusba helyezett eloszlásának megragadásához. A koncentrált paraméterekkel ellentétben ez az expozíció az egyes operátorok és munkahelyek között eltérő. Egyértelmű célkitűzés megfogalmazásához szükséges megfogalmazni a térbeli és időbeli dimenziókat egyaránt magában foglaló részletes információk iránti igényt. Ennek elérése érdekében kontextusba helyezett, a releváns adatokhoz kapcsolódó pozícióalapú információkra van szükség. Beltéri helymeghatározási adatokat építettünk be a helyalapú szenzorinformációk létrehozásához. Az IPS alkalmazása és továbbfejlesztése megoldást jelent ezekre a motivációkra. Az IPS-szenzorok és a kapcsolódó elemzési technikák alkalmazásával pontos, helyalapú információk gyűjthetők. Az IPS-érzékelők és a kapcsolódó technológiák integrálása ígéretes lehetőséget kínál a munkahelyi megfigyelés és tervezés fejlesztésére, végső soron pedig egy biztonságosabb és hatékonyabb munkakörnyezet elősegítésére.

Az szenzor-fúziós módszertant a 10.3 ábra szemlélteti. Ez a keretrendszer leírja az információs folyamatot, amelyben van egy mérési pontunk, amely magában foglalja a páratartalmat (h_t), a hőmérsékletet (w_t), a zajt (s_t) és a tényleges pozícióadatokat ($\mathbf{p}_t$), ahol t a tényleges időpontot jelöli.



9.3. ábra: Az emberi komfort szint értékelésére kidolgozott keretrendszer információs folyama.

Ehhez a jellemzéshez meghatároztunk egy úgynevezett komfort szintet. Az érték azt mutatja, hogy az operátorok milyen mértékben képesek kezelni a környezeti terhelést a gyárterület egyes zónáiban, és mennyire érzik magukat kényelmesen ezeken a területeken. Ennek az új mutatószámnak a mérésére egy mobil érzékelő egységet is kifejlesztettünk, amely a standard IPS-címke kiegészítéseként szolgál, hogy a mérés költséghatékonyabb legyen. Ezzel az ötlettel a gyárterületen található összes mozgó egységet, például az AGV-ket (automatizált vezérelt járművek) vagy az AMR-eket (autonóm mobil robotok), sőt még a kifejlesztett szenzorral felszerelt anyagmozgató gépek és kézi szállító kocsik kezelőit is felhasználhatjuk.

Az eredmények alapján az IPS egy folyamatos megfigyelő rendszerként működik, amely hozzájárul a Lean szakemberek mindennapi munkájához. Első lépésként minden munkaállomáson riasztórendszert lehet beállítani, amely jelzi, ha az adott állomáson a munka- vagy várakozási idő meghaladja, ill. a komfort szint (zaj, hómérséklet, stb.) az előre meghatározott határértéket, így a gyártósorvezető időben megteheti a szükséges támogató intézkedéseket. Az integrált IPS alkalmazás és a folyamatbányászat támogatja a gyártósor áttervezését, mivel képes felismerni a rejtett állomásokat és a folyamat állapotait. Ezenkívül az eredmények értékes információkat nyújtanak a gyártási elrendezés potenciálisan veszélyes vagy kockázatos területeinek azonosításához, amelyek hatással lehetnek az operátorok komfort szintjére. Az összegyűjtött adatok elemzésével azonosíthatjuk azokat a zónákat, amelyek potenciális kockázatot jelentenek az operátorok kényelmére, és megtehetjük a megfelelő intézkedéseket ezeknek a kockázatoknak a csökkentése érdekében. Továbbá, az időben összesített méréseket figyelembe véve nemcsak az expozíció térbeli eloszlását értékelhetjük, hanem az expozíció időbeli mintáit is egy adott időszak alatt.

Tudományos eredmények és újdonságok

A kutatás eredményeként olyan módszertan született, amely lehetővé teszi:

- az operátorok teljesítményének és komfort szintjének a folyamatos figyelemmel kísérését IPS-adatok felhasználásával,
- a gyártási folyamatokban rejtett állapotok azonosítását és az értéklánc-térképek (VSM) frissítését,
- egy új komfort szintjelző bevezetését, amely azt mutatja, hogy az operátorok milyen mértékben képesek tolerálni a különböző gyártási területeken fellépő környezeti terhelést.

A kifejlesztett IPS-alapú folyamatbányászati algoritmusok olyan további állapotokat és időbélyegeket biztosítottak, amelyeket a MES nem rögzített, így pontosabb Gantt-diagramok és Lean KPI-számítások (pl. ciklusidő, várakozási idő) készülhettek. Ezenkívül az integrált rendszer támogatja az elrendezés áttervezését és a kockázatok azonosítását azáltal, hogy kiemeli a potenciálisan veszélyes vagy a komfort szempontjából kritikus területeket.

A tézis alapjául szolgáló publikációk

- Tran, T. A., Ruppert, T., & Abonyi, J. (2021). Indoor positioning systems can revolutionise digital lean. Applied Sciences, 11(11), 5291., GS citation: 42

- Halász, G., Medvegy, T., Abonyi, J., & Ruppert, T. (2023, September). Indoor positioning-based occupational exposures mapping and operator well-being assessment in manufacturing environment. In IFIP International Conference on Advances in Production Management Systems (pp. 543-555). Cham: Springer Nature Switzerland., GS citation: 1

9.2.2 Vizuális adat alapú tevékenységfelismerés

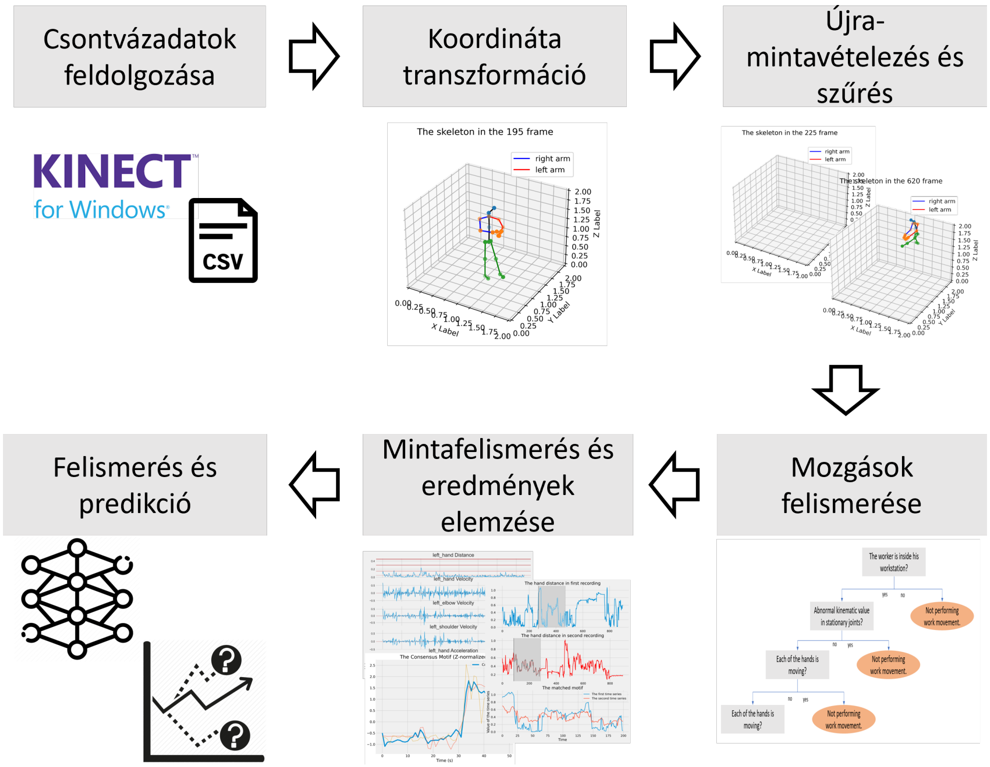
A kutatás háttere

A munkavállalók viselkedésének összetettségét és bizonytalanságát jobban meg lehet érteni, ha közelebbről megvizsgáljuk mozgásuk pályáját. Ez az alap megkönnyíti a részletes elemzést ergonómiai és termelékenység-növelési szempontból. A hagyományos kezdeményezések azonban kimerítő megfigyelést és előzetes ismereteket igényelnek a munkavállalókról, miközben a mozgás legtöbb részletét a szakértők szabad szemmel nem tudják nyomon követni.

A Kinect csontvázadatok alapján mintafelismerést és felügyelt tanulási algoritmusokat dolgoztunk ki a mozgásminták automatikus rögzítésére és mélyebb elemzésére, így automatikus munkaerő-teljesítményértékeléseket biztosítva, mint például az általános munkaerő-hatékonyság (Overall Labour Efficiency - OLE). A legfontosabb eredményeink a több szempontból (pl. termelékenység, ergonómia) történő automatikus értékelés és az értékelési eredmények alapján javasolt, emberközpontú fejlesztések, figyelembe véve az Ipar 5.0 célkitűzéseit. A Kinect nyers adatainak utólagos feldolgozásához Python csomagot fejlesztettünk ki. Az alkalmazást egy valós ipari szerelősoron gyűjtött adatsoron mutattuk be, bizonyítva, hogy az egyes munkaállomásokon az emberi teljesítmény értékelhető, és a gyártósor kiegyensúlyozható az egyes munkaállomásokon végzett mozdulatok optimalizálásával. Folyamatos fejlesztési ötleteket és hosszú távú humánerőforrás-fejlesztési (HRD) terveket javasoltunk. Az újdonság a gépi tanulási (ML) algoritmusok innovatív használatában rejlik, valós idejű működési modellel.

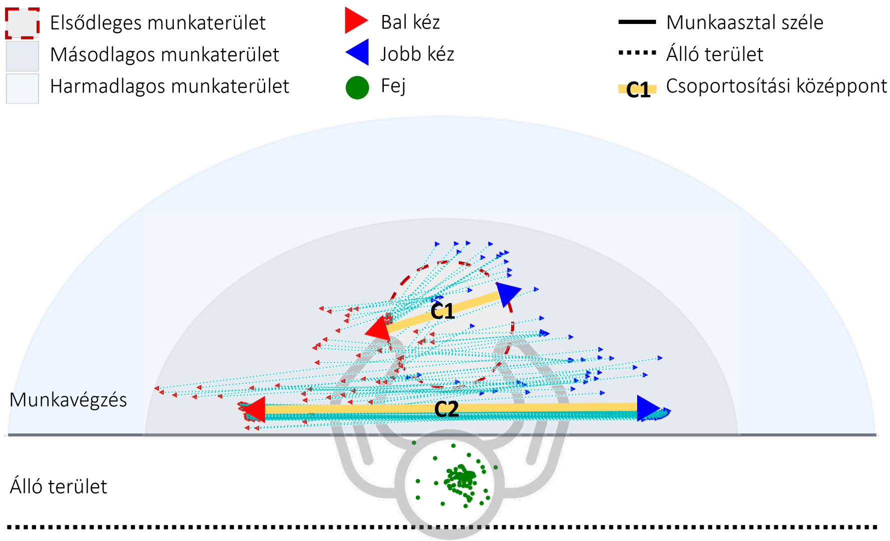
A kidolgozott módszerek

A nyers csontvázadatok feldolgozása után koordinátaátalakítás, újramintavétel és szűrési lépések következnek. Ezek a lépések a kamera beállításain alapuló matematikai műveletek. Felügyelt tanulási algoritmusokat alkalmaztunk a munkavégzési állapot és a mozgások szegmentálására és felismerésére. Ezután motívumkereső algoritmusokat dolgoztunk ki a feltárt mozgások közötti hasonlóságok megtalálására és a szabványoktól való eltérések észlelésére. A csuklópontok idősorai és kinematikai értékeik voltak az elemzéseink középpontjában. Más munkajellemzők (pl. ciklusidő) is felismerhetők az adatokból. Minden munkával nem kapcsolatos mozgást ki kell zárni (pl. járás, várakozás, pihenés). Ez a megközelítés figyelembe veszi a munkával kapcsolatos mozgások belső jellemzőit, mint például a fej és a kezek pozícióját és kinematikáját. Például a fej mozgása nagyon alacsony sebességű, közel mozdulatlan ízület, a kezek pedig a munkavégzés során a legaktívabb ízületek. A kinematikai értékeket (azaz a sebességet) is felhasználtuk küszöbértékekként a mozgások azonosításához. Figyelembe vettük a munkaállomás egyéb jellemzőit is, például a szállítószalag geometriáját és az ergonómiai munkapozíciót.



9.4. ábra: A Kinect szenzor csontvázadatainak feldolgozására javasolt folyamatábra.

Az azonosított munkaminták alapján statisztikai jellemzők vonhatók le a humán tevékenységfelismerési (HAR) modell felépítéséhez. Az azonosított eredmény felhasználható a munkavállalók mozgásának előrejelzésére valós idejű alkalmazásokban. Az összesített eredmények összefoglalhatók az egyes munkavállalók vagy több munkavállaló teljesítményének értékelésében. Ezen értékelések alapján kidolgozhatók rövid és hosszú távú stratégiák az operátorok teljesítményének javítására, szem előtt tartva az Ipar 5.0 célkitűzéseit. A kidolgozott folyamatábra a 10.4 ábrán látható. A kidolgozott lépések a következőképpen írhatók le:



9.5. ábra: A fej és a kéz helyzetének sémája munkapozícióban. Példaadatok egy munkaállomásról.

- Az operátorok a munkaállomásukon vannak-e: Az álló zóna a fej és a kéz ízületeinek pozícióadataira kNN klaszterezés alkalmazásával határozható meg, és a fej pozíciója és alacsony sebessége alapján ellenőrizhető (lásd a 10.5 ábrát).
- A munkavállaló végez-e munkát: Ha a munkavállaló dolgozik, a fejének lassan kell mozognia az álló zónán belül. Ha a munkavállaló sétál, a sebessége sokkal nagyobb, mint a munkavégzés közben.
- A munkavállaló keze mozog-e vagy sem: Az egyes kezek mozgási jellemzői, például a mozgási távolság, a sebesség és a gyorsulás alapján felismerhetők azok a képkockák, amelyeken a munkavállaló munkát végez, és nem áll tétlenül. Ezt a lépést követően létrehozható a munkavégzés idővonala.
- A fent említett lépéseket követően meghatározhatjuk azokat a releváns képkockákat, amelyeken a munkavállaló munkamozgást végez. Ezekben az időszakokban ergonómiai értékelés alkalmazható. A megadott munkavégzési utasítás felhasználható a mozgás azonosítására, és a motívumkeresési technikák alkalmazásával megtalálható a mozgásminta.

Tudományos eredmények és újdonságok

A kifejlesztett módszer lehetővé teszi:

- a munka teljesítményének automatikus értékelését több dimenzióban (pl. termelékenység, ergonómia),
- a munkával kapcsolatos mozgások felismerését és osztályozását egyéni és gyártósori szinten egyaránt,
- a gyártósorok kiegyensúlyozásának és a munkaállomások optimalizálásának javítási lehetőségeinek azonosítását.

A javasolt munkafolyamat automatizált folyamatot biztosít a HAR és OLE számításához. Az újdonság abban rejlik, hogy a felügyelt tanulás és a motívumkereső algoritmusokat valós idejű mozgáskövetéssel kombinálja, így folyamatos és objektív értékelési rendszert hoz létre. A módszertan támogatja mind a rövid távú fejlesztési intézkedéseket, mind a hosszú távú HRD stratégiákat az Ipar 5.0 paradigmán belül.

A tézis alapjául szolgáló publikációk

- Tran, T. A., Ruppert, T., Eigner, G., & Abonyi, J. (2023). Assessing human worker performance by pattern mining of Kinect sensor skeleton data. Journal of Manufacturing Systems, 70, 538-556., GS citation: 14
- Jeskó, Z., Tran, T. A., Halász, G., Abonyi, J., & Ruppert, T. (2024, September). Enriching Scene-Graph Generation with Prior Knowledge from Work Instruction. In IFIP International Conference on Advances in Production Management Systems (pp. 290-302). Cham: Springer Nature Switzerland. GS citation: 0

9.3 II. téziscsoport: Emberközpontú digitális modellek

A tudásgráfokhoz hasonló információs rendszerekkel összekapcsolt, szigorúan ellenőrzött és elemzett folyamatok fontossága egyre növekszik. Ezenkívül az operátorok integrációja sürgetővé vált a magas költségek és a társadalmi szempontok miatt. Az ember-központú gyártási rendszerek megközelítés megvalósításához megfelelő keret szükséges, amely hatékony adatcserét tesz lehetővé egy rendkívül összetett gyártási hálózatban, az erőforrások és információk kihasználása érdekében. Ezenkívül az emberi és gépi szereplők közötti együttműködés folyamatos fejlesztése alapvető fontosságú az ipari kiberfizikai rendszerek számára, mivel a munkaerő az egyik legrugalmasabb és leginkább alkalmazkodóképes gyártási erőforrás. Az emberi digitális iker szükségessége is felmerül, de ennek megvalósításához gondosan ki kell dolgoznunk azokat az adatmodelleket, amelyek az ipari környezetben emberközpontú módon figyelembe veszik az emberi tényezőket. Az Asset Administration Shell (AAS) egy jól megtervezett megközelítés a digitális iker fejlesztéséhez, amely kiemeli az emberi AAS (HAAS) igényét.

9.3.1 Human-Asset Administration Shell

A kutatás háttere

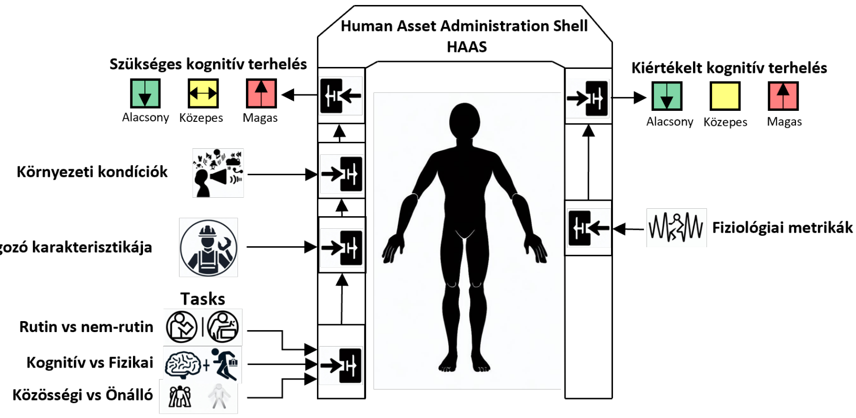
Az Ipar 4.0-hoz kapcsolódó technológia gyors fejlődése paradigmaváltást hozott az eszközökkel való interakciók módjában különböző területeken. Ez a fejlődés vezetett az Emberi Digitális Iker (Human Digital Twin - HDT) koncepció megjelenéséhez, amely egy személy kognitív, pszichológiai és viselkedési jellemzőinek virtuális ábrázolása. A HDT stratégiai eszközként bizonyította potenciálját a termelékenység, a biztonság és az együttműködés javításában az ember-központú gyártási rendszereken belül. Kutatásom két fő területre összpontosít, amelyek az ipari digitalizációra való átállás során merülnek fel, és megoldásokat javasol rájuk: „Mekkora kognitív terhelést jelenthet egy adott feladat az operátor számára, és mi az a kognitív határ, amelyet az operátor nem léphet túl, hogy a feladatot a legjobb teljesítmény mellett végezze el?”, figyelembe véve az egyéni képességeket, valamint „Az első kérdés eredményei alapján szükséges-e szabályozni a feladat kognitív terhelését, és ha igen, hogyan?”.

Alkalmazott módszerek

Hét fő modult azonosítottunk: a feladat, a munkavállalói készségek, a környezeti feltételek, a pszichológiai állapot, a kinematikai paraméterek, az antropometriai paraméterek és a fiziológiai mutatók. Kutatásom újdonsága négy modulon alapul: a fiziológiai mutatókon (GSR és HRV) a munkavállaló kognitív terhelésének értékeléséhez és alacsony, közepes vagy magas besorolásához, míg a másik három modul, a feladat, a munkavállaló készségei és a munkavállalót körülvevő környezeti feltételek a szükséges kognitív terhelés becsléséhez és szintén alacsony, közepes vagy magas besorolásához használatosak, hogy összehasonlítsák a munkavállaló értékelte kognitív terhelésével.

A kifejlesztett modell egy olyan folyamatot biztosít, amely a GSR-t fiziológiai markerként használva követi nyomon az emberi kognitív terhelést, és egy újszerű módszert javasol a kognitív terhelés kezelésére a kibővített Human Asset Administration Shell (HAAS) alapján. A javasolt HAAS keretrendszer integrálja a hordható érzékelőkből származó valós idejű adatfolyamokat, a felhasználói készségeket, a kontextus információkat, a feladat sajátosságait, valamint a környezeti és környező feltételeket, hogy átfogó képet adjon az egyén kognitív állapotáról, fizikai jólétéről és készségeiről. A készségek, a fizikai, fiziológiai és pszichológiai változók, valamint a feladatparaméterek beépítésével a kifejlesztett HAAS keretrendszer lehetővé teszi az egyéni képességek azonosítását, kezelését és fejlesztését, ezáltal elősegítve az egyénre szabott képzést és a tudáscserét.

Az általunk javasolt HAAS modell négy alapvető modulra épül, amelyek alapját képezik a modell felépítésének és működésének. Ezek a modulok a fiziológiai paramétereket, a munkavállalók jellemzőit, a feladat típusát és szintjét, valamint a környezeti feltételeket tartalmazzák. Amint az a 10.6 ábra jobb oldalán látható, a fiziológiai mutatók a GSR- és HRV-adatokra koncentrálnak, amelyeket a feladatot végző egyénekre helyezett érzékelőkkel mérnek. Ez a kulcsfontosságú modul rögzíti ezeket a paramétereket, majd értékeli és három mérhető kategóriába sorolja a kognitív terhelést: alacsony, közepes és magas, amint az a jobb felső sarokban, a „Kiértékelt kognitív terhelés” alatt látható.



9.6. ábra: A javasolt kiterjesztett HAAS modell

A 10.6 ábra bal oldalán három modul látható: a munkavállalók jellemzőinek modulja, amelynek célja, hogy hatékonyan rögzítse az egyes munkavállalók egyedi készségeit és jártasságait, és felismerje, hogy az egyéni képességek nagyban eltérhetnek egymástól. Ez a modul az egyes munkavállalók képességeinek előzetes értékelése alapján frissül, mielőtt azok konkrét feladatokba kezdenének. A feladat típusa és szintje a kidolgozott modell másik modulja. Ez a modul nemcsak a feladat kategóriáját veszi figyelembe, hanem a munkavállaló veleszületett készségeit és képességeit is beépíti az elemzésébe. Például egy kognitív igényeket támasztó feladatot két, eltérő fizikai erővel rendelkező munkavállaló eltérően értelmezhet, ami jól illusztrálja, hogy egy feladat komplexitása sokrétű. Modellünk utolsó modulja a környezeti feltételek, amely kezeli a külső tényezők döntő szerepét a kognitív terhelés meghatározásában. Ez a modul folyamatosan figyelemmel kíséri és kiigazítja a környezet változásait, például a zajt, a hőmérsékletet stb. A bal oldalon található modulok a bevitt adatok alapján három szintre becsülik a szükséges kognitív terhelést: alacsony, közepes és magas, amint az a bal felső sarokban a „Szükséges kognitív terhelés” alatt látható. Ezzel a négy modullal a kibővített HAAS-modell dinamikus kölcsönhatást hoz létre. Az értékelt és a szükséges kognitív terhelés összehasonlításával a feladatok és a környezeti feltételek modulálását célozza, biztosítva az optimális munkavállalói kényelem és a megnövekedett termelékenység közötti egyensúlyt.

Tudományos eredmények és újdonságok

A kifejlesztett HAAS-modell:

- lehetővé teszi az operátor kognitív terhelésének valós idejű értékelését fiziológiai és kontextuális adatok alapján,
- becsüli a feladathoz kapcsolódó kognitív igényeket, és összehasonlítja azokat az egyéni kognitív állapotokkal,
- dinamikusan javasolja a feladat és a környezet módosítását az optimális kognitív terhelés szintjének fenntartása érdekében.

Az újdonság abban rejlik, hogy a hagyományos AAS koncepciót kiterjesztettük az eszközök közötti interoperabilitáson túl a feladatparaméterek és a környezeti feltételek aktív manipulációjára, lehetővé téve az emberközpontú optimalizálást az ember-központú gyártási rendszerekben. A kognitív, fiziológiai és kontextuális dimenziók integrálásával a modell támogatja az egyénre szabott képzést, a tudáscserét és az emberi képességek folyamatos fejlesztését.

A tézis alapjául szolgáló publikációk

- Eesee, A. K., Jaskó, S., Eigner, G., Abonyi, J., & Ruppert, T. (2024). Extension of haas for the management of cognitive load. IEEE Access, 12, 16559-16572. GS citation: 7
- Cutrona, V., Bonomi, N., Montini, E., Ruppert, T., Delinavelli, G., & Pedrazzoli, P. (2024). Extending factory digital Twins through human characterisation in Asset Administration Shell. International Journal of Computer Integrated Manufacturing, 37(10-11), 1214-1231. GS citation: 25

9.3.2 Tudásgráfok az emberközpontú gyártáshoz

A kutatás háttere

A kollaboratív robotok gyártási folyamatokba való integrálása, más néven ember-robot kollaboráció (Human-Robot Collaboration - HRC), jelentős előrelépést jelent az Ipar 4.0 területén. A hagyományos ipari robotokkal ellentétben, amelyek izolált cellákra korlátozódnak, a kollaboratív robotok úgy vannak kialakítva, hogy beágyazott interakciós, érzékelő és biztonsági technológiák segítségével emberekkel együtt dolgozhassanak. Ez lehetővé teszi egy hibrid gyártási környezet létrehozását, ahol az emberi és robot erőforrások dinamikusan oszthatók el a termelékenység, a rugalmasság és az átalakíthatóság optimalizálása érdekében. A HRC-környezetek célja a kézi és robotizált szerelősorok korlátainak leküzdése egy újszerű megközelítéssel a feladatok elosztására és végrehajtására, amely javítja a gyártás általános hatékonyságát és alkalmazkodóképességét.

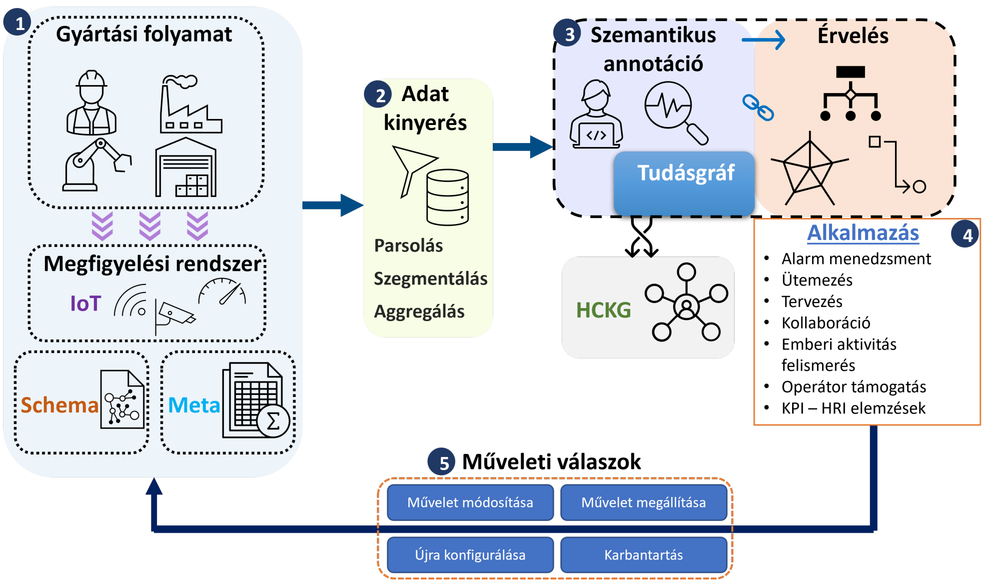
A folyamatinformációk kezeléséhez szemantikus hálózatok és gráf alapú elemzések használata ajánlott, linkelt adatfunkciók alkalmazásával. A tudásgráf technikák képesek adatokat kivonni strukturált, félig strukturált vagy strukturálatlan forrásokból, majd ezeket az információkat beépíteni egy gráf alapú tudásreprezentációba. Az operátorok munkakörülményeinek javítása érdekében különböző monitoring rendszerek, például érzékelőhálózatok használhatók az operátorok mozgásának és fizikai állapotának figyelemmel kísérésére, lehetővé téve a teljesítménymutatók értékelését.

Alkalmazott módszerek

Ontológiák és szabványok adaptálásával kifejlesztettünk egy emberközpontú tudásgráf (Human-centric Knowledge Graph - HCKG) keretrendszert, amely modellezi az operátorral kapcsolatos tényezőket, például a mozgások figyelemmel kísérését, a munkakörülményeket vagy a robotokkal való együttműködést. Emellett egy ipari esettanulmányon keresztül bemutattuk a gráf alapú adatlekérdezést, vizualizációt és elemzést. A munka fő hozzájárulása egy tudásgráf-alapú keretrendszer, amely az operátor által végzett munkára összpontosít, beleértve a mozgások értékelését, a gépekkel való együttműködést, az ergonómiát és egyéb feltételeket. Ezenkívül a keretrendszer használatát egy komplex, gyártósoron alapuló esettanulmányban mutatjuk be, példákkal az erőforráselosztásra és a gyárterületen dolgozók közötti együttműködés szempontjából nyújtott átfogó támogatásra.

Az elsődleges hozzájárulás egy HCKG néven bevezetett keretrendszer, amely ontológiát és szabványokat használva modellezi az emberi operátorral kapcsolatos elemeket, mint például a mozgás figyelése, a munkakörnyezet és a robotokkal való együttműködés. A keretrendszert egy ipari esettanulmányon keresztül szemléltettük, és grafikon alapú adat-lekérdezést, vizualizációt és elemzést tartalmaz. Egy komplex kábelköteg-összeszerelési folyamatot bemutató példán keresztül illusztráltuk az erőforrás-elosztás és az ember-gép együttműködés átfogó támogatásának példáit.

A HCKG tervezési koncepció célja egy keretrendszer létrehozása az ember-gép együtt-működés figyelemmel kísérésére és irányítására, a rugalmasság javítására, valamint az operátorok munkakörülményeinek javítására. A tudásgráf magában foglalja az operátor tevékenységével, a környezettel, valamint a gyártási térben található összes robottal és berendezéssel kapcsolatos figyelemmel kísért adatokat. A tudásgráfban összegyűjtött adatok elemzésével javítható az együttműködés, testreszabhatók a operátor számára a munkautasítások, és adaptív módon kezelhetők az esetleges módosítások. A 10.7 ábra szemlélteti a HCKG koncepció integrációs megközelítését.



9.7. ábra: A HCKG tervezési koncepció integrálása a gyártási folyamattal, öt szegmens felhasználásával

Részletes esettanulmány készült, amely alaposan figyelembe veszi az operátorok által végzett feladatokat, beleértve a mozgásértékelést, a gépekkel való együttműködést, a munkasorrendet és az ergonómiai szempontokat. Hangsúlyozzuk továbbá, hogy az aktivitásfelismerő technológiák integrálása gazdagíthatja a tudásgráfban található értékes adatokat egy intelligens gyár környezetben. Célunk az volt, hogy összefoglaljuk a szemantikai fejlesztés jelenlegi módszereit és eszközeit, és bemutassunk egy koncepciót az emberközpontú együttműködés szabványos modelljeinek létrehozására, amelyet egy ipari esettanulmányon keresztük illusztráltunk.

Tudományos eredmények és újdonságok

A legfontosabb eredmények a következők voltak:

- hangsúlyoztuk a humán tényezők kiber-fizikai rendszerekbe való beépítésének fontosságát,
- javasoltuk az automatizálási szabványok (ISA-95, AutomationML, B2MML) kiterjesztését az emberrel kapcsolatos folyamatok beépítésével, és bemutattuk a szemantikai technológiák használatát,
- a koncepciót egy megismételhető ipari esettanulmányon keresztül validáltuk. Különböző típusú gráfok, például normál, irányított vagy hipergráfok felhasználásával különböző gráfalapú elemzéseket végeztünk, beleértve az erőforrás-elosztási elemzést, a KPI értékelést és a DAS integrációját,
- a HCKG-n alapuló alkalmazás megkönnyítette az összeszerelési folyamatban az emberek és a gépek közötti különböző együttműködési formák azonosítását.

A tézis alapjául szolgáló publikációk

- Nagy, L., Abonyi, J., & Ruppert, T. (2024). Knowledge Graph-Based Framework to Support Human-Centered Collaborative Manufacturing in Industry 5.0. Applied Sciences, 14(8), 3398. GS citation: 8
- Tóth, A., Nagy, L., Kennedy, R., Bohuš, B., Abonyi, J., & Ruppert, T. (2023). The human-centric Industry 5.0 collaboration architecture. MethodsX, 11, 102260. GS citation: 72
- Nagy, L., Ruppert, T., & Abonyi, J. (2022, September). Human-centered knowledge graph-based design concept for collaborative manufacturing. In 2022 IEEE 27th international conference on emerging technologies and factory automation (ETFA) (pp. 1-8). IEEE. GS citation: 18
- Nagy, L., Ruppert, T., Löcklin, A., & Abonyi, J. (2022). Hypergraph-based analysis and design of intelligent collaborative manufacturing space. Journal of Manufacturing Systems, 65, 88-103. GS citation: 23

9.4 III. téziscsoport: Emberközpontú mutatók és fiziológiai paraméterek

A gyártási környezetben végzett fiziológiai adatokra vonatkozó kutatások továbbra is korlátozottak, és szembetűnő a megbízható alapadatok és átfogó adatbázisok hiánya. E hiányosság orvoslására kognitív pszichológusokkal együttműködve több kontrollált kísérletet terveztem és hajtottam végre laboratóriumunkban, amelyek gyártással kapcsolatos helyzeteket szimuláltak. Ezen tanulmányok célja az volt, hogy szilárd alapot teremtsenek a fiziológiai mérések integrálásához az emberközpontú ipari kutatásba.

9.4.1 Kognitív terhelés a feladatok végrehajtása során

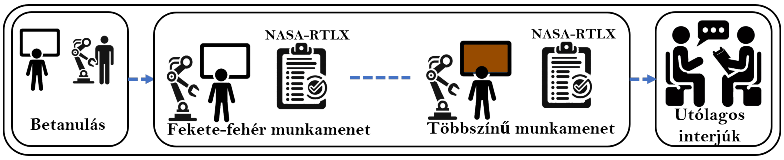
A kutatás háttere

Multitasking környezetben vizsgáltuk a figyelem mérésének a vizsgálhatóságát az ember-robot együttműködésen alapuló összeszerelésben. Kísérleti tanulmányt végeztünk, amelyben a résztvevők egy kobottal végrehajtottak egy vezetékbekötési feladatot, miközben egyidejűleg egy Go/No-Go teszt segítségével egy párhuzamos, figyelmet igénylő feladatot is elvégeztek. A multitasking hatásainak értékeléséhez két nehézségi szintű Go/No-Go tesztet terveztünk a figyelmet igénylő feladatok tekintetében. 16 résztvevővel végeztünk felhasználói tanulmányt, és kvantitatív mutatókat gyűjtöttünk a feladat teljesítéséről és a válaszadási arányokról, valamint kvalitatív visszajelzéseket, hogy értékeljük a másodlagos figyelmet igénylő feladatok elvégzésének képességét.

A multitasking hatásának megfigyelése érdekében a másodlagos feladat nehézségét két szinten változtattuk, és elemeztük annak hatását a munkateljesítményre és a munkaterhelésre. Eredményeink megerősítik a szálakba rendezett kognitív elméletet, amely szerint az ember-robot együttműködés csökkentheti a kognitív kapacitást azáltal, hogy kiterjeszti a figyelmi erőforrásokat, ami több hibához és hosszabb ciklusidőhöz vezet a multitasking során. Ez alátámassza az ember-robot együttműködés figyelmi tényezőinek részletes megértésének fontosságát.

Kísérlet tervezése

A kísérletet úgy terveztük meg, hogy megossza a résztvevők figyelmét, és egy valósághű összeszerelési helyzetet teremtsen, amelyben a résztvevőknek egyensúlyt kellett teremteniük a fő feladat figyelmi terhelése és a másodlagos feladat követelményeinek teljesítése között, hogy szimulálják a multitaskingot. A fő feladat egy UR5e cobot segítségével végzett vezetékköteg-szerelés volt, míg a másodlagos feladat egy Go/No-Go teszt volt, amely megnövelte a figyelemigényt. A kísérleti tanulmányt a Pannon Egyetem Ipar 5.0 laboratóriumában végeztük el. Az 10.8 ábra szemlélteti a kutatásban használt kísérleti folyamatot.



9.8. ábra: A vizsgálat felépítésének és eljárásának áttekintése. A feladatok sorrendje kiegyensúlyozott volt: 8 résztvevő a fekete-fehér feltételekkel kezdte, 8 pedig a többszínű munkamenettel.

Tudományos eredmények és újdonságok

Kísérleteink eredményei arra utalnak, hogy a többfeladatos helyzetek hosszabb ciklusidőket és potenciálisan még több hibát is eredményezhetnek, és az operátorok kénytelenek lehetnek alkalmazkodni a figyelmi terheléshez azáltal, hogy csak az egyik feladatot részesítik előnyben. Bár a HRC-ben a többfeladatos munkavégzést megvalósíthatónak tartjuk, eredményeink felhívják a figyelmet a termelékenységre gyakorolt potenciális hatások miatt, és további kutatásokat szorgalmazunk olyan HRC-alkalmazások tervezésére, amelyek nem merítik ki az operátoroknak figyelmi erőforrásait .

Eredményeink azt is mutatják, hogy a HRC-környezetben végzett multitasking során a résztvevők alkalmazkodhatnak stratégiájukhoz, és prioritást adhatnak az egyik feladatnak a másik rovására, ami több hibához vezethet az adott feladatban. Feltételezzük, hogy ez vagy a figyelem több feladat között való megosztásának nehézségéből, vagy egyszerűen abból adódik, hogy az egyik feladat hatékonyságának maximalizálását részesítik előnyben, miközben a másik feladat hatékonyságát feláldozzák.

A tézis alapjául szolgáló publikációk

- Eesee, A. K., Kostolani, D., Kang, T., Schlund, S., Medvegy, T., Abonyi, J., & Ruppert, T. (2024). May I Have Your Attention?! Exploring Multitasking in Human-Robot Collaboration. IFAC-PapersOnLine, 58(19), 241-246. GS citation: 2

- Eesee, A. K., Kostolani, D., Varga, V., Kang, T., Schlund, S., & Ruppert, T. (2025, June). Studying Dual-Task Awareness in Industrial Settings Through Reaction Times and Physiological Signals. In 2025 IEEE Conference on Cognitive and

Computational Aspects of Situation Management (CogSIMA) (pp. 151-156). IEEE. GS citation: 0

9.4.2 Munkautasítások értékelése

A kutatás háttere

Az ipari környezetben a rosszul megtervezett munkautasítások jelentősen ronthatják a termelékenységet, növelhetik a hibák valószínűségét és csökkenthetik az általános munkával való elégedettséget. Ezenkívül a rossz utasítások káros gazdasági és társadalmi következményeit széles körben dokumentálták, amelyek az felhasználó-elégedettség csökkenéséhez, a működési költségek növekedéséhez és a döntéshozatali folyamatok hatékonyságának romlásához vezetnek. Bár számos tanulmány vizsgálta az egyszerűsített vagy digitális munkautasítások – például szöveges útmutatók vagy kiterjesztett valóság (AR) alapú megoldások – előnyeit, ezek a megközelítések gyakran nem validálják szisztematikusan az objektív mutatókat a munkavállalók szubjektív tapasztalataival az alkalmazott utasítások alapján. A szubjektív kérdőíveket és objektív fiziológiai mutatókat integráló kutatások, amelyek átfogóan értékelik a munkavállalók kognitív terhelését és hatékonyságát a munkautasítások alapján, továbbra is korlátozottak. Ez a hiányosság különösen sürgető a modern összeszerelő környezetben, ahol a feladatok növekvő komplexitása olyan munkautasítások kidolgozását igényli, amelyek mind kognitív szempontból átgondoltak, mind pedig működési szempontból hatékonyak.

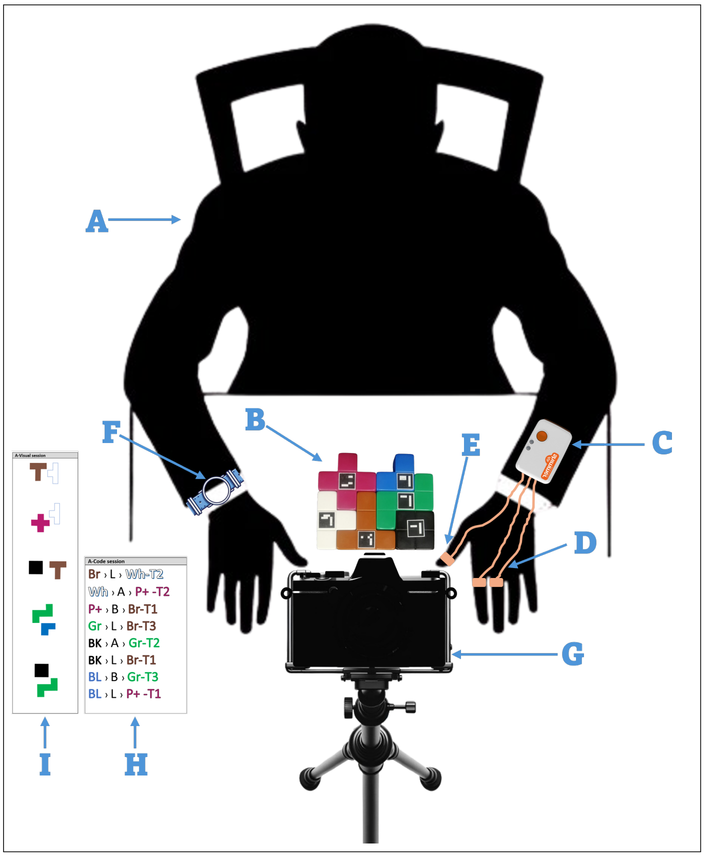
A kidolgozott módszerek és a kísérlet tervezése

Szisztematikusan összehasonlítottunk két különböző utasítás-megközelítést – a kódalapút és a vizuális alapút – egy szerelés jellegű forgatókönyvben. Konkrétan azt a hipotézist állítottuk fel, hogy a kódalapú utasítások, amelyek alfanumerikus kódokra támaszkodnak a szerelési folyamat irányításához, nagyobb szubjektív kognitív terhelést jelentenek, mivel a kódok dekódolásához nagyobb mentális erőfeszítésre van szükség. Ezzel szemben a vizuális alapú utasítások várhatóan csökkentik a kognitív terhelést, mivel ugyanazokat a feladatokat intuitívabb, grafikus ábrázolással mutatják be. Ez az egyszerűsített megközelítés azonban gyakrabban igényel kézmozdulatokat és ismételt feladatciklusokat, ami a megnövekedett fizikai aktivitás miatt potenciálisan jelentősebb változásokat eredményezhet a fiziológiai jelekben (galvanikus bőrreakció, GSR és fotopletizmogram, PPG). Ezeknek a hipotéziseknek az értékelése során mind a szubjektív kognitív terhelést (a NASA Task Load Index „NASA_TLX” és a rövid Dundee Stress State Questionnaire „short DSSQ” segítségével), mind az objektív mutatókat (fiziológiai jelek és feladatvégzési mutatók) mérjük, hogy átfogó képet kapjunk arról, hogyan befolyásolják a munkautasítások az operátorok jólétét és hatékonyságát. Ezért a következő kutatási kérdést tettük fel: *Hogyan illeszkednek a kognitív terhelés és a teljesítmény szubjektív észlelései a kognitív terhelés és a teljesítmény objektíven mért változásaihoz, amikor különböző utasítási módszereket alkalmaznak?*

A szakirodalomban azonosított hiányosságok miatt olyan kontrollált kísérletet terveztünk, amelyben a résztvevők kétféle utasítási módszerrel – kódalapú és vizuális utasításokkal – szerelték össze a „Make »N« Break Extreme” építőelemeket. Ezt a protokollt kifejezetten azért választottuk, hogy elkülönítsük a külső terhelést, miközben a feladatok során konzisztens belső terhelést tartunk fenn. A munkánk célja volt, hogy kontrollált, összeszereléshez hasonló helyzetben vizsgáljuk a munkautasítások hatását az operátorok kognitív terhelésére és teljesítményére.

A tanulmány két különböző utasítási megközelítést alkalmazott: *Vizuális* utasításokat az alacsony kognitív terhelés és *Kódalapú* utasításokat a magas kognitív terhelésű mérésen. A vizuális alapú munkamenetben a résztvevők egy sor lépésről lépésre bemutató képet láttak, amelyek pontosan ábrázolták, hogyan kell összekapcsolni az egyes blokkokat. Más szavakkal, minden kép egyértelműen megmutatta, hogy a darabok melyik oldala érintkezzen, lehetővé téve a résztvevők számára, hogy vizuálisan igazítsák a blokkokat, amíg azok meg nem felelnek az ábrázolt mintának. Az ebben a kontextusban bemutatott vizuális utasítások egyértelműségükkel jellemezhetők, mivel egyszerű és egyértelműen ábrázolják a végső célt. Ez a megközelítés célja, hogy minimálisra csökkentsék a résztvevők értelmezési erőfeszítéseit.

A másik esetben színalapú kódrendszert használtunk az összeszerelési utasításokhoz, hogy növeljük a kódalapú nehéz feladat nehézségi szintjét. Egy kód, amely általában a szín első két betűjéből áll, hivatkozik az egyes darabokra. Például a „Re” a piros darabot jelöli, és piros szöveggel jelenik meg, míg a „Gr” a zöld darabot jelöli, és zöld szöveggel jelenik meg. A munkautasítás ezeket a kódokat biztosítja a résztvevőknek, amelyeket felhasználva meg kell határozniuk a darabok pozícióját és érintkezési pontjait. A darabok közötti térbeli viszonyokat „A” jelöli a „fölött”, „B” az „alatt”, „L” a „balra” és „R” a „jobbra” jelentéssel. A két szomszédos darab közötti érintkezés mértékét „T1”-gyel jelöljük egy érintkezési terület esetén, és fokozatosan növeljük „T4”-ig négy érintkezési terület esetén. A kódok megkövetelik a résztvevőktől, hogy az absztrakt utasításokat a blokkok összeállításának konkrét feladatává alakítsák át, ami tükrözi a valós életben gyakran előforduló kognitív terhelést, amikor az ilyen utasítások értelmezése kihívás lehet. Az 10.9 ábra bemutatja a kutatásban végzett kísérlet felépítését.



9.9. ábra: Ez az ábra szemlélteti a kísérletünkben használt átfogó felépítést.

Tudományos eredmények és újdonságok

Kutatásunk új betekintést nyújt a munkautasítások kialakítása és az operátorok kognitív terhelése közötti kapcsolatba ipari jellegű összeszerelési helyzetekben. A legfontosabb tudományos hozzájárulások és újdonságok a következők:

1. **Integrált értékelési megközelítés:** Szisztematikusan kombináltuk a szubjektív munkaterhelés-értékelő eszközöket (NASA-TLX és rövid DSSQ) az objektív fiziológiai mérőeszközökkel (galvanikus bőrreakció és fotopletizmogram) és a feladatvégzési mutatókkal, hogy átfogó képet kapjunk a szerelési feladatok során fellépő kognitív terhelésről.

2. **Kísérleti bizonyítékok az utasítások típusairól:** Két különböző utasítástípust – a vizuális és a kódalapú módszert – összehasonlító kontrollált kísérletet terveztünk és hajtottunk végre. Eredményeink azt mutatják, hogy a vizuális utasítások jelentősen csökkentik a szubjektív kognitív terhelést, míg a kódalapú utasítások magasabb

mentális igénybevételt jelentenek, mivel az absztrakt kódokat konkrét cselekvésekre kell dekódolni és lefordítani.

3. **A kognitív és fizikai terhelés közötti kompromisszumok feltárása:** Bár a vizuális alapú utasítások csökkentették a kognitív terhelést, azok a kézmozdulatok számának növekedésével és a feladatciklusok ismétlésével jártak, ami a fiziológiai jelekben is megmutatkozott. Ez rávilágít a munkaterhelés kognitív és fizikai dimenziói közötti kompromisszumra, amelyet a szakirodalom nem tárgyal kellőképpen.

4. **Gyakorlati következmények az utasítások tervezése szempontjából:** Eredményeink megvalósítható bizonyítékot nyújtanak a kognitív szempontokat figyelembe vevő és működési szempontból hatékony munkautasítások kidolgozásához a modern ipari környezetben, különösen ott, ahol a feladatok összetettsége növekszik.

E munka újdonsága a holisztikus módszertani megközelítésében, a munkautasítások által kiváltott munkaterhelés-különbségek empirikus validálásában, valamint a kognitív terhelés szubjektív és objektív mutatói közötti interakciós hatások azonosításában rejlik.

A tézis alapjául szolgáló publikációk

- Eesee, A. K., Varga, V., Eigner, G., & Ruppert, T. (2025). Impact of work instruction difficulty on cognitive load and operational efficiency. Scientific Reports, 15(1), 11028. GS citation: 0
- Gugolya, M., Varga, V., Medvegy, T., & Ruppert, T. (2025, August). The Impact of Work Instruction Simplification on Operator Performance and Learning Curve Efficiency. In IFIP International Conference on Advances in Production Management Systems (pp. 148-162). Cham: Springer Nature Switzerland. GS citation: 0

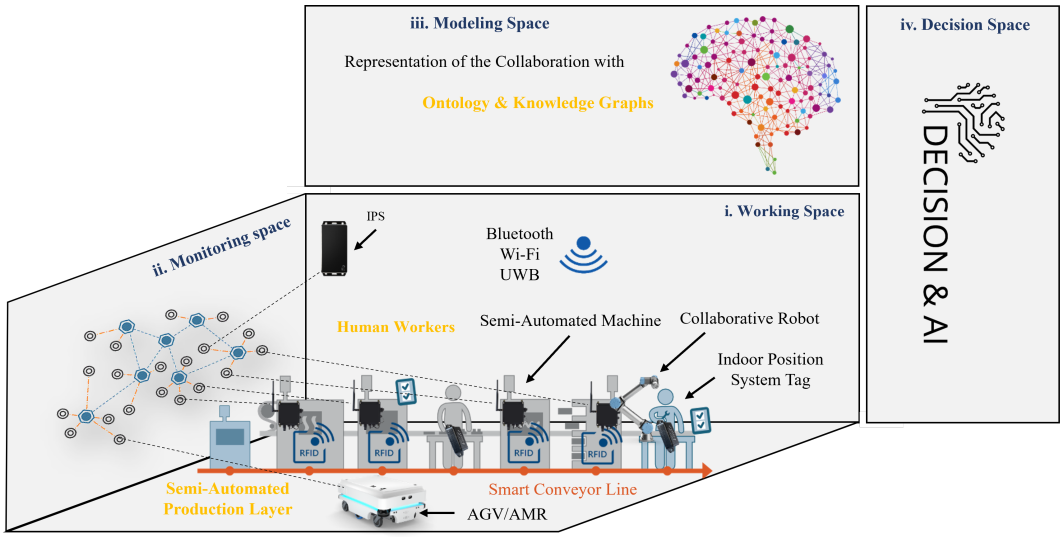
10 Habilitációs tézisek angolul

For the past five years, I have focused on human-centered manufacturing challenges and solutions. After earning my Ph.D. in a related field, I began formulating the Industry 5.0 laboratory and assembling a team. The human labor-intensive nature of industries in Hungary and across Europe is raising concerns about the aging workforce and the need for change in human resources. The most important aspect within the business area is always performance and return on investment (ROI). As Europe faces a labor shortage, these aspects have become more important in recent years. Understanding the main reasons for the decline in performance of human workers is increasingly important since the market requires more human-centric and enthusiastic workplaces.

Understanding human activities is the first step in creating a supporting system. To this end, we have developed various methods for human-centered performance evaluation, combining traditional Lean methodologies with the latest technologies. I have significant experience with real-time locating systems (RTLS), also known as indoor positioning systems (IPS). We are also working on different solutions for visual-based activity recognition.

To integrate information about our workers into our current system, we need human-centered models and data structures. We developed a Human-Asset Administration Shell (H-AAS) model that includes physiological parameters and calculated human-centered factors, such as cognitive load and stress level. We also proved that human-centered knowledge graphs are useful for modeling human behavior. Overall, I developed the Intelligent Collaborative Manufacturing Space (ICMS) as a human-centric manufacturing framework. I was motivated to lay the groundwork for human-centered systems based on the developed ICMS framework. We conducted several laboratory experiments to demonstrate the applicability of physiological signals in manufacturing using wearable sensors. Since work instructions play a significant role in industry, we developed an evaluation method to assess their effectiveness.

In the following I will shortly introduce the ICMS framework as it is shaped my research in the past 5 years. ICMS is proposed to create a next-level collaborative environment where human workers and automated and semi-automated production assets can work together in the same area to achieve productivity, flexibility, and resilience levels that neither can achieve on their own. To accomplish this, Intelligent Automation Systems are necessary to achieve "Human-Automation Symbiosis". ICMS aims to create a framework for supporting collaborations based on smart sensor networks and data science techniques. Figure 10.1 shows the elements of the proposed ICMS, which aims to showcase a real-time monitoring-based control for automated and semi-automated production assets to make collaboration between the human workers and the machines more safe and precise. Four main elements or sub-spaces characterize this "Intelligent Workspace": (i) the Working Space, (ii) the Monitoring Space, (iii) the Modelling Space, and (iv) the Decision Space.



10.1. ábra: The four spaces of Intelligent Collaborative Manufacturing Space

The ICMS is a framework envisioned for supporting the effective collaboration between humans and automated and semi-automated production assets based on activity recognition and prediction paired with machine learning optimization algorithms.

10.1 Thesis overlook and summary

10.1.1 Thesis group I.

I developed a set of algorithms and methods to evaluate the human-centered performance indicators based on the real-time locating system (RTLS) information and the visual-based activity recognition. We connected these digital solutions with the traditional Lean techniques to provide real-time and data-based process development.

We proved that RTLS can be use not just for performance evaluation but also to asses the comfort levels of the workers applied in a real-life manufacturing scenario. The results show the indoor positioning data is valuable to not just tracking the human movements and activities but also provide information about the actual environment information (like noise, temperature) to assess the human well-being in space and time.

The traditional skeletal data-based analyses is applied to assess the human performance on a production line to provide valuable information for better task allocation and work schedule. We paired the MS Kinect data with the traditional Lean technique to assess the human performance on a real-life production dataset. The results are shown the applicability of the sceletal data and also proved the usefulness in case of human-centric performance evaluation.

In sum, the thesis group is proven a valuable toolset to track the operator performance within real-life production scenarios and connect these visual- and sensor-based information with the traditional Lean techniques to create more efficient processes.

10.1.2 Thesis group II.

To handle the real-time performance measurements, I developed a Human-asset administration shell model as a basics of the human digital twin to support the human-factors integration, also I proved the usability of the knowledge graph and developed a human-centered library.

We developed a Human-Asset Administration Shell (HAAS) to handle the operator-related information regarding the task allocation. From the one hand, the model is able to manage the actually perceived cognitive load based on the real-time physiological metrics and in the other hand the model is handling the task requirements also, like the environmental conditions, the worker's characteristics and the task specific information (like routine or nonroutine, cognitive or physical demanding and individual or team required) to pair the assigned tasks with the operator's capabilities. The model is proving a foundation of the cognitive load management with a valuable data schema for task allocation.

A Human-Centric Knowledge Graph (HCKG) is developed to create a knowledge graph for human-related process management with the standard ontologies, data extraction methodologies and the possible applications. The developed graph is a valuable solution for the production management where different assets/actors (robots, operators, sensor and actuators) need to be handled within one system.

10.1.3 Thesis group III.

To extend the physical activity performance monitoring with the specific human-centered information, I started to work on the physiological information monitoring within the manufacturing environment to prove more human-centric and personalized solutions according to the performance monitoring, task-allocation and process development. I proved the physiological signals usability and applicability with simple wearable sensors for manufacturing processing integrate the real-time human states and behavior within the systems.

I started the journey of manufacturing related experiments to measure the cognitive load in subjective and objectively with dual-task scenarios where the participants needed to handle a specific secondary task during the primary task execution. In both cases the results are shown some promising correlation between the perceived cognitive load and awareness level and the measured physiological data with industry ready wearable sensors. These open source experiment datasets are valuable information for further research within these areas as a foundation of the applicability of the industry ready sensors usage within the manufacturing processes to assess the cognitive load of the human workers.

The work instruction is one of the most used interface to support the human workers as they are providing all the necessary information to execute the actual tasks. We objectively measured the usability and efficiency of different type of work instruction (like code- and visual-based) during an assembly-like task within a laboratory environment. Both performance and quality metrics are measured paired with the physiological measurements, also with the subjective evaluation of the participants. The results are proved valuable information about the right usage of the code- and visual-based work instruction and also the applicability of the wearable sensors.

10.2 Thesis Group 1: Human-centered performance evaluation

The importance of monitoring operator performance in human-centric manufacturing is steadily increasing. This trend is driven by the growing shortage of skilled labor, the integration of real-time locating systems, and the rising usability of visual-based activity tracking technologies. These developments enable a more precise, responsive, and worker-oriented approach to managing industrial processes, ensuring both operational efficiency and enhanced human well-being. In this thesis, I demonstrate the applicability of real-time positioning systems and visual observation tools in the recognition of human activities.

10.2.1 Usability of the real-time locating system for worker well-being and performance evaluation

Background and objective

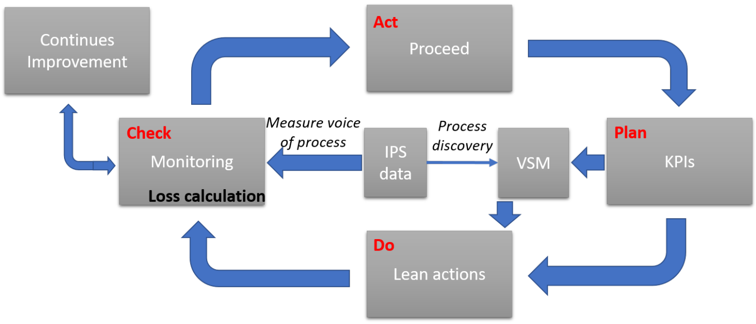
The evaluation of human workers is a difficult task since we are all different is such way especially within a complex manufacturing process. As a human-centric solution, a human-oriented and personalized evaluation system is needed. For this purpose, I developed different algorithm to explore valuable and human-centered information from the so-called Indoor Positioning System (IPS and also known Real-time Locating System - RTLS) information paired with the traditional Lean techniques.

The powerful combination of lean principles and digital technologies accelerates waste identification and mitigation faster than traditional lean methods. The new Digital Lean (also referred as Lean 4.0) solutions incorporate sensors and digital equipment, yielding innovative solutions that extend the reach of traditional lean tools. The developed algorithms and methods are able to assess not just the performance indicators but also the actual well-being parameters of the human workers.

The developed methods

A framework (see on Figure 10.2) is proposed based on the indoor position data and the Plan–Do–Check–Act (PDCA) cycle for assessing the well-being and the performance of the operators in indoor environments, with the operator comfort level serving as a measurable indicator. It is a detailed guideline about how the information provided by IPS can be utilised in Lean management. The proposed method is embedded into the concept of continuous development. The structured DMAIC (Define-Measure-Analyze-Improve-Control) approach utilised in Six Sigma methodology also follows the concept of the PDCA cycle, which has been proven effective in reducing non-value-added activities in the supply chains and assembly lines.

The core element of the method is the process model (represented as a VSM in the Figure 10.2) that contains all the essential information about the manufacturing process. The proposed improvement cycle continuously updates the model with the help of IPS data. The motivation is to continuously and automatically monitor the production. The developed framework can discover the real process model continuously based on the IPS data with the toolset of process mining. The resulted models are used to update the VSMs, evaluate the performance of the process by calculating the Lean KPIs. We applied



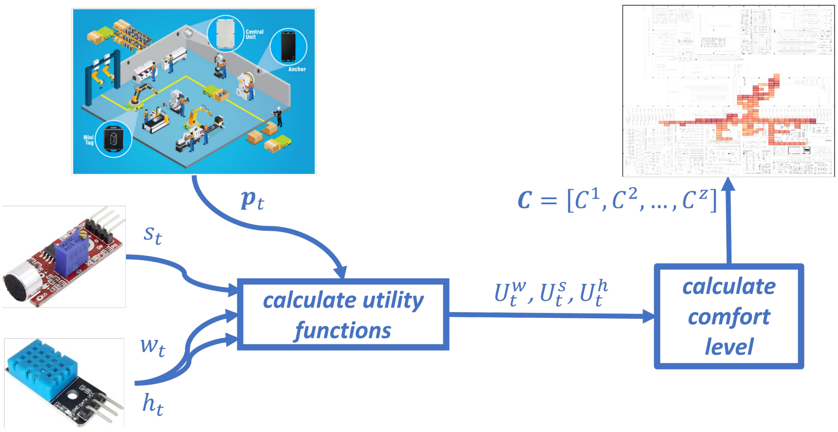
10.2. ábra: IPS data is the key element of the proposed PDCA-based methodology

Gantt diagrams to analyze the periods of operations. Based on the analysis of positional data additional states of the manufacturing process can be defined and assigned to the product and material flows and states of the resources (e.g. temporal inventories can be defined). The explored states and additional time-stamps provided by the IPS process mining algorithms can be utilised to update VSMs. Thanks to the real-time position of the process flows motion-based anomalies can be detected.

Understanding the specific areas and conditions where workers are exposed to various environmental factors is essential. Distributed information is essential to capture the spatial and contextualized distribution of occupational exposures. Unlike concentrated parameters, this exposure varies between operators and workplaces. To formulate a clear objective, it is necessary to articulate the need for detailed information that encompasses both spatial and temporal dimensions. To achieve this, it is necessary to have position-based information that is contextualized and linked to relevant data. We incorporate indoor positioning data to create location-based sensor information. The application and further development of the IPS serve as a solution to address these motivations. By employing IPS sensors and associated analysis techniques, it becomes possible to gather precise position-based information. The integration of IPS sensors and related technologies offers a promising avenue for advancing workplace monitoring and design, ultimately promoting a safer and more efficient working environment.

The sensor fusion methodology is represented in Figure 10.3. This framework describes the sensor information process, where we have a measurement point that includes humidity (h_t), temperature (w_t), the noise (s_t) and the actual position data ($\mathbf{p}_t$) and the 2D position from the IPS is denoted by $\mathbf{p}_t = [x_t, y_t]$ where t is the actual time point.

For this characterization, we have determined a so-called comfort level. The value represents the extent to which the operator can handle environmental load in each zone of the shop floor and how comfortable they feel in these areas. To measure this new



10.3. ábra: The steps of the developed framework for human well-being assessment

indicator, we have also developed a mobile sensor unit as an extension of the standard IPS tag to make the measurement more cost-effective. With this idea, we can utilize all the moving units on the shop floor, such as AGV (automated guided vehicles) or AMR (autonomous mobile robots), or even the material handler operators equipped with the developed sensor.

As the results are shown the IPS serves as a non-stop monitoring system that contributes to the everyday work of Lean specialists. As a first step, an alarm system can be set up at each workstation to notify if the working or the waiting times in that station exceed their predefined limits; so the line advisor can take required supportive action on time. The integrated application IPS and process mining supports the redesign of the layout thanks to its ability of the detection of hidden stations and states of the process. Also, the results provide valuable insights for identifying potentially hazardous or at-risk areas in the manufacturing layout that can impact the well-being of operators. By analyzing the collected data, we can identify zones that pose potential risks to operator comfort and take appropriate measures to mitigate these risks. Furthermore, by considering the time-aggregated measurements, we can not only evaluate the spatial distribution of exposures but also assess the temporal patterns of exposure over a given period.

Scientific results and novelty

The research resulted in a methodology that enables:

- continuous monitoring of operator performance and well-being using IPS data,
- identification of hidden states in manufacturing processes and updating of Value Stream Maps (VSM),

- introduction of a new comfort level indicator representing the extent to which operators can tolerate environmental load across different shop floor zones.

The developed IPS-based process mining algorithms provided additional states and time stamps that were not captured by the MES, enabling more accurate Gantt diagrams and Lean KPI calculations (e.g., cycle time, waiting time). The methodology also allows for the implementation of alarm systems to notify line advisors if cycle or waiting times exceed predefined limits. Furthermore, the integrated system supports layout redesign and risk identification by highlighting potentially hazardous or comfort-critical areas.

Publication background

- Tran, T. A., Ruppert, T., & Abonyi, J. (2021). Indoor positioning systems can revolutionise digital lean. Applied Sciences, 11(11), 5291., GS citation: 42
- Halász, G., Medvegy, T., Abonyi, J., & Ruppert, T. (2023, September). Indoor positioning-based occupational exposures mapping and operator well-being assessment in manufacturing environment. In IFIP International Conference on Advances in Production Management Systems (pp. 543-555). Cham: Springer Nature Switzerland., GS citation: 1

10.2.2 Visual data-based activity recognition

Background and objective

A better understanding of the complexity and uncertainty of worker behavior can be achieved with a closer diagnosis of their movement trajectory. This foundation enhances detailed analysis from ergonomic and productivity improvement aspects. However, traditional initiatives require exhaustive observation and prior knowledge of human workers, while most movement details can not be traced by the naked eyes of experts. There is no development regarding segmentizing camera-captured movement into patterns in the literature.

A Kinect skeleton data is utilised by applying pattern mining and supervised learning algorithms to automatically capture and analyze deeper the movement patterns, thus providing automatic labor performance assessments such as Overall Labor Effectiveness (OLE). Key contributions are the automatic assessment in several aspects (e.g., productivity, ergonomics) and the suggestion of possible human-centric improvements based on assessment results, considering Industry 5.0 objectives. A Python package is developed for post-process the Kinect raw data. A use case is performed on an electrical assembly line, proving that the human performance in each workstation can be assessed, and the manufacturing line can be balanced, with each movement in its workstations optimized. Continuous improvement ideas and long-term Human Resources Development (HRD) plans are suggested. The novelty lies in the innovative usage of Machine Learning (ML) algorithms with a real-time operation model, which can be the core foundation for organizational data-driven improvement in the Industry 5.0 era.

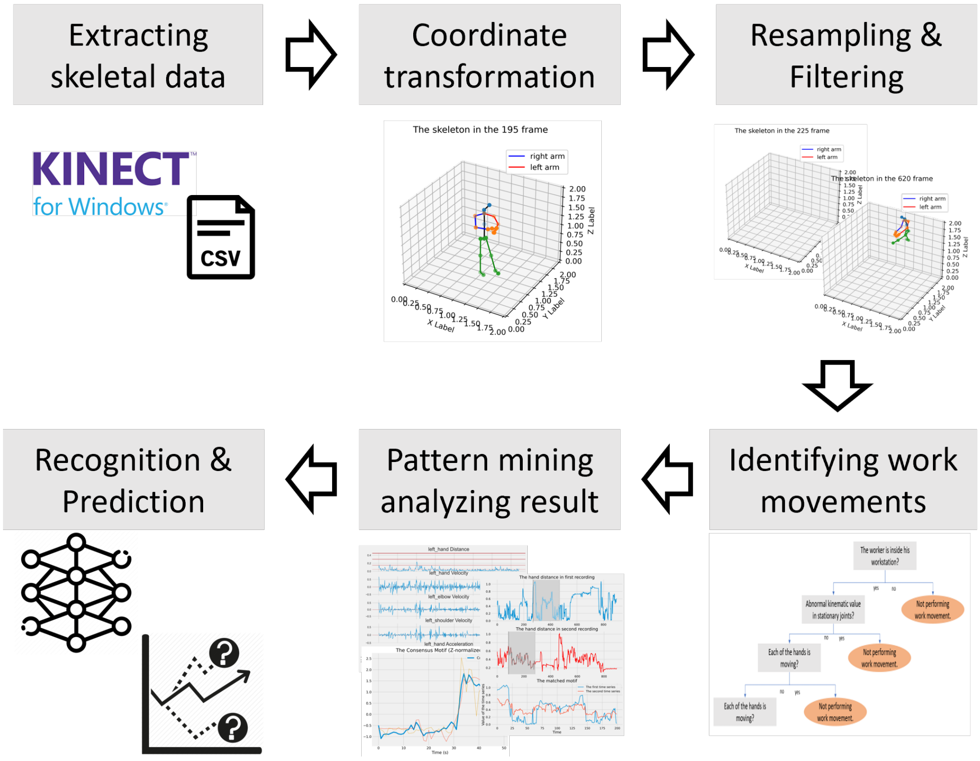
The developed methods

After extracting the raw skeleton data, coordinate transformation, re-sampling, and filtering steps are applied. These steps are mathematical operations based on the camera setup. Supervised learning algorithms are applied to segmentize and recognize working status and movements. Then, motif-searching algorithms are applied to find the similarities between the extracted movements and detect deviation from the standard. The objects of interest are the time series of the joint coordinates, along with their kinematic values. Other work characteristics (e.g., cycle time) can also be recognized. Every job-unrelated movement should be excluded (i.e., walking, waiting, resting). This approach considers intrinsic characteristics of work movements, such as the position and kinematics of the head and the hands. For instance, the head will be the stationary joint with a very low velocity, and the hands will be the most active joint during the work session. Kinematics values (i.e., velocity) are also utilized as thresholds to identify the movements. Other workstation features, i.e., conveyor geometry and ergonomic working posture, are also considered.

With the recognized work patterns, statistical features can be extracted to build a Human Activity Recognition (HAR) model. The recognized result can be used to predict worker movement for a real-time application. The overall results can be synthesized into the performance assessment of each worker or the line of multiple workers. Based on these assessments, short- and long-term strategies to improve human performance can be elaborated, keeping in mind the objectives of Industry 5.0.

The processing flowchart is described in Figure 10.4. After extracting the raw skeleton data, coordinate transformation, re-sampling, and filtering steps are applied. These steps are mathematical operations based on the camera setup. Supervised learning algorithms are applied to segmentize and recognize working status and movements. The developed steps can be described as:

- Whether the workers are in their workstation: The standing zone can be defined by applying kNN clustering on the position data of the head and the hand joints, and



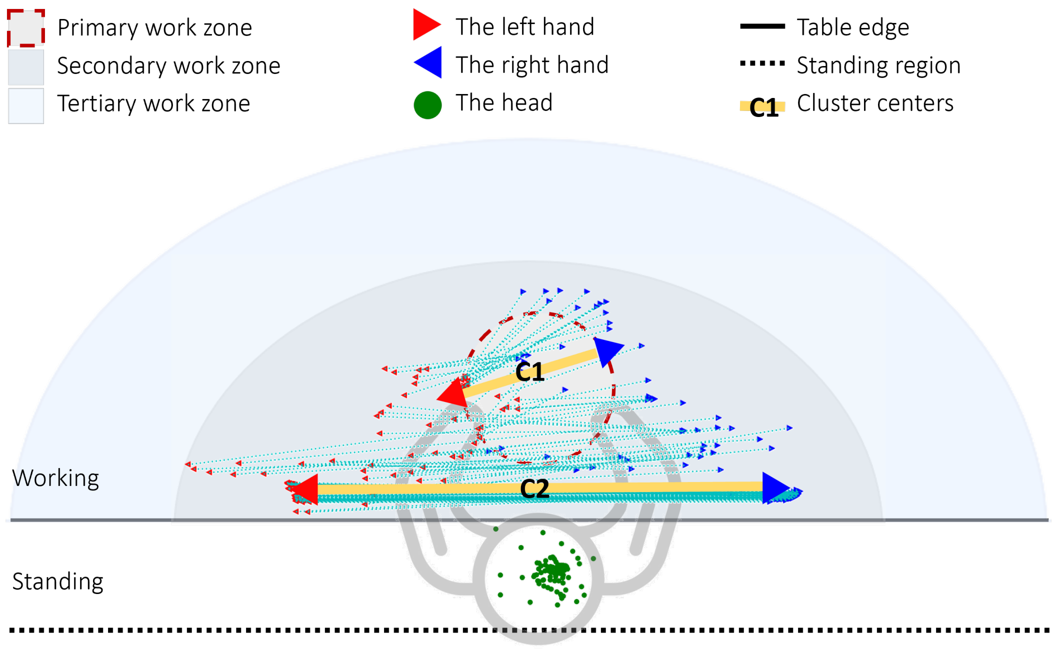
10.4. ábra: The proposed flowchart to process Kinect sensor skeleton data.

can be confirmed by the position of the head and its low velocity (see on Figure 10.5.

- Whether the worker is performing the work: If the worker is working, the head should be moving slowly within the standing zone. If the worker is walking, the velocity is much higher than the working state.

- Whether the hand of the worker is moving or not: Based on the kinematic characteristics of each hand such as moving distance, velocity, and acceleration, the frames in which the worker is performing work and not standing idle can be recognized. After this step, the timeline of the working state can be created.

- After the aforementioned steps, we can define the relevant frames in which the worker is performing work movement. Ergonomics assessment can be applied during these periods. The given work instruction can be utilized to identify the movement, and the motif searching techniques are performed to find the movement pattern.



10.5. ábra: The schema of the head and hand positions in working posture. Example data from one workstation.

Scientific results and novelty

The developed method enables:

- automatic assessment of labor performance across multiple dimensions (e.g., productivity, ergonomics),
- recognition and classification of work-related movements at both individual and line-level scales,
- identification of improvement opportunities for balancing manufacturing lines and optimizing workstations.

The proposed workflow (Figure 10.4) provides an automated pipeline for HAR and OLE calculation. The novelty lies in combining supervised learning and motif-searching algorithms with real-time movement tracking to create a continuous and objective assessment system. The methodology supports both short-term improvement actions and long-term HRD strategies within the Industry 5.0 paradigm.

Publication background

- Tran, T. A., Ruppert, T., Eigner, G., & Abonyi, J. (2023). Assessing human worker performance by pattern mining of Kinect sensor skeleton data. Journal of Manufacturing Systems, 70, 538-556., GS citation: 14
- Jeskó, Z., Tran, T. A., Halász, G., Abonyi, J., & Ruppert, T. (2024, September). Enriching Scene-Graph Generation with Prior Knowledge from Work Instruction. In IFIP International Conference on Advances in Production Management Systems (pp. 290-302). Cham: Springer Nature Switzerland. GS citation: 0

10.3 Thesis Group 2: Human-centered digital models

The importance of highly monitored and analysed processes, linked by information systems such as knowledge graphs, is growing. In addition, the integration of operators has become urgent due to their high costs and from a social point of view. An appropriate framework for implementing the Industry 5.0 approach requires effective data exchange in a highly complex manufacturing network, to utilise resources and information. Furthermore, the continuous development of collaboration between human and machine actors is fundamental for industrial cyber-physical systems, as the workforce is one of the most agile and flexible manufacturing resources. The necessity of the Human Digital Twin is arising this year but to achieve this we need to carefully develop the data models which can consider the human factors is a human-centric way within the industrial environment. The asset administration shell (AAS) is a well designed approach for the digital twin development which highlighting the needs of the Human AAS.

10.3.1 Human-Asset Administration Shell

Background and objective

The rapid advancement of technology related to Industry 4.0 has brought about a paradigm shift in the way we interact with assets across various domains. This progress has led to the emergence of the concept of a Human Digital Twin (HDT), a virtual representation of an individual’s cognitive, psychological, and behavioral characteristics. The HDT has demonstrated potential as a strategic tool for enhancing productivity, safety, and collaboration within the framework of Industry 5.0. My research is centered on addressing two primary areas of concern that arise during the transition toward industrial digitization and suggesting solutions for them: “What is the cognitive load level that a specific task may induce on an operator, and what is the limit of cognition that the operator should not exceed to tackle that task's load with the best performance?", factoring in the individual skills and "Based on the outcomes of the first question, is there a need to control the cognitive load of that task, and if so, how?".

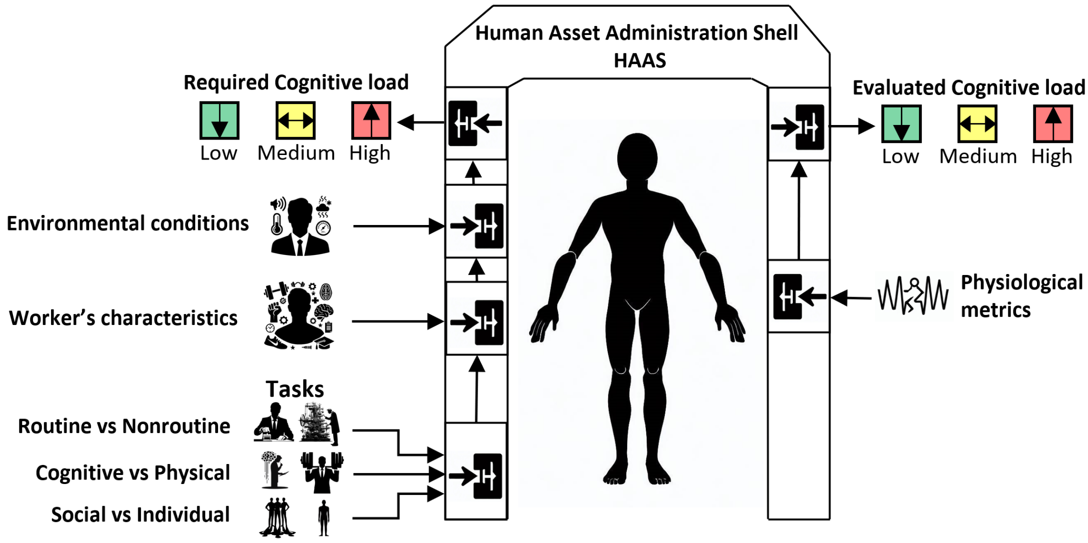
Applied methods

We identified seven main modules: the task, worker skills, environmental conditions, psychological state, kinematic parameters, anthropometric parameters, and physiological metrics. My research novelty is depending on four of these modules: the physiological metrics (GSR and HRV) to evaluate the worker's cognitive load and classify it as low, medium, or high, while the other three modules, the task, the worker's skills, and the environmental conditions surrounding the worker, will be used to estimate the required cognitive load and also classify it as low, medium, or high to compare it with the evaluated cognitive load of the worker.

The developed model provides a process for tracking human cognitive load using the GSR as a physiological marker and proposes a novel method for managing cognitive load based on the extended Human Asset Administration Shell (HAAS). The proposed HAAS framework integrates real-time data streams from wearable sensors, user skills, contextual information, task specifics, and environmental and surrounding conditions to deliver a comprehensive understanding of an individual's cognitive state, physical wellness, and skill set. Through the incorporation of skills set, physical, physiological, and psychological variables, and task parameters, the developed HAAS framework enables the identification, management, and development of individual capabilities, thereby facilitating individualized training and knowledge exchange.

The HAAS model we proposed is built around four fundamental modules that serve as the basis for its structure and operation. These modules include physiological parameters, workers' characteristics, task type and level, and environmental conditions. As seen in Figure 10.6 located on the right side, the physiological metrics focus on the GSR and HRV data, which are acquired using sensors placed on the individuals doing the tasks. This crucial module records these parameters and subsequently evaluates and categorizes the cognitive load into three noticeable categories: low, medium, and high, as shown on the upper right side under the "Evaluated Cognitive load".

On the left side of Figure 10.6 are three modules, the workers' characteristics module, which is designed to effectively capture the distinct skills and proficiencies possessed by each worker and recognizes that individual capabilities can vary widely. This module is



10.6. ábra: Extended HAAS proposed diagram

updated based on a preliminary assessment of each worker's abilities prior to engaging in specific tasks. Task type and level is the other module in the developed model. It takes into account not just the categorical nature of a task but also integrates the worker's innate skills and capacities into its analysis. As an example, a task with cognitive demands might be perceived differently by two workers of varying physical strengths, illustrating that the complexity of a task is multifaceted. The final module in our model is the environmental condition, which acknowledges that external factors play a crucial role in determining cognitive load. This module continuously monitors and adjusts the changes in the environment, such as noise, temperature, etc. These modules on the left side will estimate the required cognitive load based on their inputs into three levels: low, medium, and high, as shown on the upper left side under "Required Cognitive load". With these four modules in place, the extended HAAS model establishes a dynamic interplay. By comparing the evaluated and required cognitive loads, it aims to modulate tasks and surrounding conditions, ensuring a balance between optimal worker comfort and heightened productivity.

Scientific results and novelty

The developed HAAS model:

- enables real-time evaluation of operator cognitive load based on physiological and contextual data,

- estimates task-related cognitive demands and compares them to individual cognitive states,
- dynamically suggests task and environmental adjustments to maintain optimal cognitive load levels.

The novelty lies in extending the conventional AAS concept beyond interoperability between assets toward active manipulation of task parameters and environmental conditions, enabling human-centric optimization in Industry 5.0. By integrating cognitive, physiological, and contextual dimensions, the model supports individualized training, knowledge exchange, and continuous development of human capabilities.

Publication background

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10.3.2 Knowledge graphs for human-centered manufacturing

Background and objective

The integration of collaborative robots into manufacturing processes, known as human-robot collaboration (HRC), represents a significant advancement in Industry 4.0. Unlike traditional industrial robots that are confined to isolated cells, collaborative robots are designed to work alongside humans, using embedded interaction, sensing, and safety technologies. This enables a hybrid production environment where human and robot resources are dynamically allocated to optimize productivity, flexibility, and reconfigurability. HRC environments aim to overcome the limitations of manual and robotic assembly lines by providing a novel approach to task allocation and execution that improves overall manufacturing efficiency and adaptability.

Semantic networks and graph-based analytics are recommended to handle process information using linked data features. Knowledge graph techniques are capable of extracting data from structured, semi-structured or unstructured sources and then incorporating this information into a graph-based knowledge representation. To improve operator working conditions, various monitoring systems, such as sensor networks, can be utilized to monitor operator movements and physical states, enabling the assessment of performance metrics.

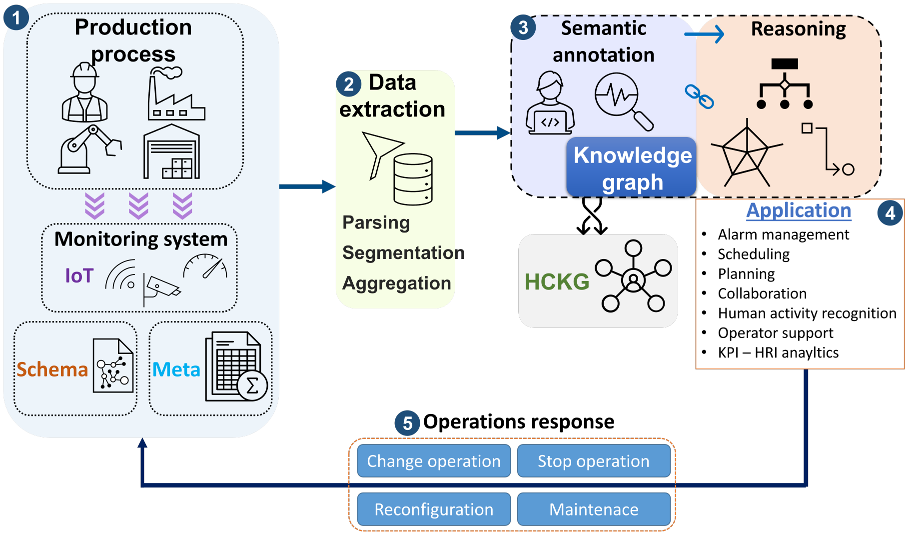
Applied methods

We developed a Human-Centric Knowledge Graph (HCKG) framework by adapting ontologies and standards to model the operator-related factors such as monitoring movements, working conditions, or collaborating with robots. It also presents graph-based data querying, visualisation, and analysis through an industrial case study. The main contribution of this work is a knowledge graph-based framework that focuses on the work performed by the operator, including the evaluation of movements, collaboration with machines, ergonomics, and other conditions. In addition, the use of the framework is demonstrated in a complex use case based on an assembly line, with examples of resource allocation and comprehensive support in terms of collaboration aspect between shop-floor workers.

The primary contribution is the introduction of a framework known as HCKG, which models elements related to the human operator, such as monitoring movement, work environment, and collaboration with robots, using ontology and standards. The framework is exemplified through an industrial case study and incorporates graph-based data querying, visualization, and analysis. An instance involving a complex wire harness assembly process illustrates instances of resource allocation and comprehensive support for human-machine collaboration.

The objective of the HCKG design concept is to establish a framework to monitor and control human-machine collaboration, improve resilience, agility, and improve working conditions for operators. The Knowledge Graph incorporates monitored data concerning the operator's activities, the environment, as well as all robots and equipment within the manufacturing space. Through the analysis of the collected Knowledge Graph data, collaboration can be enhanced, work instructions can be customized for the operator, and any modifications can be adaptively managed. Figure 10.7 illustrates the integration approach of the HCKG concept.

A detailed case study is developed thoroughly considers the tasks performed by operators, encompassing movement assessment, collaboration with machines, work sequences, and ergonomic aspects. It is also emphasized that the integration of activity recognition technologies can enrich the valuable data within a Knowledge Graph in a smart



10.7. ábra: Integration of the HCKG design concept connect to the production process, using five segments

factory setting. Our objective was to summarize current methods and tools for semantic development and to introduce a concept for creating standard models of human-centered collaboration, illustrated through an industrial case study.

Scientific results and novelty

The key contributions were as follows:

- Emphasized the importance of incorporating human factors into cyber-physical systems.
- Proposed an expansion of automation standards (ISA-95, AutomationML, B2MML) to include human-related processes and demonstrated the use of semantic technologies.
- The concept was validated through a replicable industrial case study. Various graph-based analyses were conducted using different types of graphs such as normal, directed, or hypergraphs, including resource allocation analysis, KPI evaluation, and the integration of a DAS.
- The application based on HCKG facilitated the identification of various forms of collaboration between human and machine actors in the assembly process.

- Furthermore, a conceptual design was put forward for a human-centric manufacturing dashboard.

Publication background

- Nagy, L., Abonyi, J., & Ruppert, T. (2024). Knowledge Graph-Based Framework to Support Human-Centered Collaborative Manufacturing in Industry 5.0. Applied Sciences, 14(8), 3398. GS citation: 8
- Tóth, A., Nagy, L., Kennedy, R., Bohuš, B., Abonyi, J., & Ruppert, T. (2023). The human-centric Industry 5.0 collaboration architecture. MethodsX, 11, 102260. GS citation: 72
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10.4 Thesis Group 3: Human-centered indicators and physiological parameters

Research on physiological data within manufacturing environments remains limited, with a notable lack of reliable ground truth and comprehensive databases. To address this gap, I collaborated with cognitive psychologists to design and execute multiple controlled experiments in our laboratory, simulating manufacturing-related scenarios. These studies aimed to establish a solid foundation for integrating physiological measurements into human-centric industrial research.

10.4.1 Cognitive load during task executions

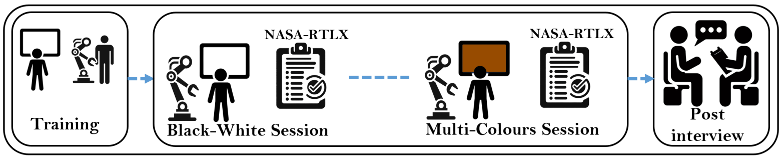
Background and objective

We investigate the feasibility of attentional multitasking in collaborative human-robot assembly. We performed an exploratory study in which participants carried out a wire harnessing task with a cobot, while simultaneously engaging in parallel attention-demanding task through a Go/No-Go test. To evaluate the effects of multitasking, we designed the Go/No-Go test with two levels of difficulty in terms of their attentional demands. We conducted a user study with 16 participants and gathered quantitative metrics on task performance and response rates and qualitative feedback to evaluate the ability of engaging in secondary attentional tasks.

To observe the effect of multitasking, we varied the difficulty of the secondary task across two levels and analysed its impacts on work performance and workload. Our results confirm threaded cognition theory, suggesting that human-robot collaboration could reduce cognitive capacity by extend attentional resources, leading to higher errors and cycle times during multitasking. This underscores the importance of a detailed understanding of attentional factors in human-robot collaboration.

Design of Experiment

The experiment was designed to divide participants' attention, providing a realistic assembly scenario where the participant must balance the attentional load of the main task while also responding to the demands of the secondary task to simulate multitasking. The main task involved working on a wire harnesses in collaboration with a UR5e cobot, while the secondary task involved a Go/No-Go test to impose increased attentional demands. The experimental study was carried out at the Industry 5.0 laboratory at the University of Pannonia. Figure 10.8 illustrates the experimental setup used in this research.



10.8. ábra: Overview of the setup and the procedure of the study. The task order was counter-balanced, with 8 participants starting with the black-white condition, and 8 starting with the multi-colour session.

Scientific results and novelty

Our experiment suggests that multitasking scenarios may lead to higher cycle times and potentially even increased errors, and operators might be prompted to adapt to the attentional load by prioritising only one of the tasks. Although we view multitasking in

HRC as feasible, we raise concerns about potential effects on productivity and call for future research on designing HRC applications that don't deplete attentional resources.

Our results also show that, when multitasking in HRC settings, participants may adapt their strategy and prioritise one task over another, leading to more errors in the respective task. We speculate that this can be either due to the inability to split attention between multiple tasks, or simply because of the preference to maximising the efficiency in one task while sacrificing efficiency in another.

Publication background

- Eesee, A. K., Kostolani, D., Kang, T., Schlund, S., Medvegy, T., Abonyi, J., & Ruppert, T. (2024). May I Have Your Attention?! Exploring Multitasking in Human-Robot Collaboration. IFAC-PapersOnLine, 58(19), 241-246. GS citation: 2

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10.4.2 Work instruction evaluation

Background and objective

In the industrial setting, poorly designed instructions can significantly undermine productivity, increase the likelihood of errors, and lower overall job satisfaction. Moreover, the detrimental economic and social consequences of poor instruction have been extensively documented, resulting in reduced levels of customer satisfaction, increased operational costs, and inefficient decision-making processes. Although numerous studies have explored the benefits of simplified or digital work instructions—such as textual guides or augmented reality (AR)-based solutions—these approaches often do not systematically validate the objective metrics with the subjective experience of workers based on the utilized instructions. Furthermore, research that integrates subjective questionnaires and objective physiological metrics to comprehensively evaluate worker cognitive load and efficiency based on work instructions remains limited. This gap is particularly pressing in modern assembly environments, where rising task complexity calls for instruction designs that are both cognitively considerate and operationally effective.

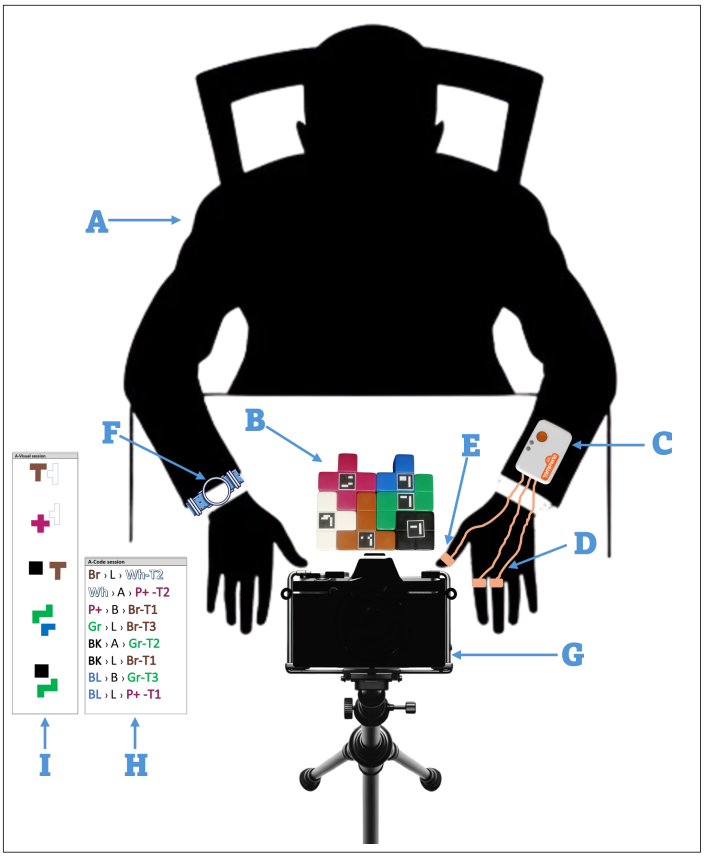
The developed methods and Design of Experiment

We systematically compared two distinct instructional approaches—code-based and visual-based—within an assembly-like scenario. Specifically, we hypothesize that code-based instructions, which rely on alphanumeric codes to guide the assembly process, impose a higher subjective cognitive load due to the increased mental effort required to decode the codes. By contrast, visual-based instructions are expected to reduce cognitive load by offering more intuitive, graphical representations of the same tasks. However, this simplified approach may induce more frequent hand movements and repeated task cycles—potentially resulting in more pronounced changes in physiological signals (Galvanic Skin Response GSR and Photoplethysmogram PPG) due to increased physical activity. In evaluating these hypotheses, we measure both subjective cognitive load (using the NASA Task Load Index 'NASA_TLX' and short Dundee Stress State Questionnaire 'short DSSQ') and objective indicators (physiological signals and task performance metrics) to capture a comprehensive view of how work instructions influence operator well-being and efficiency. We therefore pose the central question: *How do subjective perceptions of cognitive load and performance align with objectively measured changes in cognitive load and performance when different instructional methods are employed?*

Given the gap identified in the literature, we designed a controlled experiment in which participants assembled "Make 'N' Break Extreme" blocks using two instructional methods: code-based and visual-based instructions. This protocol was chosen specifically to isolate extraneous load while maintaining consistent intrinsic load across tasks. The present study aims to investigate the impact of work instructions on operator cognitive load and performance within a controlled, assembly-like scenario.

The study involved the use of two instructional approaches for two distinct sessions: *Visual-based* instructions for the low cognitive load session and *Code-based* instructions for the high cognitive load session. In the visual-based session, the participants see a series of step-by-step images depicting exactly how each pair of blocks should connect. In other words, each image clearly shows which sides of the pieces should touch, allowing participants to visually align the blocks until they match the illustrated pattern. The visual instructions presented in this context are characterized by their clarity as they provide a straightforward and unambiguous representation of the final goal. This approach aims to minimize the need for interpretive effort from the participants.

On the other hand, we utilized a color-based coding system for the assembly instructions to increase the difficulty level in the code-based hard session. A code, usually consisting of the first two letters of its color, references each piece. For example, 'Re' signifies the red piece and appears in red text, while 'Gr' signifies the green piece and appears in green text. The instructional material provides participants with these codes, which they must use to determine the position and contact points between pieces. The representation of spatial relationships between pieces is denoted by 'A' for Above, 'B' for Below, 'L' for Left of, and 'R' for Right of. We denote the degree of contact between two adjacent pieces as 'T1' for a single contact region and progressively increase it to 'T4' for four contact regions. The codes require participants to translate abstract instructions into the concrete task of assembling the blocks, reflecting a cognitive challenge often encountered in real-life situations where such instructions can be difficult to interpret. Figure 10.9 shows the setup of the experiment in this study.



10.9. ábra: This figure illustrates the comprehensive setup used in our experiment.

Scientific results and novelty

This study provides new insights into the relationship between work instruction design and operator cognitive load in industrial-like assembly scenarios. The key scientific contributions and novel aspects are as follows:

1. **Integrated evaluation approach:** We systematically combined subjective workload assessment tools (NASA-TLX and short DSSQ) with objective physiological measures (Galvanic Skin Response and Photoplethysmogram) and task performance indicators to obtain a comprehensive understanding of cognitive load during assembly tasks.

2. **Experimental evidence on instruction modalities:** We designed and executed a controlled experiment to compare two distinct instruction modalities: visual-based and code-based. Our results show that visual-based instructions substantially reduce subjective cognitive load, while code-based instructions impose higher mental demands due to the need for decoding and translation of abstract codes into concrete actions.

3. **Revealing trade-offs between cognitive and physical load:** Although visual-based instructions lowered cognitive load, they were associated with increased hand movements and repeated task cycles, which were reflected in physiological signals. This highlights a trade-off between cognitive and physical dimensions of workload not sufficiently addressed in the existing literature.

4. **Practical implications for instruction design:** Our findings provide actionable evidence for the development of cognitively considerate and operationally effective work instructions in modern industrial environments, particularly where task complexity is increasing.

The novelty of this work lies in its holistic methodological approach, its empirical validation of instruction-induced workload differences, and the identification of interaction effects between subjective and objective indicators of cognitive load.

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Legfontosabb 10 publikáció

Ruppert Tamás

2025

1. T.-A. Tran, T. Ruppert, and J. Abonyi, "Indoor positioning systems can revolutionise digital lean," *Applied Sciences*, vol. 11, no. 11, p. 5291, 2021
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IF: 4.6 **D1**

applied sciences

MDPI

Article

Indoor Positioning Systems Can Revolutionise Digital Lean

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Abstract: The powerful combination of lean principles and digital technologies accelerates waste identification and mitigation faster than traditional lean methods. The new digital lean (also referred to as Lean 4.0) solutions incorporate sensors and digital equipment, yielding innovative solutions that extend the reach of traditional lean tools. The tracking of flexible and configurable production systems is not as straightforward as in a simple conveyor. This paper examines how the information provided by indoor positioning systems (IPS) can be utilised in the digital transformation of flexible manufacturing. The proposed IPS-based method enriches the information sources of value stream mapping and transforms positional data into key-performance indicators used in Lean Manufacturing. The challenges of flexible and reconfigurable manufacturing require a dynamic value stream mapping. To handle this problem, a process mining-based solution has been proposed. A case study is provided to show how the proposed method can be employed for monitoring and improving manufacturing efficiency.

Keywords: Industry 4.0; Lean 4.0; indoor positioning system; Lean management; smart manufacturing; real-time locating system; process mining; internal inventories

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1. Introduction

Internal Positioning Systems provide the possibility of full traceability of manufacturing processes [1]. The main research innovation of this work is to highlight that data provided by IPS systems can be transformed into information that is valuable for Lean-based process improvement.

Lean management (LM) is a well-known concept that is widely accepted in manufacturing industries due to its effectiveness in cutting waste and improving operation performance [2–5]. The tools of Industry 4.0 that advance LM to the next level include simulation and optimization [6,7], process mining [8–10], data mining [11–14], data analytics [15,16], big data analysis [17,18], digital twins [19–22], machine learning [23,24], virtual reality [25–28] and cyber-physical systems (CPSs) [17,29–31]. An integrative model for LM and Industry 4.0 was studied in [32], which resulted in a flexible and reconfigurable manufacturing system. This brand-new generation was labelled Lean 4.0, with the promise of a different perspective of designing, operating, monitoring and optimizing manufacturing systems [33]. Lean 4.0 follows LM principles as it is built upon a strong foundation of communication and connectivity between equipment and personnel, which allows the key performance indicators (KPIs) to be automatically collected, analysed and modified according to LM measures. Recently, the Lean Industry 4.0 concept has been introduced to surpass the production context within enterprises and to cover the extended supply chain and the logistics network [34].

The tracking of flexible and configurable production systems is not as straightforward as in a simple conveyor, which provides difficulties in controlling internal inventories.

The potential of digital lean is unlocked by the integration of operational technology (OT) and information technology (IT) as IT tools can improve the real-time visibility of the value stream. One of the most promising IT elements that can support Lean 4.0, is the Indoor Positioning System (IPS) [35]. This work aims to present how positional data can enrich the toolkit of Lean 4.0-based continuous development of flexible manufacturing systems.

The primary function of indoor positioning is similar to GPS, track on a map a tagged mobile unit that can be an asset or person [36]. A typical IPS is an indoor wireless positioning technology [37] that works with radio-frequency, optical, or acoustic tags and chips [38]. The IPS tags are always-active and continuously broadcast signals to beacons [37]. Tags and fixed reference points can be transmitters, receivers, or both, resulting in numerous possible technology combinations [39,40]. IPS can identify objects' location in a closed structure, thus widely applied in an office building, hospitals, facilities, and warehouses [41].

Compared with other technology including RFID and bar-code scanner, IPS can exclude human error and systematic flexibility, and is robust to any layout change. Due to its intrinsic appropriateness for monitoring logistics units within a manufacturing facility—from items up to packages, transport units, and pallets—IPS has been widely applied in many aspects such as cycle time optimization [42], monitoring production line activities [43], logistics management [44], pallet management [45], safety management [46], and human resource monitoring [47].

This paper aims to develop a detailed guideline about how the information provided by IPS can be utilised in lean management. The proposed method is embedded into the concept of continuous development. The structured DMAIC (Define-Measure-Analyze-Improve-Control) approach utilised in Six Sigma methodology also follows the concept of the Plan–Do–Check–Act (PDCA) cycle [48], which has been proven effective in reducing non-value-added activities in the supply chains and assembly lines [49].

Value Stream Mapping (VSM) is the standard tool for recording processes and identifying waste. The challenges of flexible and reconfigurable manufacturing require a dynamic VSM (DVSM). Our key idea is to handle this problem based on process mining that has already been applied for VSM of a mixed-model assembly line [50], utilised in Six Sigma projects [51] and also used for the analysis of IPS-based data [37].

According to the structure of the paper, the main contributions are the following:

- We explored and categorized the possible situations in which the IPS can be applied in LM in Section 2. The novelty of this section is that it defines how positional data can be transformed into actionable information for LM.
- We developed a data-based framework to integrate and analyze positional and manufacturing data. As Section 3 presents, the novelty of the methodology lies in the process-mining-based identification of VSMs.
- We provided a detailed industrial case study with several KPIs to demonstrate the applicability of the proposed framework in Section 4. Our case study is based on a real manufacturing problem where the IPS monitors the day by day production, so the applicability of the developed framework is demonstrated.

2. Utilisation of Location-Information in Lean 4.0

LM is based on the continuous improvement of the processes based on the following concepts:

- identifying wastes in production processes to eliminate them [52];
- shortening the lead time of production [53,54];
- reducing inventory and stock levels [53,55];
- standardizing tasks and motion to stabilize the output quality [56];
- developing a continuous flow of information and materials in the organization [52,57];
- balancing the manufacturing line to avoid bottleneck [55,58];
- employing a comprehensive scheme to maintain productivity [59,60].

The proposed method is based on the assumption that the wastes, the processing and activity times, and the stocks can be automatically measured by IPS without labour- and time-consuming measurements. Table 1 shows the key performance indicators (KPIs) of the Lean concepts and their measurement possibilities. The listed measurement systems not only help organize and optimize the production procedure by easing monitoring activity with a real-time value stream but are also aligned with LM principles as well as supporting philosophies such as total quality management (TQM) and just-in-time (JIT) [61].

As Table 1 shows, RFID-based systems are particularly suitable for monitoring LM parameters [62,63]. Utilizing RFID tags within an IPS is a favourable approach in different industries, such as construction [64,65], fast-moving consumer goods production [66], automotive part manufacturing [67], automobile assembly manufacturing [68], agriculture equipment machine part manufacturing [69] and the job shop floor environment [70]. In the manufacturing shop floor environment, IPS can be beneficial as it can enrich data acquisition for LM [71] and it can be used to obtain dynamic spaghetti diagrams, which are used for the visualization of the value streams [72].

Table 1. The traditional concepts of LM with the potential of IPS.

Lean Concept	KPIs	Measurement Tools	Potential of IPS	Relevant Application of IPS
Shortest lead time	Average lead and cycle time	Camera [73,74]; Bar-code scanner [73]; RFID [62,75]; Machine/Event logs [76]; IPS [37]	high	Real-time monitoring of the position of semi-finished products and resources, calculation of the lead and cycle times [42,43].
7 wastes elimination	Waste of Transportation	RFID [66]; Machine/Event logs [76]; IPS [72]	high	Real-time spaghetti diagram [72].
	Waste of Inventory	Camera [30]; RFID [62,66]; IPS [72]	high	Tracked items in inventory areas [77,78].
	Waste of Motion	Camera [74]	low	-
	Waste of Waiting	Camera [73,74]; Bar-code scanner [73]; RFID [62,75]; Machine logs [76]; IPS [37]	high	Tracked semi-finished products, waiting times, internal stock levels [71].
	Waste of Over-processing	Manual audit [79]	low	-
	Waste of Over-production	RFID [66]; IPS [37,72]	high	Discovered overproduction based on the tracked semi-finished products [71].
	Waste of Defect	Optical sensors [80]; RFID [81]; [72]	medium	Reduced defect based on IPS-based poke-yoke solutions and better monitored rework flows.
Less inventory	inventory value	RFID [66]; IPS [72]	high	Improved control of the inventory level [78] and e-kanban solutions reduce internal inventories [82].
Standardized work	Deviation from standardized work	Camera [74]; RFID [62]; IPS [37]	high	IPS based dynamic work instructions improve operator work (Smart operator) [83]
Continuous flow	Queueing time	RFID [62]; IPS [37,72]	high	Discovered queueing areas near the workstations [1].
Line balancing	Line balance factor	Camera [74]; RFID [62]; IPS [37]	high	Improved activity time analyses thanks to sensor fusion [43].
Quick changeover	Set-up and changeover time	Machine logs [84]; Manual audit [85]	high	Supported SMED projects [86]

Locating sensors only may fail to comprehend the actual activities performed in the production. For example, locating sensors can signal that the product is in a workstation, but they cannot indicate whether the product is currently processed, especially in a manual processing step, while the operators were busy looking for tools or reading work instructions. Therefore, it is beneficial to use multiple sensory data for Lean 4.0, so IPS is mostly beneficial to enrich the existing information collected by other sensors and data stroded in an MES system.

3. IPS-Driven Development Framework for Lean 4.0

The previous section presented that the application of IPS in Lean 4.0 could open new possibilities if the positional data could be transformed into real-time contextualised and actionable information. This section proposes a framework that we developed for this purpose.

The proposed framework that also utilizes information sources of a typical Industry 4.0 manufacturing system is presented in Figure 1. In addition to location data, acquired data from existing technologies such as bar-code scanners, machines and event logs can be incorporated to provide a comprehensive view of the current system state. The facility information, such as the overall layout and designated area map, can provide supportive data to clarify the facility context. The information of the overall layout is added, as well as some designated areas for buffer inventory, waiting for queues, and maintenance preparation. After data processing and computation of LM KPIs, different system monitoring techniques can be applied, such as optimal material route, optimal labour assignment and JIT preparation. Process- and data mining are performed on the collected and contextualised data to explore frequent patterns of material flow and states of the production process.

We applied Gantt diagrams to analyze the periods of operations. As it will be presented in the application example there are many missing time periods in the Gantt diagram when the states of the material flow and the resources are not monitored in the MES. Based on the analysis of positional data, additional states of the manufacturing process can be defined and assigned to the product and material flows and states of the resources (e.g., temporal inventories can be defined). The explored states and additional time-stamps provided by the IPS process mining algorithms can be utilised to update VSMs. Thanks to the real-time position of the process flows, motion-based anomalies can be detected.

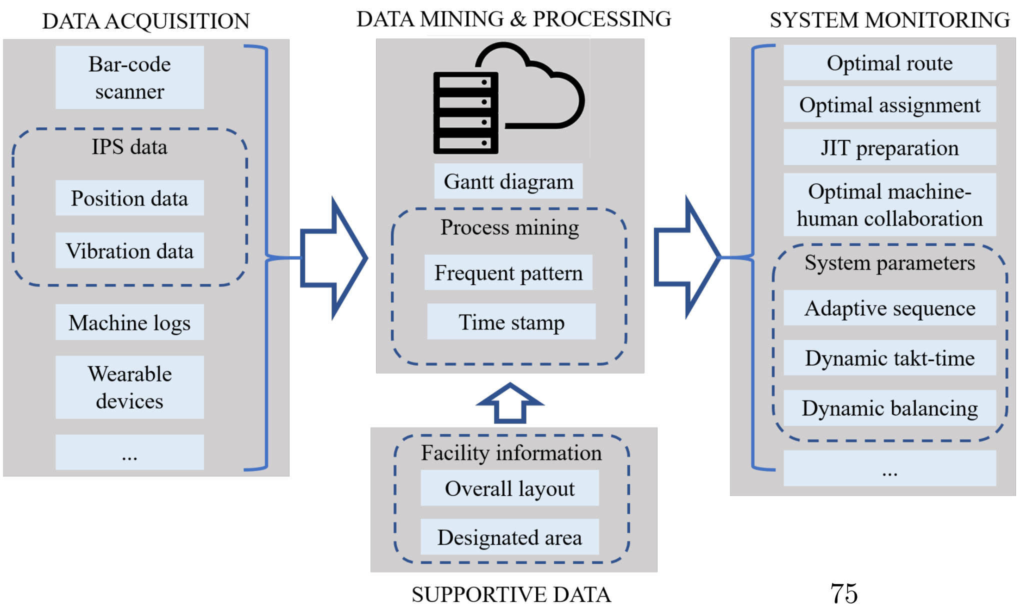


Figure 1. The proposed framework of Lean 4.0 data-driven development.

Figure 2 shows that proposed methodology follows the PDCA (Plan, Do, Check, Act) cycle of continuous improvement. The core element of the method is the process model (represented as a VSM in the figure) that contains all the essential information about the manufacturing process. The proposed improvement cycle continuously updates the model with the help of IPS data. The motivation is to continuously and automatically monitor the production. The developed framework can discover the real process model continuously based on the IPS data with the toolset of process mining. The resulted models are used to update the VSMs, evaluate the performance of the process by calculating the Lean KPIs. The most apparent benefit of Lean 4.0 KPIs are the readiness of decision making and optimisation based on real-time information about the manufacturing system.

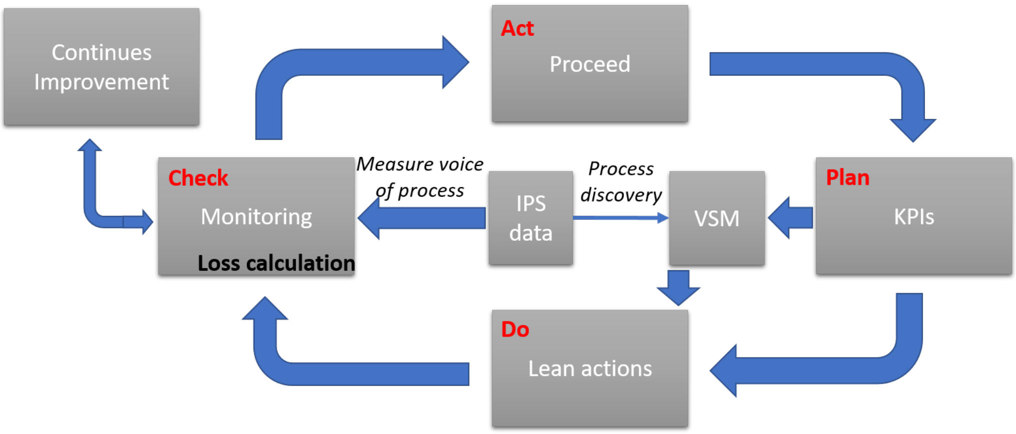


Figure 2. IPS data is the key element of the proposed PDCA-cycle-based methodology.

4. Application to the Monitoring of a Flexible Manufacturing Process

In this section, a manufacturing use case is represented to prove the applicability of the proposed methodology. We introduce the studied production process and the purpose of the continuous improvement project and show the details of the application of IPS.

4.1. Purpose of the Project

The presented study focuses on the monitoring of CNC machines and assembly stations used to produce metal parts for an automotive company. There are five CNC machines, one assembly station, one assembly line and a packaging station. The orders (tasks) move along different paths during the production, depending on the production plan. The project aims to reduce transportation waste, identify the waiting and queueing times, and monitor the cycle times. Due to the changing number and variations of product families, this process is not a one-time activity. One small change in the product architecture can cause changes in the assembly sequence, which can lead to significant performance losses.

Traditionally, LM masters will detect these 3M (Muda—Mura—Muri) via eye observation, then conduct re-calculation and re-arrangement to find a new optimal point. By using the IPS, the manufacturing activities can be easily tracked and automatized. The positional data from the moving carts are analyzed to identify whether they are not in a pre-defined value-added area (like assembly stations). The extracted cycle times are used to find the potential wastes of human works (changing times, manual work) and focus on these areas, such as defining a standardized digital work instruction that depends on the current position information of the semi-finished product.

4.2. Description of the Applied IPS

The hardware architecture of the IPS is illustrated in Figure 3. The applied ultra-wide band (UWB)-based real-time locating system (RTLS) uses active tags and anchors for localization. There are 15 anchors installed on the shop floor, which is nearly 2000 m^2.

The anchors are connected to two central units. The raw sensory data are transferred into the position calculation server. The calculation of the position is based on the TDoA (Time Difference Of Arrival) method and applies a Kalman filter to obtain more accurate information. The IPS is installed to track carts with the shop floor's semi-finished products. These carts are moving (manually) between the workstation and the IPS sends information to the MES if the actual cart with the defined (paired) product has arrived at the actual station. There are 40 carts, every cart has a dedicated IPS tag. Each time a semi-finished product was put on a cart, the operator paired the order number with the tag ID with a timestamp. The positional data accuracy is around 0.5 m, which is sufficient to obtain an accurate spaghetti diagram (Figure 4a) from each produced order. The shop floor with a tracked motion of one product is shown in Figure 4a. As this figure illustrates, the analysis of the positional data allows the identification of the temporary stations and motion paths.

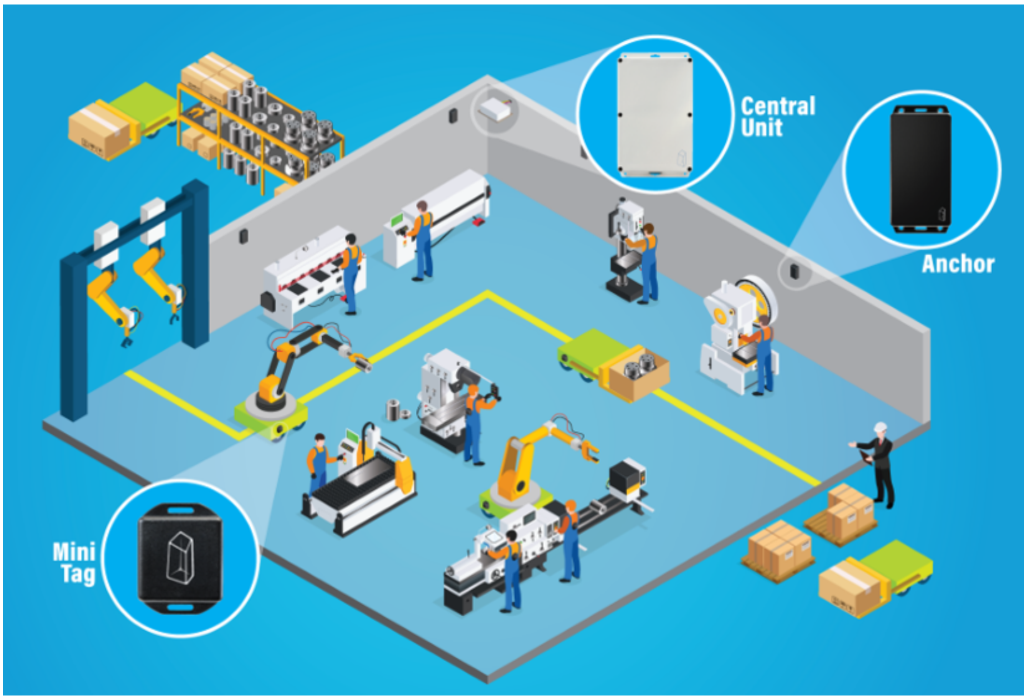
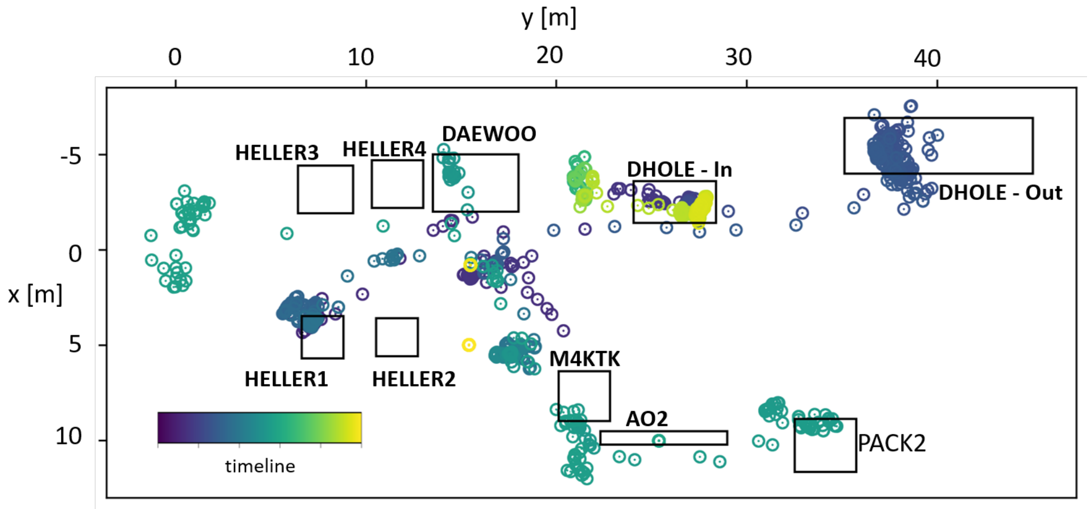


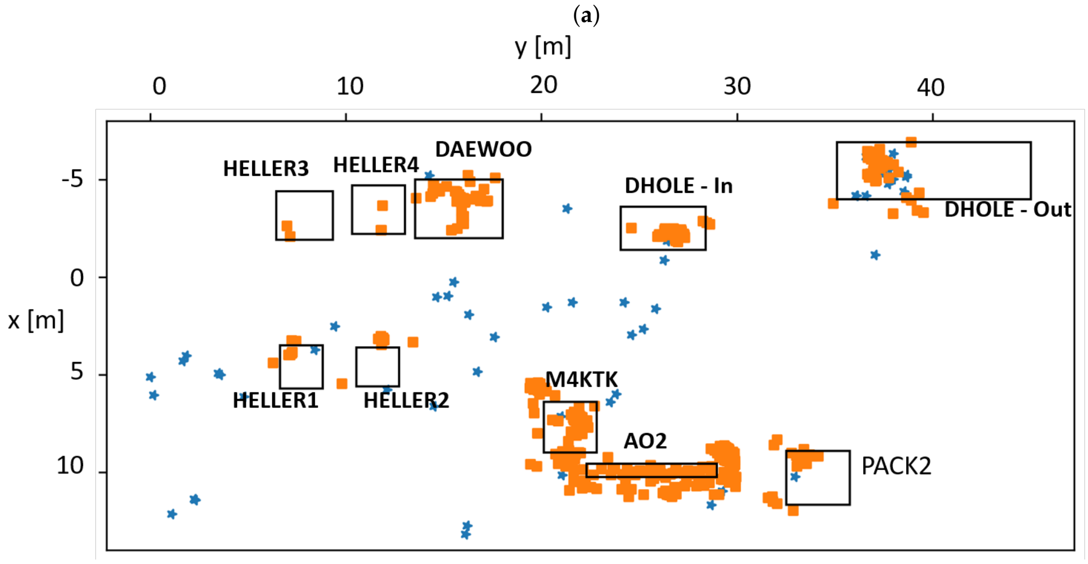
Figure 3. The hardware architecture of the applied IPS (based on Sunstone-RTLS Ltd.—Hungary).

The proposed lean analysis was performed on the production data from MES and positional data (where the sample time is three seconds) from IPS. The process-flow was discovered with a process mining algorithm based on the MES data. We used the Disco software for process mining, and in the following subsection, the results are shown. The positional data are used to calculate the loss of process. We analyzed the transportation path, where we calculate the transportation periods for orders and the hidden temporary storage and queuing times are identified.

The collected positional data contain the tag IDs with the x–y position $[m]$ according to the predefined coordinate system (fitted for the shop floor layout). These data are updated every three seconds (the sample time can be set—maximum 1 kHz) to ensure most of the carts' motion is covered in this production scenario. The factory layout with the zone (workstation) definitions is provided by the rectangles (Figure 4a) to match the activity order. This layout is elaborated based on the facility's overall layout, and with the designated area represented where the production activities are performed. These areas are determined with the hardware's capability, and the system can detect the corresponding processes that are occurring. The entering and exiting times define the time that a product spends on one process step. The information (resources, produced pieces, quality issues) for every *Task* ID, which includes the *Start* time when the tag entered the zone (*Workplace*), is stored in the MES.



(**a**)



(**b**)

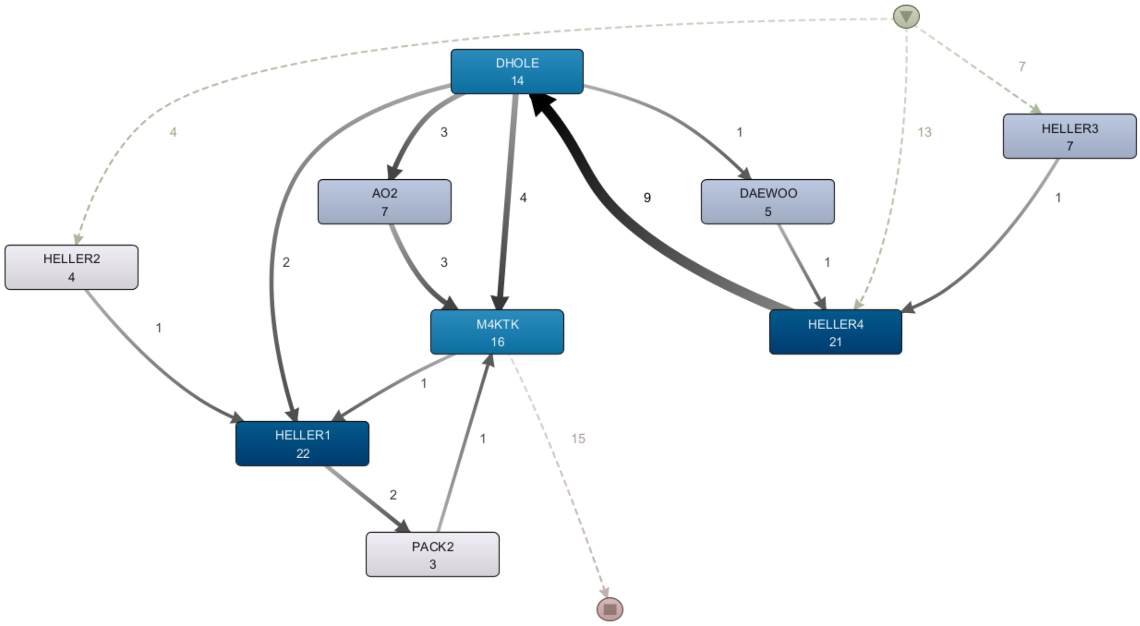
Figure 4. The distribution analysis of the positional data supports the identification of the states of the internal inventories, and the waiting and cycle times. (**a**) Tracked path of one product on the shop-floor. The rectangles define the workstations and the dots represent the positional data. The timeline is presented by the colours of the dots. (**b**) The discovered status is based on positional data. The blue stars are the transportation, while the orange markers are the queueing positions.

4.3. Calculation of the IPS-Based Indicators

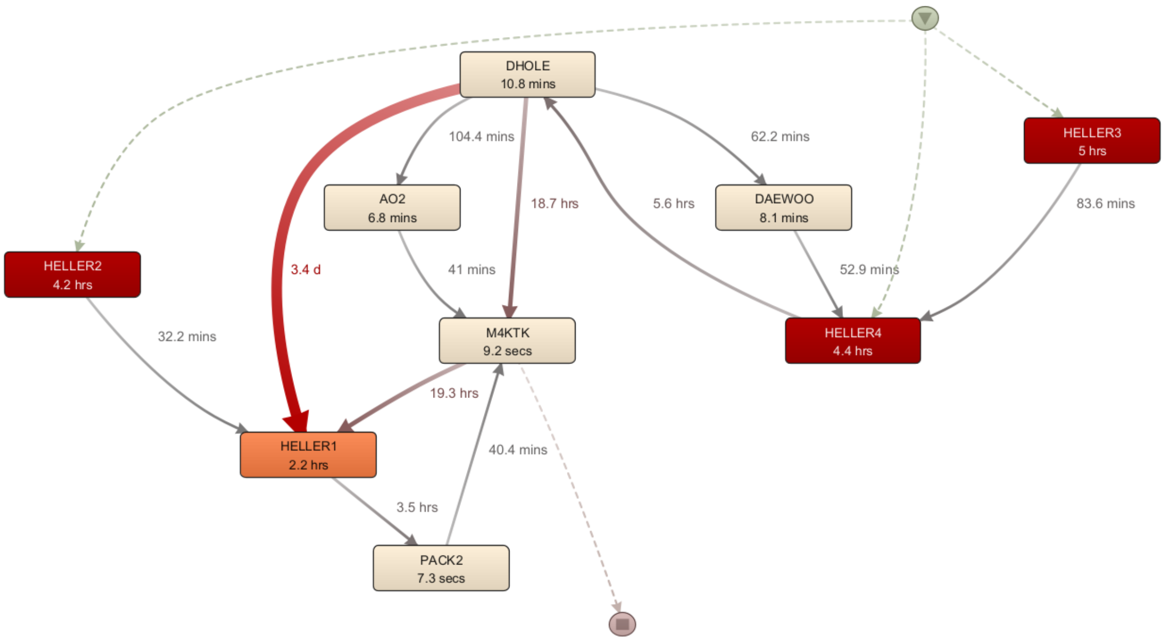
This section shows how the data from MES and IPS can be utilised based on the relevant KPIs.

The IPS sends signals to the MES when the actual cart arrives at the pre-defined station. The applied process mining algorithm determines the process model of the production flow. An illustrative result is presented in Figure 5. Due to the flexibility of the manufacturing process, the extracted model is not trivial and varies over time; therefore, the model is continuously updated based on the real-time positional data.

The discovered process flows serve as input for work standardisation projects. According to the most frequently conducted steps, a pattern of main material flow is recognized in Figure 5a, where the main workstations and machines are highlighted in blue. We note that there is no leading process flow. Along with the material flow map, the average cycle times are recorded, as illustrated in Figure 5b. The thickness of the arrows represent the time delay between the two stations. The result can be compared to the manufacturing processes standard times so that non-conformance stands out. The main process mining-based KPIs are summarized in Table 2.



(**a**)

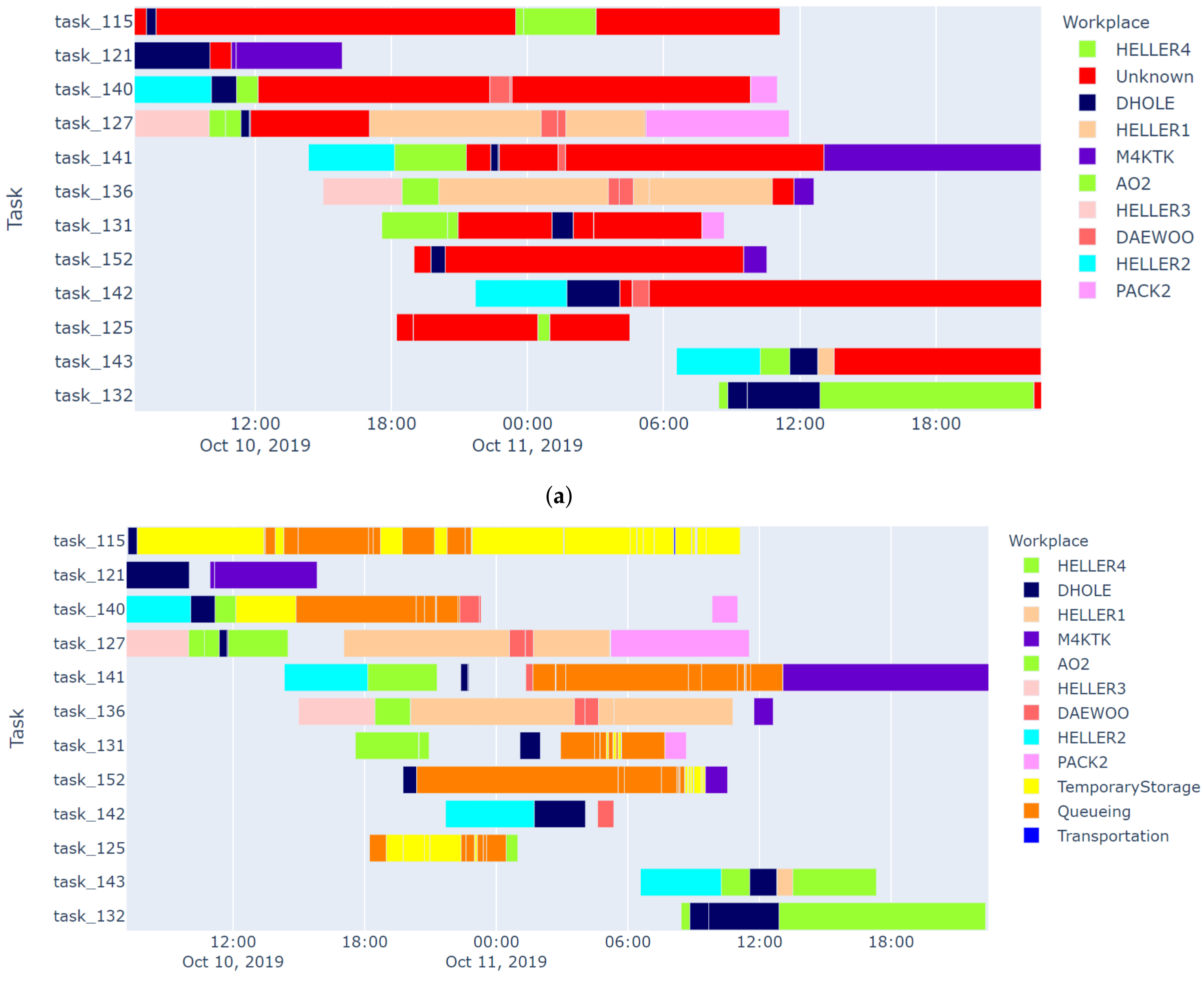


(**b**)

Figure 5. A production flow model discovered by process mining based on IPS and MES data. (**a**) The frequency of the material flows. The colours of stations represent utilisation of the workstations. (**b**) The discovered average cycle and transition times. The colours of stations represent the cycle times. We can notice that the *HELLER* stations are the bottlenecks of the process. The transition times are represented by the arrows, which highlight the possible hidden wastes.

A Gantt diagram has been developed to further study the reason for the long transition times of the semi-finished products (see Figure 6a). The rows of the Gantt chart show the orders (*Tasks*) and colours represent the workstations. We defined the *Unknown* station to show the period where we have no data (from MES). These periods are denoted in

Figure 6a with red lanes and these periods could be the source of the long time period between two stations on the results of process mining and could be the hidden wastes of the manufacturing process. The *Unknown* period is the 19.74% of the studied time period.



(b)

Figure 6. The Gantt diagrams show the states of the production of a given product. The comparison of the two diagrams shows the benefit of the additional information of the IPS. (**a**) Gantt diagram based on MES data. (**b**) Gantt diagram based on IPS and MES data.

In the next step, we discovered the status of thee *Unknown* periods based on the positional data. We analysed 22 days of production data for this purpose. Based on the positional data from IPS, the velocity is calculated to determine the *Waste of transportation* periods. An example for that period is shown in Figure 4b with the blue stars. Temporary storage is the positions that are closely located out of the pre-defined zones (workstations). When the carts with the products are located in a pre-defined zone (but it is not logged to the MES, so it is not under production), we assumed these products are queueing before the actual workstation (see the orange points on Figure 4b). Figure 6b shows the new Gannt chart with three more defined stations related to queueing, temporary storage, and transportation.

4.4. Discussion, Utilisation of the Results

The results are shown in Figure 7, where we note that the *Queueing time* and *Wasting time* are almost 20% of the analysed manufacturing time. Table 2 summarises these times according to the stations and shows that the *AO2* workplace has the most significant queuing time, so the continuous improvement project should focus on that first.

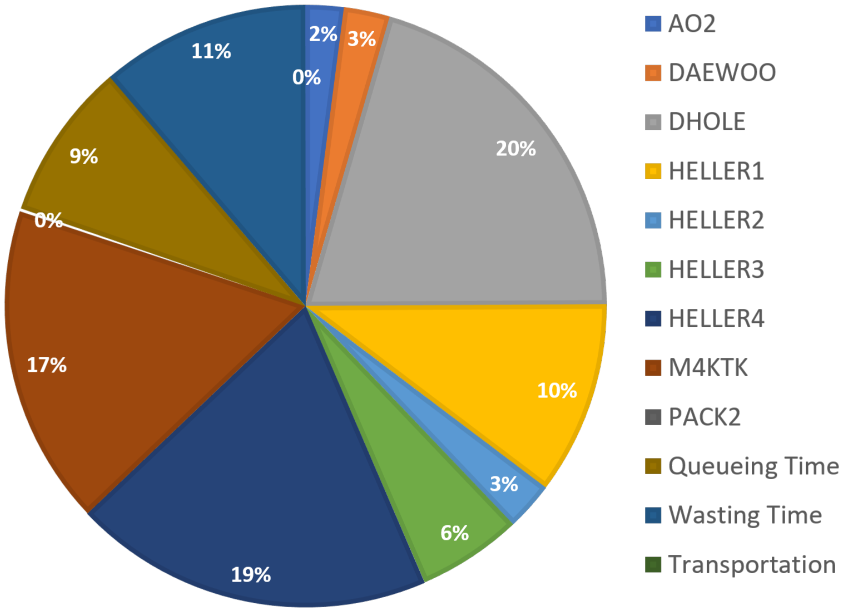


Figure 7. The distribution of the average times calculated based on the IPS and MES data.

Table 2. The cycle and queueing times calculated with the help of the positional data.

Workplace	Average Cycle Time [min]	Queueing Time [min]	Produced Tasks
Waiting time	119.47	-	54
Waste of transportation	2.73	-	27
AO2	77.73	102.86	56
DAEWOO	84.71	84.05	49
DHOLE	88.69	5.09	163
HELLER1	99.36	91.80	72
HELLER2	228.53	46.74	34
HELLER3	197.16	59.56	32
HELLER4	124.82	42.18	146
M4KTK	61.91	84.61	145
PACK2	30.30	47.72	31

The IPS serves as a non-stop monitoring system that contributes to the everyday work of Lean specialists. As a first step, an alarm system can be set up at each workstation to notify if the working or waiting times in that station exceed their predefined limits; so the line advisor can take required supportive action on time.

The integrated application IPS and process mining supports the redesign of the layout thanks to its ability to detect hidden stations and states of the process.

5. Conclusions

In this paper, the possible applications of indoor positioning systems in Lean 4.0 are explored. The proposed IPS incorporates different kinds of sensors to acquire not only positional data but also other data such as vibration, which enables them to recognize motion and transportation activities. Along with this IPS architecture, the traditional set of

Lean KPIs are redefined and redesigned to be derived automatically from IPS-based data. The process mining-based analysis of the collected data can provide insight into the key factors that determine the productivity and efficiency of production systems.

The proposed method of data acquisition enables further system optimization, which assists managers in monitoring their system effortlessly and in a stress-free manner. In the trend of Lean 4.0, the use of such a system is expected to soon be dominant due to its hardware maturity, as well as the readiness of data and the need from the manufacturer. The framework for process analysis can provide the basis for further optimization and enhancement of human–machine activity cooperation, which will constitute our future research. A case study is conducted in a mechanical manufacturing firm to show the possible output of Lean 4.0 KPIs, and improvements can be made based on activity data.

The accuracy of the result from the system is much dependent on the hardware characteristics. The most frequent error occurs when the location sensor cannot recognize which area is between two adjacent ones. Due to the current technology limitation, the defined space of workstations needs to be separated with a distinct distance. Fortunately, with process mining tools, meaningless noise and error can be excluded. However, the authors believe that this problem can be mitigated soon, with advancements in the new hardware system.

According to the intensive use of data in monitoring a smart factory, one particular concern is personal privacy. When a tag is attached to an operator, then every movement can be tracked. To ensure personal privacy, the tag is only active in the production zones.

Besides, with a large amount of operation data and production monitoring parameters from the system, the management dashboard needs to be discussed and adjusted at a managers' meeting, not by any single person. As the system can improve the facility operation—through line speed changes, human assignment and dynamic line balancing—it is unwise to teach it in the wrong way. The consultation of an LM expert in setting the KPIs and allowable adjustment is necessary.

We believe that the proposed framework and the presented results provide a practical starting point for lean management practitioners and can initiate further research projects.

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Indoor positioning-based occupational exposures mapping and operator well-being assessment in manufacturing environment

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Abstract. This research was motivated by the need for detailed information about the spatial and contextualized distribution of occupational exposures, which can be used to improve the layout of the workspace. To achieve this goal, the study emphasizes the need for position-related information and contextualized data. To address these concerns, the study proposes the use of Indoor Positioning System (IPS) sensors that can be further developed to establish a set of metrics for measuring and evaluating occupational exposures. The proposed IPS-based sensor fusion framework, which combines various environmental parameters with position data, can provide valuable insights into the operator's working environment. For this, we propose an indoor position-based comfort level indicator. By identifying areas of improvement, interventions can be implemented to enhance operator performance and overall health. The measurement unit installed on a manual material handling device in a real production environment and collected data using temperature, noise, and humidity sensors. The results demonstrated the applicability of the proposed comfort level indicator in a wire harness manufacturing setting, providing location-based information to enhance operator well-being. Overall, the proposed framework can be used as a tool to monitor the industrial environment, especially the well-being of shop floor operators.

Keywords: Operator 4.0, operator well-being, environmental sensors, mobile sensor, IPS

1 Introduction

The main objective of this paper is to propose an approach for assessing the well-being of operators in indoor environments, with the operator comfort level serving as a measurable indicator. To achieve this, we propose a framework based on the utility function and information fusion to enhance the assessment of operator well-being. Additionally, we have developed a mobile measurement device that utilizes moving units to obtain a detailed layout of the shop floor. Understanding the specific areas and conditions where workers are exposed to various environmental factors is essential.

Distributed information is essential to capture the spatial and contextualized distribution of occupational exposures. Unlike concentrated parameters, this exposure varies between operators and workplaces. To formulate a clear objective, it is necessary to articulate the need for detailed information that encompasses both spatial and temporal dimensions. To achieve this, it is necessary to have position-based information that is contextualized and linked to relevant data. We incorporate indoor positioning data to create location-based sensor information. The application and further development of the Indoor Positioning System (IPS) serve as a solution to address these motivations. By employing IPS sensors and associated analysis techniques, it becomes possible to gather precise position-based information. The integration of IPS sensors and related technologies offers a promising avenue for advancing workplace monitoring and design, ultimately promoting a safer and more efficient working environment.

This transition leads us to the core concept of the study, which aims to develop a comprehensive framework for collecting and analyzing precise data that captures the detailed nature of occupational exposures. We employed utility functions to effectively represent the measurement data obtained from the environment. These utility functions serve as mathematical models that assign values or scores to the measured parameters, such as temperature, humidity, and noise levels. By utilizing utility functions, we are able to translate the raw data into a standardized representation that captures the perceived comfort level of the operator. The utility functions play a crucial role in quantifying the operator's comfort by assigning higher scores to favorable conditions and lower scores to unfavorable conditions. This allows us to assess and compare different environmental scenarios in terms of their impact on the operator's well-being and comfort.

For this characterization, we have determined a so-called comfort level. The value represents the extent to which the operator can handle environmental load in each zone of the shop floor and how comfortable they feel in these areas. To measure this new indicator, we have also developed a mobile sensor unit as an extension of the standard IPS tag to make the measurement more cost-effective. With this idea, we can utilize all the moving units on the shop floor, such as AGV (automated guided vehicles) or AMR (autonomous mobile robots), or even the material handler operators equipped with the developed sensor.

As a result, we can identify specific areas that require attention or modifications to create a more comfortable and conducive workspace for the operators. The utilization of utility functions in representing the measurement data greatly contributes to our understanding of the operator's comfort and aids in the development of strategies to prioritize their well-being. To demonstrate the applicability and effectiveness of the proposed framework, a detailed case study is conducted.

The state-of-the-art is described in Section 2. In Section 3, the developed sensors and the proposed comfort level indicator are detailed. Section 4 presents a wire harness industrial case study where we demonstrate the applicability of the developed mobile sensor unit and the relevance of the proposed comfort level indicator.

2 Assessments of well-being and comfort level

The aim of Operator 4.0 is to give operators all the information they need to discover, use, and benefit from support systems that can help them increase their critical skills for their work, thus increasing their productivity [10]. With these in mind, Operator 4.0 is intrinsically linked to the comfort of operators, minimizing negative influences and negative stimuli in their working environment. A sub-type of this is Healthy Operator 4.0, which aims to assess the stress levels and potential physical risks of the worker in a cyber-physical environment. To achieve this, it uses wearable devices to monitor the health and well-being of operators. The measured information will be used to model the operator's habits and behavior, which will help to optimize the operator's working environment. The idea behind Resilient Operator 5.0 is to combine human creativity, ingenuity, and manufacturing-informed innovation with new, sustainable, energy-saving ways to keep operators thriving in the face of exhausting and unpredictable conditions. Resilient Operator 5.0 can be broken down into two main groups, Self-resilience and System-resilience. Self-resilience broadly addresses the health, safety, and productivity of operators on the shop floor. Self-resilience is a powerful toolkit for protecting the health of operators. These include a variety of intelligent health wearables, personal protective equipment, exoskeletons technology, augmented reality technology, and virtual reality technology [8].

Well-being itself is a multi-component concept, and can refer to an individual's sense of happiness, as well as their comfort in a particular environment or situation, their health, or their financial security. A comprehensive summary of worker well-being is provided constructs, categorizes them, and offers a brief characterization based on the relevant academic literature [16]. Worker well-being encompasses the overall well-being of working individuals, distinguishing it from concepts like employee well-being and well-being at work. It also differs from work-specific well-being, which focuses on constructs originating and applicable within the work context [16]. Well-being can be assessed through both objective measures related to the "standard of living" and subjective measures based on an individual's cognitive and affective judgments about their life, with objective aspects influencing subjective well-being levels [14]. A comprehensive overview of worker well-being, including its multi-faceted nature and various constructs is done in Ref. [16]. It addresses questions about the definition of worker well-being, measurement approaches, and considerations for selecting appropriate measures, aiming to enhance researchers' understanding and facilitate effective strategies for promoting worker well-being.

Among these factors, we have examined and quantified the sense of comfort. Acoustic comfort goes beyond simply providing an acceptable indoor environment for occupants; it involves the examination of various factors that influence acoustic comfort and mitigate discomfort [3].

Comfort is the combination of many factors so that even people who are in the same geographical area at the same time and the same age can also show conflicts in their perception of thermal comfort. The lack of inadequate indoor comfort can cause dissatisfaction in the occupants and negatively affect their productivity and performance, as well as various problems such as dryness, health and morality. These factors collectively contribute to overall comfort, which in turn affects the productivity and energy consumption of the factory, ultimately influencing its profitability. Several investigations have shown that the overall comfort of occupants depends on the ambient conditions, the characteristics of the building, and the individualities linked to the occupant. Human productivity is strongly believed to be highly dependent on acoustic, visual, thermal, and air quality conditions of the built environment [3] It follows that it would be optimal for the industry if the operator felt as comfortable as possible at work, thus preventing health problems and improving performance.

The temperature, humidity and noise levels are usually measured considered the comfort-level [12]. Occupational hazards [18] and exposures [11] play a significant role in determining the well-being and comfort level of operators. Understanding and managing these occupational hazards is crucial for creating a safer and more conducive working environment that promotes operator well-being and ensures optimal comfort levels during their daily tasks [2]. However, the thermal sensation is not significantly altered by humidity. Too low a humidity level will result in dry air, which will cause various respiratory problems on a closed and hot shop floor. Too high, on the other hand, increases perspiration, can cause breathing difficulties, and promotes mold growth on the shop floor, thus increasing the risk of allergies and reducing comfort levels. Noise, as a significant factor, can greatly impact the ability of individuals to work effectively, with high noise levels hindering concentration. To ensure optimal working conditions, it is crucial to measure and control noise levels, as prolonged exposure to noise can lead to severe issues. For instance, even a noise level of 80 dB can result in long-term hearing damage, while 140 dB can cause immediate harm. To mitigate these risks, different protective measures are utilized, emphasizing the importance of identifying areas with high noise levels.

Local exposure refers to the level of exposure to a particular environmental harmful substance [17], such as noise, in a specific location or area. An example of local exposure to noise in an industrial setting could be the noise level experienced by workers on a factory floor near a particularly loud machine. In this case, the noise exposure is specific to the workers in that area and may be higher than in other parts of the factory. Daily exposure [9], on the other hand, refers to the total level of exposure to a particular environmental harmful substance, such as noise, over a period of time, typically a day. An example of daily exposure to noise in an industrial setting could be the noise level experienced by workers throughout their workday, including breaks and rest periods. In this case, the noise exposure is not specific to any particular location but rather represents the total exposure throughout the day.

The perception of comfort is broadly defined for the indoor environment of residential buildings, offices, hospitals, schools, workshops, shopping centers, etc. Maintaining comfort in the occupied zone is the daily activity of man. The average person in an urban area spends about 85–90% of the time indoors. [3] To accurately measure and assess environment information, which serve as crucial indicators of cognitive and physical well-being in individuals [6], the utilization of an IPS becomes essential. By employing a location-driven sensing approach, the monitoring and measurement of these activities can be effectively carried out, enabling a comprehensive understanding of individuals' well-being and supporting personalized care and intervention strategies. Sensors and wireless sensor networks have emerged as a vast research and development domain, garnering significant attention and prompting numerous reviews and studies across various disciplines, due to their potential to revolutionize data collection, monitoring, and control processes by enabling real-time and remote sensing capabilities, facilitating the measurement and analysis of diverse environmental parameters, ranging from temperature and humidity to motion and pollution levels, and offering extensive applications in fields such as environmental monitoring, healthcare, agriculture, infrastructure management, and industrial automation [1], [4], [5], [13].

In our study, we propose a novel method to measure the operator comfort by utilizing environmental data and mobile measurement units, eliminating the need for individual sensor units for each person. By incorporating indoor positioning data, we can assess the real-time conditions in the manufacturing space, capturing both the spatial and temporal aspects of operator well-being. This approach not only enhances our understanding of operator comfort but also enables us to efficiently evaluate the layout, identifying critical areas that require attention from a well-being perspective. The integration of environmental sensors with the IPS ensures a cost-effective and continuous monitoring process, underscoring the significance of ongoing evaluations in promoting operator well-being. The developed framework and the proposed mobile measurement unit is introduced in the next section.

3 Developed framework to discover the location-based comfort level

In this section, we employ temperature, humidity, and noise sensors, accompanied by time and position stamps, to capture comprehensive data on the working environment. To ensure a holistic understanding of the operator's experience, it is crucial to fuse this information effectively. Therefore, we propose a comprehensive methodology for data fusion based on the utility functions, integrating the various sensor inputs to provide a unified and contextualized analysis (Section 3.1). In addition to the sensor development, we have also designed and implemented a location-based evaluation technique to enhance the accuracy and relevance of the collected data (Section 3.2). This involves capturing the precise position in relation to the environmental parameters, allowing for a more nuanced assessment of the operator's exposure and comfort level. The integration of these sensor technologies and the development of a location-based evaluation technique significantly contribute to the overall effectiveness of the proposed framework (Section 3.3), enabling a more comprehensive analysis of the working environment and its impact on operator well-being and performance.

3.1 Methodology

In this section, we present the methodology for fusing the sensors we use. The sensor fusion methodology is represented in Figure 1. This framework describes the sensor information process, where we have a measurement point that includes humidity (h_t), temperature (w_t), the noise (s_t) and the actual position data ($\mathbf{p}_t$). 2D position from the IPS is denoted by $\mathbf{p}_t = [x_t, y_t]$. The noise level is denoted by s_t, the temperature is w_t and the humidity is h_t. Here, t is the actual time point.

We defined the values of the three environmental sensors as utility functions to define the mathematical relationship that combines the different variables to calculate the overall utility to get the comfort level. Figure 2 shows these three utility functions. First, the utility function of the temperature is calculated on the basis of the following equation:

$$U_t^w = \begin{cases} 0, & \text{if } w_t < w_{\min} \\ \min\left\{\frac{w_t}{||w_{\text{ideal}} - w_t||} \frac{1}{w_{\text{ideal}}}, 1\right\}, & \text{if } w_{\min} \leq w_t \leq w_{\max} \\ 0, & \text{if } w_t > w_{\max} \end{cases} \tag{1}$$

,where U_t^w is the utility function for temperature, w_t is the temperature in the t-th timepoint and w_{ideal} is the ideal temperature assign to the maximum

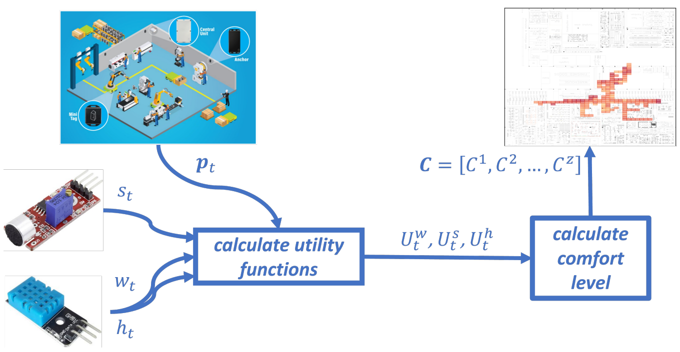


Fig. 1. The steps of the developed framework

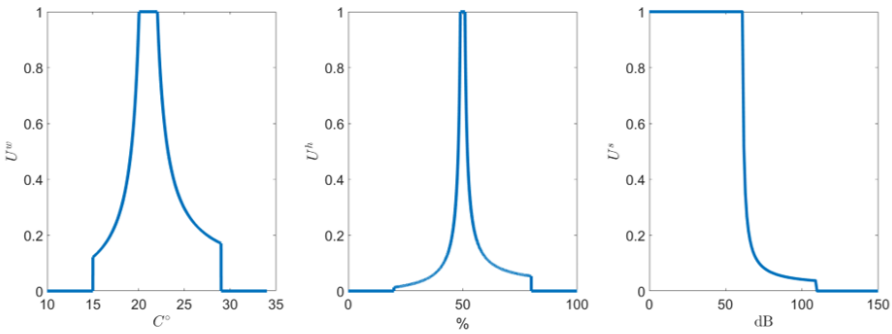


Fig. 2. Utility functions of the temperature (left), humidity (middle) and noise (right)

utility score (1). In Figure 2 (left), the ideal temperature is $22C^\circ$, $w_{\min}$ is $15C^\circ$, and $w_{\max}$ is $29C^\circ$.

The utility of the humidity (U_n^h) is calculated on the same formula as we did with the temperature (U_n^w). In Figure 2 the ideal humidity (middle) is 50%, the minimum ($h_{\min}$) and maximum ($h_{\max}$) humidity are 20% and 80%, respectively. The utility function of noise is different, as there is some standard limit of the noise acceptance. In Figure 2 (right), s_{comfort} is 60 dB and $s_{\max}$ is 110 dB.

$$U_t^s = \begin{cases} 1, & \text{if } s_t < s_{\text{comfort}} \\ \min\left\{\frac{s_n}{||s_{\text{comfort}} - s_n||}\frac{1}{s_{\text{comfort}}}, 1\right\}, & \text{if } s_{\text{comfort}} \leq s_t \leq s_{\max} \\ 0, & \text{if } s_{\max} < s_t \end{cases} \tag{2}$$

The comfort-level (C_t) is defined as combination of the three utility functions.

$$C_t = U_t^w \cdot U_t^h \cdot U_t^s \tag{3}$$

The comfort-level can be aggregated on location- or time-based. In case of the time-based comfort-level we are able to calculate the daily exposure:

$$C_{t_1,t_2} = \int_{t_1}^{t_2} C(t)dt \tag{4}$$

Where t_1 and t_2 are the start and end times, respectively. If we define this time as a shift start and end time we can easily get the exposure of the actual shift. The integral computes the cumulative comfort-level by summing up the comfort-levels at different time-periods.

3.2 The developed mobile sensor unit for exposure measurement

In our study, we utilized a mobile sensor station, along with fixed measuring stations, to detect and localize changes in the shop floor environment caused by traffic. This approach offers significant advantages by enabling cost-effective data collection, as the entire shop floor can be mapped using just one measuring station. To achieve this, we leveraged an IPS based on Ultra-Wideband (UWB) technology. IPS tags have multiple functions, including serving as both transmitters and receivers [15].

We developed a sensor that is integrated with this IPS tag. The main objective was to combine the sensor data with position information. This integration enables us to accurately locate and track the sensor data both in time and space. By associating the sensor measurements with precise position information, we gain a comprehensive understanding of the environmental conditions at different locations, allowing us to analyze and interpret the data in a spatial and temporal context. To facilitate the transmission of position data and environmental parameters, we equipped the IPS tags with UART communication. These custom-made tags were designed specifically for our measurements, allowing us to send data to the database via UWB communication with time- and location stamps. The system can determine the location of devices indoors with an accuracy of $50cm$.

The environmental parameters of noise, humidity, and temperature were measured simultaneously by a data acquisition unit, which consists of a microphone for noise-, and a DHT11 module for temperature and humidity measurement. An MSP430FR5739 microcontroller was used for data collection and pre-processing.The signals provided by the sensors are collected by a low power microcontroller, and sent in packets via UART to the IPS tag.

3.3 Application of the method

The developed sensor and framework offer us the capability to assess the comfort level of the layout with a mobile unit based on environmental data. This means that we can effectively measure and analyze the environmental conditions in various areas of interest. By deploying the sensor in different locations, we can gather data on temperature, humidity, noise levels, and other relevant parameters, providing us with a comprehensive understanding of the environmental factors affecting operator comfort.

To represent the comfort levels in the layout, we utilize a computed utility function that assigns scores or values to different environmental conditions. We divide the space into a grid-like structure, and within each grid cell, we aggregate the measured values as an average value of the specific area. This allows us to capture the aggregated measurements for different regions of the space. By mapping these utility values onto a grid-based layout, we can create a visual representation of comfort levels across the workspace. This grid-based representation allows us to assess the comfort and well-being of operators in different areas, enabling us to identify specific zones or regions that may require attention or improvement. By aggregating the utility values based on position (x, y) and time within each grid area, we can gain insights into the overall comfort trends and variations within the workspace.

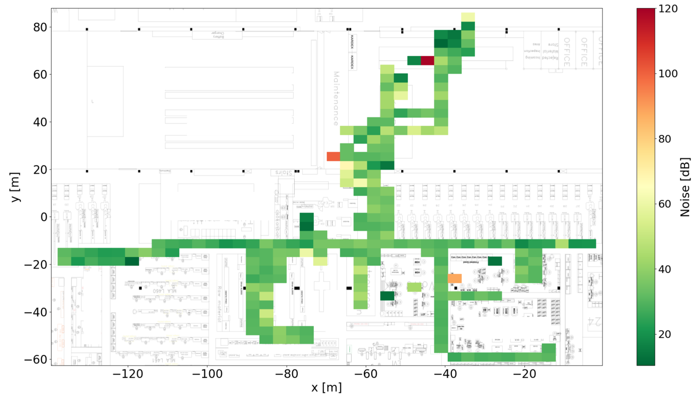
Based on this information, we can utilize the insights gained to inform the design of the layout. By identifying potentially hazardous areas or zones with unfavorable comfort levels, we can take proactive measures to mitigate risks. For instance, if certain areas consistently exhibit high noise levels or extreme temperature conditions, we can implement noise-reducing measures or adjust the ventilation system to regulate the temperature effectively. Furthermore, armed with knowledge about the comfort and environmental load in specific areas, operators can be trained and equipped with appropriate personal protective equipment to ensure their safety and well-being.

4 Case study and results

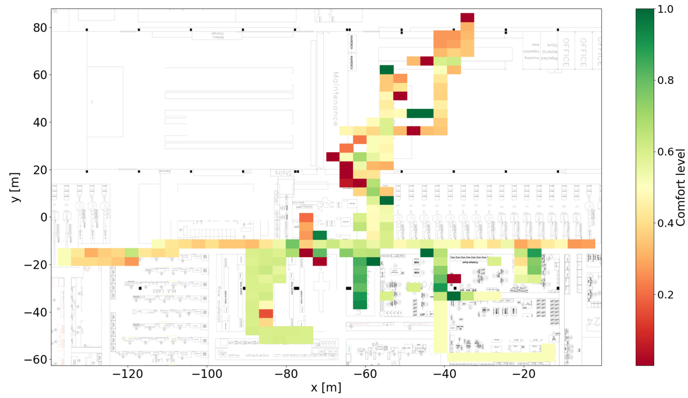
We demonstrated the effectiveness of the mobile measurement unit and the developed comfort-level indicator in a wire harness manufacturing industry. Wire harness production is a complex process that involves various activities and the operation of different machines. Wire harness production necessitates a high demand for manual labor [7]. Given the intricacy of this manufacturing environment, it becomes crucial to analyze and evaluate the environmental conditions, including factors such as temperature, humidity, and particularly noise. It is worth noting that different locations within the production layout may exhibit varying noise levels and even distinct perceptions of heat. By comprehensively assessing these environmental values, manufacturers can gain valuable insights into potential areas of improvement and implement measures to continuously monitor the working conditions for operators. Such analyses contribute not only to enhancing overall efficiency but also to prioritizing the well-being and comfort level of the workforce.

To ensure comprehensive coverage, we selected a manual material handling cart that had the highest daily distance coverage. The indoor position data shown in Figure 3 illustrates the movement of a single operator during one shift. We partitioned the layout into grids of 40×40 size. The operator covered all the cutting machines as they are the main material handlers for these machines. We have multiple measurements from these points as the operator cycles around this path. We are not able to display a more detailed layout thanks for the confidently agreement.

During the measurement, the temperature within the area ranged between $21C^{\circ}$ and $23.8C^{\circ}$, while the humidity ranged between 50% and 55%. In terms of noise (see in Figure 3 (a)), there were certain areas where it exceeded 120 dB, but in general, it can be said that the value hovered around 40 dB. According to Hungarian standards, during an 8-hour working day, a maximum of 85 dB noise is allowed in the workplace. The standard also specifies the permissible noise level for short durations (up to 30 minutes) that the healthy average human body can tolerate without adverse health effects. At the highest noise levels,



(a) Noise



(b) Comfort level

Fig. 3. Noise sensor measurement and the calculated comfort-level values with indoor position data

approaching 120 dB, it is evident that the comfort level also decreases to 0. This is naturally derived from the suggested utility functions.

Overall, the results indicate that the comfort level (see in Figure 3 (b)) ranges between 0 and 100%, largely influenced by the sources of noise. However, it is important to highlight that slight fluctuations in temperature and humidity also contribute to rapid deterioration. Based on the results, high-risk areas can be well identified. Currently, the data is aggregated for one shift, but thanks to the method, the duration can be chosen arbitrarily, such as by time of day, shift, day of the week, or any other relevant factor. Furthermore, by adjusting the grid divisions, finer or coarser measurements can be obtained. If we want to examine the comfort level based on location, we can also do so by aggregating the measurement results according to the specific coordinates.

The results obtained from our study provide valuable insights for identifying potentially hazardous or at-risk areas in the manufacturing layout that can impact the well-being of operators. By analyzing the collected data, we can identify zones that pose potential risks to operator comfort and take appropriate measures to mitigate these risks. Furthermore, by considering the time-aggregated measurements, we can not only evaluate the spatial distribution of exposures but also assess the temporal patterns of exposure over a given period. This comprehensive understanding of both spatial and temporal aspects allows us to gain a holistic view of operator well-being in the manufacturing environment. Based on our findings, it can be concluded that there are zones within the manufacturing layout that are particularly exposed to high levels of noise. These areas require special attention and measures to reduce noise exposure and ensure operator comfort. By pinpointing these noise-prone zones, we can implement targeted strategies such as noise control measures or reconfiguring workstations to minimize the impact on operator well-being. The integration of location-based information and noise exposure measurements enables us to identify specific areas where interventions are needed to create a safer and more comfortable working environment for operators in the manufacturing facility.

5 Conclusion and further work

In conclusion, the conducted study aimed to develop a comprehensive framework for quantifying occupational exposure and well-being of store floor operators, with a focus on improving their performance and comfort. Using a mobile measuring unit, we successfully collected data in a real production area dedicated to wire harness production, encompassing a typical working day. Analysis of the collected data revealed that the evaluated areas maintained acceptable comfort levels, indicating a satisfactory working environment for the operators. This valuable information provides a foundation for the company to identify and implement initiatives that promote the well-being of operators, ultimately improving both their productivity and overall satisfaction.

By integrating the collected data, design considerations of the layout, and ongoing re-evaluation, we can establish an iterative process that optimizes the ergonomic factors of the layout, operator comfort, and safety standards. This holistic approach not only enhances overall well-being and satisfaction of operators, but also contributes to increased productivity, reduced workplace incidents, and improved operational efficiency. The proposed framework, which integrates various environmental parameters with precise position data, has proven to be a valuable tool for providing insights into the operator's working environment. By identifying areas for improvement, we can implement targeted interventions to improve operator performance and safeguard their physical and mental well-being. This research underscores the importance of continuously monitoring working conditions to create a safer and more comfortable environment for all workers involved in industrial production processes.

In our future work, our aim is to expand the capabilities of our measurement system by incorporating additional information on thermal insulation, noise channels, and other relevant factors. This would provide a more comprehensive assessment of the working environment, allowing us to collect valuable data on heat distribution, noise propagation, and other critical parameters. By integrating these measurements into our existing framework, we can further enhance the accuracy and effectiveness of our analysis.

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Technical paper

Assessing human worker performance by pattern mining of Kinect sensor skeleton data

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ABSTRACT

The human worker is an in-disposable factor in manufacturing processes. Traditional observation methods to assess their performance is time-consuming and expert-dependent, while it is still impossible to diagnose the detailed movement trajectory with the naked eye. Industry 4.0 technologies can innovate that process with smart sensors paired with data mining techniques for automated operation and develop a database of frequent movements for corporate reference and improvement. This paper proposes an approach to automatically assess worker performance with skeleton data by applying pattern mining methods and supervised learning algorithms. A use case is performed on an electrical assembly line to validate the approach, with the skeleton data collected by Kinect sensor v2. By using supervised learning, the movements of workers in each workstation can be segmented, and the line performance can be assessed. The work movement motifs can be recognized with pattern mining. The mined results can be used to further improve the production processes in terms of work procedures, movement symmetry, body utilization, and other ergonomics factors for both short and long-term human resource development. The promising result motivates further utilization of easy-to-adopt technology in Industry 5.0, which facilitates human-centric data-driven improvements.

1. Introduction

Industry 4.0 (I4.0) technologies automatized many manual tasks [1], but not yet in labor performance assessment. Gemba walk is the most popular observational method for Occupational, Safety, and Health (OSH) practitioners [2] in Lean doctrine. As these techniques are knowledge- and experience-dependent [3], many research proposed innovative usages of technology to replace the traditional ways of self-reports and observations [4,5], to facilitate the digital Lean [6,7]. Motion Capture (MoCap) technologies are preferred [8], along with the development of advanced algorithms such as filtering and Machine Learning (ML).

As industrial customers require manufacturers not to store any product-related images due to proprietary reasons, anonymous skeleton data is a suitable option for production monitoring. One ideal candidate is the Microsoft Kinect (Kinect) sensor, an Artificial Intelligence (AI)-enhanced depth camera with marker- and calibration-free characteristics [9,10]. Many monitoring solutions have been developed based on the Kinect skeleton data [11], to track the movement and trajectory of workers [12], detect and predict their activities for both ergonomics analysis [13,14] and performance improvement [15]. With a tremendous amount of data captured by Kinect, different ML algorithms then can be utilized to automatically extract the human-related metrics [8], such as random forest for posture classification [16], a deep neural network for Rapid Upper Limb Assessment (RULA) score prediction [17]. However, most experiments mentioned above were applied for offline analysis, and the results were used for re-designing the process. There is no direct application for improving human performance on a larger scale (i.e., a manufacturing line, the whole workforce) or in a long-term scheme (i.e., work enlargement, work rotation planning).

A better understanding of the complexity and uncertainty of worker behavior can be achieved with a closer diagnosis of their movement trajectory [18]. This foundation enhances detailed analysis from ergonomic and productivity improvement aspects. However, traditional initiatives require exhaustive observation and prior knowledge of human workers, while most movement details cannot be traced by the naked eyes of experts. There is no development regarding segmentizing camera-captured movement into patterns in the literature.

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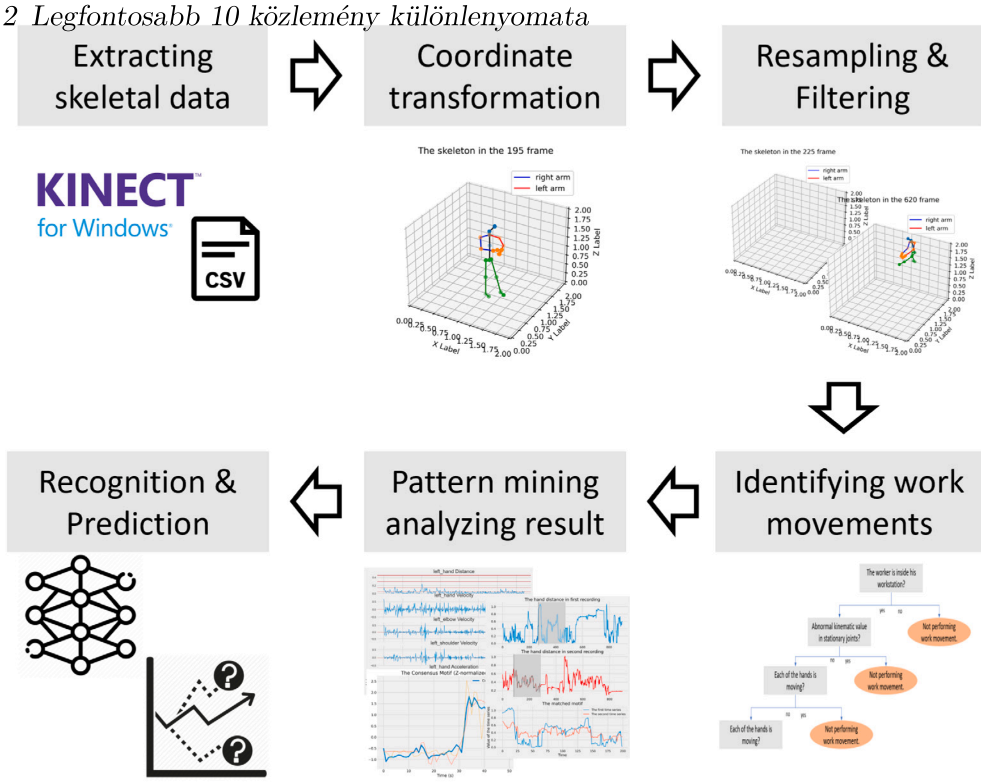


Fig. 1. The proposed flowchart to process Kinect sensor skeleton data.

Since the well-being of workforce remained untouched during the I4.0 [19], Operator 4.0 concept [20] utilized I4.0 technologies assist the human work [21,22], and Industry 5.0 (I5.0) calls for human factor re-centering [23,24]. The engineering system-resilience with Operator 5.0 concept [25] required indicators that monitor workforce well-being, resilience, and overall sustainability [19]. As digital Lean 4.0 is considered one of the essential pillars for the I5.0 transition [26], these indicators should be designed and integrated into the management system. The available surveillance technology is not ready to replace Gemba's observation thanks to the bottlenecks like lack of automation and incorporated human-centric assessment indicators.

Regarding these challenges, this paper seeks an innovative use of Kinect skeleton data by applying pattern mining and supervised learning algorithms to automatically capture and analyze deeper the movement patterns, thus providing automatic labor performance assessments such as Overall Labor Effectiveness (OLE) [27]. Pattern mining is widely applied in manufacturing operation management [28], with the matrix profile enabling motif searching more efficiently [29]. Key contributions are the automatic assessment in several aspects (e.g., productivity, ergonomics) and the suggestion of possible human-centric improvements based on assessment results, considering I5.0 objectives. A Python package is developed for post-process the Kinect raw data and made available for public use. A use case is performed on an electrical assembly line, proving that the human performance in each workstation can be assessed, and the manufacturing line can be balanced, with each movement in its workstations optimized. Continuous improvement ideas and long-term Human Resources Development (HRD) plans are suggested. The novelty lies in the innovative usage of ML algorithms with a real-time operation model, which can be the core foundation for organizational data-driven improvement in the I5.0 era.

2. Materials and methods

In this research, we propose using a camera sensor (i.e., Kinect sensor v2) paired with AI-based algorithms for human performance assessment. This section provides the theoretical basis of the proposed approach. A method of using supervised learning and pattern mining algorithms to diagnose the skeleton data is presented and shows sufficient knowledge for further human-centric improvements.

The processing flowchart is described in Fig. 1. After extracting the raw skeleton data, coordinate transformation, re-sampling, and filtering steps are applied. These steps are mathematical operations based on the camera setup. Supervised learning algorithms are applied to segmentize and recognize working status and movements.

Then, motif-searching algorithms are applied to find the similarities between the extracted movements and detect deviation from the standard. The objects of interest are the time series of the joint coordinates, along with their kinematic values. Other work characteristics (e.g., cycle time) can also be recognized. With the recognized work patterns, statistical features can be extracted to build a Human Activity Recognition (HAR) model [30]. The recognized result can be used to predict worker movement for a real-time application. The overall results can be synthesized into the performance assessment of each worker or the line of multiple workers. Based on these assessments, short- and long-term strategies to improve human performance can be elaborated, keeping in mind the objectives of I5.0. The details of these steps will be discussed in the following sections.

2.1. Processing the raw data

Considering O_C is the origin of the camera coordinate system, the origin of the world coordinate system O_W is defined by the perpendicular projection of the origin O_C into the floor. Each actual joint of the body $\mathbf{P}_W = [x_W, y_W, z_W]$ in the world system is captured as one corresponding point $\mathbf{P}_C = [x_C, y_C, z_C]$ in camera system. The observation range of Kinect sensor v2 is recommended from 0.5 to 4.5 meter [31]. It is recommended that the furthest corner of the working zone should not exceed the threshold of 3.5 m.

For clarification, we declared H_Z is the distance between O_C to O_W in the Z direction, H_Y is the horizontal distance from the O_W to the

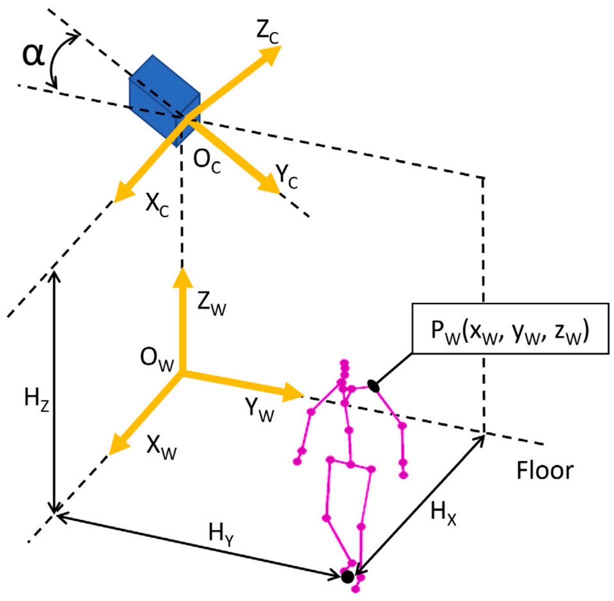


Fig. 2. The setup suggestion on the shop floor.

approximate center of the captured object in the Y direction, and H_X is the distance between O_W to object in X direction. The α is the rotation angle of the Kinect camera around its X axis. The setup is described in Fig. 2.

The Kinect for Windows SDK version 2.0 [32] is used to extract the streaming data. The PyKinect package developed by Microsoft [33] is installed to enable further programming with Python language. The Kinect sensor v2 provides the skeleton data of 25 different body joints as illustrated in Fig. 3(a). Each joint has 3D coordinates recognized in the Kinect sensor coordinates system as in Fig. 3(b), and in the form of time-series in X, Y, and Z directions as the example in Fig. 3(c). The Holt Double Exponential Smoothing filter, with a robust prediction ability on time series data [34], is deployed as a built-in filtering algorithm in the Windows SDK, while adding prediction, jitter reduction, and deviation limiting. Its performance for video game control can be found in the assessment by Edwards et al. *Ref.* [35]. The coordinate transformation can be done with the pytransform3d package [36], with details described in the Appendix A.

The Kinect sensor v2 supports up to 30 frame per second, thus the raw data is re-sampled to 1 MOD (1 MOD = 0.129 s), the basic unit of the MODular Arrangement of Predetermined Time Standards (MODAPTS) [37]. The frames that do not capture any skeleton or contain the joints further than three meters in X or Y direction will be filtered out. The left frames now include both the working and non-working movements of the worker. Two factors are used to segment the movements: supervised learning and the kinematic value of the work. Supervised learning models (e.g., k-nearest neighbors (kNN) clustering, Gaussian mixture model clustering, perceptron, etc.) are applied to the position data of the limbs to define the work zones, while the kinematic value of the limbs confirms it. The details of identifying work movement will be discussed in detail in the next section.

After defining the frames that contain the work movement, the time series of joint coordinates can be used as input data for pattern mining. Besides the raw coordinates, we suggest the use of derivatives such as:

- The distance between joints: The Euclidean distance between two arbitrary joints (e.g., the distance between two hands).
- The angle between three joints: The 3D angle formed by three arbitrary joints (e.g., the arm extension angle that is formed by the shoulder, elbow, and wrist).
- The kinematic characteristics of an arbitrary joint (e.g., moving distance, velocity, acceleration, jerk) can be calculated from the displacement in time of the raw coordinates of the joint.

Once these time series are extracted, different work performances by one worker or multiple workers can be compared.

2.2. Identifying work movement and work characteristics

The working movement can be extracted based on the decision tree in Fig. 4. Every job-unrelated movement should be excluded (i.e., walking, waiting, resting). This approach considers intrinsic characteristics of work movements, such as the position and kinematics of the head and the hands. For instance, the head will be the stationary joint with a very low velocity, and the hands will be the most active joint during the work session. Kinematics values (i.e., velocity) are also utilized as thresholds to identify the movements. Other workstation features, i.e., conveyor geometry and ergonomic working posture, are also considered.

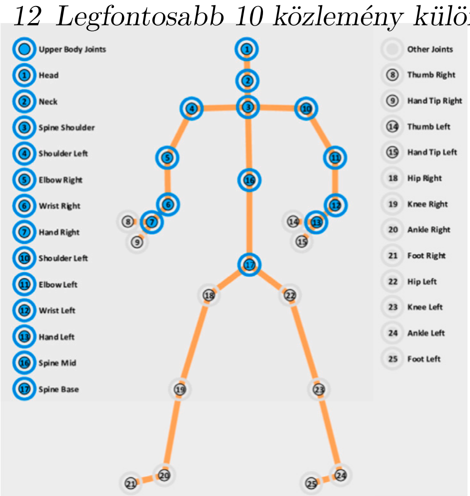
The steps can be described as:

- Whether the workers are in their workstation: The standing zone can be defined by applying kNN clustering on the position data of the head and the hand joints, and can be confirmed by the position of the head and its low velocity.
- Whether the worker is performing the work: If the worker is working, the head should be moving slowly within the standing zone. If the worker is walking, the velocity is much higher than the working state.
- Whether the hand of the worker is moving or not: Based on the kinematic characteristics of each hand such as moving distance, velocity, and acceleration, the frames in which the worker is performing work and not standing idle can be recognized. After this step, the timeline of the working state can be created, as described in the following section.
- After the aforementioned steps, we can define the relevant frames in which the worker is performing work movement. Ergonomics assessment can be applied during these periods. The given work instruction can be utilized to identify the movement, and the motif searching techniques are performed to find the movement pattern. These techniques will be described in the next section.

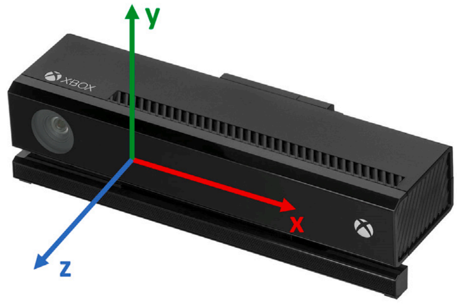
The machine learning models for clustering are developed with the Scikit-learn library in Python environment [38]. The rationale of clustering can be described in Fig. 5, which shows the top-view working posture of the worker in a workstation with three work zones. The primary work zone is the comfortable region for repetitive access, while the secondary and tertiary work zone are for occasional and seldom access, respectively [39]. For ergonomic reasons, the parts will be placed in the primary work zone, and the hands will repetitively move around it to perform the working movements. The hand will be actively moving within the secondary work zone for other movements such as waiting, resting, and taking additional parts. Based on these characteristics, it can be observed that the position of the head and two hands will define different clusters in the $X-Y$ plane. If for each frame, we define the vector $\left[x_{left}, y_{left}, x_{right}, y_{right}\right]$, in which:

- $\left[x_{left}, y_{left}\right]$ is the X and Y coordinates of the left hand.
- $\left[x_{right}, y_{right}\right]$ is the X and Y coordinates of the right hand.

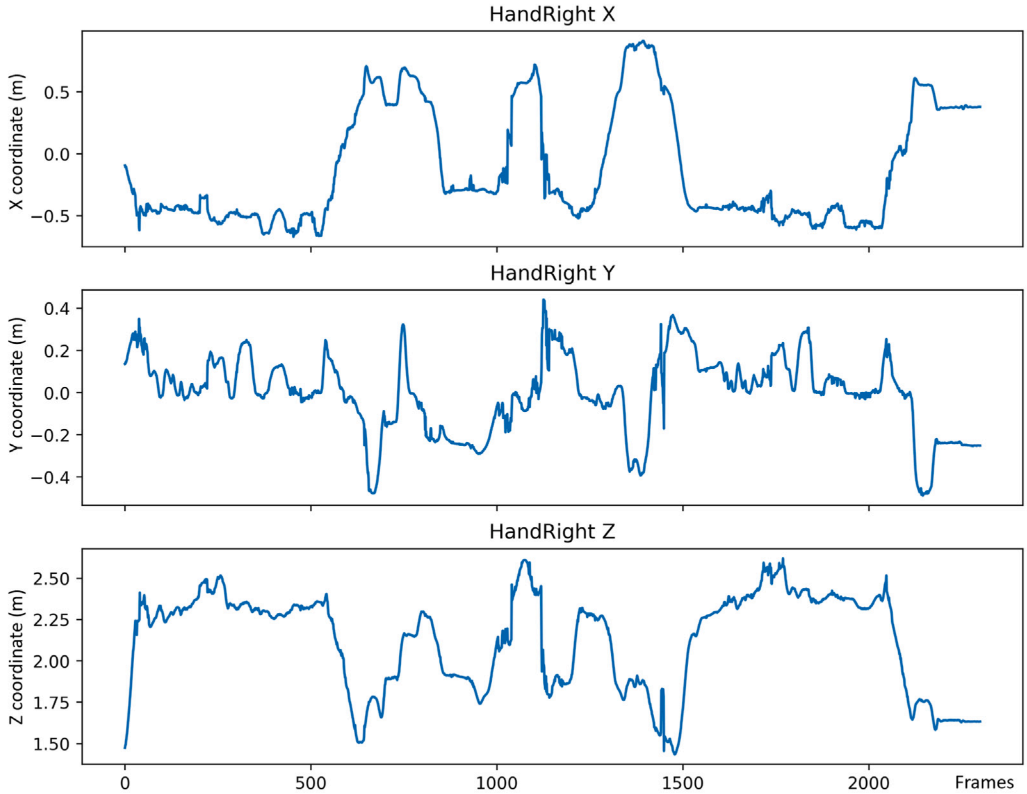
By applying the kNN clustering algorithm on the set of the hand point vectors, we can have the cluster centers which have the same size of four with the hand vectors, in the form of $\left[x^c_{left}, y^c_{left}, x^c_{right}, y^c_{right}\right]$. Each is represented as one line connecting the centroids for the left and right hands. The number of clusters can be defined based on the working area. If the working area is small, a smaller number of clusters is needed. In Fig. 5 two clusters can be seen: the cluster 1 (c = 1) is



(a) Kinect sensor body joint system.



(b) Kinect sensor coordinate system.



(c) 3D coordinates of one joint - the right hand. Example from data of one workstation.

Fig. 3. The Kinect sensor description and the raw skeleton data.

right in the primary work zone, and the cluster 2 ($c = 2$) is in the secondary work zone. These cluster centers have different positions, which represent different working postures. By recognizing the clusters of the hand positions, the working status of the worker can be defined when the hand access the respective working zones. The same process can be applied to position data of the hands in the X and Z plane, which will show the different heights at which the hands were working.

It can be noticed that while working, the head of the workers mostly stayed within a small region, while their hands moved around the processing parts. The zone in which the head stays will be an elbow distance from the primary work zone for a comfortable working posture. A straight line can always be drawn to separate the hand points and the head points, representing the physical edge of the table or the conveyor and forming an area where the head barely appears. The line can be defined by any linear classification algorithm. In this research, a linear perceptron model is used. The region where the head stays during work can be named the standing region, while the region where only the hand points can be found is named the working region. Based on ergonomics working distance, the boundary between the standing and working regions can be defined by offsetting the conveyor edge. It is recommended to use an elbow-wrist length from the conveyor edge (450 mm) to determine the standing region, assuming the worker stands straight during work. The working region is defined on the conveyor so that the maximum distance from the standing region to the working region equals an upper limb length (750 mm). These metrics are taken from anthropometric measurements of Europeans [40], and should be adjusted according to the male–female ratio of the workforce population.

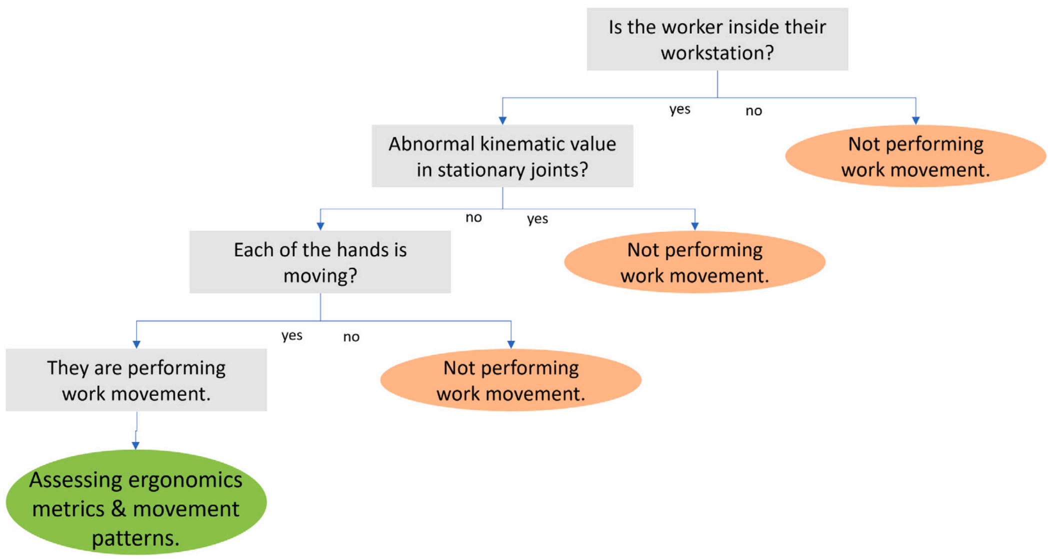


Fig. 4. The decision tree to filter the relevant movements from the initial data.

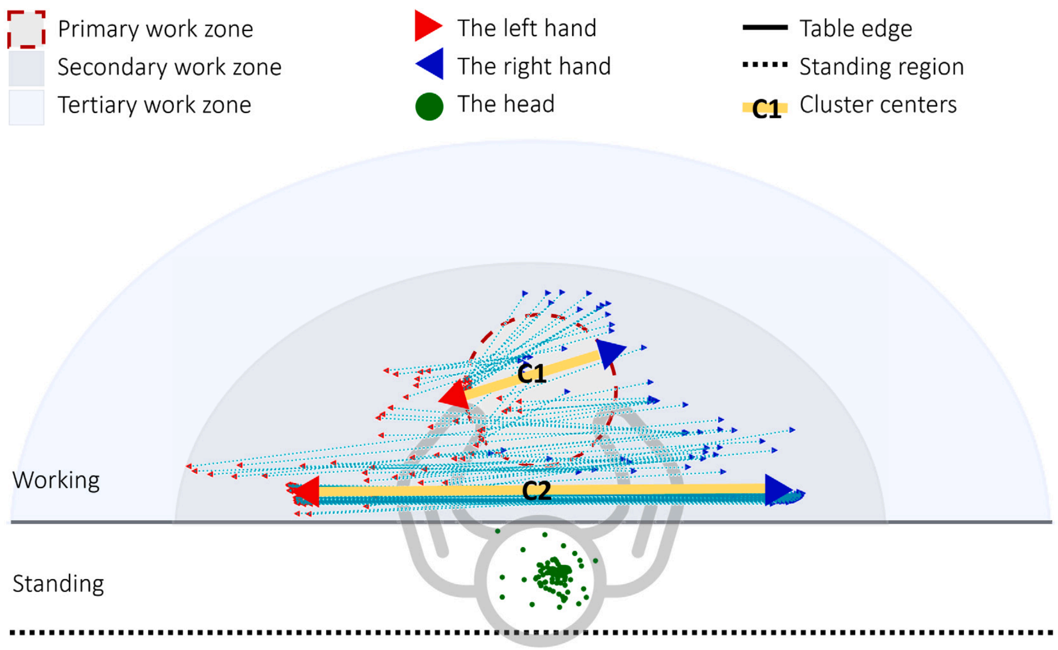


Fig. 5. The schema of the head and hand positions in working posture. Example data from one workstation.

The other factor to consider is the velocity of the moving limbs during work. As working movements may not exceed a certain velocity, faster movements can be identified as non-working. For example, if the worker is working, the head should be moving slowly within the pre-defined standing zone. If the worker is walking, the velocity is much higher than the working state. The same principle can be applied to the hand. The criteria described in Table 1 are considered based on the position and velocity of the head and the hands of the worker. Therefore, several elementary movements, along with the working and non-working statuses, can be identified.

The recommended working posture is the worker has his head in the standing region and moving with a velocity lower than v_{max}^{head}, and has at least one of his hands in the working region with a velocity lower than v_{max}^{hand}. These velocity limits can be taken from the raw data and consulted by the production supervisors. As illustrated in Fig. 6, by filtering out the head position with a higher velocity than $v_{max}^{head} = 0.2\frac{m}{s}$, the clusters show the head position in the standing area. The distant points indicate the worker is resting outside of the workspace. The same velocity threshold can be set for the hand movements with v_{max}^{hand}. However, to filter out the resting status of the hands, its timestamps should be examined. If the hand moves at a very low velocity (i.e., $\leq 0.05\frac{m}{s}$) and remains for a period longer than t_{max} (with $t_{max} = 3MODs = 0.516$ s), it can be considered staying idle. This t_{max} value is chosen as three MODs is the sufficient time for the worker to move his arm and get something.

Considering that the work is done in a work cycle, one can look for cyclic behaviors of the time-series data. Other work characteristics can be accessed based on the achieved results.

- Work cycle time: There are several ways to perform this recognition, such as accessing the auto-correlation of the time series of the distance between two hands or clustering the coordinates of the two hands and looking for the sign of moving to the original position. The cycle time can be recognized when the hands come

Table 1
The criteria to distinguish working movements.

No.	Head position	Head velocity	Hand position	Hand velocity	State
1	Out of the standing region.				Out of the workstation.
2	In the standing region.	High ($> v_{max}^{head}$)			Moving in the workstation.
3	In the standing region.	Low ($\leq v_{max}^{head}$)	At least one hand in the working region.	High ($> v_{max}^{hand}$)	Reaching.
4	In the standing region.	Low ($\leq v_{max}^{head}$)	At least one hand in the working region.	Low ($\leq v_{max}^{hand}$)	Working with one hand.
5	In the standing region.	Low ($\leq v_{max}^{head}$)	Both hand in the working region.	Low ($\leq v_{max}^{hand}$)	Working with both hands.
6	In the standing region.	Low ($\leq v_{max}^{head}$)	Both hand in the working region.	Too low (≈ 0), for $\geq t_{max}$	Staying idle.

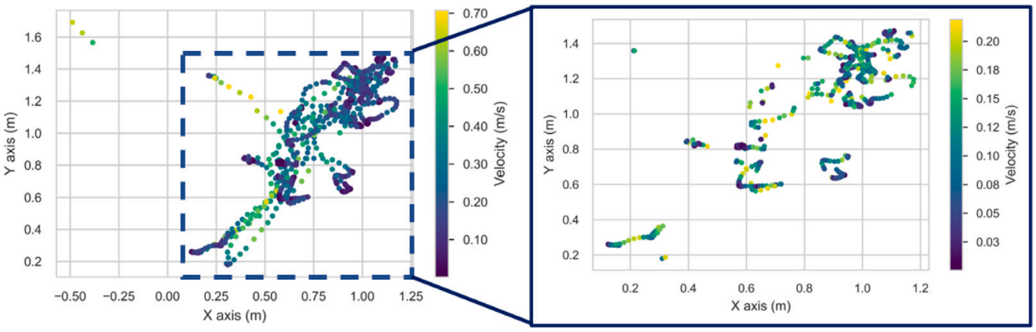


Fig. 6. The head with its velocity is filtered. Example data from one workstation.

back to their original position, with the same working distance between the two hands. This concept is applicable to the location of the head but on a larger scale than inside a workstation.

- Personal efficiency: The utilization efficiency of one worker can be calculated in different ways, such as by comparing his movement to the standard proposed by industrial reference (i.e., MODAPTS). Besides, his value-added ratio can be calculated based on the segmentation between his working and not working periods. This information can be used to calculate his OLE.
- Body part utilization: The usage frequency and characteristics of the different parts of the body can be considered once the movements are recognized and their timestamps are collected. For simplicity, states such as working and non-working, working with comfort gestures, and non-comfort gestures can be defined. The assessed result can be visualized in a timeline.
- Body asymmetry: Body symmetry is an essential factor to prevent fatigue and occupational disease. The period in which only one side of the body is working can be calculated and can be a target for improvement.
- Work complexity: The complexity of the work within a workstation can be assessed by several criteria such as the cycle time, the performance variation (e.g., the same work performed by different workers or by the same worker in multiple times, same work in different product variant), the body asymmetry. This information can be used to design the workload in each workstation and balance the workload, thus alleviating the time variation [41].

An example of cyclic behaviors of the position of the limbs can be seen in Fig. 7. In this scenario, the worker performed the work on a conveyor and took the product to a nearby cart. After completing the clustering algorithm on the head position of the worker, three cluster centers can be identified in the left part of the figure as $C1$, $C2$, and $C3$, which represent the conveyor, the moving area from the conveyor to the cart, and the cart itself. The right part of the figure shows the cluster labels over the frame. It can be observed that the worker works in the conveyor for 300 frames before moving to the cart, and then comes back to the conveyor at the 550th frame as indicated by an abrupt change of the cluster label. This sign indicates that a new cycle starts at this time, and the recognized cycle time is $\hat{t}_C = 550(MODs)$, or 70.95 s.

This recognition can be more precise in a smaller area of the interested workstation, with the clusters of the hand positions. If several recordings are taken, the recognized cycle time will be the average value of all work cycles. Other important parameters can be defined such as:

- The cycle time difference is the ratio of the absolute difference between the recognized cycle time $\hat{t}_C$ versus the theoretical value t_C, over the theoretical value.

$$C_{diff} = \frac{|\hat{t}_C - t_C|}{t_C} \quad (1)$$

- The cycle time variation is the ratio of the absolute difference between the maximum value of recognized cycle time $\hat{t}_C^{max}$ versus the minimum value $\hat{t}_C^{min}$, over the theoretical value t_C.

$$C_{var} = \frac{|\hat{t}_C^{max} - \hat{t}_C^{min}|}{t_C} \quad (2)$$

For one recording of one worker in one workstation, based on the classified work movements, the total ratio of each movement can be calculated as a relative percentage of the entire recording duration. More information can be extracted on the manufacturing line scale for several workstations with different workers. The following section will discuss this concept in more detail.

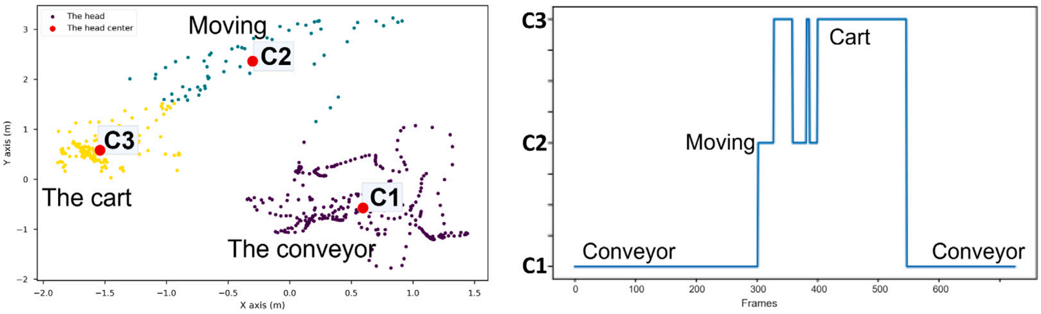


Fig. 7. The cyclic pattern in the head position clustering labels. Example data from one workstation.

2.3. Movement patterns and possible application

In the previous section, after the processing of raw skeleton data, we have original data of joint coordinates with other derivatives in the form of time series. This section described the patterns that can be recognized with corresponding usages for industrial management purposes. The input as well as mining tools are described in Tables B.6 to B.7 in the Appendix B.

By comparing the same moving pattern conducted by one worker, the normalities and the abnormalities in his movement can be recognized. While the normalities exhibit his skill competence (e.g., the time variation between each performance), the abnormalities can show his achievement in learning a new movement or a recent physical problem that could cause occupational disease.

By comparing the same moving pattern of one worker to the others, the technical skill competence of the workers can be assessed. This information is helpful for the workforce allocation [42], especially with the scenarios of multi-skilled operators. The best movement can be found and used as a reference for best practice sharing between workers as a byproduct. This practice helps to improve the performance of the workforce systematically.

Pattern mining techniques (such as AB-Join, multi-variate, and consensus motif searching) are performed with STUMPY open-source package [29] to find the motif pattern that happened within these time-series of the joints, analyze their characteristics, to have an insight into how the worker performs his work. These patterns can guide the process engineers to work on their accumulated database from their workforce. The optimized work movement and the acceptable patterns can be recorded for later reference when setting up a new production line and training purposes.

Another critical application of movement pattern results is the real-time ergonomics assessment, based on the time series of several elements, such as the distance of the hand from the hips and the angles between the joints. Instead of the traditional assessment done by a human expert, the standards can be integrated into the physical limit for the distance and angle between joints and limbs, thus making it easier to implement real-time monitoring and warning. These assessments can be used as a clue for further improvements. There are popular industrial standards applied in this way, such as RULA [43,44], Ergonomic Assessment Worksheet (EAWS) [45], and MAC.

When multiple workstations are set together to form a manufacturing line, the ergonomics assessment can be performed on each station with the same principle. By comparing the work pattern performed by different workers in the same workstation, the ergonomics setup of that workstation can be assessed. For example, the workstation that causes the same bending posture for most workers should be elevated, and the specific worker with the bad working posture can have customized support. With the discovered movement patterns, statistical features can be extracted to build a Human Activity Recognition (HAR) model [30]. The recognized result can predict the movement of workers for a real-time application.

2.4. Machine learning model for automated application

As several ML algorithms are proposed in this approach with available open-source packages that have data streaming possibilities (e.g., STUMPY), a real-time assessment model by Kinect sensor can be built for more convenient usage. This model can automatically process the acquired data and perform the HAR function with more in-depth analysis such as movement recognition and prediction. In order to facilitate end-to-end ML software development, the iterative-incremental process in the Machine Learning Model Operationalization Management (MLOps) proposed by Larysa et al. (2022) [46] is adopted. A framework with three main steps: *Model Design*, *Development*, and *Operation*, is illustrated in Fig. 8, with step-by-step details in building such an ML application for a particular manufacturing industry.

These steps are complementary to each other in a continuous loop and enable the minimum viable product for earlier model adoption. In the first step of *Model Design*, the engineering requirements for industrial practice should be defined. These requirements should take into consideration the nature of the work movement (i.e., how many joints are required to perform the work) and the workplace (i.e., how many workstations need to be under observation), the suitable sensors (i.e, video-based or wearables), the types of connectivity and database that are compatible. After that, a use case should be well-defined. This use case can be developed for a smaller facility area where there is no obtrusion from other objects. For the use case, the engineers may prefer the line with a similar type of work movement (such as assembly or material handling), and each workstation has a pre-defined work cycle and designated area of work. An open workstation with no designated area and no cyclic work pattern can be troublesome to assess, even with human observation. The data availability will be checked and tested with the sensor. The essential criteria here can be: how long the recording duration should be, how much data distortion is caused during work (due to the natural obtrusion of the worker), and how long the distortion last (due to the appearance of facility equipment, such as the conveyor). The engineers need to consider if these skeleton data are sufficient for the assessment.

In the second step is the *Model development*, the architecture, such as data acquisition and storage, should be ready, and the connectivity should be established to connect them. Time series databases (such as InfluxDB or OpenTSDB) can be suitable candidates for storing the processed raw data from the Kinect sensor. The number of required Kinect sensors and the setup positions are also considered. Based on the available data, the model can be developed with real-time ML and pattern-mining algorithms and packages. The teaching criteria for supervised learning should be described in this step. Online matrix profile [29] can be integrated to handle streaming data and facilitate the real-time usage of motif searching. The model then should be tested and validated by the confusion matrix between principal movements that can be recognized.

In *Model operation*, the model can be deployed with the established data pipeline and become ready for real-time monitoring application. There should be pre-defined signs to trigger the model (i.e., abrupt

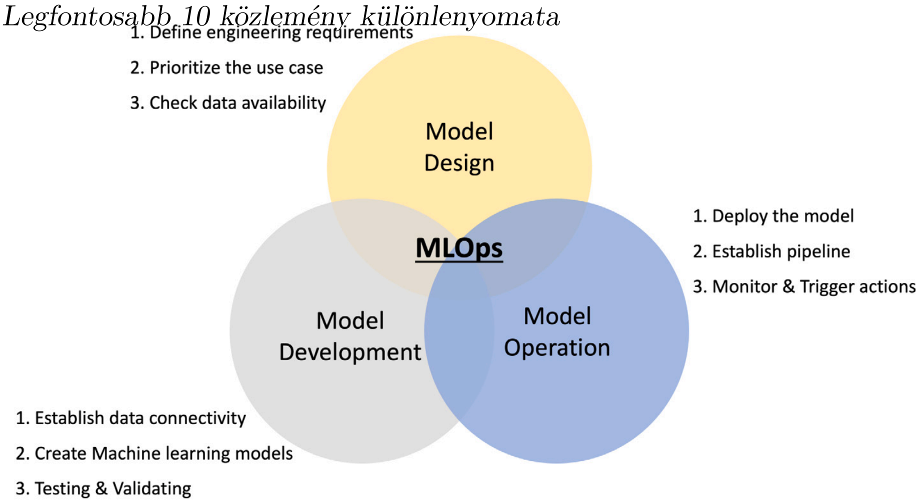


Fig. 8. The proposed machine learning model development with Kinect sensor.

changes of the cluster label during the production period). These signs may come from the natural characteristics of the work movement.

By applying these MLOps principles during the development phase, the early adoption and fast delivery of the resultant real-time industrial application can be expected. The authors endorse the practicability of this approach for ML-based software, which aligned with the key assessment metrics from high-performing software development organizations [47].

2.5. Human performance improvement in industry 5.0

Using the method described in Section 2.4, the different movements can be mined from Kinect sensor skeleton data, and their application for human performance assessment is discussed. Thanks to these results, the normal and abnormal patterns in the movement of workers can be considered, and industrial managers can seek improvement on two scales: individual level or systematic level:

- Individual improvement: the changes that can be applied to each specific individual, affecting the work of a single worker, or changing a workstation layout (e.g., customized skill training, ergonomics posture training, work-cell arrangement).
- Systematic improvement: the changes that can be applied to more than one worker, affecting the work of multiple workers, or changing the entire manufacturing line (e.g., workload design principles, line balancing, job rotation)

As inspired by the Human Resource Development (HRD) approach of Lean manufacturing in knowledge sharing and skill development [48], these improvements can be categorized into short-term and long-term initiatives. As I5.0 aims to build a resilient workforce, the long-term HRD is one of the main pillars for the sustainable and competitive growth of a firm.

- An example of an HRD short-term initiative is developing a customized job training program, providing workers with specialized training based on their skills. A cross-training program between workstations is proven to have a positive impact on worker performance, and long and variable process lead times [49]. By endorsing workers to improve their skills, greater flexibility can be achieved within the workforce [50].
- An example of an HRD long-term initiative is the job rotation, switching the worker between a routine of different workstations with different skills to avoid occupational hazards and physical ergonomic risks [51]. This initiative will alleviate the boredom of the workers [52], while increasing work satisfaction in the long term [53].

The combination of these two initiatives can yield a positive impact on production performance and quality [54]. Considering that the I5.0 objectives are human-centricity, sustainability, and resilience, the improvements mentioned above facilitate the firm to achieve its I5.0 goals. Their corresponding contribution to the I5.0 objectives is as illustrated in Fig. 9.

- By examining the work behavior and preference of a worker in a workstation, individual improvement can be made to help him achieve higher performance, according to his special physical condition. As this individual improvement can establish a new standard in designing and performing work, the human-centric improvements in the firm can be continuously facilitated, which takes the human worker as the center.
- After successful implementation of short-term improvement such as enhancing work ergonomics, performance, and productivity in one workstation, systematic improvement can be deployed on a larger scale of a manufacturing line. The results will improve the performance of more workers, ensuring robustness and resilience productivity.
- The long-term HRD plan plays a vital role in permeating the effect within the workforce and ensuring the long-term sustainability of the firm. As the PDCA circle is carried on, short- and long-term improvements are achieved, and the resilience level of the whole workforce is increased.

These improvements can be data-driven and carried out continuously, as the skeleton data from the Kinect sensor is sufficient, and with the aid of a real-time ML model. The overall initiative is depicted as a Plan-Do-Check-Act (PDCA) framework established around the organizational database of the movements, with its steps illustrated in Fig. 10.

As the traditional kaizen starts with Gemba observation, our approach deployed the pattern mining in the *CHECK* phase. A Kinect sensor data acquisition system should be established to collect human-centric data. Any arbitrary type of additional sensor can further enhance the data accuracy, such as wearables, smartphones, etc. Then ML and pattern mining tools can be applied to the acquired data with preliminary and in-depth analysis. The mined patterns are stored in a database structured by each operator, work instruction, and specific conditions of the environment. This storage serves as the organizational database. Additional data properties such as the cell setup, the work instruction, and the line allocation can be stored for later reference.

In the *ACT* phase, movement pattern mining results can be categorized into ergonomics assessment or personal work behavior, or in another perspective, ergonomics and economics performance [55].

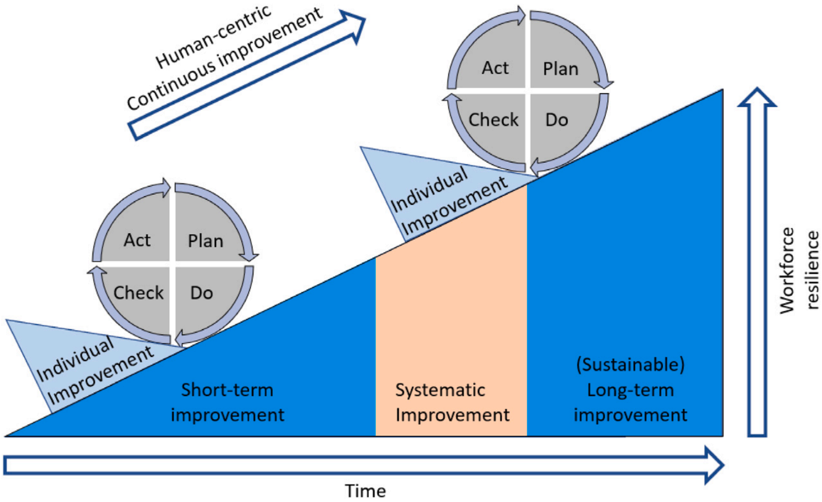


Fig. 9. The proposed human-centric improvements with Industry 5.0 focuses.

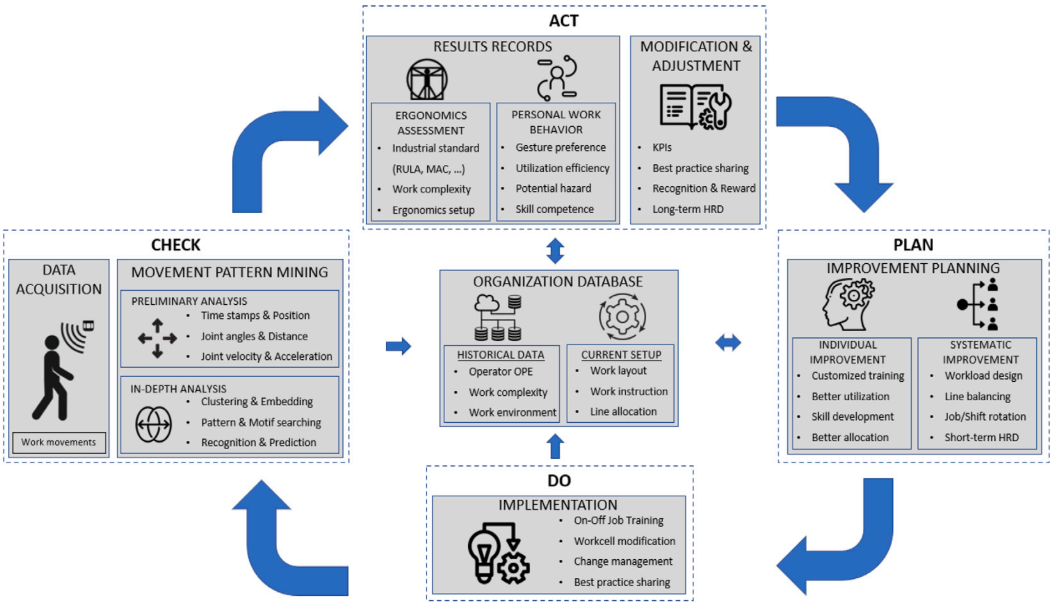


Fig. 10. The proposed PDCA circle with pattern mining framework.

These results can be compared with the database records to modify and adjust the KPIs and long-term HRD strategy or reasoning for recognition and reward activities.

In the *PLAN* phase, the individual and systematic improvements can be planned based on the result records and the benchmark from the database. While individual improvements aim to utilize human skills and customized development for the individual, systematic improvements focus on a larger scale and on short-term effects, such as balancing a line, creating a skill training schedule, or a job rotation plan for the next month.

The *DO* phase will integrate the planned improvements through the on- or off-the-job training and best practice sharing with other implementations, such as modifying and rearranging the work cell. The changes in this phase should be recorded in the database as a change management practice to differentiate the performance improvement of different factors.

After any change, the effect of kaizen implementation is recorded in the *CHECK* phase, with the new movement patterns recognized and diagnosed. It is noticeable that the proposed PDCA approach is built in a human-centric way, utilizing the movement pattern mining techniques fully.

3. Result from a use case in an electrical product assembly line

The previous section discussed the usage of Kinect sensor skeleton data to assess human worker performance and generate improvement ideas. In this section, a use case is described to show the practical application of the proposed approach. The real problem is discussed in the following paragraphs, with the purpose of the improvement projects and the utilized equipment setup. Then the data processing details and assessment results are given. Based on this foundation, we aimed to seek improvement ideas to improve the human performance of this manufacturing line at both individual and systematic levels.

3.1. Use case description of an assembly line

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The use case is conducted in an electronic assembly line that creates several varieties of personal computers. The manufacturing company had already implemented a Lean system with OLE computed using

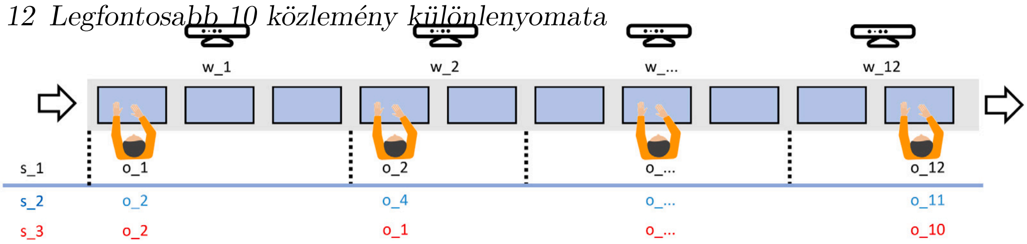


Fig. 11. The designed experiment in an assembly line with Kinect sensors.

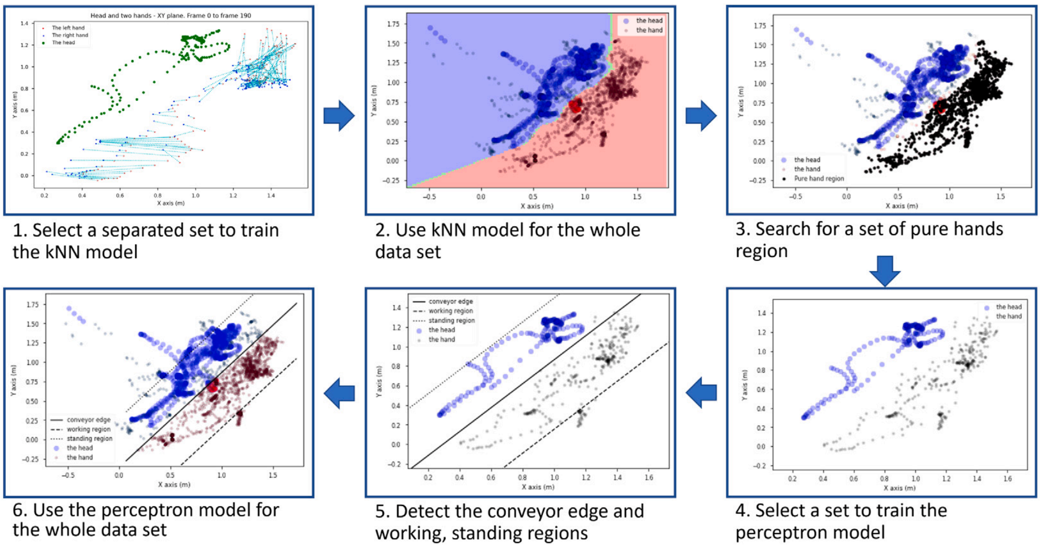


Fig. 12. The steps to perform the conveyor detection. Example data from the first workstation.

the classic Gemba technique. However, as they adopted the modular product design approach, performance evaluation and line balance for multiple product variants became labor- and time-intensive. The process engineering department wants to develop an automatic monitoring tool that can assess elementary movements and times to serve the line balancing purpose, aiming at a robust balance against unexpected problems or conveyor speed changes. The monitoring tool should be operated in a continuous real-time manner, and be able to detect movement deviations and abnormalities during production shifts. Based on this motivation, our project aims to automate the worker performance assessment while capturing the movement pattern for further diagnosis. The manufacturing company agreed to use the Kinect sensor considering its ability to capture anonymous skeleton data. This section describes the actual production condition of the line, along with the technical setup and software being used.

The full manufacturing line consisted of $N_{ws} = 12$ workstations, denoted by w_i, where $i = 1, 2 \dots N_{ws}$. The main assembly tasks of every workstation are performed on a moving conveyor, requiring both hands to work on the current product. As assembly tasks require manpower, human workers are irreplaceable. The workflow description in each workstation is roughly defined from the previous similar product in the product family. However, as the manufacturing time is measured from a long time ago by the performance of the old batch of workers, the task time becomes unreliable and cannot be used to ramp up a new production line.

The experiment is set as illustrated in Fig. 11, in which each workstation in the assembly line is equipped with one Kinect sensor from the most convenient angle to observe the working gesture of the workers. Each workstation is limited within a defined space and assigned a predefined workflow, while the conveyor moves at a predefined pace. According to the actual operation of the line, some workstations can be run by more than one worker. As the plant engineers also want to observe the different movements performed by different workers, we captured the skeleton data from the total number of $N_w = 15$ workers, which is larger than the number of workstation N_{ws}, and denoted by o_j, where $j = 1, 2, \dots, N_w$. In different shifts, 12 workers are allocated in the line by the line supervisor. The recorded shift is denoted by (s_k), where $k = 1, 2, \dots, N_k$, with N_k as the number of shifts per day.

The recorded skeleton data from Kinect sensors are stored under the label of each workstation, each operator, each shift, with the syntax of $yyyymmdd.wX.oY.sZ$. For example, $20220506.w1.o2.s1$ is the recording in the first workstation, with the work done by the second operator in the first shift of the sixth of May, 2022. Data is extracted with Kinect for Windows SDK and programmed in Python language.

3.2. Performance assessment results by pattern mining

In this section, supervised learning is applied to segmentize the movements and pattern mining tools are used to find the work characteristics in the form of time series.

3.2.1. Identify work movements for each workstation

As described in Fig. 1, after re-sampling and filtering the raw skeleton data, the work movements should be identified. The first identification step is to recognize whether the worker is in his workstation and performing work movements. Considering that the assembly movements are performed on a conveyor, we look for the sign of the conveyor edge as a rigid physical separation between the position of the working hands and the head during the production period. This task can be done by using supervised ML algorithms: kNN clustering and followed by a linear perceptron. The steps are described in Fig. 12, with the example data from the first workstation:

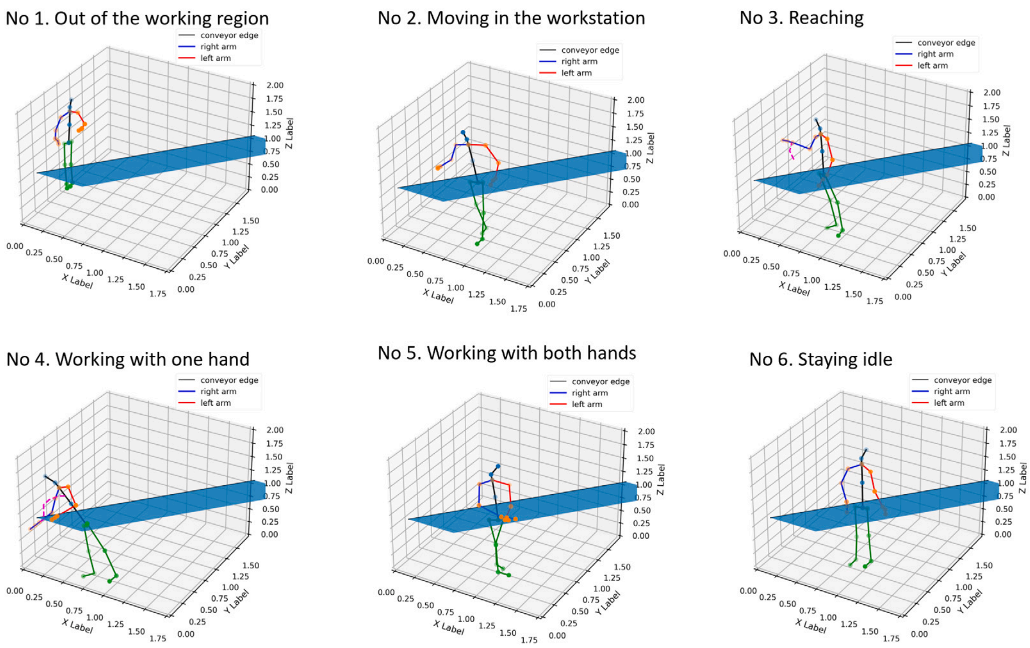


Fig. 13. The different recognized movements. Example data from the first workstation.

- At first, a set of data with the head and two hands positioned in the X-Y plane are collected as training data for the kNN model. This set is taken from the working period, so we can observe that the head and two hands are separated in the different regions by the conveyor.
- Secondly, the result of the kNN model is used to predict the label of the whole data set. The decision boundary is not perfectly a straight line, as the hands and head points can be mixed in some regions (i.e., while the worker is walking toward the conveyor).
- Thirdly, based on the suggested label from the kNN, a set of hand positions can be identified, whose neighbors are hands only, without any head position. It can be named the "pure hand region", and mostly this region is on the conveyor. There are a few unusual cases the pure hand region is out of the conveyor, but we can neglect them as the minority.
- Fourthly, a set of hand positions from the pure hand region is taken to train the linear classifier, as scattered as possible, along with the head position.
- Fifthly, the conveyor edge is detected. Based on ergonomics working distance, the boundary of the standing and working regions can be defined by offsetting the conveyor edge. The offset value is mentioned in the previous section, taking into consideration the male–female ratio of the facility workforce.
- Based on the perceptron classifier result, the whole data set will be examined.

Noticeably, the conveyor edge detected here does not reflect the actual edge of the physical conveyor. However, it can serve a similar function as a rigid boundary between the working and standing regions and is critical for our movement identification purpose. Based on these criteria, the different movements in one workstation can be recognized as depicted in Fig. 13, with the conveyor represented.

The velocity limits (v_{max}^{head} and v_{max}^{hand}) for working posture are taken from the raw data, as the 90th percentile of respective velocity in all recordings, from all workers during their working period. After consulting the production supervisors, and taking into consideration the nature of the assembly work, we choose $v_{max}^{head} = 0.2\frac{m}{s}$ and $v_{max}^{hand} = 0.8\frac{m}{s}$. A hand moves at a very low velocity (i.e., $\leq 0.05\frac{m}{s}$) for a period longer than $t_{max} = 3MODs = 0.516$ s will be considered staying idle.

By applying the same procedure, the whole conveyor with its workstations and the head and hands position of workers can be constructed as in Fig. 14. The first workstation (w_1) has a broader distribution of the head and hands location; since it is the beginning of the line, the worker needs to take the raw product from a separate cart to process. The other workstations have smaller scatter since the workers mostly perform their work in a smaller defined space.

3.2.2. Cycle time recognition

Due to the characteristics of assembly work, the hands of the worker follow a periodic trajectory in the working space (i.e., they come back to the original area when they start a new cycle). Since mostly the work movements are done on the flat surface of the conveyor, we do not consider the Z component. One work cycle can be traced with the cyclic pattern of the hand position. In this section, the cycle time is recognized by applying K-means clustering on the vector $[x_{left}, y_{left}, x_{right}, y_{right}]$. The result of clustering applied in one workstation with its different recordings is illustrated in Fig. 15.

In Fig. 15(b), the cluster centroids from the first recording of a workstation are illustrated. Based on the cluster label plotted in Fig. 15(b), it can be observed that for one work cycle, the hands move near the clusters $C0$ and $C1$ for a while, then into the clusters $C2$, $C3$ and $C4$ which are further away. For every new work cycle, the hands come back to cluster $C0$ and $C1$ and repeat the pattern, which results in an abrupt change from cluster $C4$ to $C0$ (the quick movement in a short period - defined by $t_{max} = 3MODs = 0.516$ s will not be considered, as the worker sometimes forget the tools and reaching out to take it).

The first recording shows two work cycles as cycles $A1$ and $A2$, which last for 200 and 305 frames, respectively. The existing cluster centroids are applied to predict the cluster labels of the other recordings from the same workstation. In Fig. 15(c), the second recording shows the worker was working on the conveyor in the same position. However, as the rack for the work-in-process (WIP) is further away from the first recording, this worker needs to reach out further than cluster $C4$ to take it to start a new work cycle. Consequently, the cycle B1 lasts longer for 340 frames. The different cycle times from these two recordings are calculated in Table 2.

3.2.3. Body part utilization

The hands are the most frequently used limbs in assembly work on a conveyor. Thus the utilization ratio of two hands is essential information for industrial managers. Based on the movement identification, the

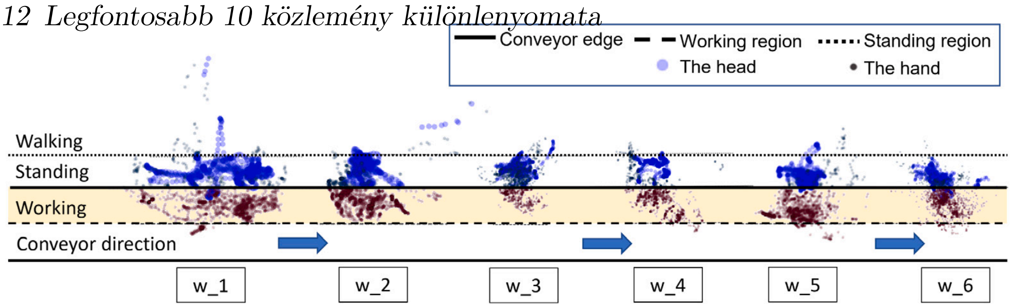
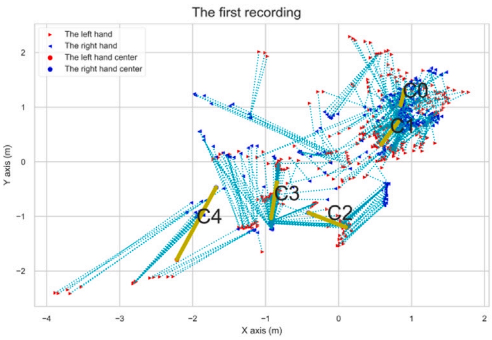
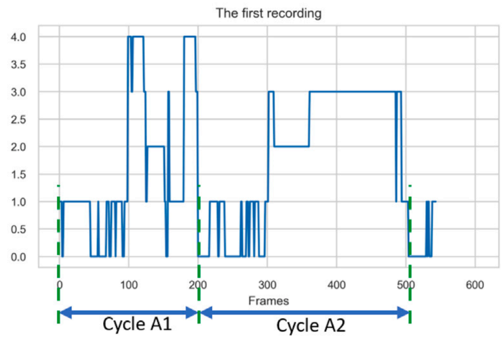


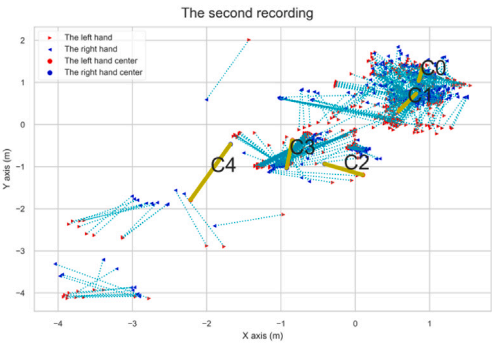
Fig. 14. An elaborated section of the assembly line. Example data from the use case.



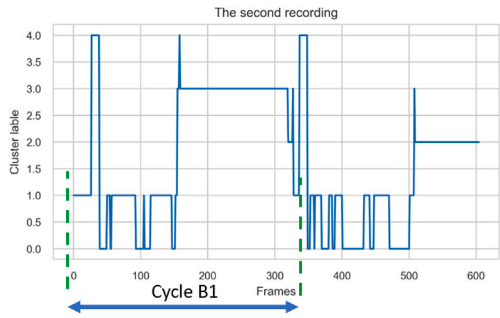
(a) Clusters result from the first recording



(b) Work cycle from the first recording



(c) Clusters result from the second recording



(d) Work cycle from the second recording

Fig. 15. Cycle time recognition in different recordings. Example data from one workstation.

Table 2
The calculated cycle time from two recordings in one workstation.

No.	Work cycle	Number of frames	Number of MODs	Time (sec)
1	A1	200	200	25.8
2	A2	305	305	39.345
3	B1	345	345	44.505
Average cycle time			**283.3**	**36.55**

timestamps of the head and the hands between each working duration can be recorded. A timeline is built, as illustrated in Fig. 16 to show the status of the worker during the work period. It can be seen in the first recording, that the worker spent most of the time in the standing region, but only partly in his working state, and even less time spent on working the assembly task with two hands.

From this information, the utilization ratio can be calculated for this workstation, as metrics exhibited in Table 3. By comparing different recordings from different workers, it can be observed that the worker only works with both hands for half of the total recording time. Besides, this worker was working slightly more with only the right hand than with only the left hand. Further investigation is needed to see if it is due to the workstation arrangement or the natural right-handedness.

3.2.4. Movement pattern searching with kinematic characteristics

The kinematic characteristics of interest are the moving velocity and acceleration of each hand of a worker. These kinematic characteristics in the form of time series will be a curious object for the next step of pattern searching. Besides this information, the calculation of RULA angles (such as arm abduction, arm extension, etc.) mentioned by Manghisi et al. (2017) [43] can be considered for a similar approach. However, only kinematic time series are chosen to be diagnosed further. Based on the previous result of cycle time recognition and body part utilization, we can analyze these characteristics for a specific part of the work cycle as illustrated in Fig. 17. From the previous result in Fig. 17(a), it can be seen that during the first period of the first work cycle, both of the hands are working in the cluster $C0$ and $C1$. A closer look at the kinematic characteristics in Fig. 17(b) can show us that though the two hands were working together, the right hand was more preferred, characterized by a higher velocity value and a more extended period with acceleration.

The motif searching technique is applied to looking for the same movement patterns that appear during the work period, performed by the same worker or by different ones. The purpose of finding the same pattern of one worker will show us an insight into his work

Table 3
The assessment result of body part utilization of the worker in one workstation.

No.	Metrics	Recording 1			Recording 2		
		MODs	Seconds	Ratio (%)	MODs	Seconds	Ratio (%)
1	Total recorded duration	900	116.10	100	896	115.58	100
2	In standing region	879	113.39	98	867	111.84	97
3	In working state	626	80.75	70	623	80.37	70
4	Working with both hands	418	53.92	46	458	59.08	51
5	Only left hand working	69	8.90	8	36	4.64	4
6	Only right hand working	117	15.09	13	97	12.51	11

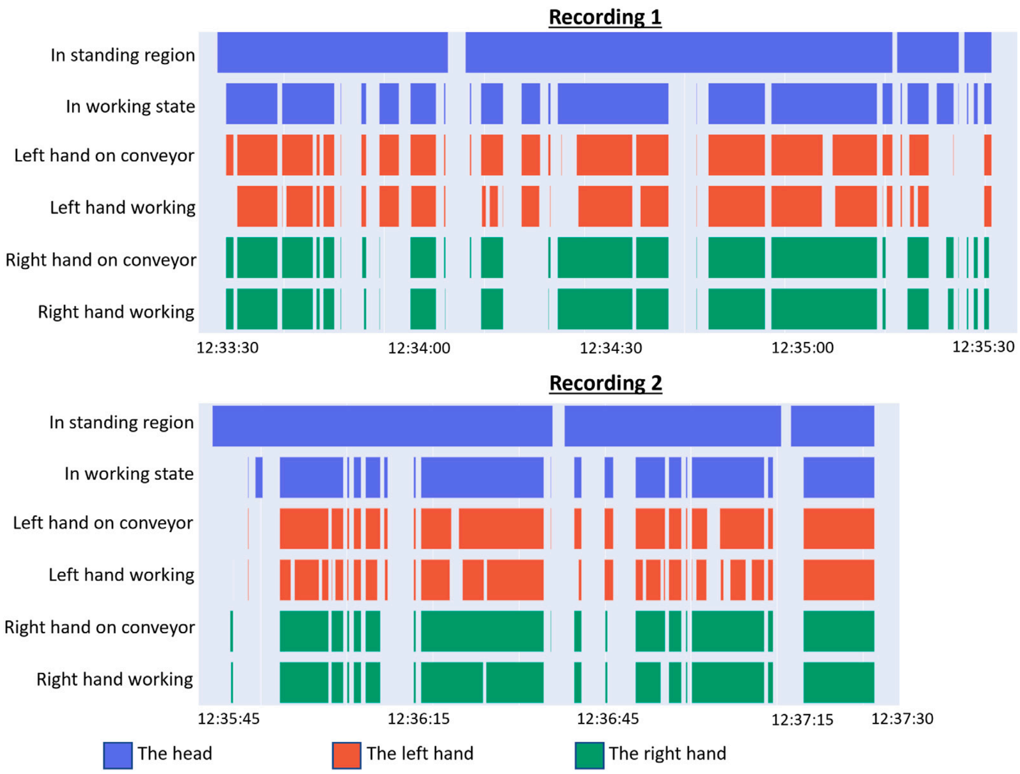
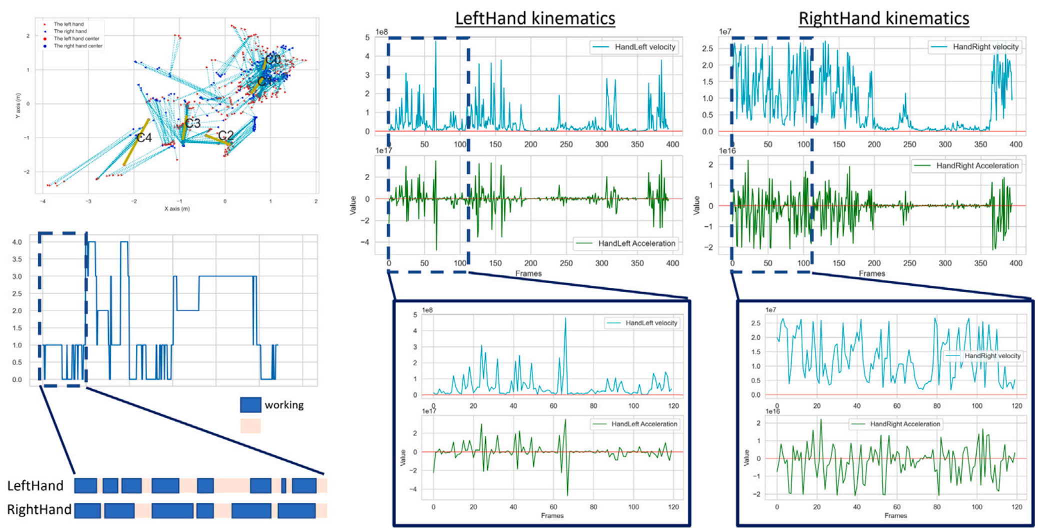


Fig. 16. The timeline of the worker status. Example data from one workstation.



(a) Working status. (b) Kinematics characteristics of left and right hands.

Fig. 17. The kinematics of two hands in the first area. Example data from one workstation.

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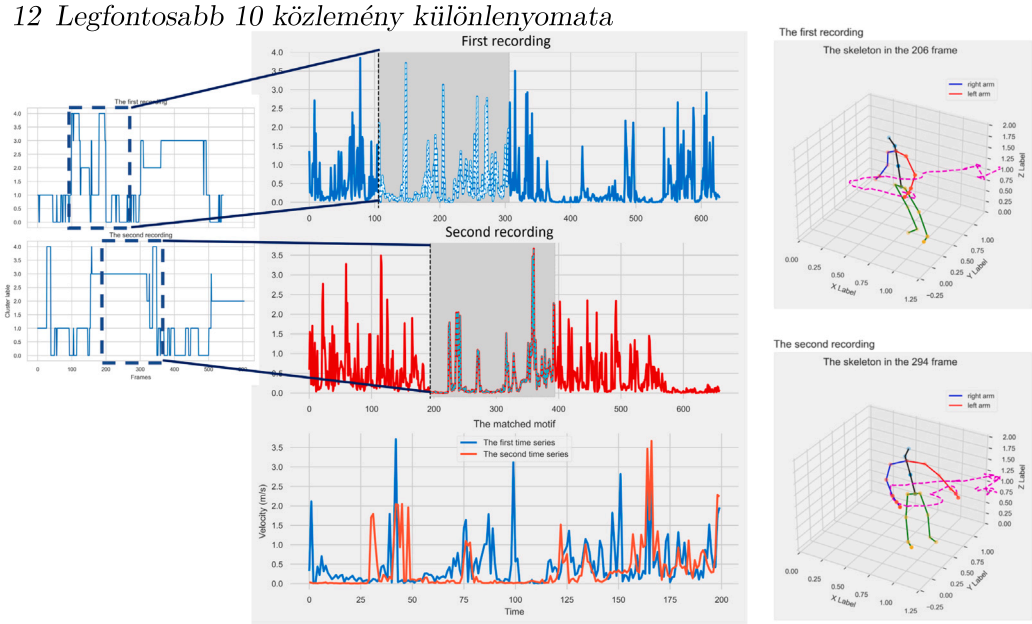


(a) The motif in the velocity of the left hand.

(b) Actual movements.

Fig. 18. The matched motif in left-hand movements of workers. Example data from the use case.

Table 4
The assessment result from the first six workstations in the assembly line.

Metric	Calculation	Unit	Ideal value	w_1	w_2	w_3	w_4	w_5	w_6
Utilization ratio	The average of working duration over the recorded duration.	%	The higher the better	70	69	69	65	58	67
Hard-to-perform ratio	The average of working duration where the gestures exceed RULA recommended limit angle.	%	The lower the better	21	14	19	6	23	12
Cycle time difference	The difference between the recognized cycle time over the line takt-time	%	The lower the better	15	32	22	18	35	19
Cycle time variation	The cycle time variation from different cycles over the recognized cycle time	%	The lower the better	34	17	26	41	39	13
Left-hand utilization	The duration when the left hand is working.	%	The higher the better	55	61	57	26	35	59
Right-hand utilization	The duration when the right hand is working.	%	The higher the better	61	52	29	15	25	63
Body asymmetry	The total accumulated duration in which only one hand is working.	%	The lower the better	18	22	36	24	21	14

while finding the same pattern by many workers helps us find the best movement practice.

By applying the AB-Joins with STUMPY [29] on the velocity time-series of the left hand from two different recordings, a motif can be found as illustrated in Fig. 18. The respective movements of two different workers with their left hand are shown in Fig. 18(a). The movement happens when the workers finish one work cycle and need to bring a new product from the rack into the conveyor to start a new one. The trajectory of the left hands as the dotted lines in Fig. 18(b) indicate that the worker in the second recording has a better way of performing the work and did not need to turn around.

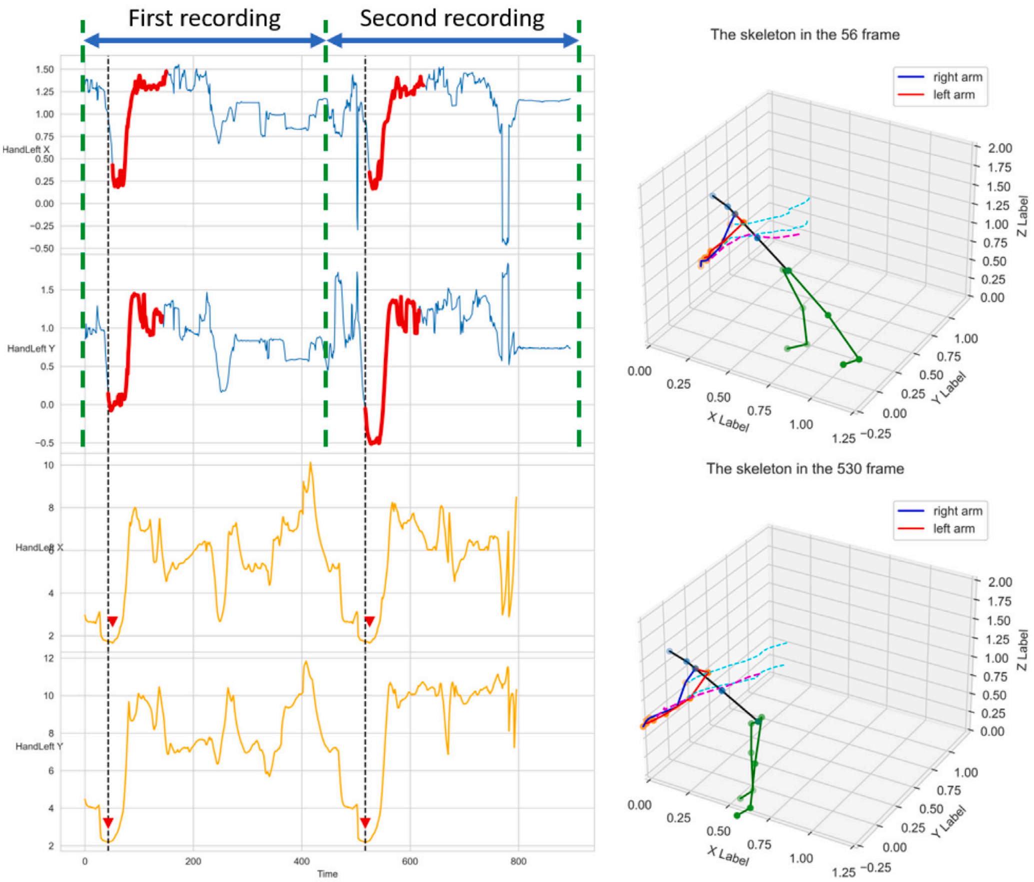
To recognize the work movement pattern performed by both hands, multi-dimensional motif searching is deployed on the velocity time series of the left hand and right hand. As in Fig. 19, the time series from different recordings can be joined together in Fig. 19(a), and similar movements with both hands are spotted. The actual movements are shown in Fig. 19(b). The dotted lines marked the trajectories of the wrist-elbow-shoulder system indicate that the upper body movements are similar; however, different workers have different working postures.

To expand the motif searching for many workers, a time-series consensus search can be performed on simple data, such as the Z-coordinates of the left hand, as shown in Fig. 20. The consensus is found in different recordings as in Fig. 20(a), while the worker executed a “swing” movement with his left hand. These movements are indicated by dotted lines in Fig. 20(b).

By aggregating the metrics from the constituent workstations, an overall picture of the assembly line can be constructed as in Table 4. Six criteria are proposed to assess each workstation, and their ideal values can be set from the historical standards. The information from the first six workstations is given here for demonstration purposes.

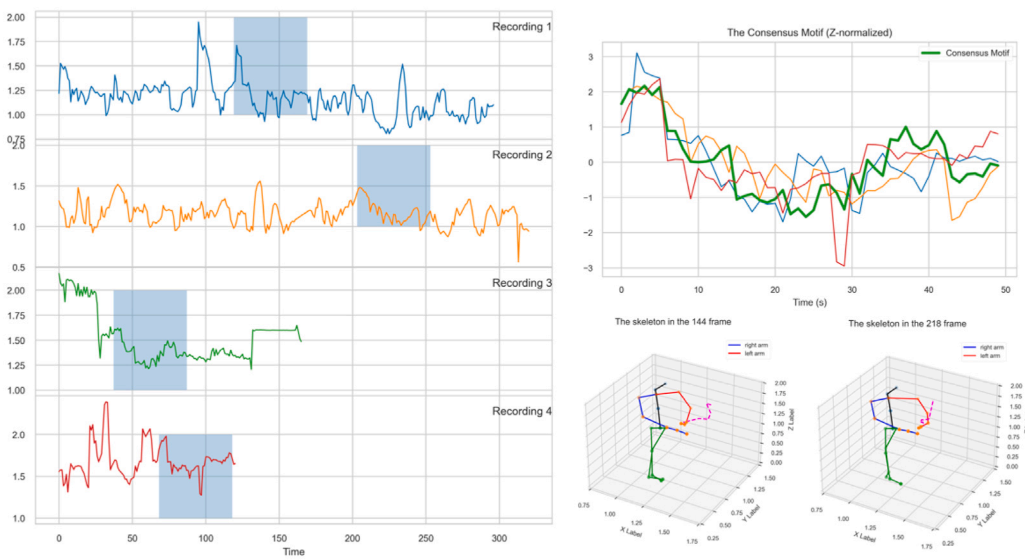
Besides this automatic assessment with the Kinect sensor, the manufacturing firm also organizes random assessments in several workstations by the Lean experts with similar criteria. At the end of the examination period, a team of process engineers and Lean experts of the firm held a meeting, where the result from the expert and automatic assessment were compared and discussed. A high consensus was achieved as the team agreed upon several points that distinguish the two results:

- The automated calculation based on the position of the limbs, such as cycle time recognition and moving status of the hands, were accurate. Minor errors happen due to the signal noise or occlusion caused by another object.
- The proposed motif searching approach was performed faster with more accurate details, as the human eyes of experts cannot



(a) The positions while the motif happens. (b) The motif and the actual movements.

Fig. 19. The matched motif of two hands movements performed by different workers. Example data from the use case.



(a) The positions while the motif happens. (b) The motif and the actual movements.

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Fig. 20. Consensus motif in the height of the left hand performed by different workers. Example data from the use case.

Table 5
The possible improvement ideas based on the assessment result.

Indicators	Physical meaning	Possible improvement	Possible initiative
High cycle time variation & High difference between left and right-hand utilization	The work procedure is complicated The workload is not distributed equally for the hands.	Modifying work instruction	Enhance hand utilization Enhance body symmetry Reduce work complexity
Low utilization ratio & High or varied hard-to-perform ratio	More irrelevant movements than working. The workstation layout does not fit the workers.	Re-arranging work-layout	Reduce non-value-added moving Avoid reaching and awkward gestures
High variation of hard-to-perform ratio, cycle time difference, and cycle time variation	The workstation is not optimized. The work procedure is complicated.	Line balancing	Reducing the complexity of work procedure. Risk-based line balancing
Unbalanced value of left and right-hand utilization & Varied value of body asymmetry ratio	The workstations require different parts of the body and dynamic asymmetry.	Job rotation	Rotate workers to balance their body usage
High cycle time variation & Varied body asymmetry ratio or best movement is found	The un-skilled workers cause the cycle time variation. There is better movement in ergonomics or fatigue aspects.	Job training	Serve the rotation plan Increase individual skills Multiple the best movement

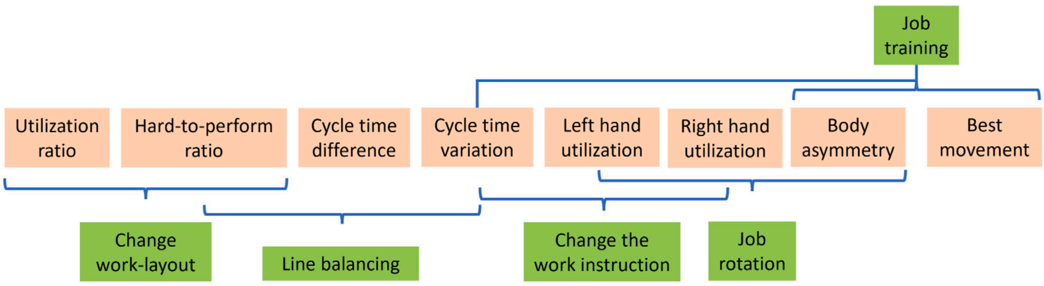

Fig. 21. The criteria hierarchy of possible improvements.

recognize the micro-movements of the workers. In addition, comparing the movements of different workers takes lots of time and effort and is prone to human error.

Despite these minor problems, the team approved that the automatic assessment result is reliable and sufficient for developing further human-centric improvements. The following section will describe several relevant ideas that align with the objectives of I5.0.

3.3. Possible human-centric improvements

Based on the aforementioned assessment, several improvement ideas can be brainstormed as described in Table 5 follow in the order of execution priority. The sole intention is to create favorable physical work condition that suits the current human workers, from the workstation scale to the line scale. The suggested relationships between the possible improvements with the assessed value are proposed in Fig. 21.

A high value in the cycle time variation of the same workstation by different workers indicates that the work procedure is hard to follow; thus different workers require different times to finish a work cycle. Low utilization of the hands can be due to rest or hesitation during work. And a high difference between left and right-hand utilization can be an indicator of a poor work design. These problems (as in workstation w_4) should be addressed in the workstation scale using the Left and Right-Hand process chart. The process engineer should reduce the work complexity and aim at equal use of two hands.

The low utilization ratio within a workstation indicates that the worker paid more time for other movements (i.e., walking, searching, quality checking) than working, and the high hard-to-perform ratio can reflect the unreasonable arrangement of the work cell. Varied values of the hard-to-perform ratio by different workers indicate that the cell arrangement is not suited for most of the workforce. As these problems occurred in workstation w_5, a new arrangement should be made to remove unnecessary body movement based on the ergonomics of most of the workers.

If the work procedure is not optimized, time variation is too high, and uncertain; then the line becomes harder to balance. The solution for this line is to stabilize the worker performance in its workstation (such as in workstation w_1, w_4, and w_5), then re-balance the line based on the new value or add risk-based factors into the calculation of the line performance.

The unbalance usage of the body part can cause localized muscle fatigue and occupational disease for a long time. The varied value of the body asymmetry ratio proved the heterogeneity of the work in the workstation. To avoid these negative consequences, workers should be rotated between workstations based on these values (i.e., w_1 and w_2), both short and long-term. The cycle time is another essential factor to consider when assessing the fatigue impact of the body asymmetry.

The high variation of cycle time performed by one worker can indicate that the worker lacks work proficiency. Along with preparing for the proposed work rotation plan, job training initiatives should aim at increasing the skills of individuals and sharing the best movement within the workforce. One best example is the movement described in Fig. 18.

4. Discussion, limitation & suggestion for future research

This paper proposes an approach of pattern mining the Kinect sensor skeleton data to assess human worker performance. On-the-shelf production management softwares are not incorporated with a Machine learning model to recognize patterns of human action. Consequently, they do not have the knowledge foundation for human resources development planning, such as training and rotation scheduling. To compensate for this lack, a Python package for post-processing the skeleton data from the Kinect sensor is developed, specialized for Industry 5.0-related human-centric improvement projects for manufacturing processes.

The process takes advantage of supervised learning and motif-searching algorithms to discover the characteristics of work movement. The elementary movements and times with associated patterns can be collected and analyzed for line balancing purposes, and variance monitoring for real-time production. The mined patterns reflect the working behavior of the workers. The assessment result can be utilized for performance enhancement and individual and systematic human-centric improvement in the short and long term.

A use case is conducted on an electrical assembly line to validate the approach. As the work movements are segmented, the work behavior can be diagnosed, and these data can be used to develop a HAR model for recognition and prediction. The work performance of each workstation and the whole manufacturing line can be assessed in several aspects, saving human expert efforts and generating data for further mining activities.

Regarding the proposed procedures, several customizations can be made according to the actual industrial application. The re-sampling time in this paper is one MOD, as the MODAPTS standard is deployed in the company where the use case is conducted, and the process engineers want to compare the extracted movement patterns with the standard movement from MODAPTS as a benchmark. A similar approach of associating Kinect-acquired data with MOD is utilized by Leon-Duarte et al. (2018) [56].

Some limitations are associated with the use of the Kinect sensor. Firstly, data distortion happens due to the limited capability of the sensor and the occlusion of the human body. This can be solved by the installation of multiple Kinect sensors as studied by Bortolini et al. (2020) [15]. The distortion correction model suggested by Herrera et al. (2012) [57] can be used to improve joint accuracy. If any obstruction causes distortion, these distorted frames can be classified due to the intrinsic value of human movement limitations, such as distance and angle between joints. Missing joint data in an unconstrained environment can be solved with PyHAPT [58]. To enhance the accuracy of the solution, wearable inertial sensors can be incorporated as proposed by Gowing et al. (2014) [59]. The proposed procedure can apply to MoCap sensors in general besides using the Kinect sensor. As there are plenty of commercial sensors on the shelf that are suitable and capable of delivering the same result, industrial managers can choose the hardware that fits their needs.

5. Conclusions

The initial result from the use case is promising and provides helpful guidance for the engineering team further develop their improvement ideas. As the data processing is rooted in MODAPTS standards, the productivity aspect can be diagnosed by comparing the movements with the ideal sample. The induced details from the result are helpful in understanding the work ergonomics from a management viewpoint in an automated way. They can contribute to the Healthy Operator pillar [60] of the Operator 4.0 and Operator 5.0 concept. The individual and systematic improvement plans are beneficial for the organization in both the short and long term and facilitate the Lean 4.0 transformation. This innovative solution facilitates the future of human workers in manufacturing industries. The proposed pattern mining-based continuous improvement approach in this paper is aligned with I5.0 objectives since it is human-centric and aims at sustainably building a resilient workforce. This solution can be disseminated within industries to encourage similar practices. Further research can be conducted to serve more advanced applications of Kinect sensor data, such as ergonomics design with digital human modeling [61], OHS integrated assessment in a digital factory [45], or interactive modeling for the collaboration between human and robot [62].

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Skeleton data coordinate transformation

The transformation procedure is described in two steps in Fig. A.22. As the Kinect sensor coordinate system with the origin O_K is different from the standardized Cartesian system with the origin O_C, then every point $\mathbf{P}_K = [x_K, y_K, z_K]$ in the Kinect sensor system should be transformed into corresponding point $\mathbf{P}_C = [x_C, y_c, z_C]$ in the camera system, which is the standardized Cartesian, with the rules as Eq. (A.1):

$$x_C = -x_K \quad ; \quad y_C = z_K \quad ; \quad z_C = y_K \tag{A.1}$$

To reconstruct the interpretable coordinates of the skeletal joints in the world coordinate system associated with the floor, every point $\mathbf{P}_C = [x_C, y_C, z_C]$ in camera system should be transformed into its corresponding point $\mathbf{P}_W = [x_W, y_W, z_W]$ in the world system, whose the origin point O_W is the perpendicular projection of the origin O_C into the floor. The transformation can be done by using the 3D affine transformation matrice as in Eq. (A.2) with pytransform3d package [36]. In which, (τ) is the 3D affine transformation matrice in Eq. (A.3), which contains the information of the camera setup.

$$P_W = \tau * P_C \tag{A.2}$$

With $\mathbf{P}_W = [x_W, y_W, z_W, 1]^T$ and $\mathbf{P}_C = [x_C, y_C, z_C, 1]^T$.

$$\mathcal{T} = \begin{pmatrix} 1 & 0 & 0 & H_X \\ 0 & cos(\alpha) & sin(\alpha) & H_Y \\ 0 & -sin(\alpha) & cos(\alpha) & H_Z \\ 0 & 0 & 0 & 1 \end{pmatrix} \tag{A.3}$$

For simplicity, the camera setup information consists of the transitional vector $\mathbf{H} = [H_X, H_Y, H_Z]$, and the rotation angle α.

Appendix B. Movement patterns and possible application

The following tables list the movement patterns that can be mined from the dataset. The input series can come as the original series from the Kinect sensor, or from the derivative series. The physical meaning of each series is described with the relevant mining techniques. The result and application are given as suggestions.

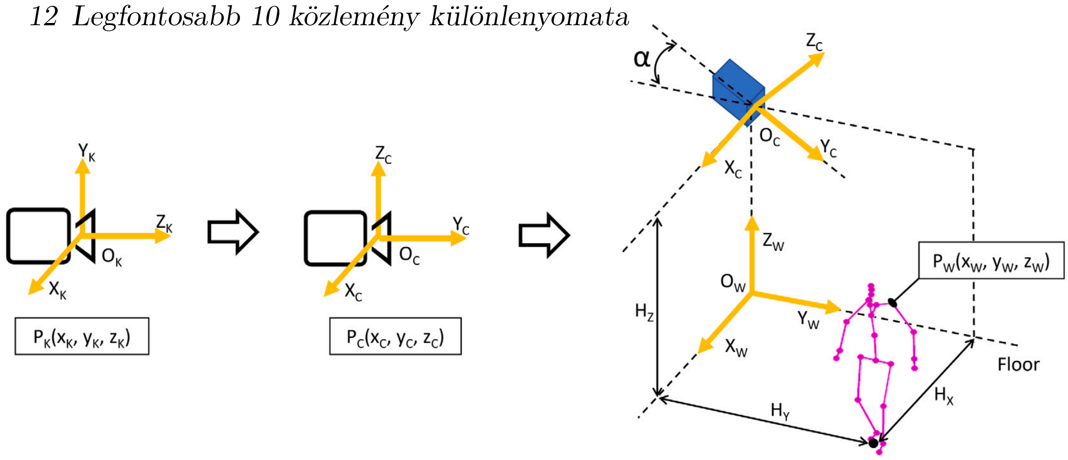

Fig. A.22. The coordinate transformation of the data captured by Kinect sensor.

Table B.6
The movement patterns and possible application.

Objects of interest	Input series	Physical meaning	Mining techniques	Result	Application
Movements of one worker in one workstation	The position and kinematic of the stationary joints (e.g., head, spine)	The principal movement of the body.	Segmenting the moving-working movement based on the joint velocity and acceleration.	The segmentation of the frames.	Calculating the utilization efficiency.
	The position of two hands	Position of the hands while the worker is working	Clustering.	The different areas in the workspace.	Recognize the work area. Segmenting the work movement.
	The joint angles	Different angles in standard (e.g., RULA) such as arm extension/abduction, shoulder elevation, elbow extension, etc.	Compare to the limit of the corresponding standards.	The uncomfortable gestures duration.	Ergonomics assessment. Potential occupational hazard.
	The joint distance	Different distances in standard (e.g., MAC) such as hand to hip, hand to shoulder, etc.	Compare to the limit of the corresponding standards.	The time percentage of uncomfortable gestures.	Ergonomics assessment. Potential occupational hazard.
Movements of one worker in one workstation	The distance between two hands	The variation of the distance between two hands over time.	Clustering or Embedding.	Periodic characteristics in time.	Cycle time recognition.
	The kinematic of the hand-elbow-shoulder system.	The movement of the hand with the associated joints.	Recognize the joints are moved, compared with the standard (i.e., MODAPTS).	The conformity with optimal value and movement in standard.	Calculating utilization efficiency. Customized training.
	The acceleration of the moving joints (e.g., hand, elbow).	The acceleration when the body is performing work.	Compare the value and magnitude.	The fatigue possibility and complexity of the work.	Fatigue assessment. Workload design.
	The acceleration and angles of the moving joints (e.g., hand, elbow)	The movement of each side of the body.	Compare the duration that both sides of the body is utilized.	The symmetry of the work.	Fatigue assessment. Workload design.

Table B.7
The movement patterns and possible application. (Continue).

Objects of interest	Input series	Physical meaning	Mining techniques	Result	Application
Movements of one workers in several workstation	The working/non-working duration during work.	The work utilization of the worker.	Motif searching.	The consistency pattern between work cycles.	Assess the Overall Person Effectiveness (OPE) of the worker.
	The kinematic characteristics of the moving joints (e.g. hand, elbow.)	How fast and frequently the joints are moving.	Comparison and Motif searching.	The personal tendency of the worker in using his limbs.	Understand the preferred working gesture of the worker. Customized training.
		The skill competence of the worker for a specific workstation.	Compare with the best practice - the optimal movement motif.	The most preferred workstation for that worker.	Work allocation preference.
Movements of different workers in several workstation	The distance between two hands	Similar to the movement of one worker.	Embedding the time series.	Periodic characteristics in time	Cycle time recognition. Line balancing
	The bending angle of the body trunks.	The angle that the workers bend their bodies in each workstation.	Compare the range and value.	Reveal the workstation that is too low or too high for the worker.	Improve the ergonomics setup.
	The acceleration and angles of the moving joints (e.g., hand, elbow)	The asymmetry and complexity of the work in each workstation.	Find the best match with contradicting values.	The pairs of workstations that contradict each other.	Create job/shift rotation plan.
Movements of different workers in the same workstation	The cycle time and task time.	The deviation in the similar work performed by different workers.	Comparison and assess the time deviation with standard time.	The possibilities of delay in a workstation.	Line balancing. Production planning.
	The kinematic of a body system (e.g., hand- elbow - shoulder) while performing a work movement.	The same movement is performed by different workers.	Compare with the ergonomics standard.	The best ergonomics and efficient movement.	Assess the skill competence. Sharing the best practice with other workers. Customized training.

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Enriching scene-graph generation with prior knowledge from work instruction

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Abstract. With the current focus on human resources in Industry 5.0, analysing the work movements of industrial operators is the important first step in optimising labour performance. Thanks to the popularity of camera sensors, vision-based Human Activity Recognition models have become useful engines for real-time monitoring tools, in which scene-graphs play an important role. Traditional scene-graph generation methods rely primarily on visual data for perception, neglecting a valuable source of process-oriented prior knowledge: the work instruction. Therefore, an extension of the scene-graph paradigm by integrating ground truth elaborated on elements from the work instruction is elaborated to complement and enhance the understanding of human activities in industrial environments, and improve the tracking capability with micro and repetitive movements. This conceptual paper discusses the basic design of this approach with potential applications in industrial environments, which is validated by a simulated use case of an electronic assembly process. Based on the proposed extension, the Human Activity Recognition model can be lightweight and robust. Further integration of multi-modal sensory inputs beyond visual cues, such as environmental and human-centric data, can enrich scene interpretation and provide a more comprehensive understanding of work behaviour, paving the way for more effective labour utilisation and improved productivity.

Keywords: Scene-graph · Human-centered · Activity recognition · Industry 5.0 · Operator 4.0

1 Introduction

With machines and automated robots still struggling to replace the cognitive and motor skills of human operators [20], [27], the human presence in manufacturing systems is irreplaceable, thus urging the effective management of human resources [25]. To improve human performance, Human Activity Recognition (HAR) solutions have been developed for automated detection and assessment, most of which use inertial measurement units (IMUs) or accelerometers on the target operator [26]. This sensor-based approach has the inherent disadvantage of requiring the wearer to carry the device or smartphone, which is not comfortable for industrial operators during work performance [15]. With the rapid development of image processing techniques, vision-based HAR has become a trending and preferred solution [5] to capture natural, hands-free work gestures. However, a major challenge for a continuous vision-based monitoring application is predicting the interaction between people and objects with an appropriate level of accuracy at the right time [1]. From a productivity improvement perspective, considering that work movements and micro-movements in an industrial context can be as short as a quarter of a second [7], tracking human activities with high sensitivity to repetitive micro-movements is valuable for productivity and performance assessment purposes [22], and indirectly supports the design and optimisation of macro-work tasks [30], [4] especially in labour-intensive industries such as electronics assembly.

To this end, object-graph representations have been used in several previous efforts, such as a hybrid network of scene and temporal graphs for complex activity detection [18], a spatio-temporal action graph network for multi-object interactions in near-collision events [13], or a scene context-aware graph using common-sense knowledge mapping on skeletal data [34]. Similarly, a set of actions can be automatically recognized with an image-based scene graph prediction model such as Action Genome [17]. Although promising results have been obtained, these studies were initially developed to recognize everyday activities in a general context, thus under-utilizing the specific characteristics of manufacturing processes, such as repetitiveness, or the abundance of available information, such as the work instruction for a given process. In industrial production, where processes are tightly controlled with predefined productivity and quality requirements, repetitive manual tasks are well defined within certain limits based on work instructions [2] and the heuristic behavior of operators. Although work instructions may vary within companies and industries without a general standard, they contain the prior knowledge of the process, including the interaction between work-pieces (which include parts and components), work tools, and their spatial or even temporal relationships.

Based on the advancement of Industry 4.0 (I4.0) technologies, the development of human-centered solutions has flourished to meet the needs of human operators during their work [29], as formulated in the core concept of Operator 4.0 (O4.0) [28]. In the context of Industry 5.0 (I5.0) [3], human centricity has received particular attention [24], [9] urging a deep human integration into a resilient manufacturing system as the generation of Operator 5.0 (O5.0).

Motivated by these circumstances, this study proposes an extended scene graph principle, specifically elaborated for the industrial environment with repetitive micro movements, by integrating the information from the work instruction. The process-oriented prior knowledge in each work step formulates a knowledge graph as the backbone for recognizing the activity pattern. The detected scene can be updated with cyclical behaviors, improving accuracy while providing robustness against occlusion, image loss, etc. Based on this extension, the vision-based HAR solution can be lighter and more accurate, but still computationally efficient for real-time industrial monitoring applications. A concept of an ideal HAR solution based on the proposed extension is formulated, which suggests how the scope of a HAR model can be extended to include various process and environmental sensory inputs, as well as the physiological parameters of an operator during the work session. By avoiding poor quality work instructions, higher efficiency and job satisfaction can be achieved [12]. This study expands the scope of O4.0 technologies to enhance human performance, facilitating the transition to O5.0 [8].

The paper is structured as follows: Section 2 introduces the main components and structure of the proposed extension for scene graph generation from the work instruction. Section 3 presents a conceptual use case of applying the extension in recognizing and extracting meaningful activities from video recordings of a simulated workstation with repetitive movements, while Section 4 delivers remarks on the proposed concept, and suggestions for future research.

2 Formalisation of the proposed extended scene graph

A scene graph is a structural representation that describes the content of a scene in detail, including objects, their attributes, and the associated relationships between them. A scene graph generation model takes an image as an input and generates a visually-grounded scene graph [35], with objects visualized by a set of nodes belonging to different classes and having corresponding attributes. A set of edges connecting the object nodes encode the relationships between objects.

Casual techniques of scene graph generations can be depicted on the left side of Fig. 1. Various segmentation algorithms and object recognition models are deployed to extract the objects from the input image, which also assign labels to the objects. Semantic segmentation [11] treats the elements in the image as uncountable and amorphous. Consequently, similar objects (e.g., people) are grouped into a class label. It assigns all the pixels of the image to a class. In the case of instance segmentation [10], overlapping masking is performed per object in addition to labeling, and the overlaps are resolved using non-maximum suppression. Then the predicted segment is sorted by its confidence value, and segments with low scores are removed. The algorithm goes through the sorted confidence values for each object, checking whether the previous object contained a pixel from the current one. The segment is accepted after this iteration if enough of the segment remains, otherwise, it is deleted [19]. However, these efforts all suffer from problems such as occlusion (both temporarily and perma-

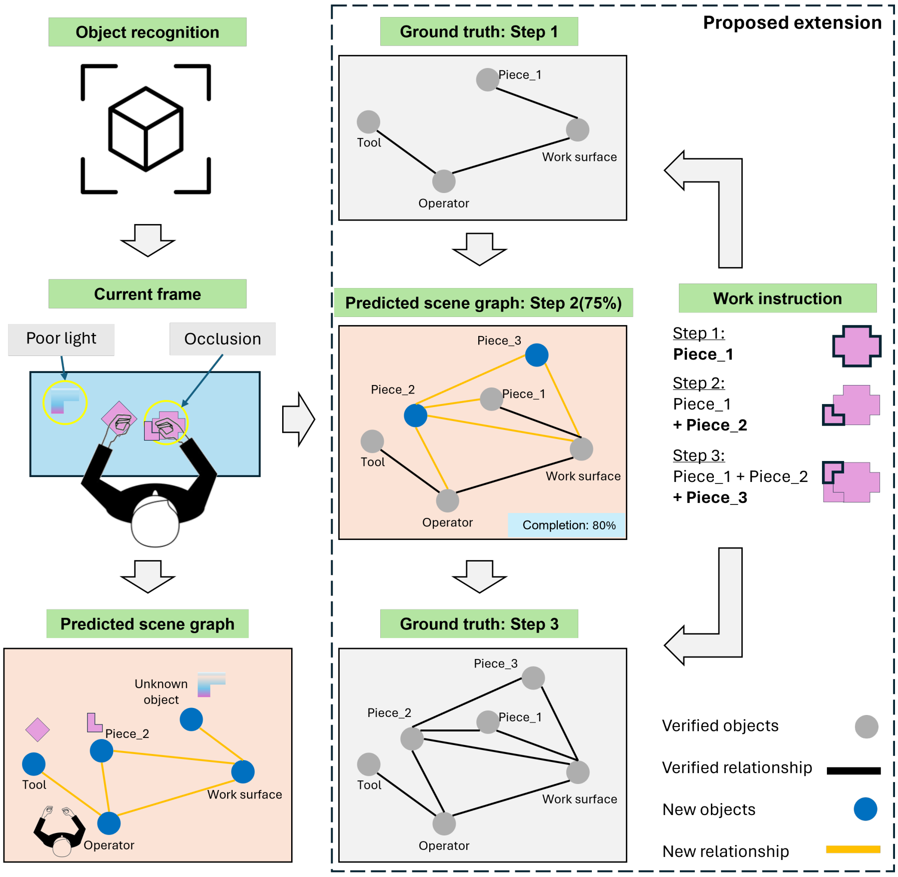


Fig. 1. The scene graph generated by the normal approach on the left, with missing objects in the predicted scene graph due to poor light and occlusion. The proposed extension is described in the right block, which utilizes the work instruction to generate the ground truth scene graphs for the previous and next steps. Thanks to these ground truths, the current frame is predicted as the second work step with 80% completed, with a 75% probability.

nently), poor lighting conditions, etc. As an aftermath, unknown objects appear, or some details are missed from the predicted graph. The more effort to cope with these problems, the more complicated the image processing techniques become.

Our proposed extended scene graph, can be described as an extension of a scene graph generation model, which utilizes the available data from the work instruction of the ongoing process. Assuming that a well-written work instruction contains sufficient information in each work step, including necessary work motions, used tool, and new work-piece that appears with the expected relationship with existing work-pieces from the previous step [2], the scene graph for each step can be elaborated to create the ground truth (or expected condition).

The information derived from work instructions into a G_W knowledge graph begins by structurally mapping the various process steps outlined in the instructions. The work instruction can be represented as a knowledge graph, like the AWI-KG (assembly work instruction knowledge graph) [21] or ARWI (augmented reality work instruction) [6]. Each work step within the workflow is represented as an individual sub-graph in the temporal knowledge graph of the whole process, thus breaking down the manufacturing workflow into manageable sub-processes.

The construction of the $G_{W,n}$ sub-processes knowledge graph of the n-th process step begins by the identification of the core entities found in the work instruction. The draft scene graph detected at the current frame is denoted as G_D, representing the scene graph extracted from the observation along with its uncertainty. The expected scene graph, G_E, is abstracted from G_W, which serves as the ideal or theoretical model of the scene based on prior knowledge.

The graphs can be formally represented as a given sets containing object classes C, attribute types A, and relations R, a scene or knowledge graph G can be defined as a tuple $G = (O, E)$ where $O = \{o_1, \ldots, o_n\}$ is the set of objects, and $E \subseteq O \times R \times O$ is the set of edges. All objects are denoted as $o_i = (c_i, A_i)$, where $c_i \in C$ represent the class of the object and $A_i \subseteq A$ represent the attributes of the object [32].

By forming the difference of the two graphs, we obtain the graph containing the uncertain nodes and edges. Above a certain level of confidence (e.g., when information has been passed on from a previous work step or when the movement of the hand of the operator or tool has occurred), the missing information can be injected, and the enriched scene graph can be generated.

Incorporating prior knowledge in the analysis of scene graphs significantly enhances holistic scene understanding capabilities [35]. Thanks to the proposed extension, the calculation effort can be significantly reduced, and the algorithm will become more robust against problems such as poor lighting, occlusion, etc. The objects in the scene graph only need to be updated when there is a change in the detected objects. For example, if the workpiece remains stationary and no work is being performed on it, there is no need to update the node and its edges. Establishing a new relationship between objects is necessary only when a new object appears on the scene or when the registered objects undergo some form of interaction.

By having a priori knowledge of the cycle time and process time of the process elements, unnecessary edges can be revised and gradually removed. After the specified time has elapsed, the task is considered completed. This allows for the removal of irrelevant objects and edges. Based on the currently detected ground-truth scene graph, these transitions can be used for anomaly detection or alarm management. For example, they can be used to signal to the worker or supervisor when the production cycle time is continuously increasing due to repetitive work load, thus predicting worker exhaustion. In such cases, the worker can be sent on a break or transferred to another workstation where they can perform different tasks. This change in working conditions may help the worker regain a state of flow, enabling them to continue working productively.

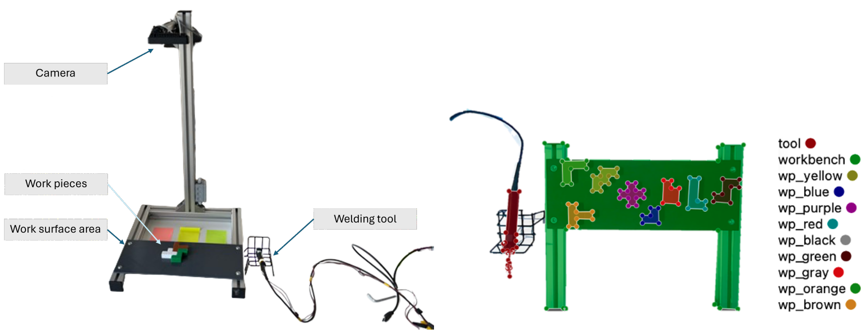
A demonstration is given in the next section, to describe the resultant advantages in the industrial work environment with micro and repetitive tasks.

3 Demonstration study of the extended scene graph

In this demonstration, a simulated workbench similar to an industrial workstation is constructed as shown in Figure 2(a). The production process focuses on assembling work-pieces by using a welding tool, similar to the manual process in electronics production. Figure 2(b) shows the work-pieces on the work surface area and the welding tool used in the assembly process, from the camera point-of-view. The objects are recognized by using a general segmentation model. During the study, an operator was required to weld the work-pieces together to complete the final product, following the work instructions provided in Table 1.

The work process is repeated to create a dataset for later data processing and improvement planning. The primary goal is to improve the processing of the output of the scene graphs by enabling the prediction of the actual process step based on the elements of the graph. Figure 3 is demonstrating the application of the proposed scene graph extension on the fifth step of the work process. The work instruction requires the operator to use both hands: holding the tool in one hand while fixing the work-pieces with the other hand during the welding process.

The "draft scene graph" (see in Figure 3) constructed from the "segmentation map" of the "current frame" contains uncertainties, which result from blind spots on the work-pieces caused by the occlusion of the left hand and its shadowing of the visible part. Even if the visible part were well-illuminated, detection



(a) Workstation setup (b) Recognized labels by the camera

Fig. 2. The constructed workstation with a camera mounted on top to capture the working activities conducted on the work surface area (a) and the work-pieces placed on the work surface area, with recognized labels by the camera (b).

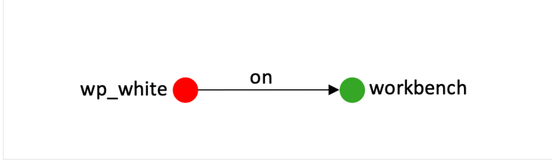
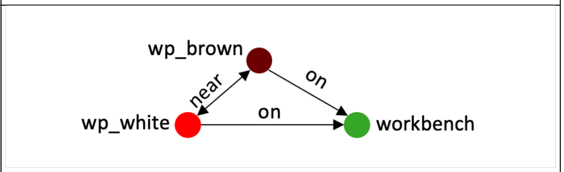
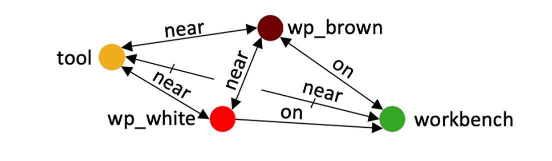
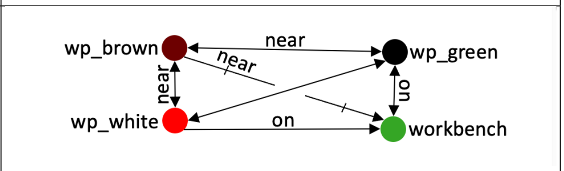
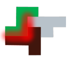
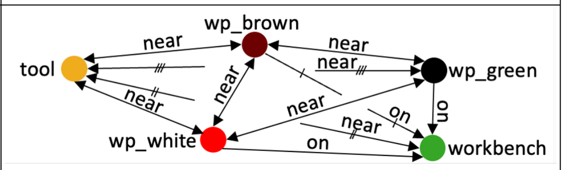
Step	Figure	Description	Ground-truth scene graph
1		Placing a white part on the table	
2		Fitting a brown work-piece to a white one	
3		Welding brown and white work-pieces	
4		Fitting green work-piece to brown and white work-piece	
5		Fitting green work-piece to brown and white work-piece	

Table 1. The work instruction with five elementary steps and corresponding generated visual ground-truth scene graph. Firstly, the process began with placing the white part in the designated work area. Secondly, the brown part is placed and aligned with the white one, then they are joined by using the welding tool. The green part was then placed and aligned with the previously assembled block of white and brown parts.

with high precision would be challenging for most object segmentation models since less than 20 percent of the object is visible. The "draft scene graph" cannot predict which workflow will take place without prior information. All work steps where the tool is to be used can be considered as potential predictions, in this case, the third and the fifth steps. Using our proposed extension by including prior knowledge, an "enriched scene graph" can be generated with a high degree of predicted certainty, which accurately describes the scene. Based on the previous iterations, the current activity is expected to align with the analysis of the ontology derived from the work instruction and by following the manufacturing process step-by-step. Considering these constraints, the expected activity should be the fifth process step, welding the green work-piece to the white and brown work-pieces.

The partially detected graph can also be completed based on the knowledge graph stored as a sequence of ground-truth scene graphs and the information from the position and processing of the work-pieces in the previous steps. As the white, brown, and green work-pieces should be positioned under the hands according to the work instruction, and considering the dynamics of the left hand, it is highly possible that the work-pieces can be found under the hand of the operator. By storing temporary information generated and captured during the production process in the model, with a timestamp, in the nodes of the graphs

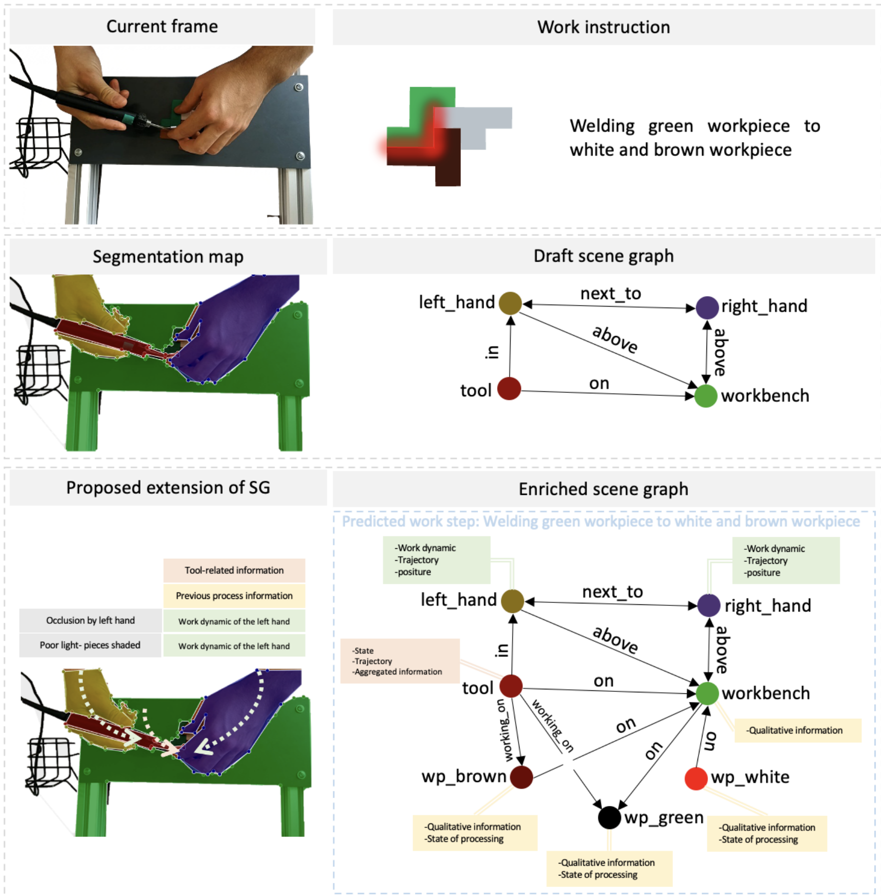


Fig. 3. Example of generating the enriched scene graph with prior knowledge from work instruction, from one frame recorded by the camera during the use case.

as feature vectors, enables further improvement of the accuracy of the model by considering the features of each node.

4 Conclusion and future works

In this study, a conceptual method for enriching scene-graph generation in the industrial environment is suggested, based on the prior knowledge derived from the work instruction. A detailed use case study will be developed in future work to prove the applicability of the proposed method, with a setup that closely imitates the manual assembly processes commonly used in factories, where components are either semi-automated or completely assembled by human labor using tools. The main focus of the study will be to compare the results of the optical-only approach and the extended prior knowledge approach in different workflow scenarios with different uncertainties.

We are also planning to develop an ontology model of the work instruction. The ontology model can be segmented into four sets of domain ontology classes because the knowledge graph comprises multiple sub-ontologies, such as resource, process, product, and monitoring ontology. Time also appears as a domain-independent core ontology[14]. The following list summarizes the industry-specific name-spaces and the ontologies can be used for the concept:

- smo- Smart Manufacturing Ontology [33] – Ontology for modelling I4.0 production lines and smart factories based on the RAMI 4.0 digitalisation framework[31].
- bbd- Body-based Gestures - An Ontology for Reasoning on Body[23] provides a framework for modeling human body model-based gestures within their context of use, utilizing extensible gesture representation.
- sosa— Sensor, Observation, Sample, and Actuator ontology[16] - Ontological description for modeling the interaction between the entities involved in observing, actuating and sampling.

Besides the concept serving as a lightweight basis for a HAR model, this approach suggests a hint for individualizing the work instructions based on the detected activities, thus assigning an operator with an appropriate workload or temporal demand, considering the level of environmental comfort and the available cognitive capacity of the operator.

For that purpose, additional multi-modal sensory inputs with environmental data (e.g., intensity and direction of light condition, machine vibration, noise), and human-centric data (e.g., acceleration of hand or body, eye response such as pupil dilation) can be integrated as illustrated in Figure 4. While the work instruction supports the ground truth scene graph and a draft scene graph can be achieved from the current frame, additional data provide useful information about the expected error and uncertainty of the current scene graph. To collect environmental data, a light sensor can provide the illumination intensity and direction, which generate an uncertainty score for the region belonging to a certain node. Shading and occlusion can be detected with the same principle, or

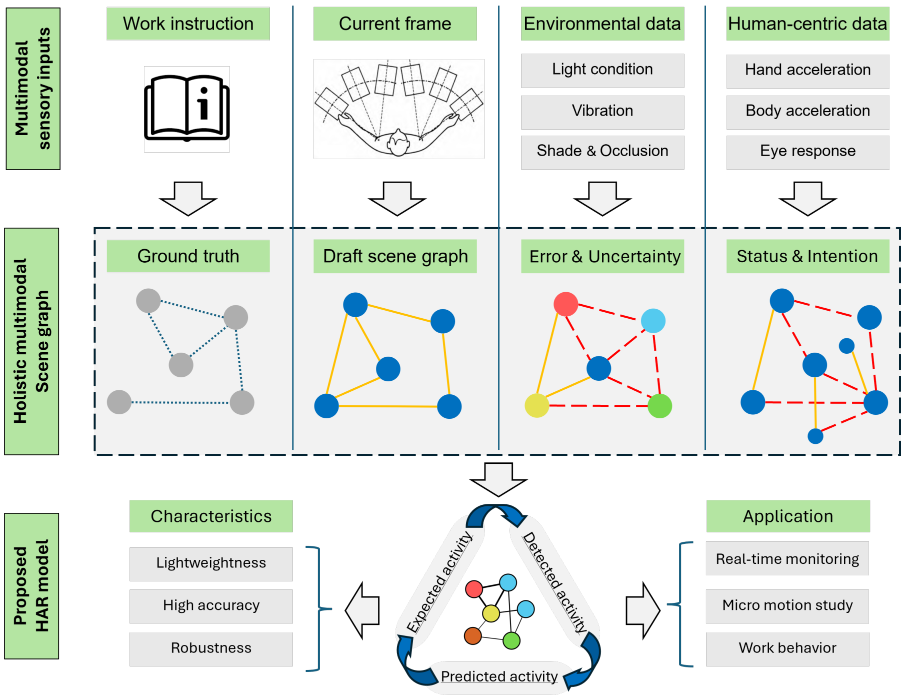


Fig. 4. The proposed video-based HAR with the extended scene graph.

from another camera that captures the surroundings of the workstation. To avoid the cases when the operators forget about the work instructions, or do the wrong steps, their intention can be strengthened with additional human-centric data from wearable such as accelerometers, or eye movements. This data generates extra nodes or edges as the possible intention of the operator for the next step.

With this extended scene graph that contains the enriched ground truth, possible error and uncertainty, human status and intention, a HAR model can be elaborated as the core of a real-time monitoring solution, that serves the purpose of establishing the "expected activity", capturing the current "detected activity", and delivering the "predicted activity". The built-in characteristics are the lightweightness, high accuracy, and robustness. The solutions that are developed on this approach are applicable for micro-motion study, as the model not only can capture each body part of the operator such as hands, but also can keep track of each temporal relationship between objects. The results from the micro-motion study enable deeper consideration of the work behavior of the operator, based on subtle gestures that suggest hesitation, forgetting work steps, wrong and unergonomic gestures, etc. The abstractions from both sensory inputs and visual domains can generate patterns or principles of the work movement in close association with surrounding conditions and human factors, providing insights into the association between specific operator experiences and activities with the process phenomena, thus deriving more general patterns and subtle connections. In future works, the authors will look for relevant methods to extract such patterns from the generated dataset.

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PERSPECTIVE

Extension of HAAS for the Management of Cognitive Load

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ABSTRACT The rapid advancement of technology related to Industry 4.0 has brought about a paradigm shift in the way we interact with assets across various domains. This progress has led to the emergence of the concept of a Human Digital Twin (HDT), a virtual representation of an individual's cognitive, psychological, and behavioral characteristics. The HDT has demonstrated potential as a strategic tool for enhancing productivity, safety, and collaboration within the framework of Industry 5.0. In response to this challenge, this paper outlines a process for tracking human cognitive load using the galvanic skin response as a physiological marker and proposes a novel method for managing cognitive load based on the extended Human Asset Administration Shell (HAAS). The proposed HAAS framework integrates real-time data streams from wearable sensors, user skills, contextual information, task specifics, and environmental and surrounding conditions to deliver a comprehensive understanding of an individual's cognitive state, physical wellness, and skill set. Through the incorporation of skills set, physical, physiological, and psychological variables, and task parameters, the developed HAAS framework enables the identification, management, and development of individual capabilities, thereby facilitating individualized training and knowledge exchange. The applicability of the developed framework is proved by an experiments in the Operator 4.0 laboratory with the detailed HAAS parameters.

INDEX TERMS Cognitive load, GSR, human asset administration shell.

I. INTRODUCTION

Nowadays, it is becoming more vital to include workers throughout the design phase of systems. The inclusion of workers is accomplished through expanding the standard of industrial engineering concepts and making them more personalized and customized work fields [1], [2], [3], [4]. The forthcoming 5th Industrial Revolution, Industry 5.0 (I5.0), aims to integrate human intellect into autonomous or semi-autonomous production processes, thereby mitigating the drawbacks of Industry 4.0 (I4.0) by embracing human centricity [5], [6], [7]. Contrary to I4.0, the human operator, known as Operator 4.0 [8] or 5.0 [9], is central in the production system and leverages technology to enhance the production quality [6]. This strategic approach emphasizes human involvement in the production processes, prioritizing operator well-being, and promoting sustainability and resilience in manufacturing systems.

Despite the growing interest in I5.0, current studies are still nascent, and their findings are not substantial [10].

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However, it is clear that the focus of I5.0 on human-centricity marks a departure from the limitations of I4.0. Pivoting to a human-centric approach in I5.0 not only signifies a paradigm shift but is a necessity for fostering truly symbiotic environments. To design an efficient human-centered system, it is principal to consider human factors like emotion, personality, workload, fatigue, and aging. This will lead to enhanced system quality and efficiency and improved working environments. Numerous studies have proved that integrating this strategy provides win-win outcomes [1], [2], [3], [4]. The goal should be to develop intelligent, age-friendly workplaces where modern technology cooperates with human employees and augments their potential, not replace them. [4].

Implementing I4.0 and incorporating human-in-the-loop control systems showed that the cognitive load on operators in work environments has significantly increased, primarily due to the increased volume of data requiring advanced mental processing [11], [12]. According to the research of some academics, some physiological markers are highly responsive to cognitive processing and exhibit significant fluctuations in response to changes in the task's demands. This finding provides evidence in favor of the hypothesis that tasks requiring higher levels of executive and sustained attention elicit more marked alterations in physiological parameters. Compared to cognitive components such as working memory and perceptual processing, these alterations are more pronounced [13].

Cognitive load is described as a multi-dimensional structure expressing the burden that a given task exerts on the worker. It also indicates the perceived effort required for learning, reasoning, and thinking as a measure of working memory pressure during the execution of the task [14]. The cognitive load brought on by an abundance of complicated knowledge has developed into a potential problem. Despite this, structured knowledge systems are still extensively employed, irrespective of the fact that individuals have varying rates of information intake [15]. For more efficient management of mental workload during crucial decision-making, there is an immediate need to design a smart data system that can adjust to the information-processing capacity of each individual [15]. The goal that the researchers are looking for is to decrease the cognitive load, which will be reflected in production efficiency. A numerical simulation study suggests that the adoption of I4.0 technologies alleviates this load by decreasing the amount of information an operator needs to manage for a task, subsequently lowering cognitive effort. This increased processing capacity enables operators to handle more complex tasks involving multiple actions [12].

Technologies in I4.0 enable the creation of digital representations of industrial entities, supporting production systems with considerable advantages and capabilities [16]. To achieve resilient, sustainable manufacturing systems, researchers have started making digital twin models (DT) that represent the physical assets in the virtual world [17]. Asset Administration Shell (AAS) is the only DT definition that explicitly supports industry-standard protocols and data formats, according to Michael et al. [18]. AAS is an I4.0 architecture that specifies the technical characteristics of an asset. It was designed to convey information as well as data in an organized way, hence facilitating interoperability between DTs models [19].

Humans are increasingly being digitalized in the cyber field through the principle of human centricity. However, most studies in this field, according to Du et al. [15], focus on the system level in modeling information processing rather than modeling behaviors at the personal level. As a result, the Human Digital Twin (HDT) was proposed to integrate human workers in the I4.0 field, which supported data collection, scheduling, communication handling, and so on [20], [21]. HDT is the cyberphase of the human entity, which is fed by dynamic real-time parameters to represent the human in the physical phase. These parameters include but are not limited to workers' characteristics, behaviors [22], geospatial and psychophysical conditions, contextual parameters, intentions, cognitions, emotional state, food income [23], motion recognition [10], and other biological parameters such as electromyogram (EMG), heart rate, heart rhythm, respiration, blood pressure, Galvanic Skin Response (GSR) [20], [21], [24], [25]. Despite the rising number of papers that talk about HDTs and the possible influence they might have in the future, there is no existing agreement on exactly how to design these kinds of systems [26].

Our research is centered on addressing two primary areas of concern that arise during the transition toward industrial digitization and suggesting solutions for them: "What is the cognitive load level that a specific task may induce on an operator, and what is the limit of cognition that the operator should not exceed to tackle that task's load with the best performance?", factoring in the individual skills and "Based on the outcomes of the first question, is there a need to control the cognitive load of that task, and if so, how?". In the graphical abstract (Figure 1), we identified seven main modules: the task, worker skills, environmental conditions, psychological state, kinematic parameters, anthropometric parameters, and physiological metrics. This paper will contribute its novelty depending on four of these modules (green-colored boxes): the physiological metrics (GSR and HRV) to evaluate the worker's cognitive load and classify it as low, medium, or high, while the other three modules, the task, the worker's skills, and the environmental conditions surrounding the worker, will be used to estimate the required cognitive load and also classify it as low, medium, or high to compare it with the evaluated cognitive load of the worker. Based on these loads, the extended HAAS will make task and surrounding condition manipulations. The other three modules in the graphical abstract colored blue are beyond the scope of this paper, and we may take them into consideration in future works.

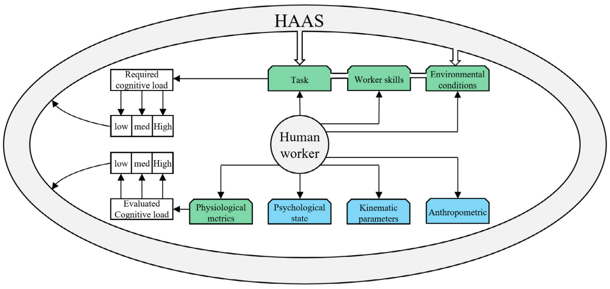

FIGURE 1. **Graphical abstract of the proposed HAAS extension with the main elements.**

The rest of the paper will cover the following sides: Section II includes several subsections to describe the extended HAAS, cognitive loads, and their analyses and measurements, in addition to the description of the use of the GSR as an indicator of cognitive load. Section III describes the developed framework of the extended HAAS for managing the cognitive load. Section IV presents both the methods of designing the tasks and their surrounding conditions and assets implementation, while Section V presents the conclusion and future work.

II. HAAS EXTENSION TO MANAGE COGNITIVE LOAD

Building an accurate HDT requires collecting data about diverse assets, such as machines, instructions for achieving the tasks, like physical movements, physiological and psychological data, the awareness and cognitive load of the worker, necessary skills, etc. HAAS will collect these parameters and provide the interconnecting process between these different assets for efficient interoperability within assets and external systems. To make an effective HAAS, it is necessary to find a wide range of standards and classifications that describe assets and tasks.

In this section, we will explore the Extended HAAS's capacity to effectively manage cognitive load. The next subsections will define the principle of the HAAS (Section II-A) in the field of cognitive load management (Section II-B) and the GSR applicability to measure cognitive load (Section II-C).

A. DEFINITION OF HAAS

I4.0 uses information and communication technologies to connect the actors in industrial processes in an intelligent network. The AAS has an important role in this process because it helps to implement the I4.0 digital twins and creates (communication) interoperability between solutions from different vendors. All in all, the AAS is a digital representation of an asset. In the case of I4.0, the AAS of machines and certain software components was clear from the start, but the emergence of humans as manufacturing entities was not nearly as obvious. The worker can be divided into two major groups in terms of AAS/digitized data. The first is psychophysical data (e.g., heart rate, galvanic skin response), while the second is static data (e.g., height, weight, smoking habits). An important requirement of AAS is to provide a minimal but sufficient description of the device according to its use cases. In parallel, it is also expected that existing standards can be mapped to the definition of an AAS.

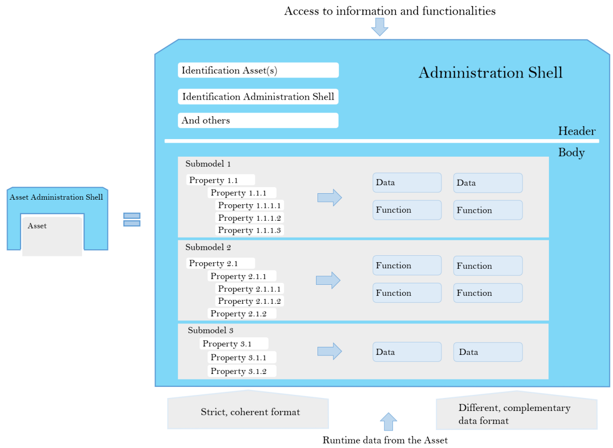

FIGURE 2. **General structure of an AAS .**

Existing research shows a tendency to integrate humans into the production environment through the HDT approach, where the Human-AAS (HAAS) is an extension of the AAS concept. The current findings indicate that this process is not yet well-defined and that several inquiries have to be addressed. Some examples of such problems may be "How should a human sub-module be designed?" or "Should a generic AAS include a HAAS, or should these two entities be separated?".There are works that show that this integration process can realistically be achieved. Some of these are the theses of Niko Bonomi Niko [27] and Sparrow Dale Eric [28] which highlight that humans can be integrated standard way into AAS with additional standard component involvement.

The AAS consists of two main components: header and body, as shown in Figure 2. The header contains basic information about the asset, such as identification, while the body handles the different submodels within the AAS. The single submodel is a hierarchical structure of properties, which refers to the information and functions associated with an asset in a given domain. This approach allows the collection of standard and fixed information. Examples are the bar code or the serial number. In parallel, it is possible to collect dynamic data such as the temperature of a probe or the current value of a pressure sensor. In addition, the submodel has functional properties that allow a program or routine to be started and stopped directly on the asset. The requirements define the structure, parameters, and properties of the AAS [29]. These requirements and compliance with them allow for the design of fully functional and I4.0-compatible AAS. There are 22 requirements, which can be divided into three major groups:

- General requirements (R1-R5) 133
- Requirements regarding the Administration Shell (R6 and R7)

- Requirements regarding identifiers (R8-R22)

Prior to delving into the HAAS, it is important to establish the nature of the data produced in HDT and the specific standards that include it. International standards are essential to achieving a high level of interoperability between different systems. AAS standardizes the way of data representation and how such data can be related to others. In addition, it allows each piece of data to be expressed in a wide variety of sub-structures. Crucially, the AAS does not dictate the specific sorts of data that should be published or the manner in which they should be published. However, it is the responsibility of the implementer to handle this task. In fact, it may be that each submodel or property refers to a specific standard that specifies the details. While relatively well-defined standards are available in this area for machinery (e.g. ecl@ss [30]), references in human-related standards are lacking for industrial production. Taxonomies of human capabilities refer to for example:

- O*Net: Occupational Information Network, is a database that is containing hundreds of job defnitions, sponsored by the US Department of Labor/Employment and Training Administration (USDOL/ETA)
- AS. Chuilef et al. proposed a hierarchical taxonomy for human goals [31].
- ESCO: Classifcation of European Skills, Competences, Qualifcations, and Occupations
- Xiao et al. researched a cryptosporidium taxonomy in the feld of human public health [32]
- P.A. David also represented a human taxonomy structure [33]

For the sake of simplicity and clarity, we will utilize P.A. David's grouping as an illustrative example (refer to Figure 3) [33]. According to this classification, human capital can be divided into two main categories: tangible assets and intangible assets. Tangible assets are, for example, health or physiological conditions, and intangible assets should be cognitive capacity or problem-solving capability. A new layer of abstraction is created in the human data - using the insights about human by Bettoni et al. [34] - and each of those can be categorized into tangible or intangible categories. Based on this, the characteristic, parameter, and condition of the worker can be as follows:

- Characteristic: an intrinsic or extrinsic quality of the worker, such as height, amount of experience, etc. In general, these characteristics are quasi-static. It means that they do not change very often or at all.
- Parameter: a value that can change several times during the day, so these values are automatically collected by some data collection technique and continuously monitored. Examples include GSR, Heart Rate Variability (HRV), or position within a room.
- Condition: This defines a worker's actual condition; this can be an intangible state such as current emotion, current level of exertion, or even a health condition, for example, irritability or physical disability. In many cases, these parameters can only be determined indirectly.

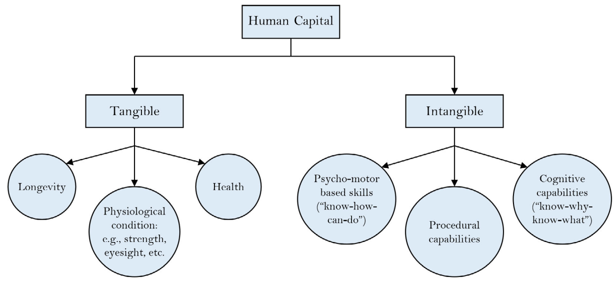

FIGURE 3. Human capital classification .

As Marcon et al. [35] have shown, ideally each production component has an AAS in the I4.0 approach. Human is one of these components too. In this research, the operator wears a unique smart jacket that can measure certain parameters (e.g., temperature) of the wearer and his environment through sensors. The concept uses several technologies, such as human-machine interfaces (HMIs) and industry-standard communication interfaces. A good and forward-looking concept has been developed but lacks formalization of the human in the AAS.

The research of Al Assadi et al. [36] has created a Human Administration Shell (HAS) that uses smart devices (e.g., smart watches, smartphones) to collect and provide information. This solution distinguished between two main categories: condition monitoring (real-time data such as heart rate, location, and accessing data) and service provider (e.g., personal skills and knowledge). This division was aligned with the grouping proposed by David [33], in which human capital was divided into tangible (condition monitoring) and intangible (service provider). The experiment has proved useful in several practical areas, such as automatic adjustment of ergonomic workstations, authentication, and automatic adjustment of HMIs. This research takes into account Human AAS, but lacks some additional components to consider humans as a general component in the I4.0 environment. In this form, it can be considered as a separate entity rather than a fully integrated entity in the production system.

Based on Sparrow in 2021 [28], the main HAAS responsibilities can be as follows:

- **Delegation representing the human**: Even though human operators can respond to various commands or instructions from other surrounding assets in different ways, like touch screens, keyboards, etc., this has consequently made the human operator a stumbling block in the communication process. To avoid this effect, HAAS can take the initiative and work as a representative of human operators by monitoring and recording their activities, behaviors, and working schedules. In this way, humans will have more opportunities to respond to more nuanced inquiries about their work or themselves.

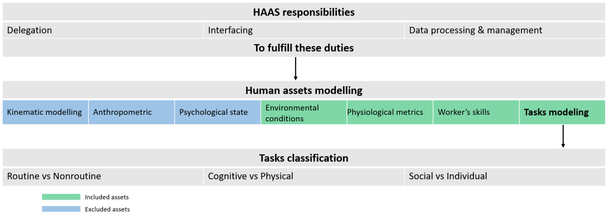

FIGURE 4. **Responsibilities and requirements of the extended HAAS.**

- **Facilitate Human Interfacing**: HAAS needs bi-directional communication for data flowing with human workers; this will allow for collecting the required data from workers such as body position, motions, eye-tracking, physiological data, etc.
- **Enhancement of digital processing and information management**: Information processing in humans' brains involves a combination of abstraction, pattern matching, heuristics, creativity, and more. These processes are time-consuming in the order of 200 milliseconds and increase much more during decision-making. On the other hand, digital assets in the HAAS may calculate and transfer data with floating-point accuracy, transmit events with statistics, and operate in milliseconds.

In order to provide a concise overview of the requirements and responsibilities associated with the HAAS, Figure 4 presents a tabular representation of them. This figure categorizes the modules that will be modeled for the construction of the extended HAAS, as well as those that are excluded due to their scope falling beyond the purview of this paper.

HAAS does not receive as much attention in industrial processes as conventional equipment, as can be seen from numerous examples in the literature. There are many reasons for this, but perhaps one of the most important is that humans contain far more uncertainty than an artificial element of production.

B. COGNITIVE LOAD AND COGNITIVE WORK ANALYSES

It is very individual how a person receives the information that is presented to them; some people may have difficulty processing visual-spatial information, whereas others may be resistant to being instructed verbally [15]. The same person's information-intake attitude can also change dramatically depending on their cognitive status, such as a preference for visual-spatial content during times of emotional disturbance [15], [37]. This implies that approaches to reducing cognitive load caused by information intake should be tailored to the individual and the situation [15]. Based on this criterion, three approaches under what is known as the "Cognitive Load Theory" (CLT) have been presented to answer the following questions: "What is the information that should be presented to the worker?" "And how exactly ought it to be presented to decrease the cognitive load?". The CLT assumes that the capacity of our working memory is limited,

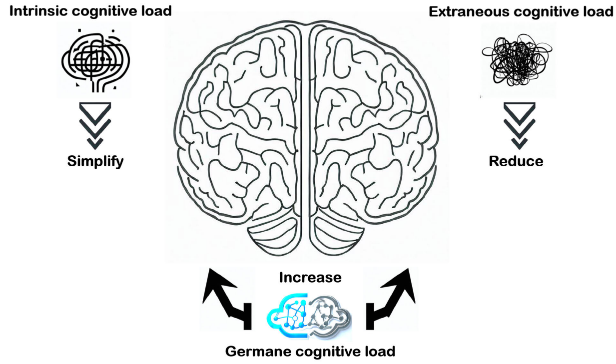

FIGURE 5. **Cognitive load theory.**

unlike the long-term memory capacity, which is considered to be unlimited [38].

The first approach of the CLT is dealing with the level of sophistication of the new information that is being obtained [39]. Building a worker's prior knowledge represented by their long-term memory will help in this case, or it is possible to modify the level of task difficulty; for example, sequential processing does not place as much of a load on the working memory as simultaneous processing does [38]. This approach is referred to as *"intrinsic cognitive load"* [38], [39].

The second approach is known as *"extraneous cognitive load."* This load is caused by the manner in which the instructions are delivered as well as the system's design. As a result, anything that diverts workers' attention from their goals must be avoided. Extraneous cognitive load is something that can be controlled by trainers, and as a result, the interacting aspects that are caused by extraneous cognitive load may be minimized or removed entirely by modifying the way that strategies or instructions are delivered. The extraneous cognitive load needs to be decreased at all times, and there should be no circumstances in which it may be raised. The final approach of the CLT is called the *"Germane cognitive load."* It is unlike the previous cognitive loads in its positive impacts on the workers through processing and constructing schemas. It focuses on learners' or workers' cognitive processes in order to motivate them to put forth effort in the learning process and facilitates the process of acquiring knowledge [38], [39]. Figure 5, shows the CLT principle and depicts the three components of CLT positioned around the brain, symbolizing their interaction area. The left side of the figure depicts the intrinsic cognitive load with a downward-pointing symbol, signifying the need for task simplification in order to reduce this particular kind of cognitive load. The right side of the figure represents the second element of the CLT: extraneous cognitive load; there is also a downward-pointing symbol that depicts the importance of decreasing this kind of load at all times. The third component, positioned at the bottom, has upward arrows, signifying the importance of increasing this element to counter the other two elements.

To monitor and measure the cognitive load, it is crucial to do these processes in real-time to provide feedback that can be used to decrease the cognitive load, which leads to an increase in the workers' performance and supports their decision-making. Hence, using psychological measurements (eg., the NASA Task Load Index) is not the best choice, as they provide feedback after the tasks are finished. On the other hand, several physiological parameters can be utilized for providing better cognitive load comprehension, such as "Galvanic Skin Response" (GSR), "Heart Rate Variability" (HRV), blood pressure, electroencephalogram (EEG), etc. [15]. However, while monitoring real-time cognitive load is essential for understanding and managing the demands placed on workers, it is equally important to understand how the work environment and system design can be structured to accommodate these demands. This is where the Cognitive Work Analysis (CWA) becomes essential.

Cognitive Work Analysis (CWA) is a framework used to analyze and design work systems in which human operators interact with complex technological systems [40]. It is based on the idea that in order to design effective work systems, it is necessary to understand the cognitive processes that humans use to perform their tasks [40], [41]. CWA consists of a set of principles and methods for analyzing and designing work systems in order to optimize the fit between the demands of the system and the capabilities of the human operators [40]. It is concerned with how people perceive, think, and act in the context of their work, and how the design of the work environment can support or hinder these processes [15]. Wearable sensors have been used in CWA studies to gather data on the physical and cognitive demands of a task [42].

Since the commencement of the I4.0 movement, the industrial shop floor has been undergoing a transformation brought on by smart and digital technology. However, to achieve efficient smart and digital representation of the diverse assets by HAAS, it is crucial to effectively understand the human operators' tasks and classify them based on specific characteristics that support their digitization processes efficiently. Based on these criteria, three-dimensional task classification was suggested by Cimini et al. [43] as follows:

- *Routine and Nonroutine tasks:* The routine tasks represent the activities that can be achieved based on preprogrammed rules. In the manufacturing fields, these kinds of tasks are characterized by their repetition, such as loading, unloading, assembling, packaging, etc. These kinds of tasks are characterized by the fact that they are easily codable, as the steps are already known. On the other hand, nonroutine tasks are not properly defined if compared with routine tasks, making these kinds of tasks hardly codable. Nonroutine activities are abstract tasks, such as those connected to management, technical, and creative roles, that demand problem-solving talents, anticipation, analytical skills, etc.
- *Cognitive and Physical tasks:* The cognitive tasks are concerned with cognitive activities, whereas the physical or manual tasks are the activities that may be characterized in terms of a series of actions and involve sensory skills.
- *Individual and Social Tasks:* The level of interactions in any activity defines the category of the task as either an individual or social task. Duties that can be performed independently by a single person are primarily characterized by a lack of or minimal social interaction. Whereas duties that require a higher level of interaction with others require more mediation. Based on the study conducted by (Frey and Osborne, 2017), the lower the sociality tasks (lower interactions), the easier the digitization process [44].

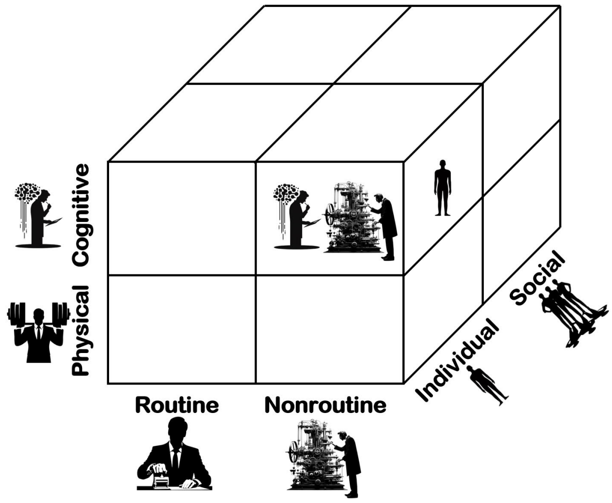

FIGURE 6. Task classification model, which has been adapted from cimini et al.,2023 [43].

Based on this three-dimensional classification, Figure 6 represents the general model that can be used to map any kind of task. Any task can be a combination of these dimensions. For instance, assembling tasks can be categorized as routine/physical tasks, whereas maintenance tasks can be categorized as nonroutine/physical tasks. On the other hand, cognitive tasks like data collection can also be routine or nonroutine based on the characteristics of the duty. Simultaneously, the third dimension of the task can take the form of either individualistic or sociocentric, depending on the presence of collaborative elements such as operators, robots, or other assets.

In light of the task characterization framework discussed, the following sections will delve into the HAAS. This will involve exploring how the HAAS, as a crucial component of the HDT, incorporates and utilizes these task classifications to optimize cognitive load tracking and administration.

C. GSR AS AN INDICATOR OF COGNITIVE LOAD

As mentioned in the previous sections, multiple and complicated technologies are aimed at improving the capabilities of workers in the working field. Yet, these technologies might potentially raise stress and workload [45]. In 2003, [46] it was observed that utilizing diagnostic automation with an accuracy of less than 80 percent to help unmanned aircraft users led to increased stress and workload in comparison to not using automation [45]. As a result of the increase in technologies, especially with the advent of I4.0 and 5.0 and the inclusion of the human-in-the-loop, it has become important to search for technical methods to estimate the value of the workload on workers and increase their capabilities through tracking their intentions.

Recent research has shown that GSR can be a reliable physiological indicator of cognitive load [47]. GSR or what is known as "Electrodermal Activity" (EDA) is the name given to the electrical events in the skin, covering both passive and active electrical aspects related to the skin [48]. GSR denotes fluctuations in endocrine gland activities that reflect the degree of human emotional state; it is also referred to as "emotional arousal" [49]. The activities of the endocrine glands are directly controlled by the sympathetic nervous system [50]. The intensity of emotional arousal varies according to the surroundings, based on whether something is terrifying, dangerous, pleasant, or anything associated with emotions. These surrounding events (stimuli) will alter the secretion of sweat in the endocrine glands, which in turn will change the GSR value. However, regardless of the kind of stimulus, the skin conductance will be changed and increased, hence the GSR does not indicate the kind of emotion, but instead its intensity [49].

GSR consists of two essential features: (1) "skin conductance level" (SCL) which represents the tonic level of the skin conductance, and (2) "skin conductance response" (SCR), which represents the phasic change in the skin conductance [51]. According to the recommendations issued in 2012 by the "Society for Psychophysiological Research Ad Hoc Committee on Electrodermal Measures," recording the electrical aspects of the skin can be achieved in one of three ways: (1) endosomatically without applying external electrical current; (2) exosomatically through applying direct electrical current DC; and finally, (3) exosomatically through using alternating electrical current AC [48], [52]. The range of studies outlined in these tables encompass a broad spectrum of methodologies, research aims, tracked features, stimuli types, and participant numbers. This richness highlights the multifaceted nature of research into cognitive load, offering several different perspectives for assessment and measurement.

A remarkable variety of analysis methods have been employed across these studies. Among the most common are statistical tests such as ANOVAs, paired t-tests, and pairwise analyses. At the same time, a number of studies have utilized decomposition methods like continuous and discrete deconvolution, largely facilitated by toolboxes like Ledalab. Notably, there is a growing reliance on machine learning techniques, with methods like Support Vector Machines, Naive Bayes, and Random Forest featuring prominently in many investigations. Moving to the central aims of these studies, a significant majority aimed to estimate and classify cognitive load, with the stimuli varying extensively across research. These stimuli range from more traditional cognitive tasks like arithmetic exercises, memory tasks, and listening tasks, to more complex assignments such as Stroop tests, puzzles, and tasks based on virtual reality. While most studies aimed at the broad estimation of cognitive load, several were designed with a more nuanced focus, delving into aspects like frustration, trust, and cognitive fatigue.

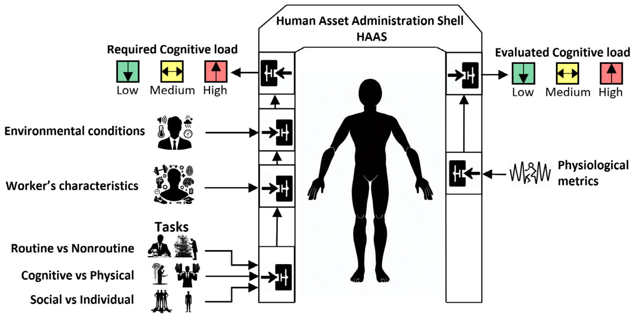

FIGURE 7. **Extended HAAS proposed diagram.**

In terms of tracked features, these largely depended on the physiological signals used in the research. For studies that leveraged GSR signals, some extracted features directly from the noise-removed GSR signals, while others decomposed GSR signals into their basic components (SCL and SCR) before extracting features. Commonly tracked features included signal intensity, peak intensity, mean, standard deviation, and the number of peaks.

Based on our analysis of several studies, it is clear that GSR has been successfully utilized to measure cognitive load in various surroundings and work settings. These results provide strong evidence for our claim that GSR is a suitable measure for inclusion in the HAAS.

III. THE DEVELOPED FRAMEWORK TO MANAGING COGNITIVE LOAD BASED ON THE EXTENDED HAAS

The HAAS model we propose is built around four fundamental modules that serve as the basis for its structure and operation. These modules include physiological parameters, workers' characteristics, task type and level, and environmental conditions. As seen in Figure 7 located on the right side, the physiological metrics focus on the GSR and HRV data, which are acquired using sensors placed on the individuals doing the tasks. This crucial module records these parameters and subsequently evaluates and categorizes the cognitive load into three discernible categories: low, medium, and high, as shown on the upper right side under the "Evaluated Cognitive load".

On the left side of Figure 7 are three modules, the workers' characteristics module, which is designed to effectively capture the distinct skills and proficiencies possessed by each worker and recognizes that individual capabilities can vary widely. This module is updated based on a preliminary assessment of each worker's abilities prior to engaging in specific tasks. Task type and level is the other module in the developed model, as seen in Figure 6. It takes into account not just the categorical nature of a task but also integrates the worker's innate skills and capacities into its analysis. As an example, a task with cognitive demands might be perceived differently by two workers of varying physical strengths, illustrating that the complexity of a task is multifaceted. The final module in our model is the environmental condition, which acknowledges that external factors play a crucial role in determining cognitive load. This module continuously monitors and adjusts the changes in the environment, such as noise, temperature, etc. These modules on the left side will estimate the required cognitive load based on their inputs into three levels: low, medium, and high, as shown on the upper left side under "Required Cognitive load". With these four modules in place, the extended HAAS model establishes a dynamic interplay. By comparing the evaluated and required cognitive loads, it aims to modulate tasks and surrounding conditions, ensuring a balance between optimal worker comfort and heightened productivity.

Given the comprehensive nature of the study, which encompasses four modules across diverse disciplines, it became vital to engage these modules inside a management system in order to augment flexibility and improve decision-making capacities. We integrated our developed HAAS with the OODA Loop framework. The OODA loop, established by military strategist John Boyd, is a decision-making process that consists of four sequential steps: Observe, Orient, Decide, and Act [53]. The primary objective of this fusion is to maximize productivity, ensure safety, and promote general well-being.

For simplification purposes, we have segmented the developed model into five methodical phases within the loop of the OODA, as seen in Figure 8. Starting with the first step, "observe," which includes both Phase 1 for establishing the cognitive load thresholds and Phase 2 for operational monitoring and cognitive load assessment. The second step is "Orient," which represents the other modules for contextual information in Phase 3. The third step is "Decide," which reflects the evaluation and comparison processes within Phase 4, and finally, the "Act" step within the OODA loop is represented by Phase 5 for adjusting and looping purposes.

Each phase serves a distinct purpose and systematically builds upon the knowledge and results obtained in the preceding phase. The core of this concept is centered upon the implementation of a responsive feedback loop that continuously monitors, assesses, and adapts using up-to-date data, with the primary objective of effectively regulating and managing cognitive load. This dynamic approach paves the way for creating optimal working conditions, leading to enhanced performance and reduced worker fatigue. The following sections provide a comprehensive analysis of each stage:

- **OODA Step 1: Observe**
  This step includes two phases for observing both the baseline and operational conditions from the physiological characteristics, as follows:

Phase 1 - Establishing the Cognitive Load Thresholds

1) Neutral Condition Monitoring Phase: The objective of this phase is to consistently observe and analyze the physiological characteristics of the worker (HRV and GSR) in a neutral situation devoid of any tasks, noise, or distractions. The signals need to be processed in order to derive the cognitive load, which is an intangible factor.
2) Low Cognitive Load Threshold: The calculated cognitive load from this phase represents a low cognitive load. Consider this value as the threshold for low cognitive load. Any measured cognitive load that falls below or equals this threshold means the worker is operating under a low cognitive load.
3) Medium and High Cognitive Load Thresholds: Determining thresholds for medium and high cognitive load depending on the previously established threshold for low cognitive load in (**Phase 1 / 2**). The medium cognitive load threshold can be operationally defined as twice the value of the low threshold. Any cognitive load measurement over this threshold would signify a high level of cognitive load.

Phase 2 - Operational Monitoring and Cognitive Load Assessment

1) Operational Condition Monitoring Phase: The worker starts the execution of different tasks amid probable auditory disturbances and interruptions. Throughout this period, it is important to consistently record the worker's physiological metrics (HRV and GSR).
2) Cognitive Load Calculation: The acquired physiological data will be processed in a continuous manner in order to compute the cognitive load experienced during the execution of a task in these circumstances.

- **OODA Step 2: Orient**

This step of the loop is not just about collecting the data as the observation step but also understanding its context with respect to workers' characteristics, task difficulty, and environmental conditions to understand the cognitive load. This step is represented by Phase 3 as follows:

Phase 3 - Other modules for Contextual Information

1) Worker's Characteristic module: This module will include the intrinsic characteristics and talents originating from the worker as well as the extrinsic elements and effects originating from outside the worker.
   Some of the intrinsic Qualities:
   - *Physical Strength and Stamina:* Numerous tasks within the industrial sector require a considerable degree of physical exertion, necessitating a commendable level of strength and stamina.

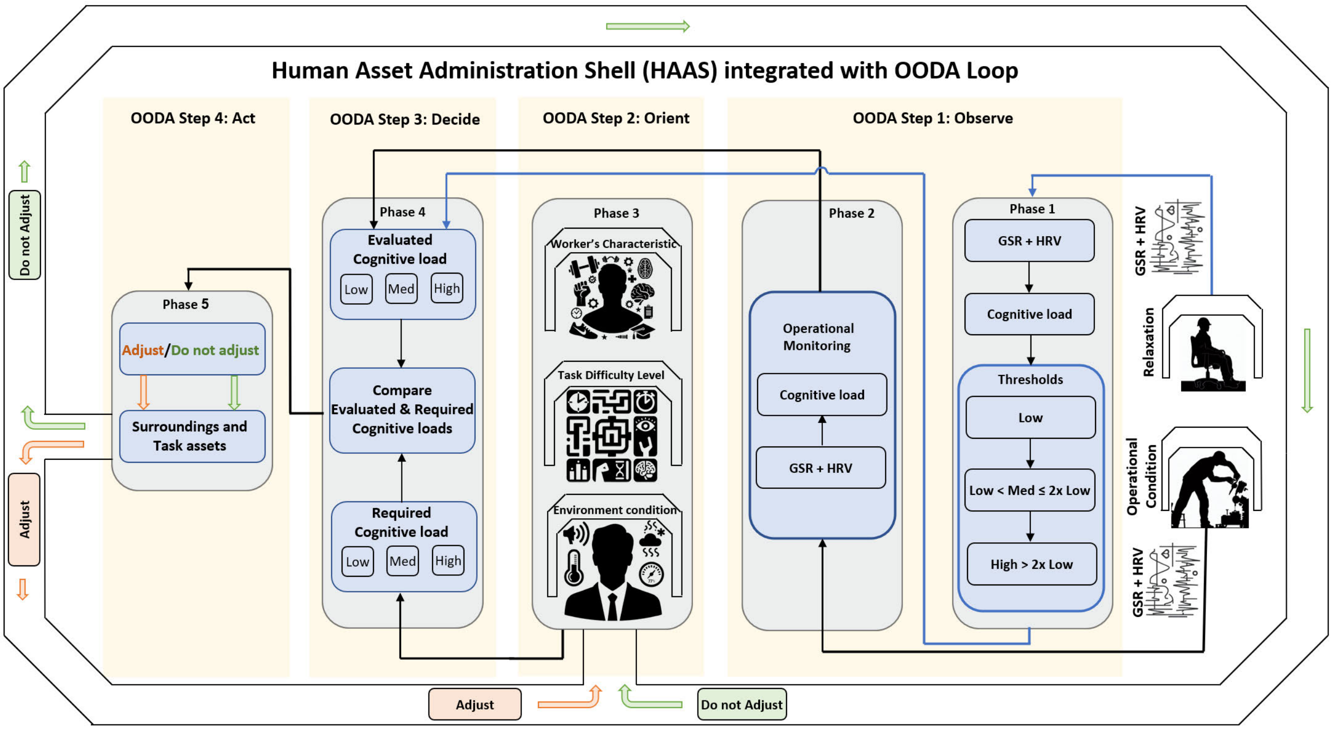

FIGURE 8. The developed concept for tracking and managing cognitive load based on the extended HAAS model integrated with the OODA loop .

- *Manual Dexterity:* Many industrial tasks require precise motor abilities, such as the aptitude to manipulate tools or assemble small parts.
- *Mental Strength:* This includes qualities such as resilience, determination, problem-solving skills, critical thinking abilities, and the capacity to acquire knowledge and adjust to novel circumstances.
- *Cognitive Abilities:* The capacity to understand instructions, follow procedures, make quick decisions, and maintain attention to detail.

Some of the extrinsic Qualities:

- *Training and Education:*Skills and expertise obtained via systematic training and academic pursuits, including both practical skills and comprehension of apparatus or equipment.
- *Work Experience:* A worker's performance is significantly affected by their prior experience in comparable positions or sectors [54].

2) Task Difficulty Level module: This module should be defined based on various parameters and characteristics of the task itself. Some of these parameters can be summarized as follows:

- *Complexity:* Defined by the number of steps, complexity, or the need for high accuracy.
- *Time pressure:* Determined by the allotted time to complete the task.
- *Familiarity:* Defined by how common or unusual the task is for the worker.
- *Required skill level:* Determined by the necessary skills or qualifications needed to perform the task.
- *Physical demands:* Identified by the physical strength or stamina required to complete the task.
- *Cognitive demands:* Determined by the level of concentration, problem-solving, or decision-making required for a specific task.

3) Environment module: It is important to consistently observe and assess the prevailing environmental factors, such as temperature, noise levels, humidity, etc.

- **OODA Step 3: Decide**

This step will decide the next action based on Phase 4. It will either decide to adjust or not adjust Phase 3 modules.

Phase 4 - Evaluation and comparison

1) Cognitive Load Assessment: Use the data of the cognitive load calculation (**Phase 2 / 2**) to evaluate the worker's cognitive load in the context of the environment based on the threshold values (**Phase 1 / 2, 3**) to get one of the following cognitive load levels (low, medium, high).
2) Required Cognitive Load Assessment: Use the data from the Worker's Characteristic module, the Task Difficulty Level module, and the Environment module (**Phase 3**) to evaluate the expected cognitive load for a specific task given the worker's skill level and environmental condition.

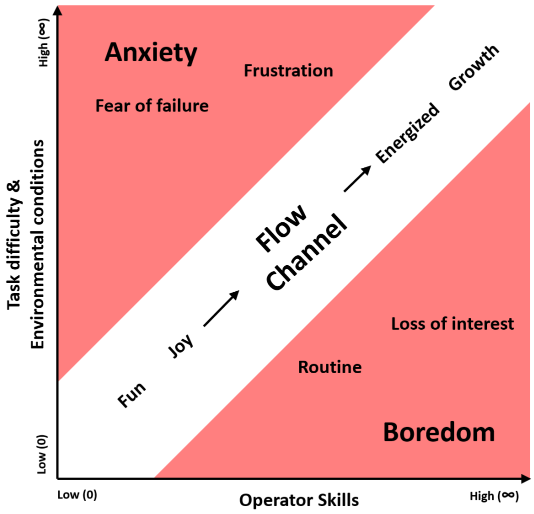

FIGURE 9. **Flow channel between the anxiety and boredom zones in the industrial fields.**

3) Comparison and Adjustment stage: The purpose of this stage is to compare the cognitive load that was evaluated during (**Phase 4 / 1**) with the required cognitive load that was assessed in (**Phase 4 / 2**). The objective of our model is to optimize cognitive load for maximum productivity while maintaining a comfortable work environment. We adopt Csikszentmihalyi's criteria, illustrated in Figure 9 [55], which identify two zones: Anxiety and Boredom, with a "flow channel" between them. The aim is to keep the individual operating within this flow channel. When the skill level is low and the task or environmental conditions are challenging, the individual experiences anxiety. Conversely, if the task is overly simple and the skill level is high, boredom sets in. Accordingly, a decision for adjustments should be made to either the environment or the task's complexity to facilitate entry into the flow channel, thereby maximizing productivity and comfort.

- **OODA Step 4: Act**

This step includes the implementation of changes based on the decision in the previous step of the OODA; it will either be monitoring the system without alteration or it will include adjusting the surroundings or the task difficulty. Phase 5 can be aligned to represent this step as follows:

Phase 5 - Looping for Continuous Monitoring and Adjustment

- *Do not Adjust*: In this case, the worker will be within the flow channel, and there will be no need for any change in the surroundings or task. The action will be restricted to continuously monitoring the cognitive load.
- *Adjust the surroundings*: In order to optimize the working environment, it is advisable to use environmental controls to minimize noise levels and eliminate potential distractions.
- *Adjust the Task*: If the provided environmental or surrounding modifications do not prove to be effective, it may be advisable to explore modifying the level of difficulty associated with the activity. This may include modifying the nature of the activity or offering supplementary aids, such as automated tools or extra instructions, to assist the worker in effectively doing the task despite their high cognitive load.
- *Continuously Loop*: Go back to (**Phase 2**) (Operational Monitoring Phase) and continue through the process. This allows for continuous monitoring and adjustments based on real-time data.

IV. COGNITIVE LOAD EXPERIMENTS AND THE IMPLEMENTATION OF THE EXTENDED HAAS

In this section, we offer comprehensive insight into the methodologies we employed to design the tasks and their surrounding environmental conditions. Subsequently, we will explore the complex procedures for implementing the included assets and the interconnection among them, aiming to provide a thorough understanding of their combined functionality and significance.

A. DESCRIPTION OF THE EXPERIMENTS

This subsection will elucidate the methodologies and sensors that are utilized to design the cognitive load experiments and record the physiological signals and other environmental parameters surrounding the participants. The Operator 4.0 laboratory [56] at the University of Pannonia has been utilized as the place for settling the experiments. The Shimmer3 wearable sensor [57] has been used to capture two principal physiological signals. The first signal is the GSR signal that is recorded from the proximal phalanges of the middle and ring fingers of the participant's non-dominant hand. The second signal is the photoplethysmogram recorded by an optical electrode attached to the earlobe, which will be used later to extract the HRV signal. Another sensor for monitoring the environmental and surrounding conditions of participants has been installed in the laboratory to record the ambient noise, temperature, and humidity. Six cognitive load experiments have been designed by the PsyToolkit online platform [58], [59] to induce and monitor participant cognitive load as follows:

- *Backward-Corsi:* In this test, participants are tracking reversed sequences of a fixed number of flashed boxes. The experiment had two difficulty levels: medium and high (more boxes in the high level) to maintain consistent cognitive load across the levels.
- *Cueing:* Participants react to rapidly presented stimuli preceded by a distracting cue. Difficulty levels (medium or high) were determined by the reaction time and inter-trial intervals.

TABLE 1. Sample of extracted features and environmental parameters.

Sessions	GSR peaks	GSR area	GSR SCR area	GSR Rising time	GSR Decay time	HRV VLF	HRV (HF/LF)	HRV SD1	HRV SD2	HRV Skew	Noise Amplitude	Temperature °C	Humidity (%)
Baseline	13	110.2177	5.7495	1.6385	3.1027	2.6770e+07	0.0081	42.0619	105.0926	0.0943	49.0753	27.6146	40.0471
Medium	12	210.2810	9.8934	1.4618	3.5098	2.9295e+07	0.0042	46.1915	105.1028	-0.5595	38.7592	27.6372	40.1425
High	12	253.6388	16.5215	1.7010	3.2255	2.9949e+07	0.0041	41.3535	72.3754	-0.6276	41.5724	27.6578	40.2312
Baseline	13	273.4448	16.9082	1.5385	2.9538	2.8421e+07	0.0045	41.1427	129.0137	-0.5035	701.7834	27.6994	40.2722
Medium	19	316.9376	19.6286	1.1369	1.7453	3.0649e+07	0.0061	50.7662	163.9415	-0.9902	921.1282	27.8278	39
High	18	329.9550	17.1582	1.2068	2.1546	2.8018e+07	0.0042	30.2529	57.0140	-0.4882	1230	27.8194	38.0278

- *N-back Task (2 back):* In this test, two difficulty levels were established by changing the time allotted for letter presentation and response.
- *Visual Search Task:* In this test, we control the time of presenting and responding to the visual stimulus to get the two difficulty levels.
- *Simon Task:* We also controlled the time of presenting and responding to the visual stimulus to achieve the two difficulty levels.
- *Stroop Task:* The test's difficulty levels were determined by controlling the time given for displaying and reacting to stimuli.

In this research, three recording sessions were conducted under two distinct conditions: a noise-free environment and exposure to ambient noise.

- *Baseline session:* Participants remain calm and seated and avoid any mental or physical effort.
- *Medium-level session:* Participants engage in the medium-level of the tests.
- *High-level session:* Participants engage in the high-level of the tests.

The recorded physiological signals during these sessions and conditions are processed to extract 30 features. However, a feature selection technique called Minimum Redundancy Maximum Relevance (mRMR) has been utilized to choose the most powerful 10 features that are highly relevant to the target. Table 1 presents a sample of extracted features from the physiological signals in addition to the ambient parameters recorded during the three sessions in each of the two conditions.

B. IMPLEMENTATION OF EXTENDED HAAS

In accordance with the previously discussed HAAS framework for managing workers' cognitive load, which encompasses four distinct modules, this section will outline the implementation procedures for the assets associated with each module. The diagram shown in Figure 10 illustrates the interconnection of the three assets, which are integrated through Industry 4.0 compatible communication to form the framework of the developed HAAS. The primary objective of this conceptual framework is to effectively manage the cognitive load of workers.

Given the clear relationship between the physiological signals, which include the GSR and HRV, and worker characteristics, we have created an AAS including two submodels to capture and analyze these data. Table 2 presents the header of the primary components of the first AAS. This contains pertinent information about the asset, such as its title, unique identifier, and the submodels included inside it. The specifics of the two submodels, namely the worker physiological parameters submodel and the worker characteristics submodel, are shown in Tables 3 and 4, respectively. The first submodel pertains to physiological features derived from the GSR and HRV signals. Every individual feature has its own distinct guide code that is utilized for later processing using the AAS. The second submodel refers to worker characteristics, whereby we have identified the key characteristics that may delineate each person and provide a distinct sense of their identity. These attributes included a range of factors, including gender, age, educational attainment, etc.

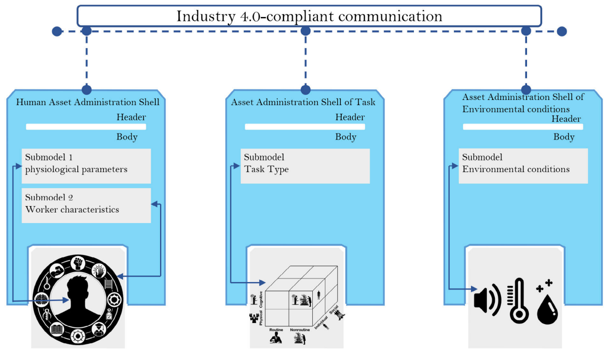

FIGURE 10. Diagram of interconnecting the assets together through an Industry 4.0-compliant connection to form the developed HAAS.

TABLE 2. Human asset administration shell HAAS header.

Field Name	Type/Example	Description	The internal GUID
HAAS ID	URI, eCl@ss	Unique identifier for the HAAS.	
Title	String	Human Asset Administration Shell.	0658d398-d7ca-4f97-a6b2-cd0925bbfd8e
Date	Date	Date of creation or last modification.	
Contact	Email, Phone	Worker contact details	
Submodel 1	String	The Worker physiological parameter submodel.	9aba4948-8000-412d-b365-54084c5d8163
Submodel 2	String	The Worker characteristics submodel.	c290d893-66be-453a-9a8d-3f5b2c649445
Manifest	Link/Reference	A directory of key information derived from the properties of the submodels.	

TABLE 3. Worker physiological parameters submodel.

Name	Submodel 1		
GUID	9aba4948-8000-412d-b365-54084c5d8163		
Properties			
GUID	Name	Type	Description
35cd4db0-24a0-47a2-bb61-dea37e34b166	GSR peaks	Numeric stream	The number of peaks in the skin conductivity signal
b5d5635d-c59f-448f-bd7c-472bf9c12c73	GSR area	Numeric stream	The area under the skin conductivity signal
2c25d961-170e-48e9-a5e0-7a0d5e80f27a	GSR SCR area	Numeric stream	The area under the Skin Conductance Response SCR
b6605b89-a3a6-4c3e-843e-739b607ea51f	GSR rising time	Numeric stream	The average time from the baseline to the peak after the stimulus
a4dfe715-babd-42fe-98e0-d0dc9f2d61ff	GSR decay time	Numeric stream	The average time from the peak to the baseline
5c34cda8-b1f0-42ae-b0a3-327cd9a6ef68	HRV VLF	Numeric stream	Very Low Frequency power of HRV in the band (0.003-0.04) Hz
f7e01fc3-f9ed-467c-a588-60113bfa7874	HRV (HF/LF)	Numeric stream	Ratio of High-Frequency power (0.15-0.4) Hz to the Low-Frequency power (0.04-0.15) Hz
fcb355df-951e-4fd8-9439-a656959e7166	HRV SD1	Numeric stream	Poincaré plot descriptor (short-term HRV)
00806cd2-d88d-4d47-a1a1-5d988f817d06	HRV SD2	Numeric stream	Poincaré plot descriptor (long-term HRV)
9c2ae141-8ccf-43b5-b714-e4469432921e	HRV Skew	Numeric stream	Skewness of RR intervals in the HRV

TABLE 4. Worker characteristics submodel.

Name	Submodel 2		
GUID	c290d893-66be-453a-9a8d-3f5b2c649445		
Properties			
GUID	name	type	description
5d4a3d25-a63d-4924-9f1c-35d9d46f5bf0	Sex	Options	Biological classification
878660fc-9252-4900-a989-36f290503d73	Birthday	Date	Date of birth
95e85567-cdd5-4247-b37b-230d9a985222	Date	Date	Hiring date.
de854b37-bd07-413c-8b47-33457ecb9109	Job Experience	Options	Selection from Entry-level, Mid-level, Senior.
021817ec-cf00-4c1b-9652-580edead6df5	Worker condition	Options	Nervous, exhausted, happy, sad, etc.
33fdabdd-a6d3-47c1-a71f-4c5476f75533	Physical strength	Options	Selection from Low, Medium, High
7cbf7941-62b2-4cd6-9503-a6eaed5dd9eb	Stamina	Options	Selection from Low, Medium, High
d2741bc0-0971-4206-b9fb-3cdfda8875e7	Manual dexterity	Options	Selection from Basic, Intermediate, Advanced
85b40d59-bb17-48f6-92a8-d5b0f1d39915	Mental strength	Options	Selection from Low, Moderate, High
7f0013e7-f18b-450e-9eb9-cf727e0cfed5	Cognitive abilities	Options	Selection from Basic, Intermediate, Advanced
2e43e074-b2ab-4745-864a-ef94c4bcc7b7	Training and education	List	List of formal education, courses, certifications, and training programs

TABLE 5. Asset administration shell header of the task types and characteristics.

Field Name	Type/Example	Description	The internal GUID
AAS ID	URI, eCl@ss	Unique identifier for the AAS.	
Title	String	Task Asset Administration Shell.	76fe9622-2868-43f0-854f-0b9f91f13950
Date	Date	Date of creation or last modification.	
Task submodel	String	Task types and characteristics submodel	c8825b55-54c9-4137-ac61-273dc4ff4ca4
Manifest	Link/Reference	A directory of key information derived from the properties of the submodel.	

TABLE 6. Task types and characteristics submodel.

Name	Task submodel		
GUID	c8825b55-54c9-4137-ac61-273dc4ff4ca4		
Properties			
GUID	name	type	description
8e6f7a8e-27ba-47ff-81fc-b2997a6b8913	Routine Aspect	Options	Select between Routine, Non-routine
e2e60564-96ff-4866-9f6d-a66833ee8524	Nature of Task	Options	Select between Cognitive, Physical
ae84b07f-af41-4a52-958e-6da5e7ed7c5d	Social Aspect	Options	Select between Social, Individual
4e2fed17-1f66-4a16-88c6-cb5ce51fc633	Task Complexity	Options	Select between Low, Medium, High
9b056d18-8abc-4ca1-b3bc-97d1e13b63b2	Time pressure of Task	Time	Specific duration or deadline for task completion
22dc1ba6-723c-4e8a-9527-816ddb100bdc	Familiarity of Task	Numeric	Frequency of encountering the task (e.g., number of times per month)
b712cbd3-0564-4db5-b326-74cfa78d7ed1	Required skills level of Task	Options	The level of expertise needed (Beginner, Intermediate, Expert)
d5d58276-bd77-4bb2-9913-d7a8395aa682	Task Physical demands	Options	The level of physical exertion required (Light, Moderate, Heavy, Very Heavy)
6ef34463-196c-4445-9832-668dcc3bcd4c	Task Cognitive demands	Options	The level of cognitive exertion required (Simple, Moderate, Complex, Highly Complex)

TABLE 7. Asset administration shell header of the environmental conditions.

Field Name	Type/Example	Description	The internal GUID
AAS ID	URI, eCl@ss	Unique identifier for the AAS.	
Title	String	Environmental condition Asset Administration Shell.	01adf4f2-2f32-472f-b893-6781f2a2cf8e
Date	Date	Date of creation or last modification.	
Environmental conditions submodel	String	Monitoring the worker's surrounding conditions	d8d345bf-2b1c-4491-abaa-b2087d3ac5ee
Manifest	Link/Reference	A directory of key information derived from the properties of the submodel.	

TABLE 8. Environmental conditions submodel.

Name	Environmental conditions submodel		
GUID	d8d345bf-2b1c-4491-abaa-b2087d3ac5ee		
Properties			
GUID	name	type	description
3848608a-1e9d-40af-aad2-d2a362abc2ce	Noise level	Numeric	Ambient noise level
c05bff0a-7dad-4963-a483-a77e58f07676	Temperature	Numeric	Ambient temperature measured in degrees (°C or °F)
d2da3eb8-e527-498f-9b4e-0df652eb0116	Humidity	Numeric	Ambient relative humidity measured in percentage (%)

Tables 5 and 6 depict the header and body of the second AAS for task types and characteristics, respectively, providing a comprehensive description of each job. There will be an opportunity to define a certain activity using the Task Classification Model shown in Figure 6. Additionally, we established a set of requirements for each task, including factors such as time constraints, physical and cognitive demands, required skills, and other relevant considerations.

The ultimate asset deals with the surrounding conditions encompassing the human workers engaged in shop floor duties. Similarly, there are two tables, 7 and 8, which correspond to the header and body of this asset, respectively. This asset incorporates three aspects, namely noise, temperature, and humidity.

V. CONCLUSION AND FURTHER WORK

Significant changes have been made to the design and functioning of industrial processes as a direct result of I4.0 and the associated digitalization. These changes have led to an increase in the amount of automation utilized. With the advent of Industry 5.0, which focused on human centricity, the working environments associated with manufacturing and logistics systems have become more detailed and complex, which has in turn led to an increase in the mental workload that is placed on human operators. Cognitive load is a multi-dimensional structure that shows how hard a task is for a worker. In addition, it provides an indication of the perceived effort necessary for learning, reasoning, and general thinking as a measurement of the pressure placed on the working memory while the activity is being carried out. In this paper, we develop a new way of managing cognitive load based on the Human Asset Administration Shell (HAAS) via gathering real-time data from a variety of assets.

The proposed HAAS is not restricted to the conventional role of AAS in providing interoperability between assets; it extends its function toward the manipulation of tasks and surrounding events based on multivariate parameters. Four modules have been covered in the extended HAAS: the physiological module represented by GSR and HRV signals, the workers' characteristics module to make the HAAS personally dependent, the task module, and the final module, which is the environmental condition surrounding the operator.

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Knowledge Graph-Based Framework to Support Human-Centered Collaborative Manufacturing in Industry 5.0

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Abstract: The importance of highly monitored and analyzed processes, linked by information systems such as knowledge graphs, is growing. In addition, the integration of operators has become urgent due to their high costs and from a social point of view. An appropriate framework for implementing the Industry 5.0 approach requires effective data exchange in a highly complex manufacturing network to utilize resources and information. Furthermore, the continuous development of collaboration between human and machine actors is fundamental for industrial cyber-physical systems, as the workforce is one of the most agile and flexible manufacturing resources. This paper introduces the human-centric knowledge graph framework by adapting ontologies and standards to model the operator-related factors such as monitoring movements, working conditions, or collaborating with robots. It also presents graph-based data querying, visualization, and analysis through an industrial case study. The main contribution of this work is a knowledge graph-based framework that focuses on the work performed by the operator, including the evaluation of movements, collaboration with machines, ergonomics, and other conditions. In addition, the use of the framework is demonstrated in a complex use case based on an assembly line, with examples of resource allocation and comprehensive support in terms of the collaboration aspect between shop-floor workers.

Keywords: human-centered; knowledge graph; Industry 5.0; manufacturing ontology; semantic reasoning; operator support

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1. Introduction

The global economy and the developers of MES (Manufacturing Execution System) and ERP (Enterprise Resource Planning) systems face the challenge of enhancing productivity while retaining human labor in the manufacturing sector [1]. With the increasing diversity and complexity of product lifecycle applications, there is a growing need to digitize knowledge related to various aspects of the industry, such as process planning, production, and design. It is suggested that the key drivers for transforming data into knowledge and advancing process automation through interoperable data will involve KGs (knowledge graphs), semantic web technologies, and multi-agent systems [2]. Effective representation and communication of domain knowledge are also vital for smart manufacturing. The primary focus of Industry 4.0 lies in achieving extensive digitization, while Industry 5.0 aims to merge cutting-edge technologies with human involvement, characterized as a value-driven approach rather than a technology-centred approach [3]. Industry 4.0 integrates digital technologies such as IoT, artificial intelligence, big data, and automation into manufacturing processes to improve their efficiency, productivity, and customization. By prioritizing connectivity, data exchange, and smart factories, it establishes a more adaptable and responsive manufacturing setting. Industry 5.0, an emerging concept based on Industry 4.0, reintroduces human-centric methods into manufacturing operations. In contrast to Industry 4.0, which focuses mainly on automation and machine-to-machine communication, Industry 5.0 emphasizes collaboration between humans and machines.

The objective is to take advantage of the distinct strengths of humans and machines, such as creativity, problem-solving, and emotional intelligence, to drive increased levels of innovation, flexibility, and sustainability in manufacturing. Industry 5.0 strives to achieve a harmonious balance between technology and humanity, using advanced technologies while giving priority to human well-being, creativity, and empowerment. Furthermore, there is growing interest in research areas such as industrial humanization [4], sustainability, and resilience [5]. Within the context of Industry 5.0, the importance of a Knowledge Graph (KG) is underscored by its ability to represent and analyze intricate data related to human operators [6].

The networked data structure of this system effectively records essential operator-related elements like ergonomics, working conditions, and machine cooperation in a systematic manner. By utilizing ontologies, a structured understanding of human actions in the manufacturing setting is achieved, guaranteeing compliance with human limitations and abilities. The graph's dynamic query and visualization features support real-time monitoring and flexibility. Consequently, the Knowledge Graph (KG) has become a key instrument for enhancing human-centered approaches in intricate manufacturing environments [7].

The human-centered aspect of the Industry 5.0 idea [3] strives for improved human–machine interaction, envisioning robots integrated with the human mind to collaborate rather than compete [8]. Throughout history, humans have influenced cyberphysical systems (CPSs) significantly, playing a vital role in their establishment and advancement. Consequently, human intelligence stands out as a crucial and predominant element in intelligent manufacturing, aligning with the concept of human-cyber-physical systems (H-CPSs) [9]. To achieve a suitable level of human–machine fusion, the concept of operator 4.0 [10,11] must be assessed. This concept promotes adaptive automation within collaborative human-automation work systems, fostering a socially sustainable manufacturing workforce. A more recent idea, the concept Resilient Operator 5.0 [12], explores improving the resilience of human operators to various workplace factors, thus facilitating the implementation of efficient smart manufacturing systems. Additionally, a proposition is made to model cognitive abilities and task requirements using a human asset administration shell [13]. Ontology models can also help contextualize key performance indicators (KPIs) [14], identify indirect effects or influences, and analyze relationships within a complex network [15]. They can also assist in visually representing KPI themes, developing dashboards [16], and consolidating KPI-related data [17]. Once this relationship with the decision variable is established, it enables responsive development and optimization. The ontologies, semantic tools, and industry standards proposed in this paper can support the development of systems that enhance operators' resilience, flexibility, and efficiency. The primary contribution of this study is the introduction of a framework known as the Human-Centric Knowledge Graph (HCKG), which models elements related to the human operator, such as monitoring movement, work environment, and collaboration with robots, using ontology and standards. The framework is exemplified through an industrial case study and incorporates graph-based data querying, visualization, and analysis. An instance involving a complex wire harness assembly process illustrates instances of resource allocation and comprehensive support for human–machine collaboration. The key innovations and contributions of this paper include the following:

- Suggested the expansion of automation standards like ISA-95, AutomationML, or B2MML to cover human-centric processes and the application of semantic technologies.
- Advocated for a Knowledge Graph (KG)-based approach to bolster human-centered and collaborative manufacturing in Industry 5.0.
- Showcased a replicable industrial case study to validate the concept. Various graph-based analyses utilizing normal, directed, or hypergraphs will be demonstrated, such as resource allocation assessment, KPI evaluation, or identification of diverse collaboration forms between human and machine agents in the assembly process.

This research builds upon a previous conference paper [18], which introduced only a portion of the concept. Initially, Section 2 presents the current state of the field, pinpointing knowledge gaps and motivations. The core contribution of the paper is outlined in Section 3, where the foundational elements of the HCKG design concept are elaborated. Section 4 outlines a wire harness assembly-based case study to trial the human-centered KG-based design concept. Lastly, the contributions and potential avenues for future research are discussed in Section 5.

2. State-of-the-Art—Knowledge Gap and Motivation

The integration of collaborative robots into manufacturing processes, known as human–robot collaboration (HRC), represents a significant advancement in Industry 4.0. Unlike traditional industrial robots that are confined to isolated cells, collaborative robots are designed to work alongside humans, using embedded interaction, sensing, and safety technologies. This enables a hybrid production environment where human and robot resources are dynamically allocated to optimize productivity, flexibility, and reconfigurability. HRC environments aim to overcome the limitations of manual and robotic assembly lines by providing a novel approach to task allocation and execution that improves overall manufacturing efficiency and adaptability [19].

Cyber-Physical Production Systems (CPPS) integrate physical processes with digital technologies to optimize production processes. These systems enable seamless communication between physical components and digital systems, fostering an adaptive and intelligent manufacturing environment that is capable of self-optimization and autonomous decision-making. Information management of emerging industry trends requires an effective solution, such as KGs, that uses a graph-based data model to capture knowledge in application scenarios that involve integrating, managing, and extracting value from diverse data sources, even on a large scale [20]. Semantic technologies such as ontologies, graph databases, semantic analytics, and reasoning provide an efficient way to process large amounts of data from multiple sources by making the entire data set transparent and accessible [21,22]. Semantic networks and graph-based analytics are recommended to handle process information using linked data features. Knowledge graph (KG) techniques are capable of extracting data from structured, semi-structured, or unstructured sources and then incorporating this information into a graph-based knowledge representation [23]. To improve operator working conditions, various monitoring systems, such as sensor networks, can be utilized to monitor operator movements and physical states, enabling the assessment of performance metrics [24,25]. In the process of ontology engineering, systematically adapting ontologies to different production systems and factory settings requires a thorough initial requirements analysis to ensure deep understanding [26]. Existing ontologies are meticulously assessed to facilitate reuse and adaptation through a modular design. Emphasizing granularity and maintaining consistent naming conventions requires thorough documentation. Seamless integration with existing factory data sources is carefully coordinated, and an iterative refinement strategy, supported by expert input and real-world tests, is integrated [1]. Utilizing specialized software and tools, along with adherence to standards like the OWL (Web Ontology Language) and the RDF (Resource Description Framework), coupled with stringent governance, guarantees compatibility and systematic updates. A knowledge reasoning framework has been suggested, using semantic data to improve real-time data processing in a smart factory setting [27]. A machine learning semantic layer has been introduced to complement augmented reality solutions in the industry, providing an intelligent layer [28]. Operators in an Industry 5.0 environment should be able to interact effortlessly with industrial assets while dealing with more complex assets. To achieve this development objective, a generic semantics-based task-oriented dialogue system framework like KIDE4I (Knowledge-drIven Dialogue framEwork for Industry) can offer a solution to reduce cognitive load [29].

The use of international standards can improve the quality of information systems by facilitating the interoperability of the software tools used. ISA-95 [30] is one of the essential standards in the field of integration of enterprise control systems and serves as a widely used basis for designing Industry 4.0 [31], IIoT (Industrial Internet of Things) [1] or smart factories [32] related to MES and MOM (Manufacturing Operations Management). To create a semantically integrated design concept, the production capability and personnel models of the ISA-95 standard are recommended as a basis for modeling.

B2MML is an implementation of IEC/ISO 62264 [33] to provide a freely available XML for manufacturing companies [34]. B2MML standard elements are recommended for the development of problem-specific ontologies, such as the concept of collaborative assembly workstations [35], where semantic technologies are used to improve interoperability with external legacy systems such as ERP and MES. AutomationML [36] aims to standardize the exchange of data in the engineering process of production systems. In an AutomationML environment, the IEC 62264-2 personnel model [37] provides a method to model the operator in a production process with the following elements: personnel class, personnel class property, person and person property. AutomationML is also recommended as an exchange file format as a step toward automated job design based on optimized resource allocation [38].

Another important point to consider is that human-centric Cyber-Physical Production Systems (CPPSs) in smart factories and active collaboration between humans and machines have introduced an ontological framework known as the PSP ontology (Problem, Solution, Problem-Solver Ontology) [39]. The research focused on integrating the three main concepts of "Problem-Solving Semantically Profile", "Problem-Solver Profile", and "Solution Profile". In addition to the semantic representation and reasoning of these core concepts, the study introduced the contingency vector, competence and autonomy vectors, and the solution maturity index for CPPS [39]. Moreover, due to the insufficient operator-based models, particularly in decision-making aspects [40], it is recommended to incorporate the human operator model into the shop floor control system. Enhancing human–machine interaction through ontologies is recommended. To prioritize human well-being while ensuring production efficiency, the development of a human-centred intelligent environment requires the consideration of various factors. There is a high demand for identifying suitable factors to evaluate human–robot collaboration and ergonomic conditions for factory workers [41]. A comprehensive framework is required to evaluate Human–Machine Interfaces (HMI) and Human–Robot Interactions (HRI) in collaborative manufacturing settings [42]. A comprehensive systematic review [15] categorized the measures, indicators, and quality factors used in the HRI literature using a methodical approach. The indicators are grouped into categories relevant to industry 5.0 research, including physical ergonomics (safety, physical workload, job design), cognitive ergonomics (mental workload, awareness), performance (efficiency, effectiveness), and user experience satisfaction/hedonomics (emotional responses, acceptance, attitudes, trust) [15]. In the field of ontology engineering, especially within the Industry 4.0 framework, a structured series of methodical procedures is adhered to [43]. Initially, a comprehensive analysis of requirements is performed to grasp the diverse points of view of stakeholders and establish the goals, extent, and requirements of the ontologies [44]. Before embarking on any new development, existing ontological resources are evaluated for potential repurposing, focusing on efficiency and the integration of well-established concepts. Throughout the development phase, specialized tools are utilized to define essential elements such as classes, relationships, and axioms. A thorough assessment process, involving expert evaluations and automated validations, ensures alignment with recognized standards and specifications. Elaborate documentation is generated that elucidates the structure and operation of the ontology to enhance comprehension and stakeholder participation. The final result is incorporated into the Industry 4.0 setting and, acknowledging the evolving nature of industrial domains, undergoes regular reviews and improvements to maintain relevance and efficiency [45].

In summary, the knowledge gaps in a semantic framework to support collaborative and ergonomic manufacturing include the need for effective human-centered design integration [46], comprehensive manufacturing ontologies [47], robust semantic reasoning techniques [48], and advanced operator support tools [49]. Addressing these gaps requires overcoming challenges related to data integration, data quality, real-time analytics, and scalability in KG-based frameworks [50]. The motivation of this paper is to propose a semantic-based framework for human-centric manufacturing and to present an industry-related case study of KG utilization. In the following section, the concept of HCKG design is presented after discussing the motivation for this research.

3. Human-Centered Knowledge Graph-Based Concept towards Collaboration in Manufacturing

This section delves into the primary contribution of this paper, which is the design concept of the Human-Centered Knowledge Graph (HCKG). Section 3.1 explores the activity model associated with the management of manufacturing operations. Section 3.2 describes the different human–robot collaboration scenarios and the key essential performance indicators of a human-centric assembly process. Lastly, Section 3.3 details the framework of the HCKG concept. The objective of the HCKG design concept is to establish a framework to monitor and control human–machine collaboration, improve resilience and agility, and improve working conditions for operators. The knowledge graph incorporates monitored data concerning the operator's activities, the environment, as well as all robots and equipment within the manufacturing space. Through the analysis of the collected knowledge graph data, collaboration can be enhanced, work instructions can be customized for the operator, and any modifications can be adaptively managed. Figure 1 illustrates the integration approach of the HCKG concept. In the initial segment, the Production Process element represents the intricate production environment encompassing all human–machine resources, processes, activities, and interactions. The Monitoring System element interacts with the production process, collecting historical and real-time data using sensors and IoT devices. Furthermore, the schema element offers semantic tools to establish a contextualized data model, while the meta-information element contains meta-information, such as industry standards, to ensure reusability. In knowledge graphs, Metal pertains to data about the data itself, providing details such as its source or properties, whereas Scheme defines the structure, properties, and relationships within the graph, organizing and standardizing the data model. The initial segment comprises a variety of structured and unstructured data sources that require preprocessing.

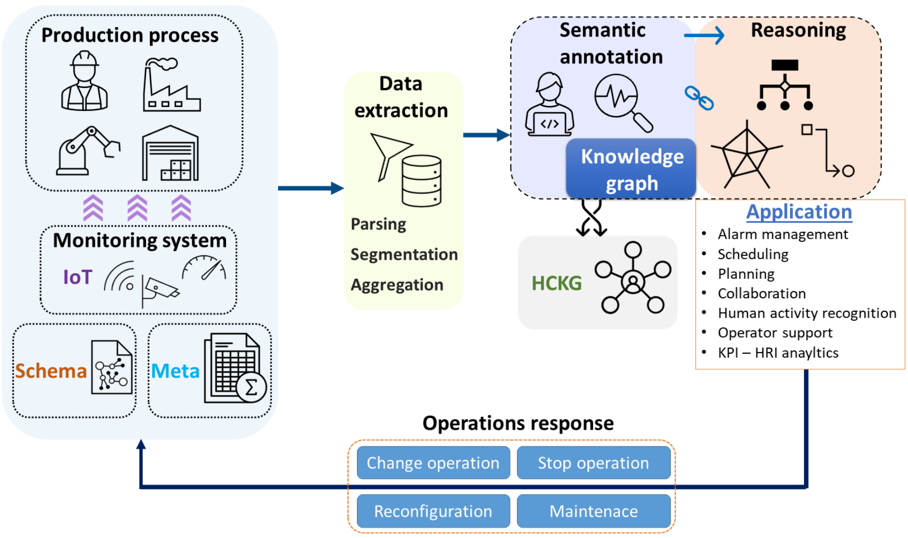

Figure 1. Integration of the HCKG design concept connected to the production process, using five segments.

Therefore, the second part involves procedures such as parsing, segmenting, and consolidating data, which constitute the Data Extraction component. The goal of data extraction is to recognize and retrieve pertinent information from unstructured or semi-structured data sources of the initial part and to transform it into a structured form for analysis and optimization. The third section encompasses the Semantic Annotation and Reasoning components, which leverage semantic modeling and data analysis in a complex

KG. The Semantic Annotation module constructs the KG utilizing the schema, metadata, and extracted data. This process entails the appending of metadata, standardized labels, or tags to entities and relationships within the KG, such as industry-specific terms or concepts from a particular domain. Within knowledge graphs, "metadata" refers to semantic details that delineate the attributes, context, and connections of the data, thereby enhancing comprehension and interpretation of the underlying information. It enables applications to recognize and classify diverse entities more precisely within the KG by furnishing additional context and facilitating more accurate categorization and identification within the data model. The HCKG module signifies the human-centric KG aspect of the established semantic network, which may encompass the entire KG or only the portion relevant to shop floor workers, depending on the specific scenario. This section is elaborated further in Appendix A and the case study in Section 4.2. The Reasoning component enhances the semantic information for the subsequent segment, the component Application . The reasoning process relies on the concept that the interrelations and links among various entities in the KG can be leveraged to derive logical inferences and form novel predictions. In the realm of analytics and optimization, semantic reasoning plays a crucial role in uncovering patterns, correlations, and causal connections between entities within the KG. Through the application of semantic reasoning, patterns and correlations among various data points can be identified, such as determining which machines are likely to cause delays on a specific production line. By engaging in reasoning across the KG, the application can determine the most efficient sequence of steps in the production process to minimize waste and improve efficiency. Human-centric KG applications can assist in managing alarms, scheduling operations or personnel, optimizing human–machine interactions, recognizing human activities, or analyzing performance metrics. This topic is further elaborated in Section 4.3 through a case study. The outcome of the application, along with the analysis results, leads to the operation response (fifth segment), which is then directed to the production process component. Examples of responses include change operation , stop operation , reconfiguration , or maintenance .

3.1. Manufacturing Operations Management

This section delves into an expanded MOM activity model, illustrated in Figure 2, where the components can be categorized based on the timing of their occurrence during the execution of the task. Although this aspect of the methodology has been previously documented by the authors in a conference paper [18], the inclusion of the associated MOMs here aims to enhance the comprehension of the HCKG framework. The temporal perspective of the general activity model concerning pre-, during, post-, and reference data is also emphasized [51]. Moreover, the supplementary modules for extending the standard activity model of MOM [52] are depicted in brown below.

The MOM approach is designed to provide a detailed insight into the mechanisms linked to the operator's role in a general manufacturing task, while also emphasizing the characteristics of the additional monitoring and support framework components. The generic activity model is segmented into four sections based on a temporal perspective, indicated by green labels in the diagram, and is evaluated and deliberated upon in a similar manner. The Reference Data encompasses all the details regarding individual operators, including their skills, capabilities, and expertise in specific domains. The Resource and Definition Management segments of the MOM system compile this data and establish the foundational information for the subsequent operational segments of the model. As an expansion of the reference data segment, the Control and Optimization component is suggested, where the integration of machine learning or artificial intelligence solutions can enhance the ongoing manufacturing processes.

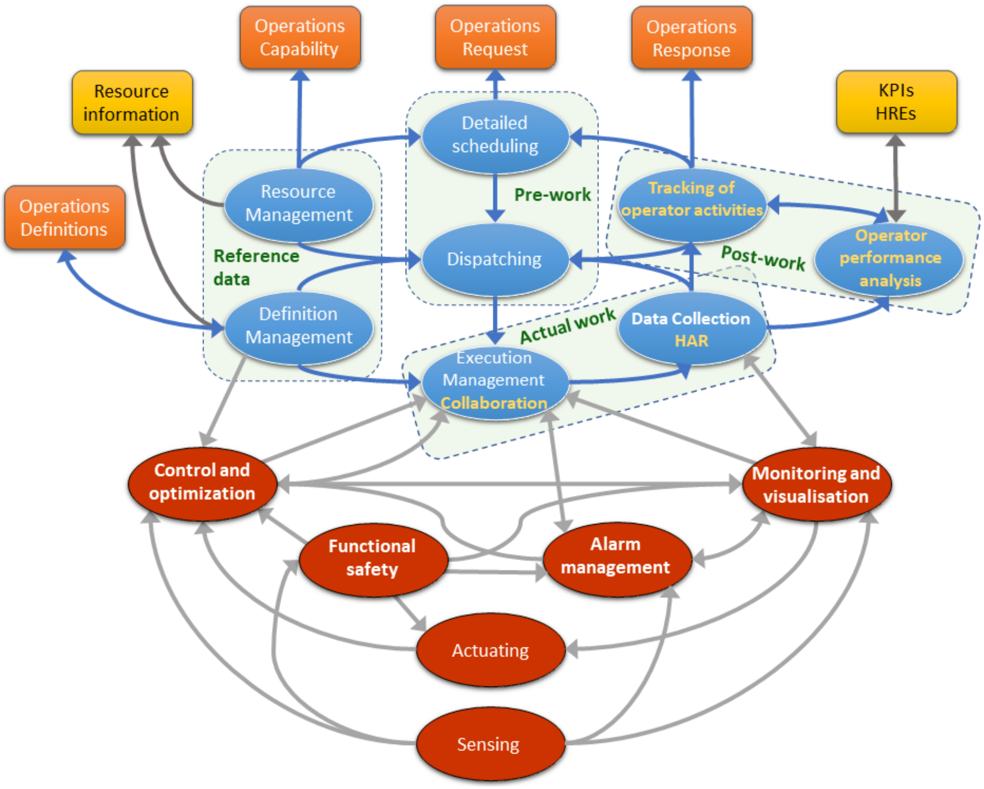

Figure 2. Activity model of manufacturing operations management from an operator-centric point of view [18].

The following section in Figure 2 represents the Pre-work phase, where Detailed Scheduling is employed based on the Operation Request, and Dispatching tasks are carried out. These actions ensure that all operators receive proper instructions, are efficiently scheduled, and are assigned tasks accordingly. The actual work segment of the MOM delineates the ongoing activities managed by Execution Management, while concurrently conducting Data Collection. Some elements centered on humans are integrated (marked in yellow text), such as Collaboration or the utilization of Human Activity Recognition (HAR) sensor technologies. To enhance real-time operator assistance, additional components like Alarm management, Monitoring and visualization are included as supplementary features. An intelligent monitoring system can gather data from various manufacturing parameters such as temperature, noise, or vibration, and display it graphically in real-time, issuing alerts in case of anomalies.

In the post-work phase of the task, monitoring of operator activities is carried out to derive an operational response for the MOM. Additionally, the evaluation of operator performance is utilized, serving as the foundation for Key Performance Indicators (KPIs) and Human Resource Effectiveness (HRE), which are crucial components in the Knowledge Graph (KG) used to establish adaptable and resilient conditions for the operators. The expansion modules of the activity model are intricately linked to the KG through semantic technologies. The advancement of intelligent cyber-physical systems establishes an environment where each aspect of the intricate manufacturing system, involving humans and machines, is effectively supervised, and the information systems are compatible. The vital components of the extended MOM model, viewed from the shop floor perspective, include Operator Performance Analysis, HAR, and Monitoring, which plays a key role in KPI and metric evaluation. A thorough examination of operator performance can support skill-based matching and the development of skill clusters. With the growing need for adaptable production lines, conventional assembly lines might be substituted by self-sufficient workstations, referred to as skill clusters, with mobile robots transitioning between them. In addition, skill clusters should be furnished with collaborative robots capable of working safely and reliably alongside operators.

3.2. Human–Robot Collaboration and Key Performance Indicators

This section delves into the various categories of workstations and collaboration scenarios that are of significance within the context of the case study under consideration. In addition, a concise summary of the primary performance metrics related to human-centered, ergonomic, and human–robot collaboration is provided. Depending on whether the actors involved are human or robotic, different types of workstations can be identified: manual, collaborative, and automatic [53]. Within a collaborative workstation setup, further categorization is established based on the nature of the interaction between human and robot actors during work tasks, aiming to yield a more comprehensive case study. Figure 3 illustrates three different types of collaboration [42,54]:

1. Separate work: Human and robot tasks are kept apart, and they do not share workspaces, tools, or workpieces.
2. Sequential collaboration: Although the human and robot actors are in a shared process flow of a workpiece, tasks are completed in succession. The workspaces, tools, and workpieces may be shared, but the tasks are strictly serialized such that any sharing is temporally separated.
3. Simultaneous collaboration: Human and robot tasks are executed concurrently and, moreover, may involve working on different parts of the same workpiece but are focused on achieving separate task goals.
4. Supportive collaboration: Humans and robots work together on the same piece of work to complete a common task.

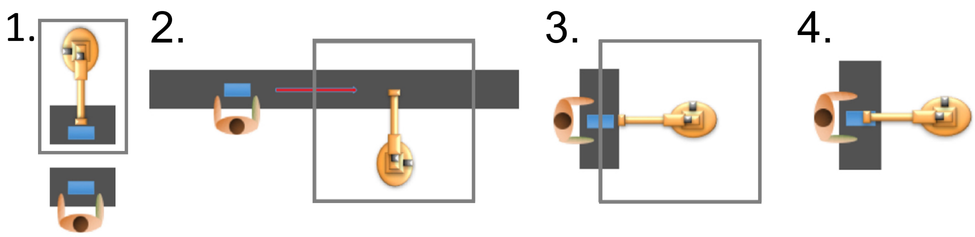

Figure 3. Separate (**1.**), sequential (**2.**), simultaneous (**3.**), and supportive (**4.**) types of human–robot collaborations [42].

The key performance indicators (KPIs) focused on human factors are outlined in Table 1 across six distinct categories: time behavior, physical measures, HR physical measures, efficiency, effectiveness, and ergonomics. Furthermore, the Operator 4.0 typologies [46] have been incorporated into these KPIs in the second column, illustrating the potential to facilitate the establishment of a harmonious relationship between humans and automation. A study that assesses the quality of human–robot interaction [15] has been partially referenced, although it does not offer a comprehensive overview of the subject matter. Additionally, a paper on ontology-driven KPI metamodeling [14] has been taken into account in this case study, focusing on a semantic technology perspective.

Table 1. The categorized human-centric KPIs for the case study.

KPI Description	Operator 4.0 Type
Time behavior category	
Average time to complete task	Analytical operator
Collaboration time—Type-3 and Type-4	Collaborative operator
Functional delays	Analytical operator
Human operation time	Analytical operator
Interaction time	Collaborative operator

Table 1. *Cont.*

KPI Description	Operator 4.0 Type
Response time	Collaborative operator
Robot functional delay	Collaborative operator
Robot operation time	Collaborative operator
Task completion time	Analytical operator
Total assembly time	Analytical operator
Total operation time	Analytical operator
Physiological measures category	
Biosignals (temperature, tactile, etc.)	Healthy operator
Ergonomics improvement	Healthy operator
Muscle activity	Healthy operator
Ocular behavior	Healthy operator
HR physical measures category	
Avg./min. length between a human hand and a robot hand	Collaborative operator
Human–robot distance	Collaborative operator
Efficiency category	
Availability	Collaborative operator
Average robot velocity	Collaborative operator
Concurrent activity	Collaborative operator
Degree of collaboration	Collaborative operator
Layout efficiency	Analytical operator
Effectiveness category	
Accuracy	Analytical operator
Interaction accuracy	Collaborative operator
Level of assignment	Collaborative operator
Level of interaction	Collaborative operator
Overall equipment effectiveness	Analytical operator
Real-time human fault	Analytical operator
Real-time robot fault	Collaborative operator
Ergonomics—environmental category	
Environmental condition—noise	Healthy operator
Environmental condition—humidity	Healthy operator
Environmental condition—temperature	Healthy operator
Environmental condition—gases	Healthy operator

3.3. Design Structure of the HCKG Concept

This section outlines the methodology and presents a summary of the proposed development framework in a block format, as illustrated in Figure 4. The main objective is to integrate the human-centric KG block within a sophisticated industrial setting. The framework comprises five distinct blocks (or sections), commencing with the metadata sources from a business or industrial network and culminating in the application that leverages the information to generate value.

The meta block includes essential data to characterize the business processes and describable elements of a plant, such as material or information flows, starting from the foundational level. Markup languages and standards like B2MML (Business To Manufacturing Markup Language), AutomationML, or ISA-95 establish the initial framework for handling and overseeing the diverse data sources and processes within a complex network. It is advisable to expand existing standards such as ISA-95. A critical aspect of industrial progress involves utilizing standardized models, which facilitate the seamless integration of a new design concept into a production system and enhance the adaptability of existing methodologies, thereby making the learning curve for technical aspects more dynamic. The next component is the Schema and PPR block, representing the three descriptive ontologies within an Industry 4.0 setting. The product, process, and resource ontologies can comprehensively depict the entire network in a semantic format. Various assets, whether physical or human attributes, characteristics, and specific values, are structured as ontology axioms (individuals) and classified into classes. Furthermore, semantic properties, rules, and queries support interoperability and the depiction of relationships, such as actors' capabilities, the sequence of manufacturing activities, or resource allocation. PPR-based modeling aligns with AutomationML and serves as a method for establishing knowledge-driven mappings of products, processes, and resources in assembly automation [55]. The primary advantage of PPR-based modeling lies in facilitating the management of engineering datasets' mappings and connecting product attributes to manufacturing processes and resources. Moreover, knowledge-driven PPR mapping can aid in dynamically configuring and analyzing assembly automation systems [56]. The IoT Block comprises monitoring devices and sensors for conducting observations, along with HAR, which are essential inputs for the higher-level human-centric block—a pivotal component. Additionally, IoT devices form a complex system that necessitates separate management due to the diversity of smart devices and sensors. The so-called VAR ontology encompasses three key elements: tangible assets, intangible assets, and dynamic status.

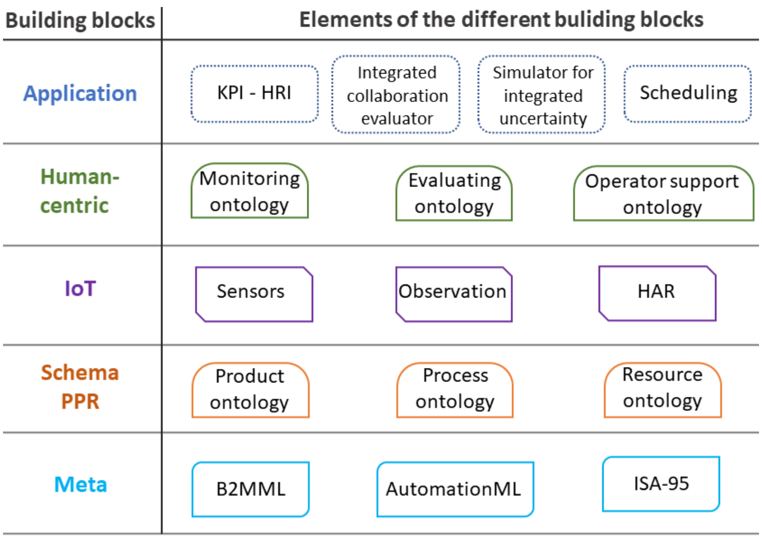

Figure 4. Theoretical structure of the proposed human-centered knowledge graph-based design concept [30].

The human-centric block includes the monitoring, evaluation, and operator support ontologies, with the goal of gathering and analyzing relevant information related to the production process, collaboration, human activities, or working conditions in the factory. Its primary aim is to keep the operator informed and assist them in various aspects such as ergonomics and collaboration. In a setting where humans and robots work together, feedback is crucial not only from the control or machine perspective but also from the human perspective, focusing on real ergonomic features, process parameters, and other input from the operator. Operators on the factory floor can offer valuable insights for the MOM's Operations Response, which should be integrated into the semantic-based data management system supporting CI/CD (Continuous Integration and Continuous Delivery) practices. The application block encompasses all the valuable information that the HCKG can provide for tasks like scheduling, resource allocation, enhancing KPIs and HRI factors, assessing collaboration aspects, or conducting simulations. The end user, whether a process engineer, factory worker, or production manager, is primarily interested in this segment as it delivers the final outcome of the semantic-based analysis. The application block can aid in exploring integrated uncertainty through simulations and assessing collaboration or business processes. Furthermore, scheduling and allocations can be optimized based on the performance metrics obtained. Other issues like the cybersecurity of large infrastructures, which are not covered here, are likely to remain significant challenges in the foreseeable future. Subsequently, a case study demonstrating the application of the proposed KG framework is presented following the discussion on the KG design concept.

4. Human-Centered Knowledge Graph Representation for a Wire Harness Assembly Process

This section illustrates the implementation of the HCKG approach elaborated in Section 3. Initially, a case study specific to the industry is outlined in Section 4.1. The establishment and organization of the generated KG are thoroughly examined in Section 4.2. Lastly, Section 4.3 demonstrates the visualization and examination of the production data.

4.1. Wire Harness Assembly-Based Case Study

A recent study on research and development [57] emphasized the importance of exploring collaborative robots in wire harness assembly. The authors of this study also delved into the analysis and design of Intelligent Collaborative Manufacturing Spaces (ICMS) using a hypergraph-based approach similar to a referenced benchmark [58]. The wire harness assembly sector served as the inspiration for the case study discussed in this paper. Specifically, the case study focused on the manufacturing processes of a multinational wire harness assembly plant. Detailed information cannot be disclosed due to confidentiality policies; however, the proposed methodology is continually undergoing validation with manufacturing experts. Figure 5 illustrates the factory floor layout, featuring a coordinate system that establishes a grid for assigning operators and production resources like robots and machinery. The case study incorporates a real-time location system (RTLS) that monitors the whereabouts of assembly workers and assets. The X and Y axes on the shop floor correspond to potential RTLS-based positions. Distances required for material handling and transportation can be determined from the grid. Furthermore, the shop floor is divided into 18 distinct areas, for instance, ST_11, which can accommodate workstations.

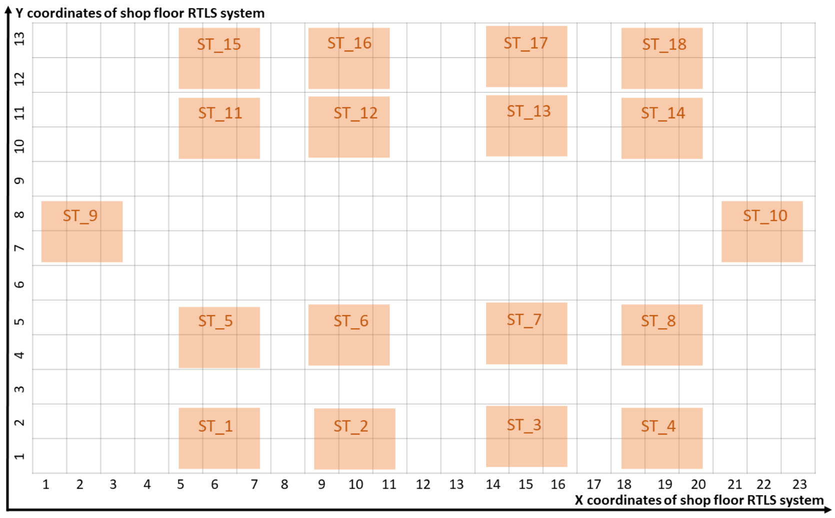

Figure 5. The grid layout of the benchmark shop floor.

A dual production system comprising batch and traditional production was specified, and the workflow is depicted in Figure 6, which is derived from an actual wire harness industry assembly line. This process involves two assembly lines that share tasks and resources. The components of these lines are detailed in Table 2. The shop floor includes two storage areas, multiple buffers, crimping stations, and assembly stations. The second group of components encompasses human–machine agents, which can be operators or robots, as well as production line assets, such as machines, tools, screwdrivers, and the AGV (Automated Guided Vehicle). Additionally, specific capabilities are necessary to perform designated tasks, along with sensor components, to oversee the collaborative environment.

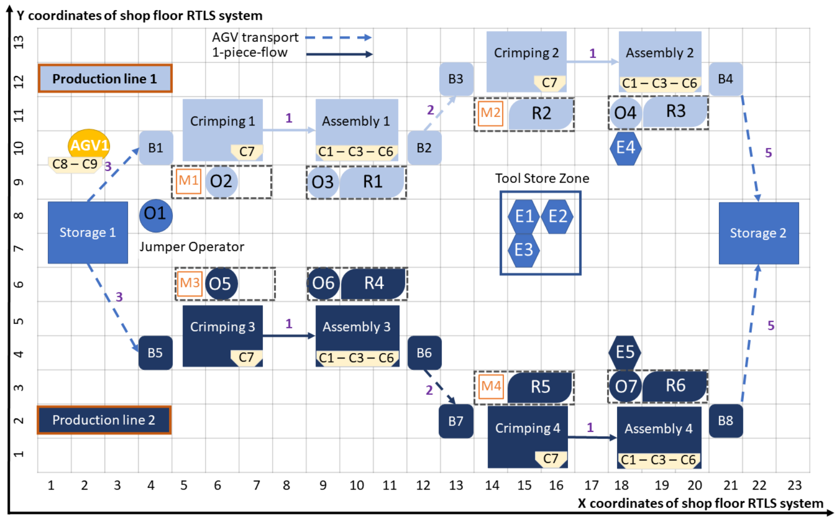

Figure 6. The process flow of the wire harness assembly line benchmark.

Table 2. The elements of the wire harness assembly lines.

Work sections of the production lines	
Storage	[K1, K2]
Buffer	[B1, B2, B3, B4, B5, B6, B7, B8]
Crimping stations	[Crimping 1, Crimping 2, Crimping 3, Crimping 4]
Assembly stations	[Assembly 1, Assembly 2, Assembly 3, Assembly 4]
Human–machine members and assets	
Operators	[O1, O2, O3, O4, O5, O6, O7]
Robots	[R1, R2, R3, R4, R5, R6]
AGV	[AGV1]
Machines	[M1, M2, M3, M4]
Tools	[E1, E2, E3, E4, E5]
Capabilities	[$C1, C3, C6, C7, C8, C9$]

A detailed list of activity types for this benchmark problem can be found in Appendix A in Table A2, encompassing categories such as the crimping process, assembly process, or material handling, along with the definitions of the outcomes associated with these activity types. It is crucial not only to define the activity types but also their results for effective process tracking and collaboration. A more comprehensive overview of the wire harness assembly benchmark is presented in Appendix B, where each activity type of the intricate industrial process is outlined in Table A1, followed by detailed descriptions of the sequence of activities in Tables A3 and A4 of the Appendix B, as highlighted in this study. In addition to the main elements listed in Table 2, other attributes of the elements include the following Capabilities necessary for carrying out specific activities: $C1$—insertion and laying of parts (cabling), $C3$—terminal handling, $C6$—terminal screwing, $C7$—crimp machine operation, $C8$—loading or unloading of the AGV, and $C9$—workpiece transport on the shop floor. Moreover, there are specialized tools, some of which are shared across the process, namely $E1$—wiring tool, $E2$—hose tool, and $E3$–$E5$—screwdrivers. Additionally, various unique Machines (M) are allocated to different Crimping Stations, while Tools (E) are considered communal assets within Assembly Stations.

In Figure 6, the brighter-colored elements represent Production line 1, while the darker ones represent Production line 2. Shared assets and resources are visualized in the middle. Material handling steps during production are indicated with arrows, which can be carried out as a one-piece-flow by operators or through an AGV-based transport system. Additionally, the distances over which materials are moved are marked with purple numbers. The process flow, illustrated in Figure 6, begins at Storage 1, where the operator known as jumper $O1$ loads $AGV1$ (using capability $C8$) with a batch, which is then transferred by $AGV1$ to either Crimping station 1 or 3 (using capability $C9$), where the unloading is performed by operator $O2$ or $O5$ into the local buffers $B1$ or $B5$. The subsequent steps are identical on both production lines, with the continuation of the process description focusing on Production line 1. As per the production plan, operator $O2$ carries out crimping-related activities listed in Table A2 that necessitate capability $C7$. Furthermore, machine $M1$ is utilized during these crimping activities. Subsequently, operator $O2$ transfers the workpiece to operator $O3$ at Assembly station 1 (one-piece-flow). Operator $O3$ and robot $R1$ collaborate, carrying out activities related to capabilities $C1, C3$, and $C6$. Additionally, tools $E1$–3 are employed during the activity steps at Assembly station 1. At the conclusion of the process, operator $O3$ places the workpiece into buffer $B2$. Upon the completion of a full batch, the same operator loads $AGV1$, which transports the batch of cables to the subsequent buffer, $B3$. Subsequently, robot $R2$ unloads the buffer and performs activities related to capability $C7$ and machine $M2$ at Crimping station 2. Following this, robot $R2$ transfers the workpiece (one-piece-flow) to operator $O4$ at the subsequent station, Assembly station 2. At the final workstation of Production line 1, operator $O4$ and robot $R3$ collaborate to carry out activities requiring capabilities $C1, C3$, and $C6$. At the end of the assembly line, operator $O4$ places the workpieces into buffer $B4$. Upon completion of a full batch, the same operator loads $AGV1$, which delivers the products to their final destination, Storage 2.

Furthermore, it is important to mention that this case study also includes different types of sensors, the purpose of which is to make observations about each activity, human, and machine of the production line, as well as to monitor the working conditions. These groups of sensors are camera systems, RTLS, robot-embedded sensor data, machine-embedded sensor data, environmental sensors, and human body sensors.

All three categories of workstations are included in this instance focusing on collaborative work. Crimping Station 1 and 3 are characterized as manual workstations, while Crimping Station 2 and 4 are classified as automatic workstations. The research features four collaborative workstations, denoted as Assembly stations 1–4. The specific case study on harness assembly delves into collaboration types 3 and 4. An illustration of concurrent and supportive collaboration is shown in Figure 7. In this simplified scenario, four distinct outcomes are observed, corresponding to the tasks executed by the entities Robot 3 and Operator 4. For instances Result 28 and 31, where both human and robot actors engage in similar activities on the same product, they engage in supportive collaborations aimed at achieving the same assembly result. On the contrary, Result 29 and 30 involve different activities, with human and robot actors operating on the same product simultaneously but pursuing different objectives. The idle period occurs when Robot 3 must wait for Operator 4.0 to complete their task, as they share the same workstation.

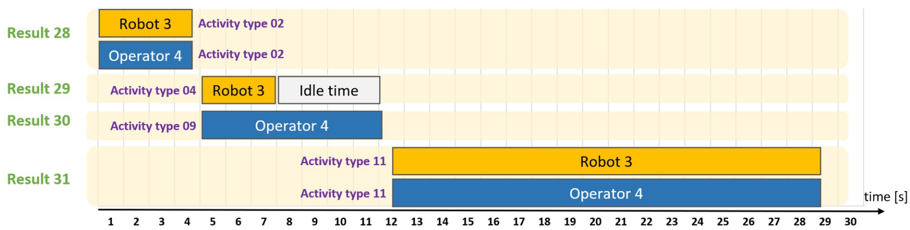

Figure 7. Gantt chart of collaboration scenarios.

4.2. Development of the Industry-Specific Human-Centered Knowledge Graph

A section of the KG that has been utilized in the case study discussed in Section 4.1 is depicted in Figure 8, excluding the distinct data properties of the ontology classes. The structural illustration in Figure 8 is segmented into six sets of ontology classes since the KG comprises multiple sub-ontologies. Moreover, the object properties, representing relationships among classes, are indicated on the arrows.

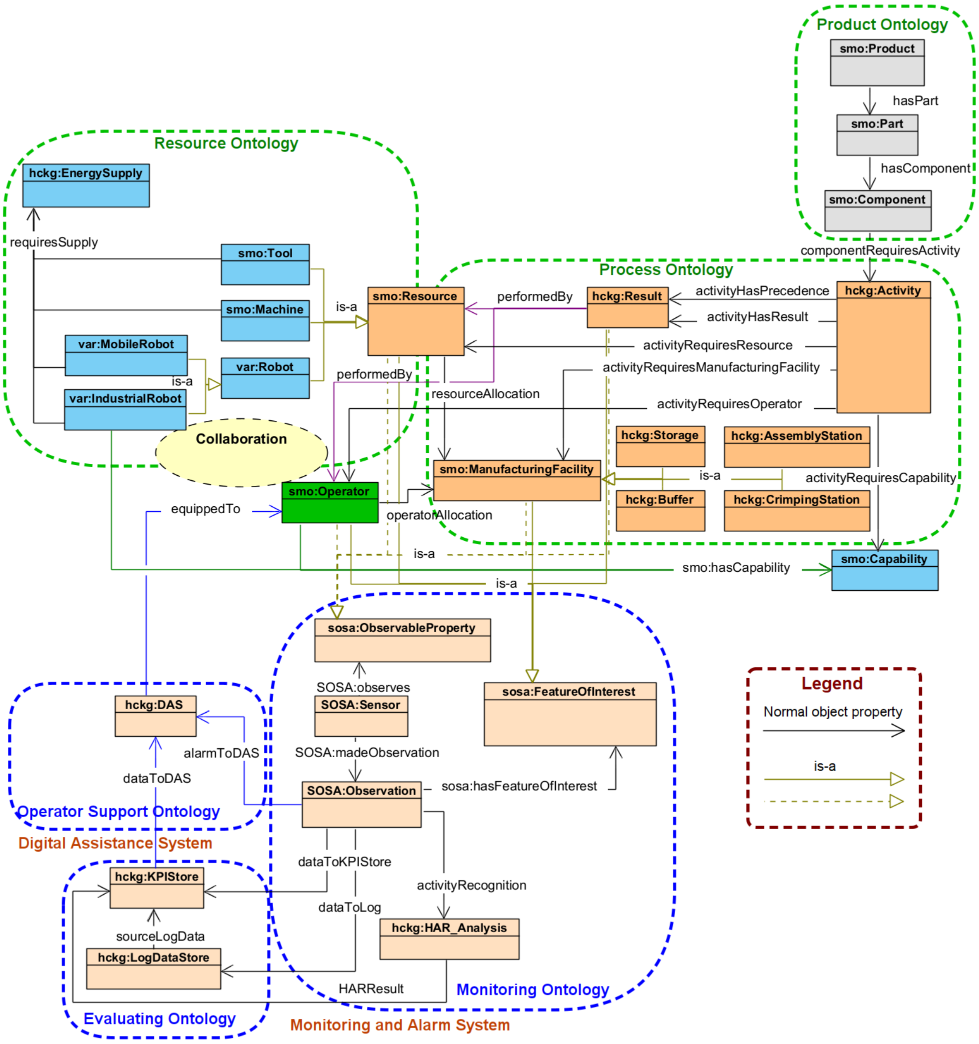

Figure 8. Partial structural diagram of the developed wire harness assembly-specific KG.

Prefixes indicating adapted namespaces from other industry-specific ontologies are included in the names of the ontology classes. The following list summarises these prefixes and the ontologies used:

- smo—Smart Manufacturing Ontology [59]: An ontology to model I4.0 production lines and smart factories based on RAMI 4.0. It highlights the sequence of processes and machines required for a produced workpiece.
- SOSA—Sensor, Observation, Sample, and Actuator ontology [60]: For modeling the interactions between the entities involved in terms of observation, actuation, and sampling. Together with SSN (Semantic Sensor Network), it can be used to describe sensors and their observations, the involved procedures, the studied features of interest, the samples used to do so, the feature's properties being observed or sampled, as well as actuators and the activities they trigger [61].
- var ontolog y [35]: A core ontology for data exchange in a semantic-oriented framework to support adaptive, interactive, assistive, and collaborative assembly workplaces.
- hckg—Human-Centric Knowledge Graph: The authors created a set of classes and properties to model the wire harness assembly-based case study semantically.

The product ontology includes three categories: product, part, and component. The complexity of this domain, previously addressed by the authors in [62], is not further explored here. The Process ontology is composed of the subsequent categories: Activity, Result, and ManufacturingFacility, which encompasses additional subclasses like Storage, Buffer, AssemblyStation, CrimpingStation, and Capability. The primary category in the

Resource ontology is Resource, which includes various subclasses such as Tool, Machine, and Robot. The Robot category is further divided into MobileRobot and IndustrialRobot. The EnergySupply category is also part of the resource ontology. The Operator category, a central element of the human-centered HC, is highlighted in green at the center of the HC structure in Figure 8. The operator category, which semantically characterizes the processes and impacts related to personnel on the shop floor, is associated with six distinct object properties. The Monitoring ontology comprises three categories: Sensor, Observation, and HAR_Analysis, storing the semantic model of sensor devices, their measurements, observation, and human activity recognition. The Evaluating ontology contains two categories: KPIStore and LogDataStore, designed to handle data from the aforementioned three categories. Lastly, in the Operator Support Ontology, the DAS category defines the digital assistance system. Considering that the categories Operator and Activity are pivotal in the KG, Tables 3 and 4 provide details on the corresponding object properties.

Table 3. Object properties of the Activity class.

hckg:Activity	
component Requires Activity	Connects individuals from the component and activity classes and provides information about the required activity to assemble a specific component on the wire harness.
activity Has Precedence	Since the assembly procedure requires a specific sequence, certain activities must be finished before another can be started. This is known as the precedence criteria.
activity Has Result	Describes the intended result of a particular activity. In the case of collaboration, several activity individuals may be connected to the same result individual.
activity Requires Resource	Interlinks Tool, Machine, or Robot individuals to an activity as a resource requirement.
activity Requires—Manufacturing Facility	Workstation requirement of an activity. Connects activity individuals with the ManufacturingFacility individuals such as Storage, Buffer, AssemblyStation, or CrimpingStation.
activity Requires Operator	Connects operator individuals to an activity as a personnel requirement.
activity Requires Capability	Describes the capability requirement of a specific assembly activity, which has to be conducted by an Operator or IndustrialRobot.

Table 4. Object properties of the Operator class.

smo:Operator	
activity Requires Operator	It provides information about a certain operator involved in certain activities.
operator Allocation	Semantically connects operators with Manufacturing Facility individuals such as Storage, Buffer, AssemblyStation, or CrimpingStation. It provides information on where the operator performs his/her work.
performed By	Connects Results with Operators and shows which operator was involved in which result(s).
equipped To	Describes the usage of devices from the Digital Assistance System by operators.

Table 4. *Cont.*

smo:Operator	
is-a SOSA: Observable Property	Semantically connects the properties, which are monitored by sensors with operators and shows how personnel are monitored.
is-a SOSA: Feature Of Interest	Main class of the feature of interest of the SOSA:Observation
smo:hasCapability	Shows which capabilities require a specific operator.

In addition, some of the key features of the use of semantic technologies and graph analysis from a human-centered approach are presented in Table 5 [63]. These analytics can help to better monitor and understand the HRE [64] and KPI [65] factors. In addition, Table 5 provides an example of its application for each network metric.

Table 5. KG metrics and analytical features.

Network Metrics	Analytical Features of KGs
Centrality computation	Which are the critical objects in the network?
	Detect the most significant influencing factors in the operator's environment.
Similarities between nodes and edges	How similar are two objects based on their properties and how are they connected to other objects?
	Solve allocation problems concerning operators and resources.
Flows and paths	What is the shortest, cheapest, or quickest way to perform a process step?
	Optimise the shop floor layout to best match operator needs.
Cycles	Are there any cycles in the graph? If so, where are they?
	Analyze tasks allocated to humans and machines in a collaborative work environment
Network communities	What communities can be found in the production network?
	Facilitate the design of human–machine collaboration or cell formation.

Once the use case-specific knowledge graph has been established and the necessary data have been imported into the semantic network, the subsequent stage involves formulating queries and examining the outcomes. Consequently, the subsequent subsection delves into the examples of graph-based knowledge analyses that were utilized.

4.3. Discussion on KG-Based Analytics of the Use Case

Initially, Figure 9 shows the graphical representation of the complete knowledge graph (KG) related to the wire harness assembly case study. This visual depiction serves as a means to validate the manufacturing process. The complete network is illustrated on the left side, encompassing all properties and entities within the KG, while a more detailed view is presented on the right side. The orange node corresponds to the equipment *E*5 and includes various associated data properties like locationID (18-4), equipmentCondition (86), equipmentID (*E*5), equipmentName (screwdriver C), and equipmentType (screwdriver).

All the SPARQL queries that have been developed are accessible on our website at https://github.com/abonyilab/HCKG (accessed on 14 March 2024). The initial instance of a SPARQL query-based data mapping, as referenced in [66], is illustrated in Figure 10. The left section of Figure 10 shows a graphical representation of the query, where four distinct rules are outlined to achieve the intended result. This particular example aims to identify RobotAssets categorized as IndustrialRobot s and seeks to present three associated data elements: Location , EnergySupply , and ManufacturingFacility. On the right side of Figure 10, a graphical representation of the result of the query is provided. Robot assets classified as IndustrialRobot s are depicted as orange nodes, each necessitating an EnergySupply referred to as g2 (electricity). Each IndustrialRobot node is linked to the corresponding workstation node (ManufacturingFacility), which represents various assembly stations, illustrated in purple in this scenario. Lastly, the location data attributes of the robots are denoted by blue nodes (indicating the robots require two zones on the shop floor). This type of visual examination can aid in exploring dependencies concerning specific assets.

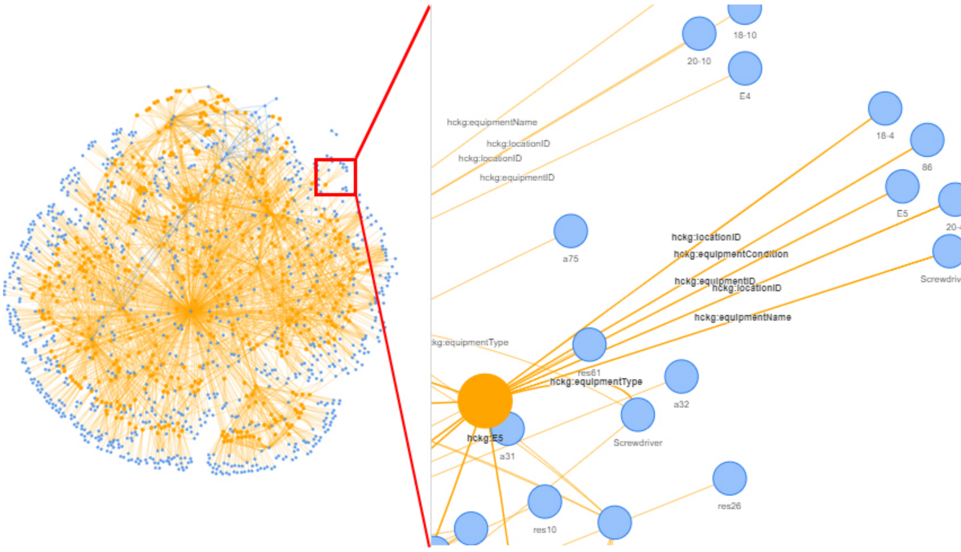

Figure 9. Visualization of the entire KG of this case study (on the left-hand side) and some of the data properties of equipment *E*5 (on the right-hand side—zoom into the red rectangle).

The resulting graph in Figure 11 illustrates the connections between Actors (operators or robots) and the Capability entities they are linked to. This illustration can be utilized for a visual examination of production capability. In Figure 11, it is evident that the majority of actors possess the capability *C*8 (AGV loading/unloading). Moreover, robots are limited to a maximum of two capabilities, whereas operators can concurrently possess up to four capabilities.

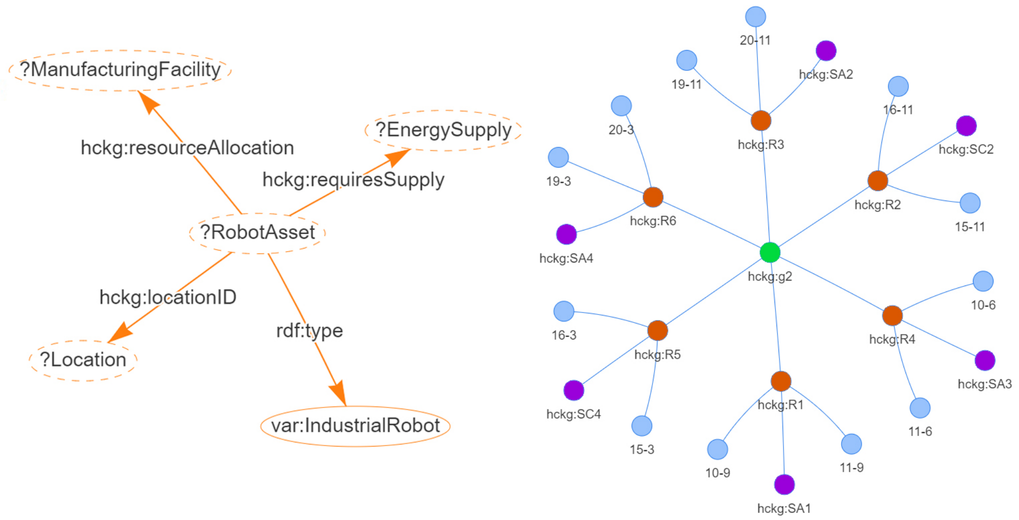

Figure 10. Visualization of the RobotAsset query (on the left-hand side) and the graph visualization of the result (on the right-hand side).

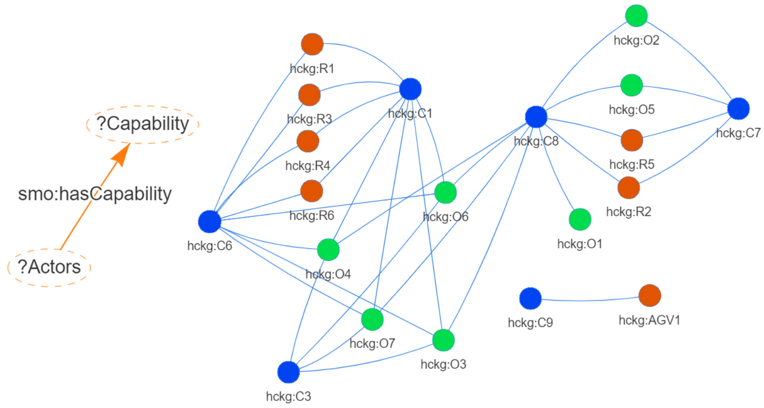

Figure 11. Visualization of the Actors-Capability query (on the left-hand side) and the graph visualization of the result (on the right-hand side).

A more intricate data query aimed at identifying sensor alerts transmitted to DAS devices is outlined in Figure 12. Initially, the KG is streamlined to include only the sensor, observation, and observed nodes, which are then refined to encompass sensor instances categorized under type names starting with "env" or "body", denoting environmental or body sensors. Subsequently, additional data are integrated into the dataset, specifying attributes such as observationValue, warningLimit, and alarmLimit. A subsequent filter is employed to isolate instances where the observationValue exceeds the warningLimit. The output comprises a compilation of the DAS device name, the message content, and the device's location. On the right-hand side of Figure 12, a graphical representation showcases only the most pertinent segment of the query outcome. Here, the purple nodes symbolize the sensor's location, the red nodes depict the message relayed to the DAS, and the green nodes correspond to the specific operator integrated into the DAS device, such as Smart Glass. Notably, in the graph located in the lower right corner of the figure, the locations of the observation sensor and the DAS device coincide, indicating that they are body sensors.

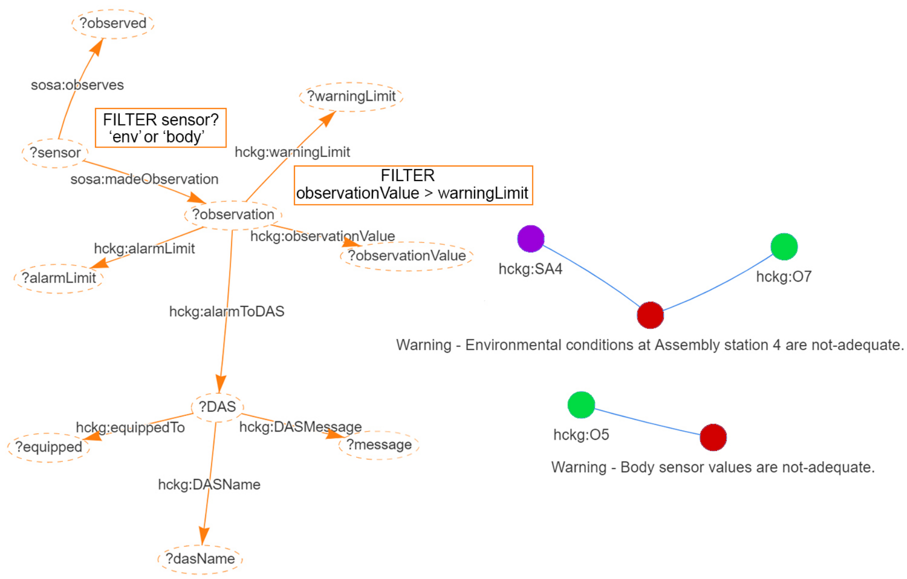

Figure 12. Visualization of the sensor-observation-DAS query (on the left-hand side) and a graph visualization of the result (on the right-hand side).

In the context of Operator 7 ($O7$) and Robots 6–7 ($R6 - R7$) collaborating at Assembly Station 4, as depicted in Figures 13 and 14 illustrates the application of the time KPI for human–machine collaboration. The graph in Figure 14 displays the total duration of supportive collaboration (type 4). Notably, $O7$ dedicated more time to collaborative assembly with Robots 5 and 6 than to individual tasks. Furthermore, the graph highlights simultaneous collaboration (type 3), particularly between Operator 7 and Robot 6 in the last two columns. To analyze both type 3 and the sequence of concurrent collaborative assembly actions, it is essential to examine the outcomes and precedence of these activities. Consequently, Figure 15 presents the results of a knowledge graph query visualized through directed graphs, depicting precedence relationships. In these graphs, yellow nodes signify the activities, while purple nodes represent the outcomes.

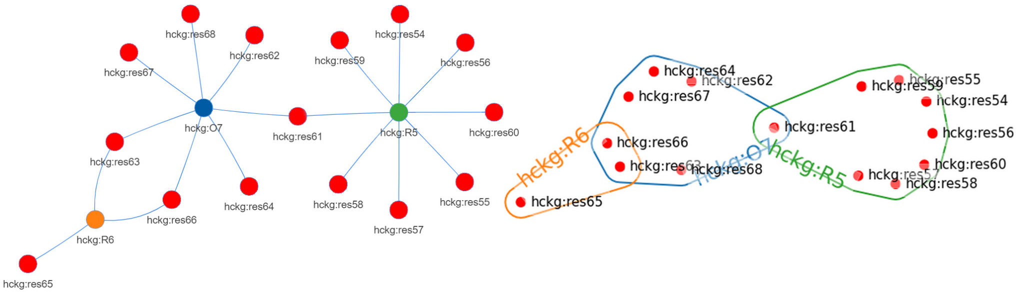

Figure 13. Visualization of human–robot actors and the performed results at Assembly station 4 in the form of a graph (on the left-hand side) and hypergraph (on the right-hand side).

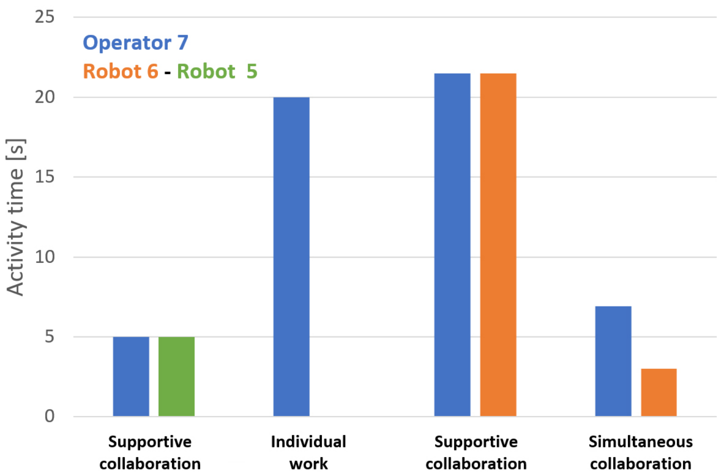

Figure 14. Distribution of assembly work in terms of operator *O7*, including the total supportive, simultaneous, and individual times.

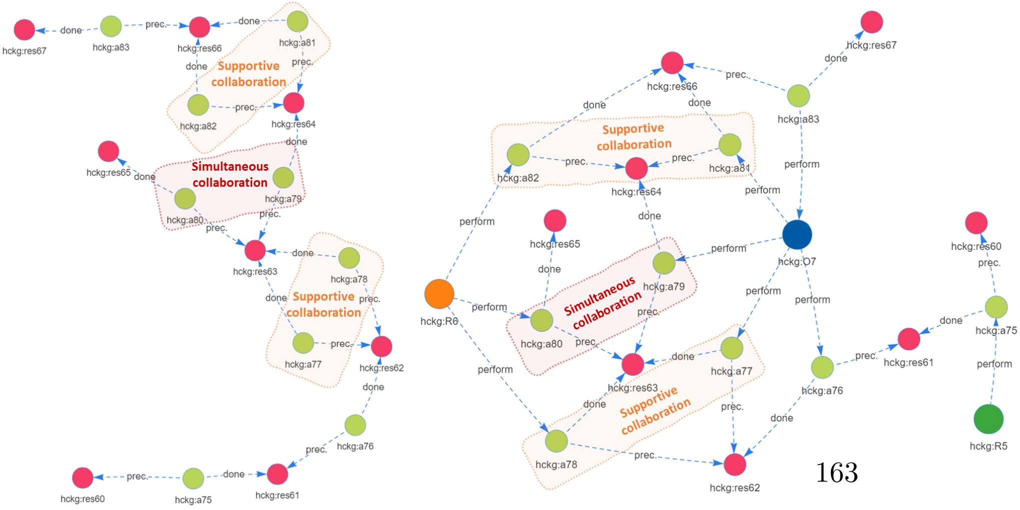

Figure 15. Directed graph result and activity nodes (on the left-hand side) as well as the same result, including the human–machine actor nodes (on the right-hand side).

The directed edges represent different object properties of the KG, namely:

- done—activityHasResult object property: shows the result condition of a specific activity if the assembly task is performed.
- prec.—activityHasPrecedence object property: represents the precedence criteria of an activity that has to be carried out before the specific activity can be started.
- perform—performedBy object property: describes the human or robot actor that performs the activity.

The tasks and outcomes that serve as a foundation for analyzing the process flow, where the order of steps and conditions can be traced from tasks $a75$ to $a83$, are presented on the left side of Figure 15. An expanded visualization, which includes the perform connections indicating that a human or robotic agent has performed a specific task, is shown on the right side of the same figure. Examining the inbound and outbound connections of a directed graph [67] enables the identification of clusters [68] within the network. By applying this approach, it can be inferred that if a result node has multiple completed incoming connections, it has been carried out through a collaborative effort involving actors of type-4 support, as indicated in the instances of tasks $a77 - a78$ and $a81 - a82$. In such scenarios, the actors are required to wait for the completion of the same outcome (priority is given) before commencing different tasks simultaneously on the same work item.

According to the precedence graph, when two or more activity nodes are assigned the same precedence (prec. edge) but lead to different outcomes (done edge), it indicates a type-3 concurrent collaboration. In Figure 15, it is evident that activities $a79$ and $a80$ are executed simultaneously after receiving the same precedence (res63), yet they generate distinct results upon completion (res64 and res65). The outcome of this section is a conceptual dashboard, shown in Figure 16, where the percentages indicate the levels of operator competence and robot health. The findings from the previous query, along with the KPIs in Section 3.2, can serve as data sources for smart glasses, shop floor dashboards, the DAS, or other intelligent devices.

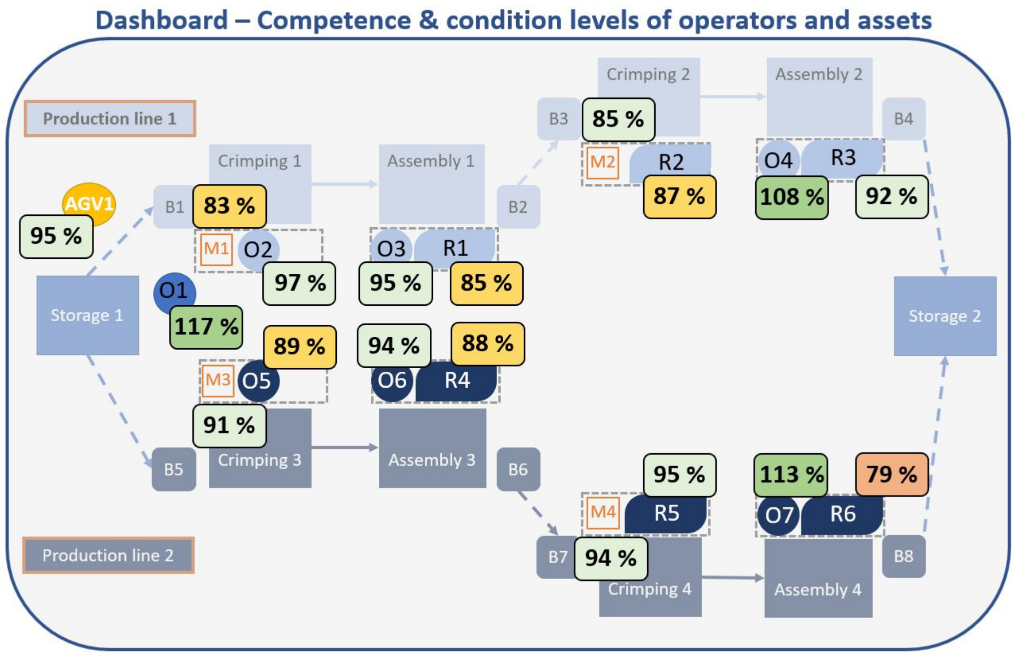

Figure 16. Conceptual dashboard for human-centric manufacturing—competence and condition levels of operators and assets.

5. Conclusions and Future Work

This article introduces the design idea of a Human-Centred Knowledge Graph (HCKG) that is based on industry norms and semantic technologies related to Industry 5.0 advancements. A block structure is presented as an enhanced version of the MOM model and the development framework. The study thoroughly considers the tasks performed by operators, encompassing movement assessment, collaboration with machines, work sequences, and ergonomic aspects. It is also emphasized that the integration of activity recognition technologies can enrich the valuable data within a knowledge graph in a smart factory setting. The issue of insufficient operator monitoring and assistance is discussed in the context of existing industry standards, advocating for a new human-centric approach to contemporary manufacturing practices. In the coming factories that use knowledge graphs, the data collection and knowledge exploration processes will be automated, thereby facilitating the creation of human digital twins and the adoption of Industry 5.0 technologies.

Our objective was to summarize current methods and tools for semantic development and to introduce a concept for creating standard models of human-centered collaboration, illustrated through an industrial case study. The key contributions of this paper are as follows.

- Emphasized the importance of incorporating human factors into cyber-physical systems.
- Proposed an expansion of automation standards (ISA-95, AutomationML, B2MML) to include human-related processes and demonstrated the use of semantic technologies.
- The concept was validated through a replicable industrial case study. Various graph-based analyses were conducted using different types of graphs such as normal, directed, or hypergraphs, including resource allocation analysis, KPI evaluation, and the integration of a DAS.
- The application based on HCKG facilitated the identification of various forms of collaboration between human and machine actors in the assembly process.
- Furthermore, a conceptual design was put forward for a human-centric manufacturing dashboard.

Future research will focus on enhancing the design of human–machine and human–human collaboration in manufacturing by implementing the HCKG concept in an intelligent environment. Several areas for improvement should be considered in future studies. One aspect is the incorporation of additional functionalities within the application block, such as an uncertainty simulator, a collaboration assessment tool, or an intelligent scheduling mechanism. Moreover, integrating HCKG into a digital twin and implementing closed-loop optimization and decision support could further strengthen the proposed approach. Lastly, it is crucial to encompass the entire HCKG pipeline and establish automated data retrieval within the shop floor and the semantic network.

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Institutional Review Board Statement: Not applicable.

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Data Availability Statement: The related dataset is freely and fully available on the website of the authors: https://github.com/abonyilab/HCKG (accessed on 14 March 2024).

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. Applied Methodologies and Software Tools

Figure A1 shows several processing stages of a data pipeline based on a study [69] that aims to create KGs for the automation industry. In addition, an end-to-end digital twin pipeline [70] has been taken into account.

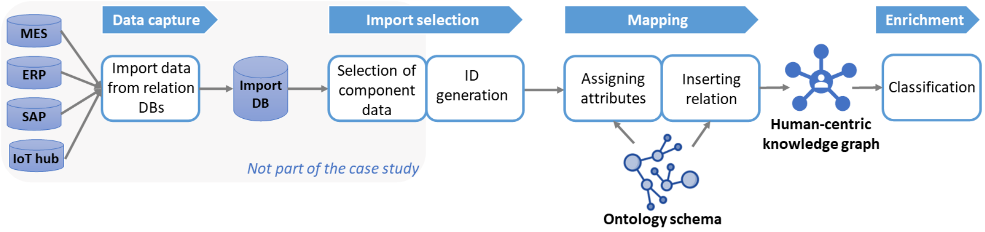

Figure A1. Knowledge graph pipeline based on [69].

It is beyond the scope of this paper to discuss the data acquisition and import selection parts of the pipeline. Only the KG, the ontology creation, the data queries, the mapping, and the data enrichment and visualization will be discussed. The phases, the methods used, and the different software stages of the industrial case study presented are shown in Figure A2.

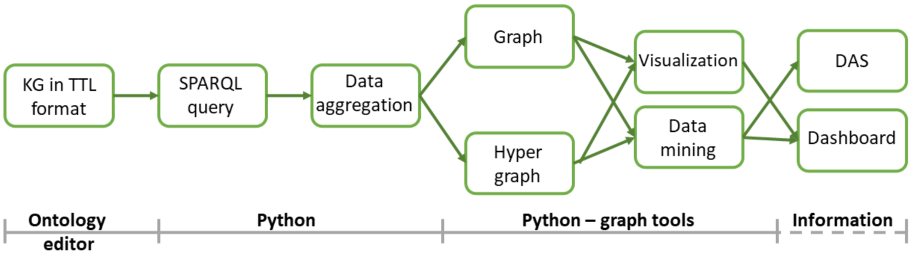

Figure A2. The steps of the applied method.

Before processing the TTL file in a Python 3.12.3 environment using Pyvis (a Python library for visualizing networks) [71] and KGlab [72,73], the sub-ontologies and the whole KG were developed using Protégé [74]. Either Protégé or KGlab can be used to import data into the ontology skeleton and to create axioms and properties in Python. For each data query, SPARQL language has been used [66]; moreover, Pyvis offers a graphical representation. Having mapped the semantic data, it was further aggregated in Python to obtain data-enriched graphs for analysis. Normal, directed, or hypergraphs can also be used for graph-based visualization of KG data. Finally, as a concept (denoted by a dashed line in Figure A2), the key information, generated charts, statements, or messages can be displayed on dashboards and DAS devices, or fill any other elements of the application block with data, as previously presented in Figure 4.

Appendix B. Assembly Activities of the Wire Harness Production Benchmark

Table A1. Description of the different activity types throughout the wire harness assembly benchmark.

Activity Type ID	Description of the Activity Type
t1	Point-to-point wiring on a chassis
t2	Laying in a U-channel
t3	Laying a flat cable
t4	Laying wire(s) onto the harness jig
t5	Laying one end of a cable connector onto a harness jig
t6	Spot-tying onto a cable and cutting it with a pair of scissors
t7	Lacing activity
t8	Lacing activity
t9	Inserting into a tube or sleeve
t10	Attachment of a wire terminal
t11	Screw fastening of a wire terminal
t12	Screw-and-nut fastening of a wire terminal
t13	Circular connector
t14	Rectangular connector
t15	Clip installation

Table A1. *Cont.*

Activity Type ID	Description of the Activity Type
t16	Loading of the AGV
t17	Transportation
t18	Manual handling of a wire from a buffer
t19	Positioning of a crimp into a vise
t20	Inserting a wire into a crimp
t21	Starting a machine
t22	Crimping
t23	Manual handling of a semi-finished product
t24	Handover of a semi-finished product
t25	Positioning of a crimp into a fixture
t26	Manual handling of a semi-finished product into a buffer
t27	Unloading of the AGV

Table A2. The activity types in the wire harness assembly process and their results.

	Crimping Process
t18	Manual handling of a wire from a buffer Result: One piece of wire is moved to the crimping station from the buffer.
t19	Positioning of a crimp into a vise Result: Crimp is positioned into a vise.
t20	Inserting a wire into a crimp Result: Wire is inserted into a crimp.
t21	Starting a machine Result: Machine is running.
t22	Crimping Result: Crimping is finished.
t23	Manual handling of a semi-finished product Result: Semi-finished product is removed from the vise.
t24	Handover of a semi-finished product Result: Semi-finished product is moved to another station.
	Assembly process
t2	Laying in a U-channel Result: U-channel is laid in the right assembly zone.
t4	Laying wire(s) onto a harness jig Result: Wire(s) is (are) laid correctly onto a harness jig.
t9	Insertion into a tube or sleeve Result: Tube is inserted into the correct sleeve.
t11	Fastening of the terminal with screws Result: Terminal screws are fastened.
t25	Positioning of a crimp into a fixture Result: Crimp is correctly positioned into the fixture.
t26	Manual handling of a semi-finished product into a buffer Result: Semi-finished product is placed into the buffer.
	Material handling
t16	Loading of the AGV Result: Parts are loaded on to the rack of the AGV.
t17	Transportation by an AGV Result: AGV moved the position from the source to its destination
t27	Unloading of the AGV Result: Parts are unloaded from the rack of the AGV.

Table A3. The sequence of activities as well as the results of the proposed wire harness assembly benchmark and their details—Part 1.

Activity ID	Activity Type ID	Result ID	Result Type ID	Process Step	Number of Process Steps
a1	t16	res1	res_type_16	Storage 1—AGV1	1
a2	t17	res2	res_type_17	Storage 1—Buffer1	1
a3	t27	res3	res_type_27	AGV1—Buffer1	1
a4	t18	res4	res_type_18	Buffer1—Crimping1	Batch size
a5	t19	res5	res_type_19	Crimping1	Batch size
a6	t20	res6	res_type_20	Crimping1	Batch size
a7	t21	res7	res_type_21	Crimping1	Batch size
a8	t22	res8	res_type_22	Crimping1	Batch size
a9	t23	res9	res_type_23	Crimping1	Batch size
a10	t24	res10	res_type_24	Crimping1—Assembly1	Batch size
a11	t24	res10	res_type_24	Crimping1—Assembly1	Batch size
a12	t25	res11	res_type_25	Assembly1	Batch size
a13	t02	res12	res_type_02	Assembly1	Batch size
a14	t02	res12	res_type_02	Assembly1	Batch size
a15	t04	res13	res_type_04	Assembly1	Batch size
a16	t04	res13	res_type_04	Assembly1	Batch size
a17	t09	res14	res_type_09	Assembly1	Batch size
a18	t09	res14	res_type_09	Assembly1	Batch size
a19	t11	res15	res_type_11	Assembly1	Batch size
a20	t11	res15	res_type_11	Assembly1	Batch size
a21	t26	res16	res_type_26	Assembly1—Buffer2	Batch size
a22	t16	res17	res_type_16	Buffer2—AGV1	1
a23	t17	res18	res_type_17	Buffer2—Buffer3	1
a24	t27	res19	res_type_27	AGV1—Buffer3	1
a25	t18	res20	res_type_18	Buffer3—Crimping2	Batch size
a26	t19	res21	res_type_19	Crimping2	Batch size
a27	t20	res22	res_type_20	Crimping2	Batch size
a28	t21	res23	res_type_21	Crimping2	Batch size
a29	t22	res24	res_type_22	Crimping2	Batch size
a30	t23	res25	res_type_23	Crimping2	Batch size
a31	t24	res26	res_type_24	Crimping2—Assembly2	Batch size
a32	t24	res26	res_type_24	Crimping2—Assembly2	Batch size
a33	t25	res27	res_type_25	Assembly2	Batch size
a34	t02	res28	res_type_02	Assembly2	Batch size
a35	t02	res28	res_type_02	Assembly2	Batch size
a36	t04	res29	res_type_04	Assembly2	Batch size
a37	t09	res30	res_type_09	Assembly2	Batch size
a38	t11	res31	res_type_11	Assembly2	Batch size
a39	t11	res31	res_type_11	Assembly2	Batch size
a40	t26	res32	res_type_26	Assembly2—Buffer4	Batch size
a41	t16	res33	res_type_16	Buffer4—AGV1	1
a42	t17	res34	res_type_17	Buffer4—Buffer9	1
a43	t27	res35	res_type_27	AGV1—Storage 2	1
a44	t16	res36	res_type_16	Storage 1—AGV1	1
a45	t17	res37	res_type_17	Storage 1—Buffer5	1
a46	t27	res38	res_type_27	AGV1—Buffer5	1
a47	t18	res39	res_type_18	Buffer5—Crimping3	Batch size
a48	t19	res40	res_type_19	Crimping3	Batch size
a49	t20	res41	res_type_20	Crimping3	Batch size
a50	t21	res42	res_type_21	Crimping3	Batch size
a51	t22	res43	res_type_22	Crimping3	Batch size
a52	t23	res44	res_type_23	Crimping3	Batch size
a53	t24	res45	res_type_24	Crimping3—Assembly3	Batch size
a54	t24	res45	res_type_24	Crimping3—Assembly3	Batch size
a55	t25	res46	res_type_25	Assembly3	Batch size
a56	t02	res47	res_type_02	Assembly3	Batch size
a57	t02	res47	res_type_02	Assembly3	Batch size
a58	t04	res48	res_type_04	Assembly3	Batch size
a59	t04	res48	res_type_04	Assembly3	Batch size
a60	t09	res49	res_type_09	Assembly3	Batch size
a61	t09	res49	res_type_09	Assembly3	Batch size
a62	t11	res50	res_type_11	Assembly3	Batch size
a63	t11	res50	res_type_11	Assembly3	Batch size
a64	t26	res51	res_type_26	Assembly3—Buffer6	Batch size
a65	t16	res52	res_type_16	Buffer6—AGV1	1
a66	t17	res53	res_type_17	Buffer6—Buffer7	1
a67	t27	res54	res_type_27	AGV1—Buffer7	1
a68	t18	res55	res_type_18	Buffer7—Crimping4	Batch size
a69	t19	res56	res_type_19	Crimping4	Batch size
a70	t20	res57	res_type_20	Crimping4	Batch size
a71	t21	res58	res_type_21	Crimping4	Batch size
a72	t22	res59	res_type_22	Crimping4	Batch size
a73	t23	res60	res_type_23	Crimping4	Batch size

Table A4. The sequence of activities as well as the results of the proposed wire harness assembly benchmark and their details—Part 2.

Activity ID	Activity Type ID	Result ID	Result Type ID	Process Step	Number of Process Steps
a74	t24	res61	res_type_24	Crimping4—Assembly4	Batch size
a75	t24	res61	res_type_24	Crimping4—Assembly4	Batch size
a76	t25	res62	res_type_25	Assembly4	Batch size
a77	t02	res63	res_type_02	Assembly4	Batch size
a78	t02	res63	res_type_02	Assembly4	Batch size
a79	t04	res64	res_type_04	Assembly4	Batch size
a80	t09	res65	res_type_09	Assembly4	Batch size
a81	t11	res66	res_type_11	Assembly4	Batch size
a82	t11	res66	res_type_11	Assembly4	Batch size
a83	t26	res67	res_type_26	Assembly4—Buffer8	Batch size
a84	t16	res68	res_type_16	Buffer8—AGV1	1
a85	t17	res69	res_type_17	Buffer8—Buffer9	1
a86	t27	res70	res_type_27	AGV1—Storage 2	1

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The human-centric Industry 5.0 collaboration architecture

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A R T I C L E I N F O

Method name:
I5arc - Industry 5.0 collaboration architecture

Keywords:
Collaboration
Industry 5.0
Artificial intelligence
Manufacturing
Industry 4.0
Human-centric
Ontology
Knowledge graph

A B S T R A C T

While the primary focus of Industry 4.0 revolves around extensive digitalization, Industry 5.0, on the other hand, seeks to integrate innovative technologies with human actors, signifying an approach that is more value-driven than technology-centric. The key objectives of the Industry 5.0 paradigm, which were not central to Industry 4.0, underscore that production should not only be digitalized but also resilient, sustainable, and human-centric. This paper is focusing on the human-centric pillar of Industry 5.0. The proposed methodology addresses the need for a human-AI collaborative process design and innovation approach to support the development and deployment of advanced AI-driven co-creation and collaboration tools. The method aims to solve the problem of integrating various innovative agents (human, AI, IoT, robot) in a plant-level collaboration process through a generic semantic definition, utilizing a time event-driven process. It also encourages the development of AI techniques for human-in-the-loop optimization, incorporating cross-checking with alternative feedback loop models. Benefits of this methodology include the Industry 5.0 collaboration architecture (I5arc), which provides new adaptable, generic frameworks, concepts, and methodologies for modern knowledge creation and sharing to enhance plant collaboration processes.

- The I5arc aims to investigate and establish a truly integrated human-AI collaboration model, equipped with methods and tools for human-AI driven co-creation.
- Provide a framework for the co-execution of processes and activities, with humans remaining empowered and in control.
- The framework primarily targets human-AI collaboration processes and activities in industrial plants, with potential applicability to other societal contexts.

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Resource availability:	Ontology-based analysis of manufacturing processes: https://github.com/abonyilab/wire_harness_assembly

Method details

Introduction

The importance of increasing productivity while not removing human workers from the shopfloor creates challenges for the production enterprises and the developers of industrial information systems. Additionally, the horizontal and vertical integration of systems requires more efficient data processing in Industry 4.0 applications.

The European manufacturing industry's key challenge is improving its productivity and resilience to possible external market turbulence and resource availability. The ongoing Industry 4.0 digitalization technologies create a fair technical condition to cope with this challenge. However, the recent digitalization impact studies indicate that developing manufacturing plants with sophisticated, in many cases, not interoperable technical systems alone will not fully address this challenge, as resulted in human-centric Industry 5.0 focus [1]. Despite the digitalization and automation focus, humans (e.g., operators, technicians) will remain as a fundamental resource for competitiveness of the manufacturers, especially for activities requiring flexibility, customization, and uniqueness [2]. Humans will have fewer physical tasks in the highly automated and digitalized factories of the future, but more decision making and problem-solving tasks [3] in the context of increasingly complex, socio-cyber-physical manufacturing system [4].

The Industry 5.0 collaboration architecture (I5arc) supports the development and implementation of human-AI collaborative process design and innovation methodology to support the design and implementation of next-generation AI-driven co-creation and collaboration tools. From this motivation, the scope of the I5arc specified as:

- Collaboration knowledge: required for efficient and resilient plant operational process (e.g., supervision, quality control, maintenance, remote assistance).
- Research: new generic, sector-independent Industry 5.0 collaboration concepts and architectures.
- IT services: management of knowledge structures (based on the Semantic web) and user-controlled creation and use of knowledge.
- Business: improving plant productivity and resilience by better multi-agent collaboration.
- Human control: the capability to customize the generic collaboration platforms and processes, with user-friendly communication, and reliable and explainable AI (Artificial Intelligence) knowledge services.
- Availability: I5arc services accessible from standard desktop and mobile wearables (e.g., smart glasses). Plant specific user-friendly Communication Language (PCL) for all collaboration agents.

The research gap is the development of a comprehensive methodology that enables effective human-AI collaboration, incorporating diverse innovative agents in plant-level processes. This includes creating adaptable frameworks, tools, and techniques that facilitate human-AI co-creation and co-execution while ensuring humans remain empowered and in control. Additionally, the methodology should be applicable to various societal contexts beyond industrial plants, extending its potential impact and relevance.

The I5arc identified five topics, that constitute the conceptual and technological challenges to be overcome:

√ AI-Human co-creation of ontology-based Plant Knowledge Base (PKB) structure.
√ Co-creation and execution of multi-agent resilient and innovative collaboration processes.
√ Explainable and trustworthy AI services for empowering users.
√ Immersive learning services for Human-AI collaboration.
√ Sustainable I5arc Innovation Methodology.

Background

This Section summarizes the background, the problem statement, the need of the industry, and the development goals of the human-centric collaboration architecture topic. First describes the needs of industry stakeholders, then presents the main goals of the Industry 5.0 collaboration architecture. Finally the semantic web-based approach of collaboration support is introduced.

The common needs of the manufacturers

The manufacturing industries must face rapid technological transformation, mass customization, and the need for advanced manufacturing. Robots must be coupled with the human mind and a strong necessity to increase productivity [2]. This problem is addressed by digitalizing human-centric plant-level collaboration activities (e.g., production unit set-up, work safety, maintenance, repairs, etc.). The common need in this domain can be summarized as follows:

(a) The collaboration activities are planned or recorded in unstructured formats [5]. Although there are simple data entry (checklist) apps on the market, the industry acceptance could be higher for several reasons: special working conditions (as free hands requiring smart glasses [6]or flexibility in the process change. These apps are mainly capable of 1:1 Human-machine interactions only.
(b) However, the core problem is the need for more approaches and solutions for the coordination and digitalization of collaboration activities of several actors [7] in real-time. Humans, IoT Machine, AI services in the future working together in a process e.g., in major production line repairs.
(c) Limited availability of user-friendly practices for structuring and reusing collected process data by other participants (e.g., plant technologists) and AI services. Furthermore, there is a clear professional user interest to act not only as an operator but as a knowledge co-creator of digital service structures and be able to access and contribute to the company's knowledge base directly from their workplace.

Aims of the Industry 5.0 collaboration architecture

The Industry 5.0 collaboration architecture (I5arc) aims to solve the question: how does the quality of collaboration in terms of technical tools, knowledge services, and the social environment provided for participants affect manufacturing process quality and operational sustainability? The main aims are the followings:

1. Availability of digital content of the collaboration processes (planned, performed, and evaluated) as part of the plant's digital twin.
2. The latest technologies are integrated into the process: wearables for in-line digitalization of user interactions [8], VR/AR, and extended reality visualization services.
3. The extent of creation and reuse of new knowledge produced by reliable AI services, alongside the whole collaboration process.
4. Availability of comprehensive methods for user-controlled creation and instant innovation of plant-specific collaboration platforms.
5. Social management of the new digital collaborating culture. Inclusion of all relevant stakeholders of the plant - from top management to frontline workers - into controlled creation and access to knowledge about the collaboration processes. Services for on-demand learning and remote work services improve plant human resources' work-life balance.

The human-centric collaboration supported by the semantic web methodologies

The Semantic Web stands for an extension of the World Wide Web with standards aiming to make the internet data machine-readable. It involves publishing in languages specifically designed for data, such as Extensible Markup Language (XML), Resource Description Framework (RDF) and Web Ontology Language (OWL). An ontology can be determined as a graph-based data model that manages how entities (individuals) are grouped into categories (classes) and which appear on the most fundamental level. Additionally, ontologies can describe real-world phenomena and their relationships among each other in a machine-readable way by using formal elements, such as instances, rules, relationships and axioms [9]. A knowledge graph is a highly flexible non-SQL database representing data as "knowledge" through a graph-like structure of nodes and edges. The nodes that refer to the knowledge are often defined in an ontology, the concepts that describe the domain. They can be traversed semantically using domain knowledge.

An ontology-based development framework is visualized in Fig. 1, where the three main steps are data collection, ontology modeling, and the so-called advanced manufacturing analytics [10]. Semantic technologies can be combined not only with manufacturing-related analytic tools, but with industrial standards and specific Industry 5.0 technologies, which can facilitate the creation of a human-centered knowledge graph [11]. Industry 5.0 will be an "Age of Augmentation" or the human-machine symbiosis [8]. However, humans must be well-aware of the decision they are making and why. Humans must establish confidence in the automatically derived predictions and suggested decisions within smart factories [12]. The Operator 4.0 concept [13] is the lead framework of human-centered solutions. Also, a common interface for Operator 4.0 applications as an architecture of a human-digital twin is proposed [14], and the enabling technologies of Operator 4.0 [13] are compared with the Industry 4.0 solutions. Furthermore, brownfield digitalization smart retrofitting solutions can be aided by integrating the Operator 4.0 concept with IoT and further Industry 4.0 solution [15].

Additional emerging graph-based modeling and analysis method relays on hypergraphs, which is a generalization of a graph, where an edge (also known as a hyperedge) can connect more than two vertices. Hypergraph-based representation and analysis can be applied to identify the indirect interactions in a complex system or data structure [16] or can support the human-centric approach

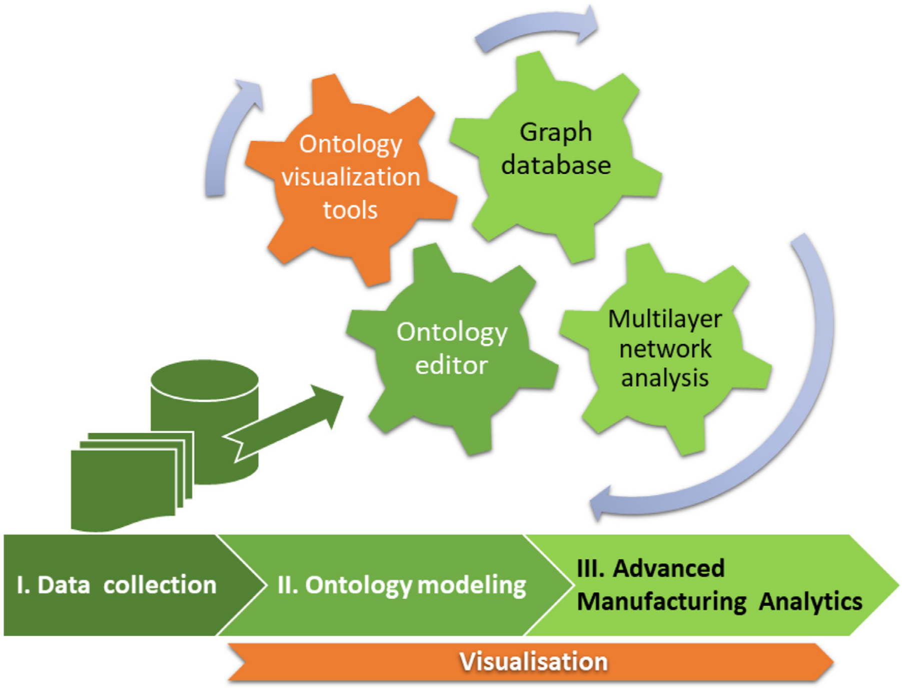

Fig. 1. Ontology-based development framework for manufacturing process analysis [10].

as described in connection with the so-called Intelligent collaborative manufacturing space [17] as well. It can be concluded, that graph or hypergraph-based semantic networks as ontologies or knowledge graphs has a high potential to facilitate data integration and contextualization in Industry 4.0 and 5.0 environments.

Several semantic web methodologies and systems are studied and tested [10,18], suitable to implement the semantic framework for a manufacturing plant: PoolParty [19], Oxford Semantics, and Ontotext. The aim is to find the ideal operational platform that provides the best user interface for creating and updating plant taxonomy and ontology. The semantic web standards have analysed, which are available for manufacturing execution systems (MES) [20]. Their disadvantages include needing more detailed collaboration, location and time concepts, and relationships.

Method details - The I5arc framework

This section introduces the I5arc approach for human-AI collaboration, starting with the main methodology, the I5arc Process Innovation Cycle. First, the Human-AI empowerment approach, then the event-driven workflow concept is presented. The proposed I5arc framework introduces a new culture for plant-level multi-agent collaborations involving the support of AI agents, where human is a center point in these processes. Therefore, the key challenge is the Human-AI acceptance of this type of collaboration. The approach aims to introduce tangible, reliable economic, technical and social benefits.

The I5arc Innovation Cycle Methodology (ICM) presented in Fig. 2 represents the integrated objective of the project and establishes a framework for co-design and execution of human-AI collaborative processes functioning and adapting towards common goals, combining the best of human and AI roles, knowledge, and abilities, as well as incorporating the societal requirements. Therefore, the proposed framework addresses six improvement opportunity domains highlighting the key results, namely: *1.* Evaluate and plan the process, *2.* Design process in PCL (Plant Collaboration Language), *3.* Consider societal aspects, *4.* Implement the process, *5.* Create digital knowledge in PCL and *6.* analyze process knowledge. The participating agents of the I5arc Process Innovation Cycle are also visualized in Fig. 2, such as Plant knowledge worker, AI agent service, Frontline worker, Collaborative robot and IoT device. Additionally, the internal tasks of the six domains are also listed in Fig. 2.

Furthermore, the I5arc framework defines the following new research concepts in RDF notations:

1. Collaboration participant: Definition of collaboration scope of the participant. Multi-agent participant classes (Human, IoT machine, Robot, AI service).
2. Participant actual tasks overview: An overview of collaboration tasks where the participant must or can participate.
3. Active participation: Participation in a task of a manufacturing process (work order). An agent can participate in several work order tasks.
4. Recommended participation: Recommended by a participant's supervisor or by Recommendation of AI services. 175

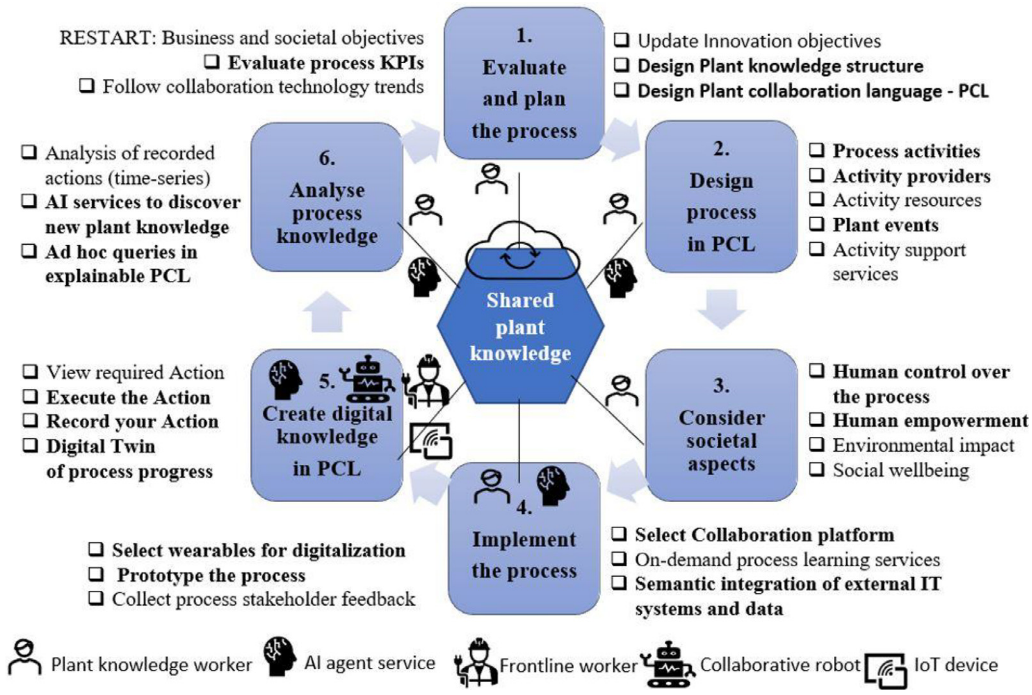

Fig. 2. The methodology of the I5arc Process Innovation Cycle, that creates the Shared plant knowledge with the combination of the six elements.

5. Plant events: Relevant plant operational events structured by process domains. Event attributes are name, value, time of setting, and plant location relevant to the event. The event can be single or composed of Boolean expressions.
6. Collaboration process: Defines the standard collaboration activity structure in the plant. Collaboration platforms and plant operational domains can structure it. Execution of concurrent workflows (work orders) is synchronized by plant events, as outlined in Fig. 2. The process can involve several concurrent workflow instances.
7. Collaboration platform: Technical, operational environment providing certain collaboration support services. (e.g., AR, VR, 3D Models) available to agents.
8. Plant operational assets: Plant asset register by locations and asset classes (machines, infrastructure, systems). The ISA-95 standard for Production model taxonomy and Plant resources is also recommended for implement.
9. Plant resources: Structured by agent, raw material, energy, tools, consumables, and services classes, and their instances.
10. Plant knowledge base (PKB): Contains formal machine-readable definitions, relationships, and instances of the *1–9.* concept. Human-centric interaction with PKB in a user-definable metalanguage.

The human-AI empowerment approach

The introduction of credible human empowerment for any new work culture requires:

- Humans with access to up-to-date tacit knowledge perform their work with high quality and satisfaction.
- AI, which services, must use the same tacit knowledge to create new and trustworthy knowledge for humans.

The cornerstone of the solution is the plant's digital memory, a consistent and common source of any activity for Humans and AI services. Therefore, the implementation of the Plant Knowledge Base (PKB) concept is key to addressing the needs and ambitions of this framework. The technical measures are summarized in Fig. 3, where the three main categories are the *Common Plant Knowledge Base (PKB)*, the *Plant collaboration Language (PCL) with user services* and the *On-line visualization services (Explainable AI)*. The relevant factors for empowerment are listed for each group on Fig. 3.

The common technical measures should be dedicated to each stakeholder group participating in the collaboration processes:

- Company managers (improved productivity and resilience).
- Plant specialists (improved governance and analytics on the process).
- Frontline workers (online support for work execution and workplace learning).
- Citizen groups (access of less qualified workforce to qualified jobs).

The implementation approach and the collaboration levels (platforms) can be adjusted to the company culture and digital maturity of the plant human resources by support services as:

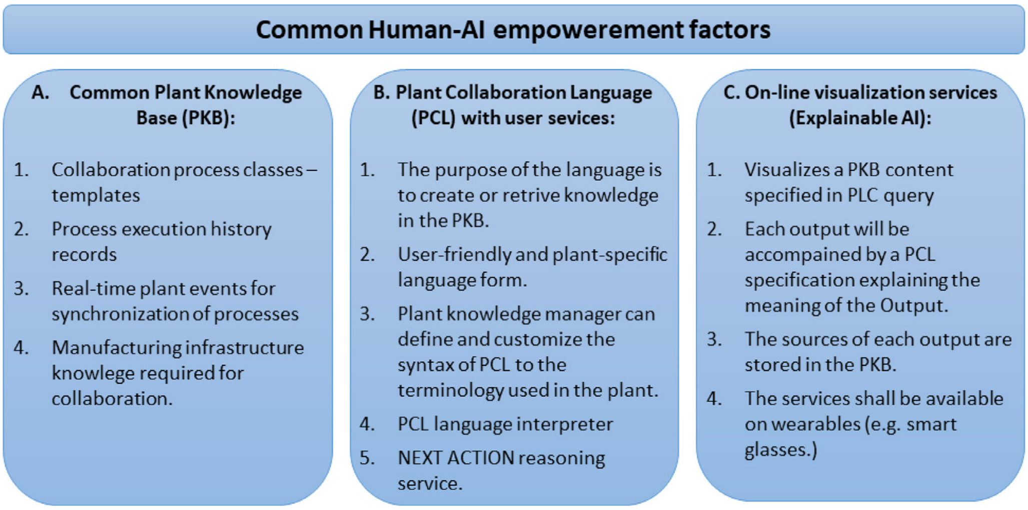

Fig. 3. Human-AI empowerment factors in three categories: Common Plant Knowledge Base, Plant Collaboration Language and On-line visualization services.

- Providing tacit and AI-generated plant knowledge *via* user-friendly communication language and visualization services.
- Real-time learning-on-demand of collaboration tasks of human participants adjusted to their role.
- Remote and extended reality collaboration services improve the work-life balance of the plant's human resources.
- Access of less qualified workers to more skilled jobs.

The event-driven workflow concept

An important feature of the approach is the generalized definition of the participant (*1.*). The most frequent scenario in many high-tech industrial plants, the bilateral Human – AI relationship is analysed and optimized in a multi-agent collaboration efficiency context. The concepts are centered around. The primary activity concept of the collaboration process (*6.*) - the I5arc event-driven workflow concept is demonstrated in Fig. 4. This innovative concept enables time and location-sensitive control of the execution of each elementary workflow action. Additionally, the interaction of PKB with collaboration scenarios (multi-agent workflows) is also outlined in Fig. 4. A *workflow* depends on the *Collaboration process*, the *Requester resource* and the *Provider resource*. Sub-steps and instructions are the building elements of a complex workflow. The results of instructions trigger the different events in Fig. 4. Additionally, the instructions are enabled by certain events only. The *steps* (group of actions) are related to a physical location (as machines or components) of the plant.

Thanks to the presented workflow, the I5arc framework enables to embed of the vital priority (human AI empowerment) into the broader perspectives of the manufacturing plant level collaboration needs as:

- Multi-agent real-life scenarios where Human agents have increased control roles.
- Creation of a solid and focused research foundation for this broader approach, resulting in increased empowerment of the introduction and use of AI in manufacturing.

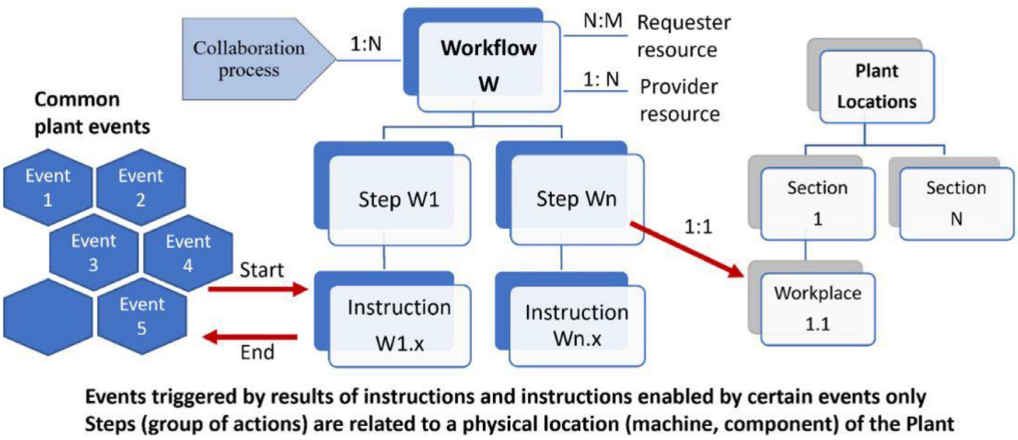

Fig. 4. The methodology of event-driven workflow concepts, which aims to support human-AI collaboration.177

- Common communication language (PCL – Plant Collaboration Language) among all agents always *via* the PKB interaction services.

Advantages and disadvantages of the proposed framework

Based on the previous discussions of the methodology, this subsection aims to summarize the potential advantages and disadvantages of the human-centric Industry 5.0 collaboration architecture.

The potential advantages of adopting the presented human-centric approach are numerous and could have significant impacts on productivity, efficiency, and innovation, including the followings:

- Improved collaboration: The human-centric approach promotes cooperation and collaboration between humans and machines, fostering a more efficient, resilient, and innovative work environment.
- User-oriented design: AI-driven co-creation of PKB ontology accommodates user needs, work culture, and plant terminology, leading to more intuitive and easy-to-use tools.
- Enhanced decision-making: The ability to incorporate human input in real-time, event-driven processes can lead to more informed decision-making, thereby improving the overall efficiency and productivity.
- Flexibility: This approach allows for the participation of multiple innovative agents, providing the flexibility to adapt to different situations and requirements.
- Continuous innovation: The model encourages ongoing innovation, with an ontology-controlled PKB IT service portfolio that supports the evolution of collaboration processes.

However, as with any transformative change, there are also potential challenges and disadvantages to consider, which may include:

- Technological complexity: The integration of various innovative agents such as AI, IoT, and robots might present technical challenges related to interoperability, data privacy and security.
- Need for training and adaptation: Implementing a new system that heavily involves human-AI collaboration could necessitate significant training for workers to adapt to the new system, and there might be resistance to change.
- Financial implications: The implementation and maintenance of such a sophisticated and technologically advanced system could be costly, particularly for smaller businesses, potentially limiting its accessibility.
- Risk of technological redundancy: Given the pace of technological advancements, there is a risk that elements of the system may become outdated, requiring continuous updates and adaptations.

It is crucial to thoroughly evaluate these potential advantages and disadvantages when considering the implementation of a human-centric Industry 5.0 collaboration architecture in real-life applications.

Conclusions

Industry 5.0 research advancements are advised to promote cooperation between humans and machines, including the AI-aided joint creation of PKB ontology that supports user-oriented design and regulation of the ontology, adapted to the specific needs, work culture, and terminology of the plant. Moreover, a universal semantic description of plant-level collaborative processes is necessary, allowing multiple innovative agents (e.g., humans, AI, IoT, robots) to participate in real-time, event-driven processes. The creation of artificial intelligence techniques is also essential for human-in-the-loop optimization, cross-referenced with alternative feedback loop models. It is vital to incorporate all individual objectives into a comprehensive innovation lifecycle for shopfloor-level manufacturing collaboration processes, taking into account both technological innovation and societal factors. Additionally, the innovation of each collaborative process is sustained by a coherent ontology-controlled PKB IT service portfolio, which provides online access and customization of the methodology for plant innovation users.

The proposed approach primarily focuses and explores the Human-AI collaboration processes in industrial contexts. The six presented domains also represent the current and potential industrial needs in the Human-AI driven co-design and co-execution of manufacturing plant-level collaboration processes. These processes involve typical collaboration human-centric activities such as production facility testing, workplace material logistics, regular maintenance, repairs, work safety audits, quality control, etc. The definition of the Human-AI driven plant-level collaboration process include the following aspects:

- Set of actions aiming to achieve a plant operational objective (e.g., weekly preventive maintenance of all water supply units of the plant, setup/repair of a machine line requiring coordinated participation of several actors, etc.).
- Each action shall be executed by the provider role defined in the workflow definition (qualified person or technical agent).
- The actual execution workflow of Actions depends on the actual plant events.
- Actions of a collaboration process can be executed in multiple locations (workplaces) of the plant.

The I5arc Innovation Cycle methodology, supported by AI services, facilitates the creation of new jobs as well, for example, plant knowledge engineer, plant robot engineer, and plant data analyst. In addition, it enables more personalized human access to plant knowledge and improve work safety and work-life balance by enabling remote plant work.

Ethics statements

NA.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Attila Tóth: Conceptualization, Methodology, Writing – original draft. **László Nagy:** Writing – original draft. **Roderick Kennedy:** Conceptualization, Methodology. **Belej Bohuš:** Conceptualization, Methodology. **János Abonyi:** Writing – review & editing, Supervision. **Tamás Ruppert:** Conceptualization, Methodology, Writing – review & editing, Supervision.

Data availability

No data was used for the research described in the article.

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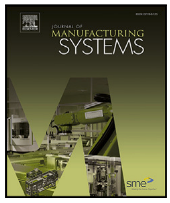

Hypergraph-based analysis and design of intelligent collaborative manufacturing space

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ABSTRACT

A method for hypergraph-based analysis and the design of manufacturing systems has been developed. The reason for its development is the need to integrate the human workforce into Industry 4.0 solutions. The proposed intelligent collaborative manufacturing space enhances collaboration between the operators as well as provides them with valuable information about their performance and the state of the production system. The design of these Operator 4.0 solutions requires a problem-specific description of manufacturing systems, the skills, and states of the operators, as well as of the sensors placed in the intelligent space for the simultaneous monitoring of the cooperative work. The design of this intelligent collaborative manufacturing space requires the systematic analysis of the critical sets of interacting elements. The proposal is that hypergraphs can efficiently represent these sets, moreover, studying the centrality and modularity of the resultant hypergraphs can support the formation of collaboration and interaction schemes and the formation of manufacturing cells. A fully reproducible illustrative example presents the applicability of this concept.

1. Introduction

Future intelligent factory ensures the synergy of the skills of machines (such as robots) and humans to increase productivity and maintains healthy, safe and sustainable working conditions [1]. One of the biggest challenges of modern manufacturing is to create an adequate human–machine relationship in complex human–machine systems, especially when a strong synergy between the capabilities of machines and humans is needed. Direct collaboration or task sharing within the same working area requires connecting machines even more closely to humans [2].

In a so-called human-in-the-loop smart manufacturing concept, digitalisation aims to facilitate relationships between humans and manufacturing sites [3]. Similarly, in a human-centric smart manufacturing concept, the goal is to develop a human-cyber–physical system (H-CPS) [4]. The human influence on cyber–physical systems (CPS) plays a dominant role in the formation and development of CPS, e.g., the cognitive skills are taken into account in interface design [5]. Therefore, human intelligence is a dominant and decisive factor in intelligent manufacturing, consistent with the concept of H-CPS [6].

The human-centric manufacturing aims that the industry should place the well-being of shopfloor workers at the centre of manufacturing processes instead of being system-centric. Practice should ultimately address human needs defined in an Industrial Human Needs Pyramid — from safety and health to the highest level of esteem and self-actualisation. The five levels of industrial human needs, and the five steps between them, are the followings: safety — coexistence, health — cooperation, belonging — collaboration, esteem — compassion, self-actualisation — coevolution, based on Ref. [7]. From the motivation of increasing productivity while not removing human workers from the manufacturing industry, the concept of Industry 5.0 [8] is considered, where robots are intertwined with the human brain and work as a collaborator. The main aspects of Industry 4.0 aim to bring about extensive digitalisation, while in an Industry 5.0 environment, the goal is to integrate innovative technologies with human actors or can be regarded as more value-driven than technology-driven approach [9,10].

The so-called industrial immersive technologies (IIT) summarise technical solutions which play a key role in forming the new industrial revolution and the human-centric cyberphysical systems for complex manufacturing processes. A wide range of papers and patents are available in this area, which also serves as a source of a domain ontology for IIT in Ref. [11]. The overview of technology specifications divides these tools into four main groups: brain–machine interfaces, virtual reality, augmented reality and industrial engineering [11].

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A new trend in the research and development of human factors as well as the stochastic nature of humans during manufacturing processes is the Operator 4.0 concept, which proposes eight different types of how workers on the shop floor can be supported [12]. A workforce is one of the most critical manufacturing resources as well as the most agile and flexible, therefore, the improvement of human operator resilience can also make manufacturing systems more resilient, which is discussed in the Resilient Operator 5.0 concept [13]. The central element of these solutions is the integrated monitoring of the activities of the operators and the manufacturing system. The Resilient Operator 5.0 concept is defined as a competent and skilled shop-floor worker using human creativity, ingenuity and innovation, aided by information and technology to overcome difficulties or obstacles. At the same time, it also aimed to develop additional and cost-effective solutions to ensure long-term sustainability and workforce well-being in manufacturing while facing unexpected conditions [13]. The development of the enabling technologies of the Operator 5.0 concept requires a wide field of research. Various frameworks integrating digital technologies such as Extended Reality, Big Data Analytics, Artificial Intelligence, and Digital Twins must be standardised for industrial usage. A survey [14] set three main characteristics as assisting parameters for this goal: human-centricity, (social) sustainability, and resilience.

Another research topic, namely the Intelligent Factory Space (IFS) concept, represents a framework for interaction between humans and an automated system (digital factory) for which three key features are proposed: Observing, Learning and Communication [2]. The IFS is composed of multiple layers (representing different services for the human user) and many modular components, which can be extended to meet the requirements of users. The IFS relies on industrial standards to communicate with existing machines while using novel two-way communication possibilities to feedback to the human user [2]. A further aspect of this emerging approach to manufacturing in the future, which needs to take into account the Smart Factory concept [15], aims to apply technologies that lead to adaptive and flexible manufacturing such as IIoT devices or cloud services [16].

The main finding of this paper is that the development of these solutions can be based on the proposed intelligent collaborative manufacturing space (ICMS) concept. ICMS aims to achieve real-time monitoring-based control for semi-automated production systems, thereby creating more precise collaboration between human workers and machines. In this paper, the goal is to highlight the effectiveness of the proposed ICMS, which offers an outstanding opportunity for collaboration between human and machine participants in the production process. The design of this ICMS requires the systematic analysis of the critical sets of interacting elements. The key idea is that hypergraphs can efficiently represent these sets, moreover, studying the centrality as well as modularity of the resultant hypergraphs can support the formation of collaboration and interaction schemes in addition to the creation of manufacturing cells.

Hypergraphs provide a sufficient description of a system with hierarchical and multilevel model techniques to describe collaboration between larger groups or complex networks. In operations research, one of the most dynamically developing fields is related to hypergraphs [17, 18] and higher order interactions [19]. In traditional networks, only pairwise interactions are defined within the vertices, which is suitable for describing collaborations between two participants but insufficient in the case of complex networks, describing collaborations between larger groups. Therefore, formalising a multilayer higher-order network can help uncover network properties such as the community structure, various centrality measures [19] and efficient clustering of data [20]. Hypergraphs are also increasingly being used in cooperative game theory [21,22] as well as in cooperative multi-agent reinforcement learning [23].

It is believed that hypergraph models will be much more widely applied in the analysis and design of manufacturing systems. The applicability of this modelling approach has already been proven in the design of knowledge-centric robot systems where, based on a structural meta-model and the related domain-specific language, a hypergraph has been designed [24].

The analytical techniques of hypergraphs can also support the design of smart manufacturing applications. The clustering-based Cloud Manufacturing Service Management Model has been developed to manage the high number of instances in which dynamically changing cloud services are applied, using three different layers [25]. Allocation problems of flexible manufacturing systems, e.g. tool switching problems, can also be handled more efficiently with hypergraphs [26]. Another application is a hypergraph convolutional network, developed to predict the removal rate of material in chemical mechanical planarisation, the benefit of which is to identify the structure of underlying equipment containing essential interaction mechanisms among different components [27].

Since a manufacturing cell can be identified as a sub-hypergraph hypergraphs can also support the field of cell formation in Flexible Manufacturing, creating multidimensional layout diagrams and analysing the internal mechanism [28]. Furthermore, the framework of a hypergraph can facilitate the optimal model-based decomposition (OMBD) of engineering design problems [29]. A Cell Formation algorithm called Hypergraph BFS (Breadth-First Search) has been developed by Kandiller, which is another efficient machine-grouping procedure [30]. The algorithm examines the vertex set of the hypergraph and tries to form machine cells based on their similarities by partitioning the dataset as well as selecting key vertices and using them as roots in each search process [31]. Furthermore, hypergraphs can also support allocation problems in the era of Industry 4.0, e.g. in robot task allocation, where a multilevel framework is required to handle assignments [32,33].

Another field where the outstanding network analysis techniques of hypergraphs can be utilised is competency mapping, an approach highlighting expertise, reusing knowledge or monitoring key performance indicators (KPI) to increase productivity. The investigation of multi-hypergraph structures offers an effective solution for competency mapping [34].

This work aims to analyse how hypergraphs can be used to design ICMS. According to this aim, the main contributions and structure of this paper are as follows:

- The concept of ICMS for the next level of human–machine cooperation is introduced in Section 2.
- The methodology of higher-order network representation to facilitate collaboration is described in Section 3.
  - Firstly, in Section 3.1 hypergraph-based modelling of complex manufacturing systems is presented.
  - In Section 3.2, the main principles of hypergraphs are discussed.
  - A simple example of hypergraph-based modelling and theoretical visualisation of a production process is given in Section 3.3.
  - Finally, in Section 3.4, the hypergraph centrality measures are proposed to identify the key elements and relationships according to the intelligent space concept.
- A hypergraph-based case study of ICMS and the discussion of the results are presented in Section 4.
  - Firstly, the wire harness manufacturing process-based benchmark problem is presented in Section 4.1.
  - In Section 4.2, several representation methods of the hypergraph-based wire harness manufacturing model are shown.
  - Section 4.3 describes the identification methods of the critical elements and collaborations in the ICMS.
  - In Section 4.4, the segmentation analysis of the production process is discussed.

- Section 4.5 summarises the benefits of hypergraph-based analysis and discusses some further application possibilities.

- Finally, in Section 5 the types of information that can be extracted from the network analysis and how those can be utilised for the redesign of manufacturing systems are concluded.

2. Intelligent collaborative manufacturing space — the next level of collaboration

Today, as manufacturers struggle with shortages of highly skilled personnel, the value of effective collaboration is more significant than ever, e.g. workers will need to share more tasks in the future [35]. Among the top manufacturing executives, 43% think that collaboration can shorten the time to market for new products and 26% expect that improvements in terms of collaboration can reduce operational costs [36]. The necessity of better collaboration between humans and machines is highlighted by the following important statement: "Humans should never be subservient to machines and automation, but machines and automation should be subservient to humans" [37].

Therefore, future human–machine teams should be defined based on the three main features of human–machine symbiosis, namely human centrality, social wellness and adaptability [38]. The development of these balanced automation systems requires human-centred automation reference architectures to integrate the life cycle and human aspects into the Enterprise Architecture Body of Knowledge [39]. Human–machine collaborative intelligence is a partnership to optimise the benefits of teams and maximise their long-term returns with regard to interactions with the environment and other agents [38].

The proposed ICMS aims to handle the collaboration between humans and the automated production system based on real-time monitoring and control systems. In line with the wording of the term, the aim is to focus on the collaboration aspect, therefore, the expanded version of the already existing Intelligent Manufacturing and Intelligent Manufacturing Space concept is used. During the formalisation of the concept, recent reviews about Intelligent Manufacturing [40] and Smart Manufacturing [41] were also considered. Intelligent- or smart manufacturing aims to optimise production and product transactions by fully using advanced information and manufacturing technologies [42]. Intelligent manufacturing [43] can be defined as the utilisation of real-time data analysis, artificial intelligence (AI) methods and machine learning in the manufacturing process to optimise production. In this paper, the combination of AI solutions and [44] the data-driven approach of intelligent manufacturing [45] has been studied, and how to integrate these pioneer technological solutions with the Intelligent space concept by Ref. [46].

The proposed approach is based on the Intelligent Space [47], which is an environmental system to support human workers with information and physically. The concept of intelligent spaces was proposed in 1999 [47], moreover, just as in the case of ICMS, the aim is to create the perfect working environment, where the human workers as well as the automated or robotised processes do not just work together in the same area but all assets cooperate with each other. Events happening inside it are understood by watching people. The Intelligent Space as a platform is introduced to extend it for robots, therefore, is no longer just for people [46]. Reconfigurable systems are required for human–machine collaboration [38]. Collaborative machines working alongside humans make manufacturing flexible and reconfigurable by augmenting human capabilities and enhancing human well-being. Intelligent manufacturing systems need to integrate built-in human-in-the-loop control to understand when human operators should be involved. Intelligent space supports reconfiguration [46] as it is:

- Modular: components can be added or removed from the intelligent space to be reconfigurable.
- Scalable: it allows integration of local spaces into larger systems.
- Integration: existing intelligent components can be simply integrated.
- Easy configuration and maintenance: the space can learn about itself, e.g. by building models and auto-calibration.

The ICMS, based on the main elements of Intelligent Space, defines a new model-based framework to understand and handle collaboration between all kinds of contributors on shop floors. The structurization of the ICMS is based on several new development trends, which have been considered, such as how to design a Human–Robot Collaboration (HRC) workspace [48], and efficient application of collaborative robots [49].

A part of the emerging smart factory development trend is to enhance the capabilities and competences of human workers, where a significant part of the formalisation is the so-called smart operator (or smart worker) development field. Technologies supporting complex man–machine interactions play an essential role in improving the learning curves of operators, as presented in a study [50], which focuses on Augmented Reality and vocal interaction-based personal digital assistant solutions. As wearable devices and smart sensors become more widespread, they offer a way to integrate operators into the concept of smart factories and develop intelligent operator workspaces [51]. Further studies on Operator 4.0 and approaches for smart factory integration have also been considered. There are promising researches about cognitive solutions [52], or semantic approaches for knowledge representation, knowledge and, digital contents management within the Smart Operator domain [53].

Since the methodology of intelligent space is applied to measure all possible factors as well as detect the connections and co-movements, the aim is to create collaboration between actors. The structure of the intelligent collaborative framework is visualised in Fig. 1. Different building blocks were defined as *Collaborative intelligence* and *Human–machine collaboration* based on Ref. [38], which has been slightly extended to highlight some of the possible connections to industrial standards. Several model blocks have been adapted from the ISA-95 standard [54] standard, namely the elements of the *Machine* section as well as the information flow elements within Collaborative intelligence and Human–machine collaboration modules such as Production capability or the definition of an Operation.

The most critical element of human–machine collaboration is the monitoring system because any decision and optimisation algorithm depends on the monitored information. The ICMS provides solutions to obtain more precise information and optimal control based on the responsibility assignment matrix (RAM, also known as the RACI matrix), which describes the participation of various roles in completing tasks [55]. The elements of the RACI matrix are paired with the needs of collaborative processes such as:

- Responsible: the participants who have to carry out the work. A responsible participant is ideally an individual based on the definition of an RACI matrix. In the case of collaboration, this participant will be the central elements of the connected (collaborated) participants or elements.
- Accountable: The RACI matrix defines this as who approves the work done by the responsible counterparts. In the ICMS concept, this rule is one of the decision-making units, which could be an optimisation algorithm or a supervisor.
- Consulted: originally, this was defined as the people who provide input regarding the completion of the task based on two-way communication. It is handled by the human–machine collaboration with the two-way communication channel as presented in Fig. 1.
- Informed: one-way information to people who are updated regarding the task, which is the *Monitoring space* depicted in Fig. 2.

The RACI matrix defines the tasks for a system framework which supports the next level of collaboration. The elements in Fig. 2 show the proposed elements of the ICMS. Three elements were defined as:

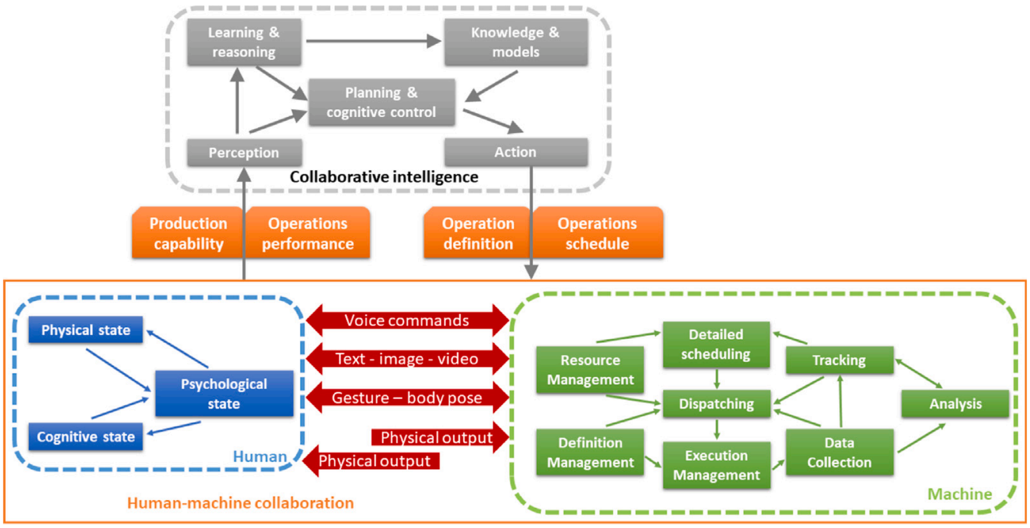

Fig. 1. Intelligent collaborative framework [38].

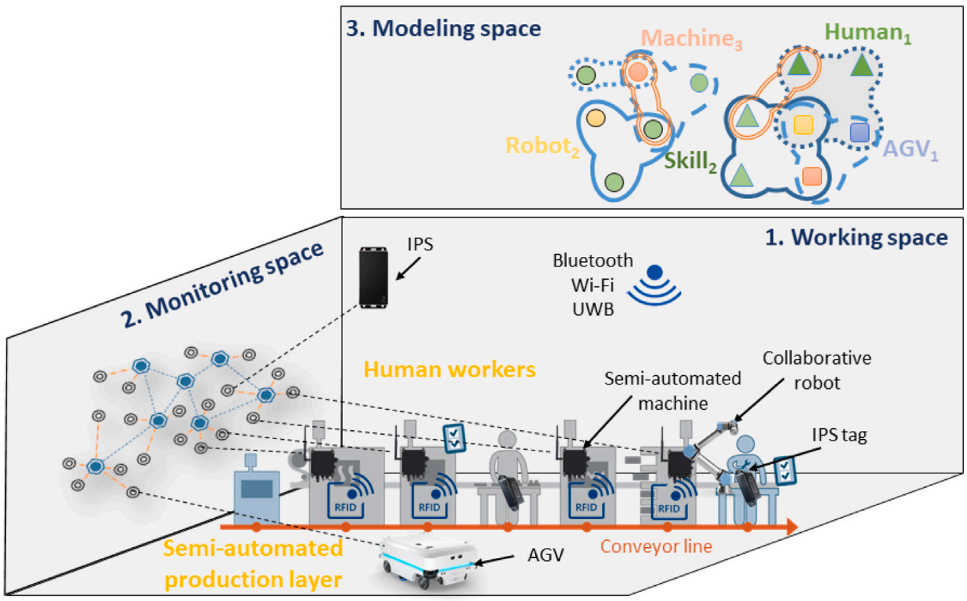

Fig. 2. The structural elements of the Intelligent Collaborative Manufacturing Space.

- *The working space* contains the semi-automated production system as the *Machine* part of the Human–Machine collaboration and the *Operator* as the human worker. This space also represents the shop floor including its assets (e.g., machines, workers, logistics vehicles) and processes.
- *The monitoring space* defines the real-time monitoring system as the sensor networks, the Indoor Positioning Systems (IPS) and the wireless connections (Bluetooth, Wi-Fi, and ultra wide-band (UWB)).
- *The modelling space* is the Hypergraph-based modelling as the vital representation of the ICMS.

In the next section, the methodology of higher-order network representation is described along with the possible analytics and KPIs.

3. Higher-order network representation to support collaboration

In this section, firstly the modelling and mathematical tools of high-order network representation and analytical methods with hypergraphs are discussed. The background of modelling a manufacturing system is presented in Section 3.1 discussing the theoretical background of hypergraph-based modelling in Section 3.2. Section 3.3 presents more detailed examples of hypergraph-based production processes models. Finally, the applied analytical methods of hypergraphs are outlined in Section 3.4.

3.1. Hypergraphs for modelling complex manufacturing systems

The goal of high-order network representations is to identify collaboration scenarios of different actors and elements of the ICMS. Hypergraphs are applied for the purpose of production modelling, not only because of their efficient community structure, centrality and data clustering features but since non-pairwise interactions in the production space in the form of multiple complex relations can be described. As in the case of the network of a trivial graph, vertices and edges are also present in a hypergraph, however, the data, which is described by these network elements, can be more sophisticated. Since edges and vertices can have multiple meanings, a distinction is made between

Table 1
Vertex types and characteristics of the ICMS.

	Event-based vertex	Resource-based vertex	Competence-based vertex
Properties	Probability of utilisation, failure rate and takt time.	Physical characteristics, capacity and availability.	Qualitative and quantitative factors of a production element.
Aggregation	Based on similarities between properties.	Based on similarities between properties.	Based on similarities between properties.
Corresponding sub-groups	Events that happen at the same time or in a sequence.	Resources with the same usage characteristics.	Network elements related to the same resources.

Table 2
Types of hyperedges and characteristics of the ICMS.

	Production flow hyperedge	Attribute hyperedge
Definition	Represents the flow of material, energy or information within vertices.	Represents the correlation between the properties of the vertices.
Direction of the edge	The direction of the hyperloop shows the sequence of the vertices during the process step.	Directed only if the utilisation of the attributes is important.
Weight of the edge	A quantitative property of the material, energy or information flow such as cost, time or quantity.	Only directed if the utilisation of the attributes is important.

different types. This paper only discusses undirected hypergraph networks, which means that the precedence that should be given to the process steps of the production is beyond the scope of this study.

To represent the competences and resources of the manufacturing space, elements that are compatible with the ISA-95 standard [54, 56], the B2MML (Business to Manufacturing Markup Language) [57], or semantic representation methods of manufacturing systems were used [58,59]. Another method that has been considered in modelling is the UML (Unified Modelling Language), which can be utilised to describe flexible manufacturing systems in an object-oriented way [60]. For example, the BOM (Bill Of Material) of a complex product can also be represented in a semantic hyper-graph-based way according to a recent study [61].

3.2. Hypergraph analytics

In this section, the basic definitions and properties of hypergraphs are discussed. Furthermore, a manufacturing example in the ICMS for each property of the hypergraph is provided.

Formally, a **hypergraph** is a structure denoted by the incidence matrix $\mathbf{H} = \langle \mathbf{V}, \mathbf{E} \rangle$, where $\mathbf{V} = \{v_j\}_{j=1}^{n}$ denotes a set of **vertices** and $\mathbf{E} = \{e_i\}_{i=1}^{m}$ a family of **hyperedges** with each $e_i \subseteq \mathbf{V}$ [18]. In a collaborative space, different types of vertices and hyperedges can be defined. Types of vertices can be, for example, resource-based such as robots and operators or defined as event-based, which can be elements of the concerning different products or steps of material handling. The hyperedges of the ICMS model also can differ, e.g. production flow- or attribute-based hyperedges, that connect certain vertices required for a specific activity or involved in a specific competence.

In Table 1, the different types of vertices in a collaborative space along with their characteristics are summarised. Additionally, in Table 2, an overview of the possible types and the properties of the hyperedges in the ICMS model is given. Two types of hyperedges are defined by, dividing the network into "classes" as the steps of production flow and the utilised attributes. Furthermore, some of the different network properties of these types of hyperedges are also described.

Hyperedges can come in different sizes $|e_i|$, ranging from singletons $\{v\} \subseteq \mathbf{V}$ (distinct from the element $v \in \mathbf{E}$) to an entire vertex set $\mathbf{V}$. Since a hyperedge $e = \{v_1, v_2\}$ where $|e| = 2$ is the same as a graph edge it follows that all graphs are hypergraphs, specifically identified as being "2-uniform" [62]. The size of a hyperedge that is, how many vertices belong to a set, includes information about the complexity of a particular step in the manufacturing process, how large a human- or machine-based workforce is required, or what type of skill configuration is necessary for a procedure.

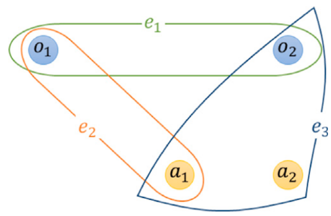

Fig. 3. The Euler diagram of the example hypergraph **H**.

Table 3
The incidence matrix of example hypergraph **H**.

H	o_1	o_2	a_1	a_2
e_1	1	1	0	0
e_2	1	0	1	0
e_3	0	1	1	1

A hypergraph **H** is determined uniquely by its Boolean **incidence matrix** $B_{n\times m}$, where $B_{j,i} = 1$ if $v_i \in e_i$ and 0 otherwise [63]. Therefore, during the modelling, the interconnecting relationships of the collaborative space in the form of a matrix can be described.

The **degree** of a vertex is the number of hyperedges to which it belongs, $d(v) = |\{e : v \in e\}|$, and the size of a hyperedge is its cardinality, $|e|$ [64]. In other words, if a vertex represents a robot in the collaborative space, then the degree of the vertex shows how many work processes the robot is involved in. Furthermore, if a hyperedge represents the allocation of an operator to a workstation, then the size of that hyperedge corresponds to the importance of the process with a higher number of involved members.

Let **H** be a simple example of a manufacturing scenario, where different groups and working procedures are defined. Let **V** denote different activities a_i and operators o_j as vertices of the network. A hypergraph can be built in the following way:

- The set of vertices is the set of manpower and activities: $\mathbf{V} = \{o_1, o_2, a_1, a_2\}$
- The family of hyperedges $(e_i)_{i\in\{1,2,\ldots,k\}}$ is built in the following way:
  - $(e_i), i \in \{1, 2, \ldots, k\}$ is the subset of operators or activities, which are involved in the ith production step.

In Fig. 3, the example hypergraph is visualised with an Euler diagram [65], where three different hyperedges can be seen, as follows: $e_1 = \{o_1, o_2\}$, $e_2 = \{o_1, a_1\}$, $e_3 = \{a_1, a_2, o_2\}$. Furthermore, in Table 3, the

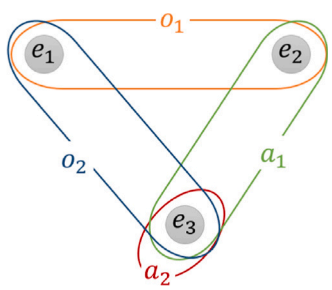

Fig. 4. The Euler diagram of the example dual hypergraph $\mathbf{H}^*$.

Table 4
The incidence matrix of the example hypergraph $\mathbf{H}^*$.

$\mathbf{H}^*$	e_1	e_2	e_3
o_1	1	1	0
o_2	1	0	1
a_1	0	1	1
a_2	0	0	1

incidence matrix of example hypergraph $\mathbf{H}$ is shown. As an example, hyperedge e_3 represents a production step, which requires two activities, a_1 and a_2, as well as the operator o_2, who performs these activities. The same information is stored in the third line of the incidence matrix (Table 3).

The **dual hypergraph** $\mathbf{H}^* = \langle \mathbf{V}^*, \mathbf{E}^* \rangle$ of $\mathbf{H}$ has a $\mathbf{E}^* = \{e_i^*\}_{i=1}^m$ vertex set and a family of hyperedges $\mathbf{V}^* = \{v_j^*\}_{j=1}^n$, where $v_j^* := \{e_i^* : v_j \in e_i\}$. Therefore, $\mathbf{H}^*$ is the hypergraph with the transposed incidence matrix B^T and $(\mathbf{H}^*)^* = \mathbf{H}$ [63]. Thanks to the dual hypergraph attribute, the hyperedges can be converted into vertices and vice-versa. This feature can facilitate the more in-depth structural investigation of a complex manufacturing system. For example, a hypergraph model about the investigated production system can be created, where hyperedges show the resources or actors of the process, and the vertices belong to work steps. After that, the visualisation can be very quickly "inverted" to a dual form, where the hyperedges stand for the resources or actors of the system, while vertices highlight the related work steps.

In Fig. 4, the dual hypergraph version of the previous example is visualised, and the incidence matrix of $\mathbf{H}^*$, where $o_1 = \{e_1, e_2\}$, $o_2 = \{e_1, e_3\}$, $a_1 = \{e_2, e_3\}$ and $a_2 = \{e_3\}$, is presented in Table 4. As a result, it can be said that $\mathbf{H}^*$ swaps the roles of vertices and hyperedges. Thanks to the dual graph feature, certain elements of the system can be modelled in several ways in a hypergraph-based manufacturing model. It is possible to represent a resource allocation scenario with a hyperedge or with different vertices as well.

The **line graph** $L(H)$ of hypergraph $\mathbf{H}$ consists of a vertex set $\{e_1^*, \dots, e_m^*\}$ and an edge set $\{(e_i^*, e_j^*) | e_i \cap e_j \neq \emptyset, i \neq j\}$ [66]. In order to additionally capture information about the size of intersecting hyperedges, line graphs of hypergraphs may be defined with additional **edge weights**, where $\{e_i^*, e_j^*\}$ has the weight $|e_i \cap e_j|$ [64].

The **weight of a hyperedge** ω_i is related to the frequency of occurrence of the hyperedge (multiplicity) and the cardinality of the hyperedge. There are different approaches of the hyperedge weights, namely as a constant, frequency-based, or according to the definitions by Newman, Gao or Network Theory [67]. In the case of a production environment, the weight of a hyperedge can hold information about the relevancy of a set of production members (as machines and operators in a production process step) or other cost parameters such as the training or time cost of a vertex set connected by the hyperedge.

3.3. Hypergraph modelling of a production process

This section aims to provide more details about how hypergraphs can be used for the modelling of the production environment.

Table 5
Examples of different types of vertices.

Resource-based vertices		
Operator	$\{v_1^o, v_2^o \dots v_{N_o}^o\}$	○
Robot	$\{v_1^r, v_2^r \dots v_{N_r}^r\}$	○
Machine	$\{v_1^m, v_2^m \dots v_{N_m}^m\}$	○
Machine-based vertices		
Milling	$\{v_1^{mi}, v_2^{mi} \dots v_{N_{mi}}^{mi}\}$	□
Drilling	$\{v_1^d, v_2^d \dots v_{N_d}^d\}$	□
Material handling	$\{v_1^{ha}, v_2^{ha} \dots v_{N_{ha}}^{ha}\}$	□
Event-based vertices		
Production of A	$\{v_1^{pa}, v_2^{pa} \dots v_{N_{pa}}^{pa}\}$	△
Production of B	$\{v_1^{pb}, v_2^{pb} \dots v_{N_{pb}}^{pb}\}$	△

Table 6
Examples of different types of hyperedges.

Hyperedges		
Activity-based	$\{e_1^a, e_2^a \dots e_{N_a}^a\}$	|
Attribute-based /competence/	$\{e_1^c, e_2^c \dots e_{N_c}^c\}$	||

Table 7
The incidence matrix of example hypergraph $\mathbf{H}_1$.

	v_1^o	v_2^o	v_3^o	v_4^o	v_1^m	v_1^r
e_1^a	1	1	0	0	1	0
e_2^a	0	1	1	0	0	1
e_3^a	0	0	0	1	0	1
e_1^c	0	1	0	0	0	1

In the case of vertices, a distinction is made between several types, such as resource-, competence- and event-based vertices, which are summarised in Table 5. Resource-based vertices of the ICMS are the human and machine members of the production process, such as operators, robots or machines. The machining-based vertices stand for manufacturing activities such as milling, drilling and material handling. Furthermore, the event-based vertices cover the production steps of manufacturing Product A or Product B.

In the proposed example model, activity and attribute-based edges are included as listed in Table 6. An activity-based hyperedge connects the vertices involved in a specific production procedure or can be defined as a set of vertices which represent collaborating resources that perform an activity. The weight of an edge can equate to the time or cost of the whole activity. Furthermore, the weight of the same hyperedge can differ within vertices which are connected to it. The other type of hyperedge in the proposed modelling methodology is attribute-based, which connects vertices with a specific type of attribute or characteristic and the weight of these edges determines the suitability.

It is important to mention that in a hypergraph network, some of the vertices and edges are convertible such as competence which can occur as an edge or as a vertex. Moreover, a further generalisation in a hypergraph is that a hyperedge as well may not only contain vertices but other hyperedges [18].

In Fig. 5**a**, a hypergraph representation example is visualised, where there are two different types of hyperedges and three types of resource-based vertices. In Table 7, the incidence matrix of hypergraph $\mathbf{H}_1$ is listed from Fig. 5**a**. To accomplish the activity covered by hyperedge e_1^a, the following vertices need to be involved: v_1^o, v_2^o and v_1^m, so two operators and one machine. Another hyperedge referred to as e_1^c connects vertices v_1^r and v_2^o and acts as an attribute-based hyperedge, which connects a *robot* and an *operator*-type, resource-based vertex.

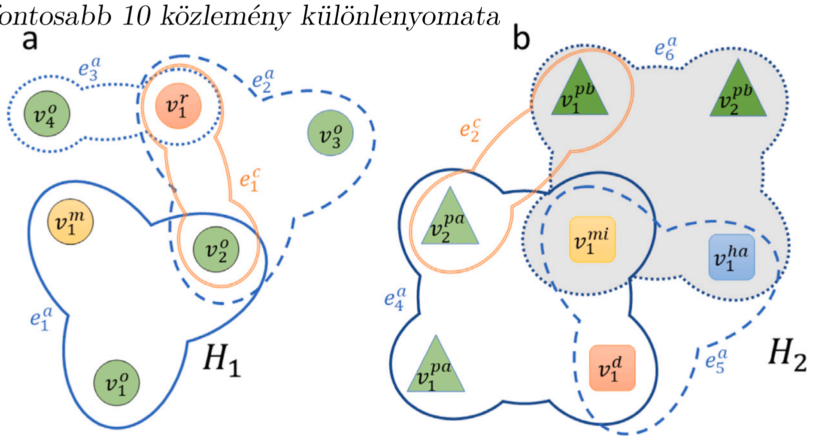

Fig. 5. $\mathbf{H}_1 = \langle \mathbf{V}_1; \mathbf{E}_1 \rangle$ is a hypergraph representation of resource-based vertices allocated by different types of hyperedges where $\mathbf{V}_1 = \{v_1^o, v_2^o, v_3^o, v_4^o, v_1^m, v_1^r\}$ and $\mathbf{E}_1 = \{e_1^a, e_2^a, e_3^a, e_1^c\}$ moreover, $\mathbf{H}_2 = \langle \mathbf{V}_2; \mathbf{E}_2 \rangle$ is a hypergraph representation of machine and event-based vertices allocated by different types of hyperedges where $\mathbf{V}_2 = \{v_1^{pa}, v_2^{pa}, v_1^{mi}, v_1^d, v_1^{ha}, v_1^{pb}, v_2^{pb}\}$ and $\mathbf{E}_2 = \{e_4^a, e_5^a, e_6^a, e_2^c\}$.

Table 8
Types of hypernetwork measures and their application in ICMS analysis.

Centrality metric	Application in ICMS
S-betweenness centrality	Show the importance of the elements
S-closeness centrality	Show how an element is shared
Modularity of the hypergraph	Show how modular the production process is

In Fig. 5**b**, a bit more complex hypergraph representation of a manufacturing process is visualised. To accomplish the activity covered by hyperedge e_4^a, the following vertices need to be involved: v_1^{Pa}, v_2^{Pa}, v_1^{mi} and v_1^d. Therefore, *Product A*-type, event-based, and two other machining-based vertices are found in this set. However, in the next set of vertex connected by activity-based hyperedge e_5^a three different types of machining-based vertices are covered, namely v_1^{mi}, v_1^{ha} and v_1^d. Finally, hyperedge e_6^a contains two types of *Product B*, that is event-based vertices (v_1^{Pb} and v_2^{Pb}) and two other machining-based vertices (v_1^{mi} and v_1^{ha}). An attribute-based hyperedge on this visualisation is also present, where e_2^c connects the vertices v_2^{Pa} and v_1^{Pb}, providing an example where hypergraphs, edges and vertices can deliver the same information as all three can describe attributes here.

After describing the principles and modelling examples of hypergraphs, more complex network analytical methods are discussed in the following section.

3.4. Advanced hypergraph-based analysis of ICMS

This section aims to provide network-based metrics that are suggested for hypergraph-based analysis of the ICMS. In Table 8, the studied hypergraph-specific centrality and analytical methods were summarised and examples of application scenarios in manufacturing analytics given.

In order to define the hypergraph centrality measures, first, the notions of a hypergraph walk and distance are introduced [64]. Given two hyperedges $e, f \in E$, an **s-walk** of length k between e and f is a sequence of hyperedges $e_0, e_1, \dots, e_k$ such that $e_0 = e, e_k = f$ and $s \leq |e_i \cap e_{i+1}|$ for all $0 \leq i \leq k-1$. In other words, an s-walk is a sequence of edges such that the size of pairwise intersections between neighbouring edges is at least s.

The **s-distance**, for a fixed $s > 0$ is defined as $d_s(e, f)$ between two edges $e, f \in E$, as the length of the shortest s-walk between them. If no s-walk is found between two edges, then the s-distance is infinite [64]. Two edges $e, f \in E$ are defined as **s-adjacent** if $|e \cap f| \geq s$ for $s \geq 1$ [68]. In addition, the **s-diameter** is defined as the maximum s-distance between any two edges and the **s-component** as a set of edges connected pairwise by an s-walk [63]. The **s-path** is referred to in the

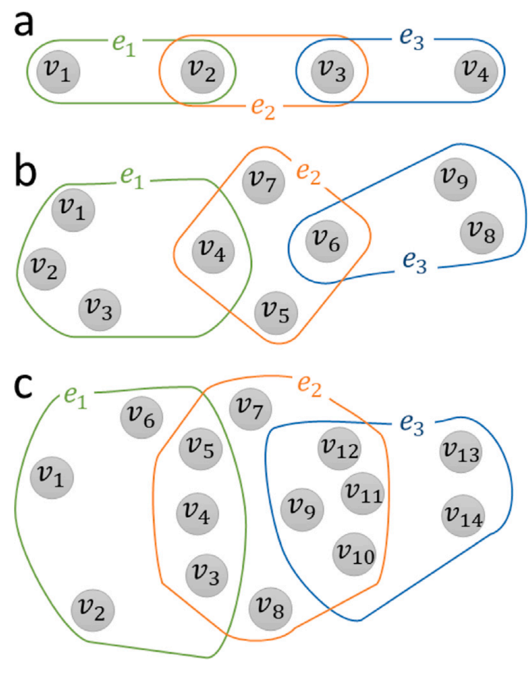

Fig. 6. Examples of walks in hypergraphs: (a) a 2-uniform hypergraph of length two and width one between e_1 and e_3, (b) one of length two and width one between e_1 and e_3, and (c) another of length of two and width three between e_1 and e_3.

case of s-walks, where the edges are not repeated, so any hyperedges from the hypergraph can participate only once in the path.

Furthermore, the walks in hypergraphs also have a certain width. In Fig. 6, three examples of walks in hypergraphs (based on Ref. [63]) are shown. In the first simple example (a), a 2-uniform hypergraph is presented. The length of the walk between hyperedges e_1 and e_3 is two (as the walk needs to go through e_1 and e_2 to reach e_3), and its width is one (as the number of vertices at interconnecting hyperedges is one). In the second scenario (b), a hypergraph is presented where the length between e_1 and e_3 is two and the interaction is one. While in the third case (c), its length is still two, but the interactions are stronger as its width is three (because the minimum number of vertices at interconnecting hyperedges is three).

Aksoy et al. [64] defined several network science methods generalised from graphs to hypergraphs, including vertex degrees, diameters and clustering coefficients. In this paper, their generalisation

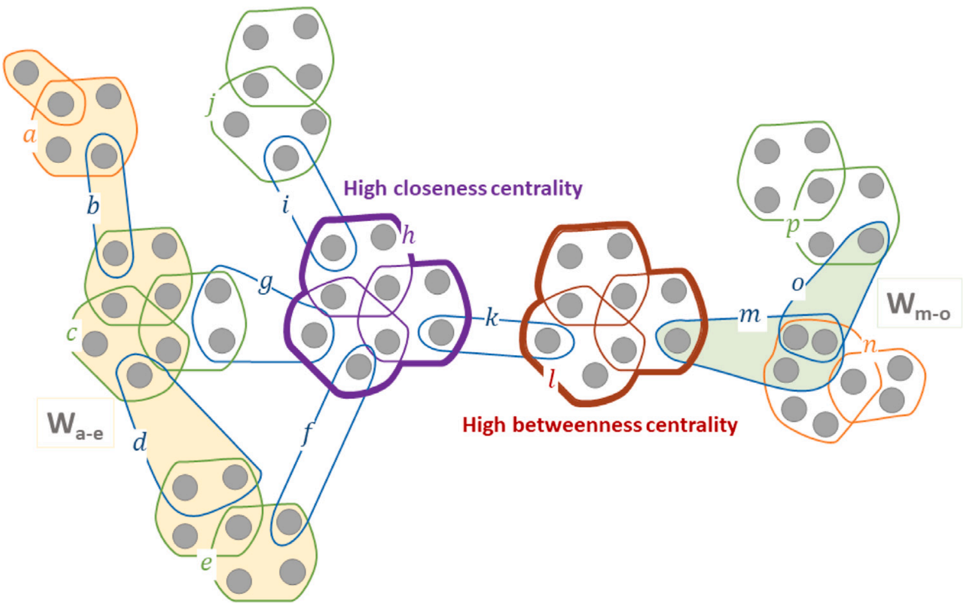

Fig. 7. Example hypergraph to demonstrate closeness and betweenness centrality metrics and s-walks.

of the betweenness centrality and closeness centrality with regard to hypergraphs is applied using the stratification parameter s.

The **s-betweenness centrality** of edge e is:

$$BC_s(e) := \sum_{f \neq e \neq g \in E} \frac{\sigma^s_{fg}(e)}{\sigma^s_{fg}}, \tag{1}$$

where σ^s_{fg} denotes the total number of the shortest s-walks from edge f to edge g and $\sigma^s_{fg}(e)$ represents the number of those shortest s-walks that contain edge e [62].

The **harmonic s-closeness centrality** of an edge e is the reciprocal of the harmonic mean of all distances from e:

$$HCC_s(e) := \frac{1}{|E_s| - 1} \sum_{f \in E_s, f \neq e} \frac{1}{d_s(e,f)}, \tag{2}$$

where $E_s = \{e \in E : |e| \geq s\}$ [62].

In order to take into account multiple s values simultaneously in the analysis, the average of the centrality values across a range of s values is calculated and the **average s-betweenness centrality** [62] is defined as:

$$\overline{\mathrm{BC}}_s(e) = \frac{1}{s} \sum_{i=1}^{s} BC_i(e), \tag{3}$$

and the **average harmonic s-closeness centrality** [62] as:

$$\overline{\mathrm{HCC}}_s(e) = \frac{1}{s} \sum_{i=1}^{s} HCC_i(e) \tag{4}$$

An example visualisation is presented in Fig. 7 to demonstrate the behaviour of centrality metrics in hypergraphs. The s-closeness centrality can be represented by a hyperedge (or hyperedges), which can most easily reach all other hyperedges in the hypergraph. In Fig. 7, the high closeness centrality element is highlighted in purple as the average distances from edges i, g, k and h are minimal compared to other groups. The s-betweenness centrality provides information about which hyperedge (or hyperedges) has the most control over the flow between other hyperedges and groups. In Fig. 7, the high betweenness centrality element is denoted in brown, as the maximum number of shortest paths go from edges k and m since they bridge two parts of the network.

Furthermore, in Fig. 7, two examples of s-walks on this slightly more complex hypergraph are presented. W_{a-e} s-walk on the left-hand side has a length of four between a and e as well as a width of one, and the s-component is 19 as W_{a-e} contains 19 vertices. W_{m-o} s-walk on the right-hand side is of length one between o and m as well as has a width of two, and the s-component is five as W_{m-o} contains five vertices.

Based on the previous discussion and Table 8, it can be concluded that hypergraph-based centrality metrics can be utilised in the design of ICMS, if:

- a job competency has a high degree of centrality, then it is highly utilised and critical in the production process;
- an operator has a high degree of centrality, then the scheduling of his/her work is critical (assembly line balancing);
- the path between two elements (as work areas) is relatively large, then it can be decomposed and the procedure reallocated.

4. Designing an ICMS for a wire harness assembly process

This section presents how the proposed method can be applied to the analysis and redesign of a manufacturing system. The studied wire harness production process is still highly manual due to the extremely complex maneuvers of the activities [69]. The modular wire harness product is produced by a modular production system. The studied wire harness assembly-based case study has already been used for the demonstration of activity time monitoring solutions [70]. The proposed model-based solution has received considerable attention, the Assembly Magazine also reported about the success of the project [71]. Additionally, a recent 'call for R&D' paper [49] highlights the need for collaborative robot-related studies in wire harness assembly. Recently, the authors presented that the process can be efficiently modelled as a multi-layer network [72,73]. From these motivations, the case study of this paper also comes from the field of the wire harness assembly industry. Based on the production processes, the case study is motivated by a multinational wire harness factory. However, due to confidentiality policies, detailed information cannot be published, but the validation of the proposed methodology is continuous with the production experts.

Firstly, in Section 4.1 a wire harness assembly-based benchmark problem is described. In Section 4.2, several visualisation applications with hypergraphs are shown. In Section 4.3, the analytical methods required to identify critical elements and collaborations of the manufacturing space are illustrated. In Section 4.4, the segmentation process is presented. Finally, Section 4.5 discusses the benefits of the proposed hypergraph-based methodology.

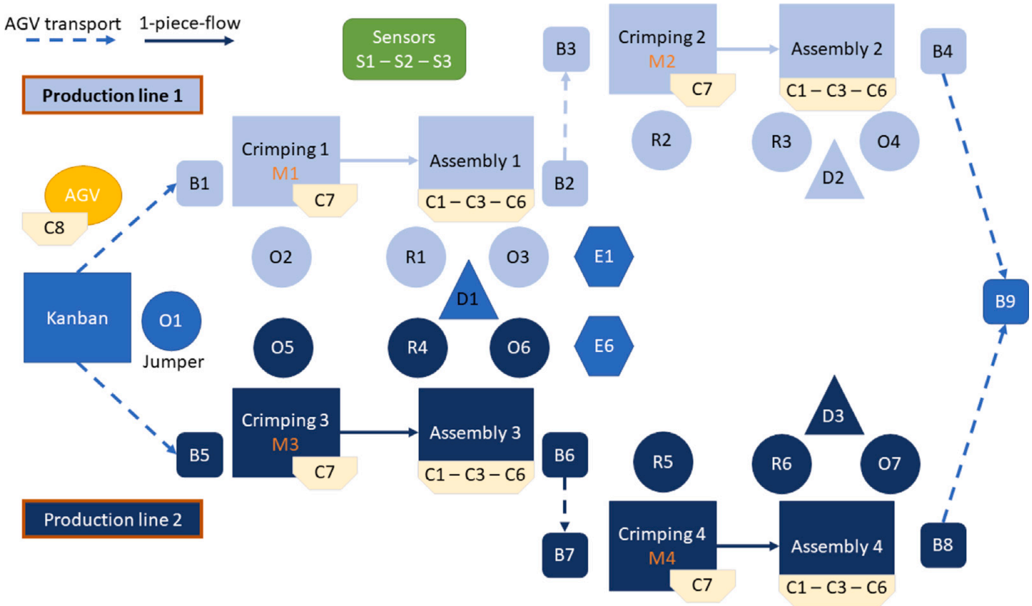

Fig. 8. The process flow of the wire harness assembly line.

4.1. Wire harness production case study

A small production line with batch and conventional production was chosen and Fig. 8 shows the process flow, which is based on a real assembly line. In Appendix, a more detailed overview of the wire harness assembly benchmark is provided, where first in Table A.10 each activity type of the complex industrial process is listed, then in Table A.11 along with the details of the sequence of activities, which is distinguished in this paper.

The process contains two assembly lines that produce shared tasks and resources in parallel. The elements of these production lines are listed in Table 9. As for the shop floor, a Kanban, several Buffers, Crimping stations and Assembly stations are defined. The second group of elements is the human–machine members, which can be Operators or Robots as well as the assets of the production line, which are Machines, Tools, Screwdrivers and the AGV (Automated Guided Vehicle). Finally, Competences are required to perform particular activities and Sensor elements to monitor the collaborative space.

In Fig. 8, the elements denoted in a brighter colour represent *Production line 1* and the darker ones *Production line 2*, while in the middle, the shared assets and resources are visualised. The material handling steps during the production process are highlighted with arrows, which can be 1-piece-flow performed by operators or AGV-based transport. The process flow (visualised in Fig. 8) starts at the *Kanban*, where the jumper operator $O1$ loads the AGV (using competence $C8$) with one batch and the AGV transfers it to *Crimping station 1* or *3*, where operator $O2$ or $O5$ unloads it into the local buffer $B1$ or $B5$. The following steps are the same on both production lines, moreover, the process description will be continued with *Production line 1*. Based on the production plan, operator $O2$ performs crimping-related activities (listed in the Appendix) that require competence $C7$. Additionally, machine $M1$ is also utilised during the crimping activities. Finally operator $O2$ hands over the workpiece to the *Assembly station 1*. Operator $O3$ and robot $R1$ collaborate with each other, while competence $C1, C3$ and $C6$ related activities are performed. Moreover, screwdriver $D1$ and tools $E1 - E6$ are used during the activity steps of *Assembly station 1*. At the end of the procedure, operator $O3$ takes the workpiece into the buffer $B2$. If a whole batch has been completed, the same operator loads the AGV, which delivers the batch of cables to the next buffer, that is $B3$. After this, at *Crimping station 2*, robot $R2$ unloads the buffer and performs competence $C7$ and machine $M2$ related activities. Then robot $R2$ hands over the workpiece to the next station, namely *Assembly station 2*. At the last workstation of Production line 1, operator $O4$ and robot $R3$ collaborate with each other to perform activities that require competences $C1, C3$ and $C6$. At the end of the assembly line, operator $O4$ moves the workpieces to buffer $B4$. If a whole batch has been completed, the same operator loads the AGV, which delivers the products to the final buffer, that is $B9$.

Table 9
The elements of the wire harness assembly lines.

Work sections of production lines	
Kanban	1 piece
Buffer	[$B1, B2, B3, B4, B5, B6, B7, B8, B9$]
Crimping stations	[Crimping 1, Crimping 2, Crimping 3, Crimping 4]
Assembly stations	[Assembly 1, Assembly 2, Assembly 3, Assembly 4]
Human–machine members and assets	
Operators	[$O1, O2, O3, O4, O5, O6, O7$]
Robots	[$R1, R2, R3, R4, R5, R6$]
AGV	1 piece
Machines	[$M1, M2, M3, M4$]
Tools	[$E1, E6$]
Screwdrivers	[$D1, D2, D3$]
Competences	[$C1, C3, C6, C7, C8$]
Sensors	[$S1, S2, S3$]

The block of *Sensors* (highlighted in green in Fig. 8) contain the elements of the monitoring system, which are follow: $S1$ — camera, $S2$ — location of the fixture with RTLS (Real-Time Location System) and $S3$ — machine logs. Further attributes of the elements (besides the list of main elements in Table 9) are the following *Competences*, which are required to perform special activities: $C1$ — Inserting and laying of parts (cabling), $C3$ — Terminal handling, $C6$ — Fastening the terminal with screws, $C7$ — Operation of the crimping machine, $C8$ — Loading of the AGV. There are also two special tools, which are shared assets of the procedure, namely $E1$ — wiring tool and $E6$ — tubing tool. Furthermore several unique *Machines* (M) are allocated to different *Crimping stations* and *Screwdrivers* (D) are regarded as shared assets within *Assembly stations*.

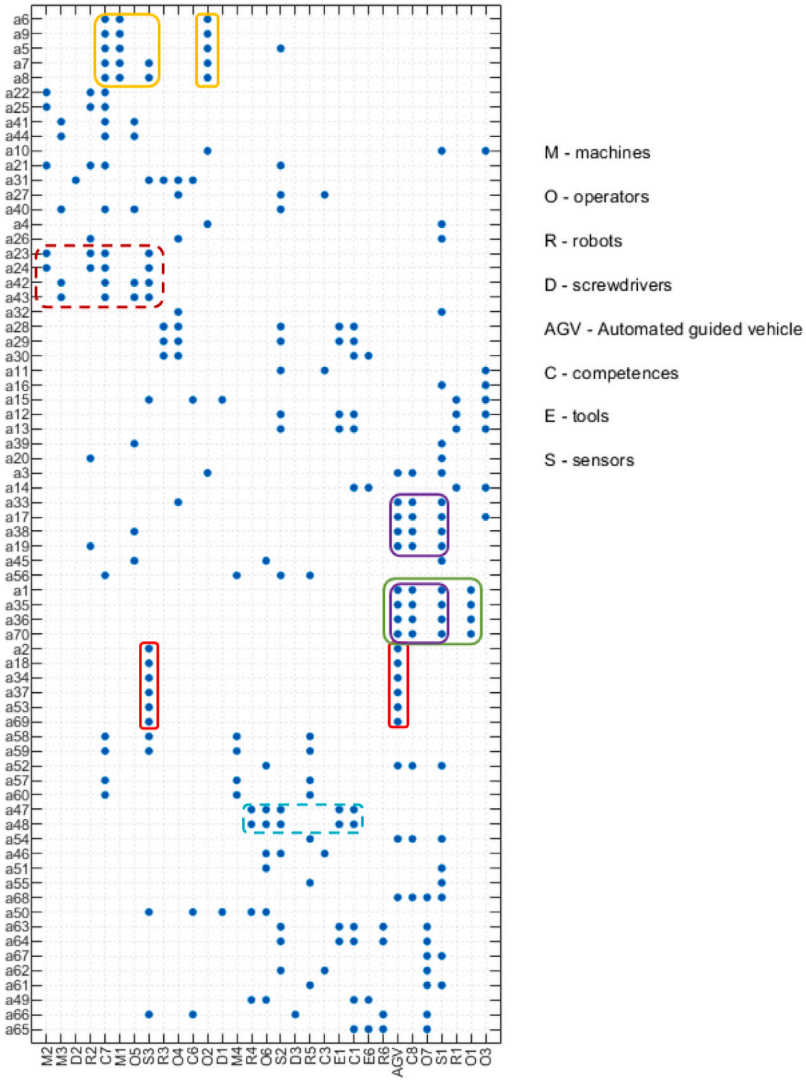

Fig. 9. The serialised incidence matrix of the ICMS concerning wire harness manufacturing. Some biclusters of the closely connected activities and items are also highlighted.

4.2. Hypergraph-based representation of the ICMS designed for the wire harness assembly line

In this section, the designed ICMS is presented by visualising the hypergraph model in three different ways, which correspond exactly to the data, however, different valuable conclusions can be drawn from them.

First, the serialised incidence matrix of the hypergraph is presented (Fig. 9), then the normal- (Fig. 10) and dual- (Fig. 11) hypergraphs of the wire harness assembly process are shown. In Fig. 9, the serialised incidence matrix of the wire harness manufacturing-based case study is visualised. On the vertical axes, the 70 different activities are listed having been re-ordered, while on the horizontal axes, the human–machine resources, competences, and other tooling or sensor elements of the ICMS are provided.

In Fig. 9, after serialisation of biadjacency matrix (**B**) and identifying clusters in the data. the closely connected activities and items of the ICMS are highlighted. The top bicluster, highlighted in yellow, is denoted by a vertex set, namely competence v_7^c, machine v_1^m, and operator v_2^o, in the case of the following activities: e_5^a, e_6^a, e_7^a, e_8^a and e_9^a. Since activities e_6^a and e_7^a from this group also connect with the v_3^s sensor, these five activity-based hyperedges create a bicluster in the ICMS model because the same operator, machine and competence are utilised in these production steps. The second bicluster, denoted in purple, consists of sensor v_1^s, AGV v_a and the competence v_8^c in the case of the following activity-based hyperedges: e_{17}^a, e_{33}^a, e_{38}^a and e_{19}^a as ll as e_1^a, e_{35}^a, e_{36}^a and e_{70}^a. Another bicluster denoted in red is related to AGV v_a and sensorv_2^s, in the case of activity-based hyperedges e_2^a, e_{18}^a, e_{34}^a, e_{37}^a, e_{53}^a and e_{69}^a. Furthermore, more possible clusters are highlighted with dashed lines in Fig. 9.

In Fig. 10, the normal hypergraph of the production network is visualised, which shows how activities involve the elements of the ICMS. This representation helps to identify what central elements affect the activities most, e.g. activity-based hyperedge e_{31}^a connects vertices v_2^d, v_3^s, v_3^r, v_4^o and v_6^c.

Fig. 11 shows a dual hypergraph with opposite meaning to the previous figure, as it represents the assets and workers with regard to the activities involved, namely is the transposed form of the previous visualisation. For example competence-based hyperedge e_3^c connects the following activities in the form of vertices: v_{11}^a, v_{27}^a, v_{46}^a and v_{62}^a. Alternatively, in a similar way, it can be sees that screwdriver $D1$-based hyperedge e_1^d is denoted by activities v_{15}^a and v_{50}^a. In this representation, hyperedge e_1^s is the largest as it contains 24 different activity-based vertices, while e_1^d and e_2^d (screwdriver-based hyperedges) are the simplest ones with only one vertex each.

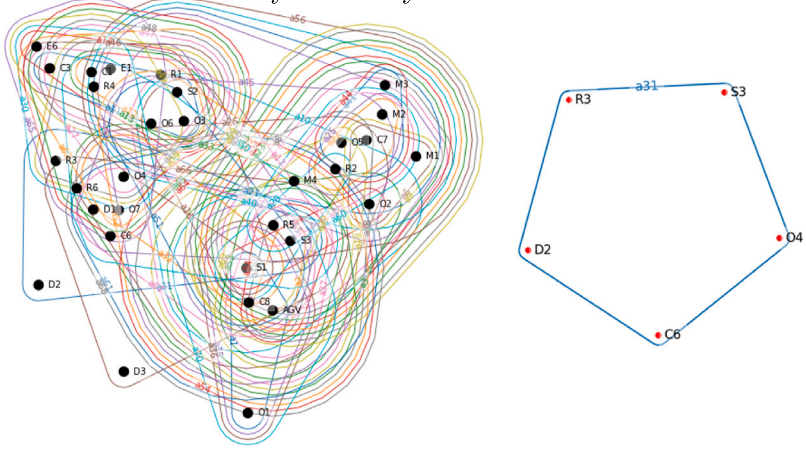

Fig. 10. Hypergraph visualisation of the wire harness benchmark (on the left-hand side) — The activities become involved as a result of the elements of the ICMS and activity-based hyperedge a_{31} (on the right-hand side).

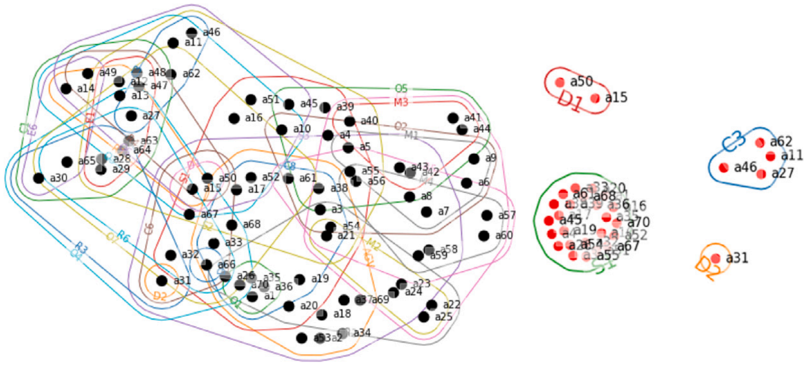

Fig. 11. Dual hypergraph visualisation of the wire harness benchmark (on the left-hand side) — The elements of the ICMS become involved as a result of the activities and hyperedges $D1$, $S1$, $C3$ and $D2$.

4.3. Identification of the critical elements and collaborations of the ICMS

The critical elements and collaborations of the ICMS can be identified based on the s-closeness and s-betweenness measures presented in Section 3.4. The closeness centrality measure indicates how close a vertex is to all other vertices in the network, while the betweenness centrality detects the degree of influence a vertex has over the flow of information in the hypergraph.

Based on the s-closeness and s-betweenness metrics, the most important elements are v_2^s (sensor $S2$ as a vertex — RTLS) and v_3^s (sensor $S3$ as a vertex — machine log) as the s-closeness values are 0.77 and 0.75 and the s-betweenness ones are 55.68 and 45.57, respectively. The results show that the most important elements (as central elements are present) of the modelled process are the sensors, given that they are connected to the most activities. The central operators are v_3^o, v_4^o, v_6^o and v_7^o with values of s-closeness and s-betweenness of 0.6 and 16, respectively. A similar conclusion can be reached if the dual hypergraph in Fig. 11 is investigated, where the central elements are determinative cooperation or interaction. The four aforementioned operators are found in the same vertices to the left of the centre of the figure and several overlaps can be noticed.

The average s-closeness centrality value of the wire harness benchmark network is 0.598, which means the vertices have a higher probability of being closer to each other in a network than far apart. Additionally, the average s-betweenness of the hypergraph network is 9.393, although it has a high deviation because most of the vertices have a high influence on the hypergraph.

Based on the determinative hyperedges, in the case of closeness and betweenness, the same activity type was the most significant, that is t_{19} (Positioning of a crimp into a vise), which is usually handled by two operators or one robot, while applying competence $C7$ and monitoring the process using sensor $S2$ (RTLS). The related activities to activity type t_{19} are v_5^a, v_{21}^a, v_{40}^a and v_{56}^a, which are visualised in Fig. 12 with a dual hypergraph.

The representation of the hypergraph can show the central element of the complex system based on the higher-order network representation. In the following subsection, how these higher order connections can be investigated with the s-walk analysis will be shown and be used for segmentation tasks such as forming manufacturing cells.

4.4. Segmentation of the ICMS

The centrality metrics presented in the previous subsection facilitate the detection of the critical or potential collaboration areas in the manufacturing network. While this subsection describes in detail how the system can be segmented, which helps to investigate them more in-depth. The hypergraph representation provides information to determine the strongly interdependent elements as the modules can be identified. These modules are the bases for forming manufacturing cells, since they show what elements should be planned together and how the process can be decomposed. The first task is to determine the strongly connected elements.

The s-walk methods are applicable to measure the connectedness in the collaborative processes where multiple participants exist. The benefit of the hypergraph representation is that the second and third walks between the vertices where these walks represent closely connected elements can also be seen. For example, the s-betweenness value in the case of v_1^s (sensor $S1$ as a vertex (*camera*) — highlighted in orange in

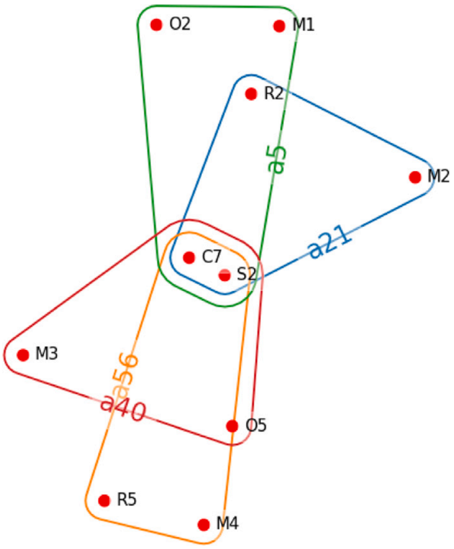

Fig. 12. Dual hypergraph representation of activity type t_{19} related assembly activities (hyperedges), and the resources, actors are shown as vertices.

the figure) is significantly higher when the second walk is calculated, as it rises from 13.99 (7th place) to 102.53 (2nd place). Furthermore, the betweenness value of v_7^c increases by more than ten times, as it is a required competence ($C7$ — highlighted in blue in the figure) for the crimping step. The graph representation of the connections between the elements in the case of the first and second s-walks can be seen in Fig. 13. Based on the resulting graph of the second s-walk and the s-betweenness value of two (as described below), it can be noticed that the centrality of $S1$ and $C7$ with regard to betweenness is described by the influence of the vertex.

The crimping competency ($C7$) is highly relevant as the production flow has four crimping stations with several shared resources. Logically, $S1$, that is, the camera sensor used to monitor many collaborative tasks such as AGV loads and transport between operators, should be given a high level of importance. In Fig. 11, it can be noticed that $S1$ covers a lot of activities. This vertex ($S1$) is denoted by the red line in the middle of Fig. 11 which covers many activities and is connected to several other elements.

The significant connections can be determined by modularity analyses. Several algorithms are used to identify modules in a network. The Louvain algorithm was applied to find some communities based on the activities and elements (human workers, robots, etc.). The algorithm identifies five activity-based communities:

1. *Crimping* 3 — related activities
2. *Assembly* 1 – 4 — related activities
3. *AGV* — related activities
4. *Crimping* 1 – 2 — related activities
5. *Crimping* 4 — related activities

The Louvain algorithm is applied to the dual hypergraph to analyse the main elements of the ICMS. Three modules were identified from the elements, the first contains all AGV-related vertices such as the AGV, the loading of the AGV competence and operator $O1$ as they only work together with the AGV. Since this module also includes the camera and machine-log sensor, it determines the elements that are collaborative multiple stations. The crimping machine-related elements are found in the second module, e.g. robots, crimping machines, related operators and competence $C7$. The third module consists of the elements related to the assembly stations with the RTLS sensor.

The central element is the key to collaboration, and this result shows what is the most critical. The central elements are the s-walk method, which provides valuable information about the complex collaborative processes, where multiple resources work together and cooperate with each other. In this case, the crimping competence is significant (in the case of the second s-walk), which shows us that training more and more operators to use the crimping station together with robots should be considered. The modules help to discover the joint elements and divide the complex problem into the most significant parts. The results identify the three significant parts of the investigated use case.

In Fig. 14, a part of the wire harness assembly-based case study is visualised. At the top of the figure, the hypergraph network is presented with activity-based hyperedges, where robot $R2$, operator $O3$, robot $R1$, and the AGV are chosen as key elements based on centrality metrics. The four elements are visualised at the bottom along with all the other related activities as vertices in the dual hypergraph to demonstrate the benefit of dual hypergraph representations. This approach could give further information about the other related assembly activities with the dual graph form after determining the four central elements. Furthermore, on the bottom dual hypergraph visualisation, activities v_{17}^a and v_{19}^a as interconnecting steps within the AGV and operator $O3$ or robot $R2$ can also be seen. An example of collaboration is the overlapping section of robot $R1$ and operator $O3$ on the bottom dual graph representation, where v_{12}^a, v_{13}^a, v_{14}^a and v_{15}^a vertices belong to activities.

Fig. 15 aims to demonstrate the features of the hypergraph-based visualisation of the collaboration analysis of a manufacturing system. Robots, operators, and the AGV are visualised in the form of hyperedges, while the red vertices belong to assembly activities. Within the AGV hyperedge in Fig. 15 the activity vertices (red dots) overlapped with other hyperedges show scenarios when operator or robot actors work together at the same time and “share” activities. Collaboration cases are also highlighted on the hypergraph, such as operator $O7$ collaborating with robot $R6$ and having a shared activity with robot $R5$ and with the AGV. In a more complex, real industrial environment, the proposed method can also facilitate the detection of critical zones, scheduling processes, improve ergonomic aspects during collaboration or layout design.

4.5. Discussion on the benefits of the hypergraph representation and suggestions for future research

The wire harness assembly case study-based examples presented in the previous subsection highlighted how an existing production system could be analysed as a hypergraph. Compared to classical and advanced multi-layer network-based analysis [72], the main benefit of hypergraphs is that it allows the set-theory-based analysis of the system. Sets represented by hyperedges can be used to study redundancy and resilience, and the intersection of sets can explore the flexibility of configurations. Higher-order network representations can better represent the superstructures of complex manufacturing systems where the superstructure is constructed from a set of alternatives.

A critical aspect of the research is the technologies needed to utilise the proposed concept in a real-world industrial application. Complex manufacturing system representation and analytics require a comprehensive data management system that covers all aspects of production. Information management of future manufacturing requires an effective solution as knowledge graphs (or knowledge hypergraphs [74]), which use a graph-based data model to capture knowledge in application scenarios that involve integrating, managing and extracting value from diverse data sources, even at a large scale [75]. Knowledge graph methods can mine information from structured, semi-structured, or even unstructured data sources and finally integrate the information into knowledge, represented in a graph [76]. Enabling technologies for the proposed hypergraph-based approach are the adequate MES (Manufacturing Execution System) and MOM (Manufacturing Operations Management) [77] supported by semantic technologies, such as ontologies and knowledge graphs.

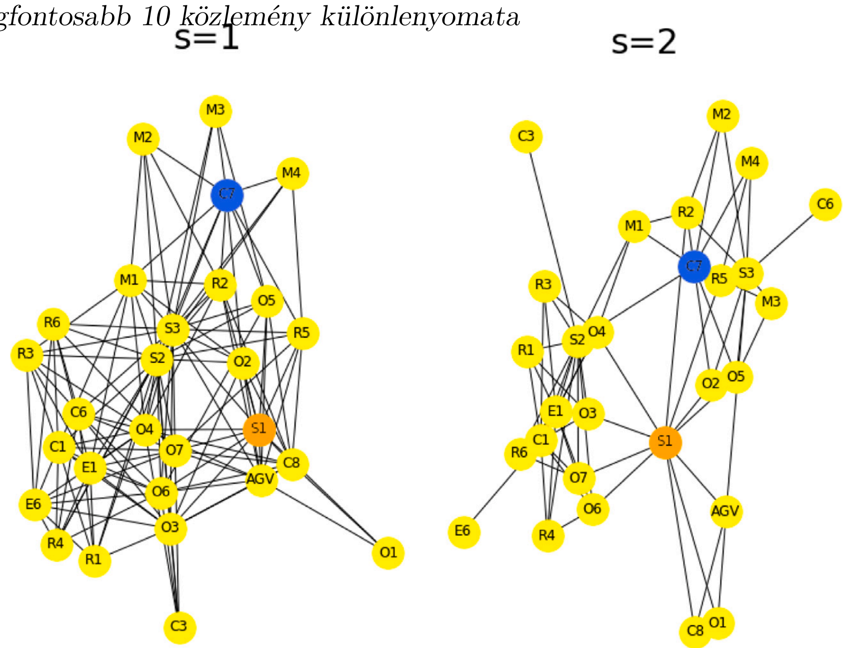

Fig. 13. The $s = 1$ and $s = 2$ walks highlight the connectedness of the elements of the designed ICMS.

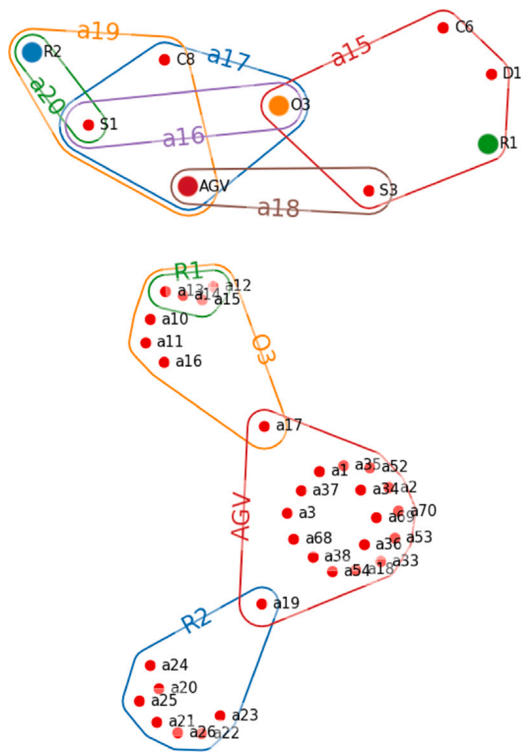

Fig. 14. Hypergraph (at the top) and dual hypergraph (at the bottom) representations of a collaboration scenario, where operator $O3$, robots $R1$–$R2$ and the AGV are the focal points.

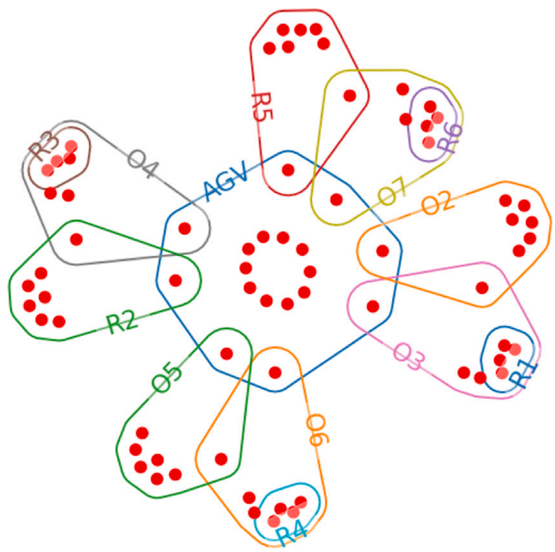

Fig. 15. Dual hypergraph representation of the collaboration between Operators, Robots, and the AGV, where the red vertices belong to different activities.

An essential additional question is what can be done with the analysis results and how the uncovered knowledge can be applied to improve the manufacturing process. It has been demonstrated that the wide range of hypergraph-based metrics provides much more possibilities than classical network centralities, mainly when collaboration should be analysed. Collaborating actors with a high influence on the production are detectable with s-walks, and the central collaborators of the intelligent manufacturing network can be found with s-closeness and s-betweenness metrics.

A non-applied but beneficial analysis tool of hypergraphs is the so-called vertex simplification, which can be used to redesign the systems by exploring the bottlenecks and critical elements of the collaborations. A method for this is a (weighted) clique expansion performed on the line graph of the dual of a hypergraph generated based on the similarities between vertices [66].

A further advantageous feature worth studying in the future is the utilisation of fuzzy set memberships in fuzzy hypergraphs [78]. A fuzzy representation of a collaborative space makes it possible to store even more detailed information in the model, such as the availability or the effectiveness of allocating an operator or activity. Such representation would allow if the total of the rows of the fuzzy incidence matrix would be calculated, the total FTE (Full-Time Equivalent) of the allocated operators can be obtained by summarising the weights of vertices.

A so-called Fuzzy Competition Hypergraphs method [79] can facilitate decision making, which could also be adaptable in an intelligent manufacturing environment.

5. Conclusions

This work proposed utilising the concept of intelligent space to support the design of human–machine and human–human cooperation in manufacturing. Intelligent Manufacturing Spaces are production areas equipped with sensors, which enable the spaces to perceive and understand what is happening in them. Based on the simultaneous and integrated monitoring of the activities of the machines, robots, operators and mobile robots, additional functions that facilitate cooperation can be developed. The proposed Intelligent Collaborative Manufacturing Space (ICMS) enhances collaboration between the operators as well as provides them with valuable information about their performance and the state of the production system.

The analysis and design of the ICMS require a tool that provides information about the impacts of their interactions. This work highlighted that hypergraphs could support the analysis and design of manufacturing systems. The vertices of the hypergraph can represent events, resources/assets or competences, while the hyperedges represent the sets formed according to the activities/cooperations or attribute-type relationships. The hypergraph centrality measures and clusters/modules of the resultant network highlight the critical elements and interactions.

When necessary, the highlighted weakly connected components could be integrated by redesigning the system. The model also supports the analysis of the robustness of the manufacturing. As it is unclear what kind of simulated perturbations should be studied and which network measures should be analysed for this purpose, developing the proposed method for business process redesign could be the main research topic in this new field.

A reproducible case study that fits the industrial framework and considers its specificities is created. The presented wire harness assembly-based case study, similarly to the previous papers of the authors, stands for a transformation of an industrial process, which is capable of reproducing aspects of the developed ICMS on real-life data. The wire harness production has emerging research interest, as it has a high labour dependency, and it is complicated to automate the complex assembly maneuvers using robots. Additionally, many recent publications and calls (like *HORIZON-CL4-2022-DIGITAL-EMERGING-02-07*) also highlight the need for collaborative robot-related studies in wire harness assembly to fill the gap in the case of automation and human–machine collaboration. Due to confidential manufacturing information, the detailed assembly line data cannot be used, although the factory-based case study will be published on the authors' webpage at abonyilab.com.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix. Assembly activities of the wire harness production benchmark

See Tables A.10 and A.11.

Table A.10
Description of the different activity types in the entire wire harness assembly benchmark.

Activity type ID	Description of the activity type
t1	Point-to-point wiring on a chassis
t2	Laying in a U-channel
t3	Laying a flat cable
t4	Laying wire(s) onto the harness jig
t5	Laying a cable connector (one end) onto a harness jig
t6	Spot-tying onto a cable and cutting with a pair of scissors
t7	Lacing activity
t8	Lacing activity
t9	Inserting into a tube or sleeve
t10	Attachment of a wire terminal
t11	Screw fastening of a wire terminal
t12	Screw-and-nut fastening of a wire terminal
t13	Circular connector
t14	Rectangular connector
t15	Clip installation
t16	Loading of the AGV
t17	Transportation
t18	Manual handling of a wire from a buffer
t19	Positioning of a crimp into a vise
t20	Inserting a wire into a crimp
t21	Starting a machine
t22	Crimping
t23	Manual handling of a semi-finished product
t24	Handover of a semi-finished product
t25	Positioning of a crimp into a fixture
t26	Manual handling of a semi-finished product into a buffer

Table A.11
The sequence of activities of the proposed wire harness assembly benchmark and their details.

Activity ID	Number of process step	Process step	Activity type ID
a1	1	Kanban - Buffer1	t16
a2	1	Kanban - Buffer1	t17
a3	1	Kanban - Buffer1	t16
a4	Batch size	Buffer1 - Crimping1	t18
a5	Batch size	Crimping1	t19
a6	Batch size	Crimping1	t20
a7	Batch size	Crimping1	t21
a8	Batch size	Crimping1	t22
a9	Batch size	Crimping1	t23
a10	Batch size	Crimping1 - Assembly1	t24
a11	Batch size	Assembly1	t25
a12	Batch size	Assembly1	t2
a13	Batch size	Assembly1	t4
a14	Batch size	Assembly1	t9
a15	Batch size	Assembly1	t11
a16	Batch size	Assembly1 - Buffer2	t26
a17	1	Buffer2 - Buffer3	t16
a18	1	Buffer2 - Buffer3	t17
a19	1	Buffer2 - Buffer3	t16
a20	Batch size	Buffer3 - Crimping2	t18
a21	Batch size	Crimping2	t19
a22	Batch size	Crimping2	t20
a23	Batch size	Crimping2	t21
a24	Batch size	Crimping2	t22
a25	Batch size	Crimping2	t23
a26	Batch size	Crimping2 - Assembly2	t24
a27	Batch size	Assembly2	t25
a28	Batch size	Assembly2	t2
a29	Batch size	Assembly2	t4
a30	Batch size	Assembly2	t9
a31	Batch size	Assembly2	t11
a32	Batch size	Assembly2 - Buffer4	t26

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(*continued on next page*)

Table A.11 (*continued*).

Activity ID	Number of process step	Process step	Activity type ID
a33	1	Buffer4 - Buffer9	t16
a34	1	Buffer4 - Buffer9	t17
a35	1	Buffer4 - Buffer9	t16
a36	1	Kanban - Buffer5	t16
a37	1	Kanban - Buffer5	t17
a38	1	Kanban - Buffer5	t16
a39	Batch size	Buffer5 - Crimping3	t18
a40	Batch size	Crimping3	t19
a41	Batch size	Crimping3	t20
a42	Batch size	Crimping3	t21
a43	Batch size	Crimping3	t22
a44	Batch size	Crimping3	t23
a45	Batch size	Crimping3 - Assembly3	t24
a46	Batch size	Assembly3	t25
a47	Batch size	Assembly3	t2
a48	Batch size	Assembly3	t4
a49	Batch size	Assembly3	t9
a50	Batch size	Assembly3	t11
a51	Batch size	Assembly3 - Buffer6	t26
a52	1	Buffer6 - Buffer7	t16
a53	1	Buffer6 - Buffer7	t17
a54	1	Buffer6 - Buffer7	t16
a55	Batch size	Buffer7 - Crimping4	t18
a56	Batch size	Crimping4	t19
a57	Batch size	Crimping4	t20
a58	Batch size	Crimping4	t21
a59	Batch size	Crimping4	t22
a60	Batch size	Crimping4	t23
a61	Batch size	Crimping4 - Assembly4	t24
a62	Batch size	Assembly4	t25
a63	Batch size	Assembly4	t2
a64	Batch size	Assembly4	t4
a65	Batch size	Assembly4	t9
a66	Batch size	Assembly4	t11
a67	Batch size	Assembly4 - Buffer8	t26
a68	1	Buffer8 - Buffer9	t16
a69	1	Buffer8 - Buffer9	t17
a70	1	Buffer8 - Buffer9	t16

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May I Have Your Attention?! Exploring Multitasking in Human-Robot Collaboration

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Abstract:
Human-robot collaboration promises to free the human to multitask and engage in cognitive work while the robots assists with physical tasks, therefore increasing productivity. However, this collaborative paradigm requires continuous attention from human operators, which could potentially strain their cognitive resources. Excessive attention demands can lead to safety hazards, increased errors, and reduced efficiency. Despite its critical importance, there is limited empirical research on attentional factors in industrial human-robot collaboration. In this study, we explore attentional multitasking in collaborative human-robot assembly settings. Our experimental setup involves participants performing a wire harnessing task with a collaborative robot while simultaneously completing a Go/No-Go test as a secondary task. To observe the effect of multitasking, we varied the difficulty of the secondary task across two levels and analysed its impacts on work performance and workload. Our results confirm threaded cognition theory, suggesting that human-robot collaboration could reduce cognitive capacity by depleting attentional resources, leading to higher errors and cycle times during multitasking. This underscores the importance of a detailed understanding of attentional factors in human-robot collaboration. We discuss our findings and their implications, and provide insights into the adjustment and design of human-robot collaboration tasks in the industry.

Keywords: Attention, Human-Robot Interaction, Multitasking, Collaborative Assembly

1. INTRODUCTION

Collaborative robots (cobots) have been designed to work alongside human operators and promise productivity gains and increased flexibility (Sherwani et al., 2020). The integration of cobots in manufacturing and assembly prompted a new line of research on human-robot collaboration (HRC), where humans work together with robots in a shared workspace. Prior works often exemplify the value of HRC as the optimal combination of automation to handle physical tasks while utilising cognitive skills of the human agent (Michalos et al., 2022; Othman and Yang, 2022). In theory, the robot taking over labourious manual tasks should free the human to engage in additional cognitive tasks. Therefore, multitasking in HRC has been proposed to further increase productivity (Chacón et al., 2021). Such applications can include simultaneous HRC and quality control, or working together with multiple cobots at the same time. However, multitasking requires the operator to split their attention among multiple tasks, which can in turn increase the load on the operator and reduce efficiency. Although cognitive load has already been studied in HRC (Carissoli et al., 2023), research on attentional factors is still lacking. Overall, depleting attentional resources through improper design of HRC applications might result in overseeing errors or reduced awareness of safety risks.

In this paper, we investigate the feasibility of attentional multitasking in collaborative human-robot assembly. We performed an exploratory study in which participants carried out a wire harnessing task with a cobot, while simultaneously engaging in parallel attention-demanding task through a Go/No-Go test. To evaluate the effects of multitasking, we designed the Go/No-Go test with two levels of difficulty in terms of their attentional demands. We conducted a user study with 16 participants and gathered quantitative metrics on task performance and response rates and qualitative feedback to evaluate the ability of engaging in secondary attentional tasks. Our experiment suggests that multitasking scenarios may lead to higher cycle times and potentially even increased errors, and operators might be prompted to adapt to the attentional load by prioritising only one of the tasks. Although we

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view multitasking in HRC as feasible, we raise concerns about potential effects on productivity and call for future research on designing HRC applications that don't deplete attentional resources.

2. RESEARCH BACKGROUND

2.1 Multitasking

Multitasking is defined in cognitive psychology as the capacity to manage more than one task at a time. Multitasking can be simultaneous execution of more than a single task (Pashler, 2000), a switching between multiple tasks that execute in parallel (Rogers and Monsell, 1995), or a combination of both in which frequent switching of attention is required. This capacity is essential in industrial environments, as individuals often handle multiple tasks, impacting both their cognitive workload and task performance. Theoretical frameworks, such as multiple resource theory (Wickens, 2008), propose that the effectiveness of multitasking depends on the cognitive resources needed for the activities. There is evidence that separate perceptual modalities follow independent attentional capacities (Alais et al., 2006; Chun et al., 2011; Arrighi et al., 2011), but recent results also suggest tasks requiring central attention based on perceptual input nevertheless share attentional resource; both unimodal and bimodal dual-tasks lead to increased overall load, with equivalent costs following increased task difficulty (Fougnie et al., 2018). The theory of threaded cognition (Salvucci and Taatgen, 2008) goes even further, suggesting that when performing multiple tasks, several mental processes run in parallel, with limitations imposed by resources such as attention and working memory. These theories explain how competing for limited mental resources when performing multiple tasks might make it difficult to focus on each task at a high enough level to ensure good performance (Taatgen et al., 2009; Rohrer and Pashler, 2003; Weigl et al., 2013), with possible detrimental effects leading to errors and accidents (Appelbaum et al., 2008; Metz et al., 2011).

2.2 Attention and Awareness in HRC

The demands of attention and cognitive load are significant factors that impact operators' situational awareness in industrial environments (Umbrico et al., 2023; Nicora et al., 2021). The concept of situational awareness, as defined by Endsley, refers to the "perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future" (Endsley, 1995). In the context of HRC, this translates to an understanding of the cobot's actions, intentions, and the overall state of the manufacturing process by the human operator. Prior research has highlighted the significance of operator awareness for task performance, safety, and productivity in HRC. Liu and Wang conducted a study investigating the impacts of awareness on manufacturing work, demonstrating that enhanced awareness leads more efficient and safer interactions with robots in a manufacturing environment (Liu and Wang, 2021). Additionally, the influence of cognitive fatigue on task performance and situational awareness in HRC was investigated in (Hopko et al., 2021). Their findings suggest that attentional demands have a substantial effect on cognitive fatigue, which in turn affects situational awareness. A study performed in (Paletta et al., 2019) investigated the correlates of visual attention measured by an eye tracker, situational awareness, and performance in HRC. Their results highlight the significance of attentional factors, with visual attention metrics being the main predictor for performance and awareness in HRC. In multitasking scenarios, operators are required to continuously adapt to changing tasks and the robot behavior, hence posing a high load on their attention and awareness. However, it is still unclear how attentional demands impact the error rates and the workload imposed on the operator in multitasking HRC scenarios.

3. EXPERIMENT

This experiment was designed to divide participants' attention, providing a realistic assembly scenario where the participant must balance the attentional load of the main task while also responding to the demands of the secondary task to simulate multitasking. The main task involved working on a wire harnesses in collaboration with a UR5e cobot, while the secondary task involved a Go/No-Go test to impose increased attentional demands. The experimental study was carried out at the Industry 5.0 laboratory at the University of Pannonia (Ruppert et al., 2022).

3.1 Participants

The study included a diverse cohort of 16 participants, consisting of 12 men and 4 women, representing a mix of university students and researchers. The age distribution among participants ranged from 21 to 42 years ($M = 30$, $SD = 6.16$), indicating a diverse demographic profile. All participants gave their consent to take part in the study.

3.2 Design and Procedure

To assess how multitasking affects HRC, we introduced two levels of difficulty for the secondary task while keeping the main task constant. Our study used a within-subjects design, where participants performed two sessions, one for each difficulty level of the secondary task (Figure 1). To mitigate order effects, we counterbalanced the sequence of the sessions for each participant. Moreover, training sessions were introduced before the experiment to further reduce potential order effects. First, the participants were introduced to the secondary task, which required participants to react to changes in screen colour through pressing a pedal on the floor. The frequency of these changes mirrored the conditions of the actual experiment; however, the training task was designed in a different manner than the task encountered in the experiment. Subsequently, the participants were introduced to the main HRC task, which involved wire harnessing in collaboration with a cobot. During this phase of training, participants practiced the wire harnessing procedure and interacting with the cobot. Besides order effects, the purpose of these training sessions was to ensure that participants were comfortable with the tasks, and minimise potential differences in dexterity.

Main task: During the main task, the cobot held a cylindrical hub that served as the central component of

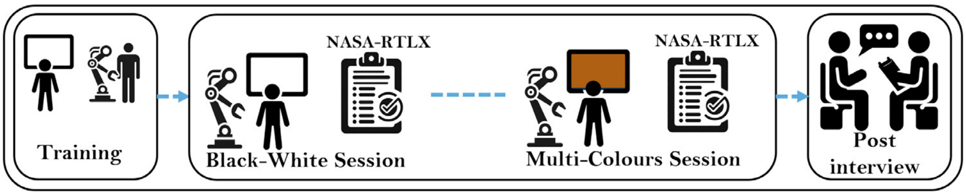


Fig. 1. Overview of the setup and the procedure of the study. The task order was counterbalanced, with 8 participants starting with the black-white condition, and 8 starting with the multi-colour session.

the task. The cobot swiftly rotated the hub to indicate the next assembly step to the operator, assisting in the assembly process. This rotation aligned the terminal block connectors, making it easier for the participant to continue the activity without any interruptions. The assembly included 24 wires with 12 emerging from the rear side and 12 from the front side of the cylindrical hub. These wires were to be connected depending on their label. The label was indicated by a combination of symbols and shapes. The labels simulated part numbers, which are commonly used in industrial assembly to recognize corresponding assembly components. To introduce a challenging aspect to the experiment, the colours of the wires were intentionally varied. The task involved three main steps: (1) Selecting one of the wires extending from the back of the cylindrical hub and attaching it to the terminal block connector using a screwdriver. (2) Identifying the correct counterpart wire based on the symbol and shape combination and attaching it to the terminal block connector using the screwdriver. (3) Verifying the integrity of the connection.

The possible mistakes in the primary task included mismatching of symbols and shapes, unintentional insertion into an adjacent terminal block connector rather than the designated one, insecure wire connections susceptible to detachment, or the total absence of a wire connection.

Secondary task: While the participants were engaged in the main task, a secondary task was introduced to evaluate their attentional capacity. The secondary task was deployed in form of a Go/No-Go test on a screen positioned in front of the participants. To evaluate the influence of attentional multitasking, we designed two conditions with different levels of attentional load.

The first condition was designed as a Go/No-Go test with a lower level of difficulty in terms of attentional demands. The test consisted of a white screen, with a black screen randomly appearing for two seconds within 15-second intervals. The timing of the stimulus was not predetermined and did not follow a regular pattern during the session, making it unpredictable. Hence, participants needed to constantly focus on the attentional test, while also focusing on the human-robot assembly. Each time when the stimulus in form of the black screen was presented, the participant was required to perform a reflexive action by pressing a pedal with their foot. This task assessed participants' ability to sustain attention and respond effectively within the requirements of the main task.

In the second condition, we implemented the same test, but with a higher level of attentional demand, primarily influenced by the increased frequency of stimuli presentation. Three different colours — grey, brown, and white — served as No-Go stimuli, with the Go stimulus again being a black screen. Each of the No-Go colours appeared briefly and randomly for two seconds. Once every 15 seconds, a Go stimulus was presented, with random timing. This experiment required the participants to sustain a higher level of attention on the frequency of the stimuli, as they had to differentiate between Go and No-Go stimuli. The responses were, again, registered via a pedal on the floor.

The possible mistakes in the secondary task included failing to react to the desired colour, or incorrectly responding to a different colour. These possible mistakes were tracked by a code used to build the secondary task. Counterbalancing the conditions was achieved by splitting the participants into two groups, with eight participants starting the experiment with the simpler (black) condition, and eight participants starting with the harder (coloured) condition (Figure 1).

3.3 Data and Analysis

We performed a quantitative analysis on self-reported data collected through post-experiment questionnaire, as well as objective metrics. The objective metrics included task completion time (TCT), the number of errors in the main task, the number of times the participant missed the stimulus in the secondary attentional tasks, and the number of errors in the secondary task. The subjective metrics were collected through the NASA RTLX questionnaire. The analysis was conducted using a two-tailed paired samples t-test. Due to the exploratory nature of our study and the low sample size, we also report descriptive statistics as supplementary metrics.

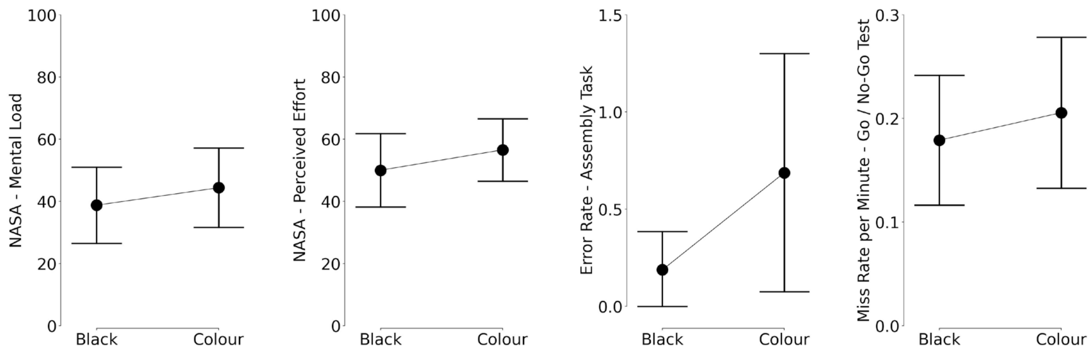
Additionally, we complemented the quantitative results by a qualitative analysis via post-interviews. The participant selection for the interviews was based on a manual data analysis, where we identified seven participants , and asked them further questions with regard to their perception of the differences among the two conditions.

For our study, we assumed that the two conditions will exhibit a difference in mental workload measured by NASA RTLX. We base this hypothesis on the theory of threaded cognition, which suggests that increased attentional demands contribute to higher cognitive load. Additionally, we hypothesised that there will be differences in the objective metrics, while the overall workload will remain statistically equal.

4. RESULTS

4.1 Quantitative Analysis

First, we analysed the differences in the perceived mental load between the two conditions. Student's t-test showed



(a) Mental load (b) Perceived effort (c) Assembly errors (d) Miss rates

Fig. 2. Comparative plots of the mean and the confidence intervals ($CI = .95$) for the two conditions and per variable.

a weakly significant effect with $t(15) = -2.087$, $p = .054$, and Cohen's d of -0.522. Our analysis also revealed a weakly significant difference in perceived effort between the two conditions ($t(15) = -1.787$, $p = .094$, Cohen's d $= -0.447$). The descriptive plots of the two variables are depicted in Figures 2a and 2b. This indicates that the colour condition was perceived as cognitively harder, with a small to medium effect size. No other subjective metrics from the NASA RTLX questionnaire showed a significant difference. This correlates with our expectation, as we controlled for an increased attentional load, while the overall workload for the task remained the same.

Regarding the performance metrics, assembly errors were analysed using the Wilcoxon signed-rank test (Shapiro-Wilk test, $p - value < .05$), which yielded no significant differences ($Z = -1.618$, $p = .134$). Although not significant, as the majority of the participants did not perform any errors in the assembly task, the descriptive statistics (Figure 2c) indicate a possible trend towards more errors during the secondary task in the colour condition. To analyse the performance of the secondary tasks, we investigated the miss rate, i.e., the number of time the participant did not react to the Go-stimulus. As the number of stimuli in the experiment was dependent on the task duration, we scaled the variable by the experiment duration to ensure comparability. The test did not reveal any significant differences ($t(15) = -1.117$, $p = .282$). The descriptive results of both errors rates are depicted in Figures 2c and 2d.

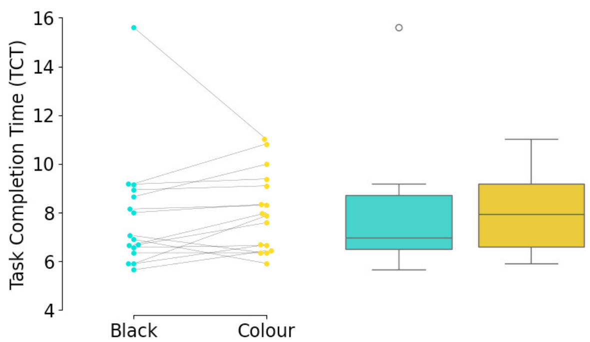


Fig. 3. Swarmplot and boxplot of the differences in task duration per condition.

Finally, we have analysed the effect of the two conditions on the task completion time (TCT). As the black condition contained a strong outlier and the Shapiro-Wilk test yielded a $p-value < .05$, we again deployed the Wilcoxon signed-rank test to analyse the data. The results displayed a Z-score of -1.647 ($p = .105$). Despite non-significant results, the effect size of -0.483 (rank-biserial correlation) and the descriptives provided in Figure 3 indicate a trend towards more time needed for the colour condition.

4.2 Qualitative Analysis

One week after the experiment, we invited selected participants for a post-interview. This included random participants, selection based on observation during the experiment, or participants whose data contradicted the trend, such as in the case of the participant with a very long task duration in the black condition (Figure 3). We analysed the statements from the participants, and clustered the data into three themes:

- *Strategy Adaptation* - the split of the attention forced some participants to reduce their focus on one task and prioritise the other to avoid mistakes. This was, for example, the explanation for the outlier TCT in Figure 3. In this case, the participant was overly focused on the secondary task not to miss the stimuli, which lead to a high completion time of the main task.
- *Learning Effect* - three participants mentioned that they got more comfortable with the experiment over the time, and thus they made less mistakes and also perceived the second session as easier, disregarding whether they experienced the black or colour condition in their second experiment.
- *Subjectivity and Fatigue* - some participants perceived one of the conditions easier, despite making more mistakes than in the condition they perceived as harder. Moreover, two participants gave different statements with regard to their perception of the two conditions, with the responses from the interview contradicted their NASA metrics. Through further questions, they attributed this to fatigue.

5. DISCUSSION 199

Prior works on HRC in manufacturing often assume that humans can effortlessly transition to cognitive tasks while robots assist them with labourious manual tasks. However, engaging in collaboration with a robot requires attention, which can deplete attentional resources required for other tasks. We studied how attentional multitasking in HRC impacts productivity and explored the potential disadvantages. Although not statistically significant due to the exploratory nature of our study and low sample size, our results indicate that workers are required to split their attention to manage multiple tasks. This can potentially reduce productivity, as evidenced by a trend towards more errors in assembly tasks. Additionally, while the miss rate in secondary tasks did not show significant differences, the descriptive results suggest that attentional multitasking could transition into workers overseeing quality-related issues and their awareness of the environment and work can be reduced. In turn, this can pose safety related issues. Moreover, we observed potential implications for task completion time, with a trend towards increased duration in conditions where the secondary task poses increased cognitive demands. These findings underscore the importance of considering the impacts of attentional requirements in HRC to optimize task performance and efficiency.

Our results also show that, when multitasking in HRC settings, participants may adapt their strategy and prioritise one task over another, leading to more errors in the respective task. We speculate that this can be either due to the inability to split attention between multiple tasks, or simply because of the preference to maximising the efficiency in one task while sacrificing efficiency in another. Preferred strategy for multitasking tends to converge towards that of minimal interference to either task, but the process of finding the optimal solution is not automatic, and is not always observed across all participants (Nijboer et al., 2013). Participants' preferred strategy itself may have impact on performance and effort, regardless of task prioritization instructions (Jansen et al., 2016).

The results of our experiments are aligned with the threaded cognition theory, which suggests that cognitive capacity might be reduced due to HRC depleting their attentional resources. It is important to consider real-life examples of such attentional multitasking such as concurrent HRC and quality control, supervision of and collaboration with multiple robots, or being able to flexibly react to short-term interruptions or a problem in the process. Instead of dichotomously adding up the physical capabilities of the robot with the cognitive skills of the operator, we propose to view humans collaborating with robots as a blend of cognitive constraints that are affected by the physical actions of the robot. We aim to challenge the notion of clear-cut boundaries between the agents, and call for a reevaluation of claims related to HRC and productivity gains. Designing HRC applications requires a more nuanced understanding of how attentional and cognitive resources are used, yet, empirical research on such applications in manufacturing is missing.

Finally, we give two design implications based on our experimental study. First, we believe that the integration of collaborative robots should not lead to the exploiting of the limits of cognitive resources by placing additional tasks on workers. Our study indicates that potential consequences might include increased cognitive load and perceived effort, as well as reduced productivity. Still, multitasking can be feasible in opportune moments, such as at times when the engagement in the HRC task is reduced. Transferring this into HRC applications requires an improved communication of robot's intent to the human, indicating when the human agent can reduce their awareness of the robot movement and focus their attention on other tasks. Alternatively, multitasking in HRC could be supported by attention management systems, which have been shown to limit attention fragmentation (Anderson et al., 2018). Second, we advise against the design of HRC applications with parallel, simultaneous multitasking, and propose the sequential approach instead. This involves a clearer definition of task boundaries, for instance, by task allocation and scheduling algorithms, mitigating the risk of having to prioritise one task over the other.

5.1 Limitations and Future Work

The primary constraint in this experiment was the limited sample size due to the exploratory nature of the study. Given the relatively low effect size, there is need to adequately test the generalizability of our results. As such, we intend to reevaluate our findings with a larger sample size study. Our results also indicate the presence of a possible floor effect. This suggests our main task may not have been sufficiently difficult to fully evaluate the whole spectrum of multitasking abilities. Performance effects from multitasking are more apparent when the main task is deemed difficult by the participants (Adler and Benbunan-Fich, 2015). As such, we aim to further tune main task difficulty and study design to better emulate multitasking in real-life manufacturing conditions.

Furthermore, based on our results, we believe that there might be evidence for an interaction between task completion time and errors, both in the main and secondary task. This might provide additional insights into how performance metrics are interrelated in multitasking scenarios. However, our study design did not allow us to perform this investigation. For example, manipulation of stimulus onset asynchrony and task order in dual-tasks have been reported to affect response times, while having no effect on error rates (Kamienkowski and Sigman, 2008). It should be noted however that a common criticism of dual-task design lies in the difficulty of replication due to specificity and customized nature of instruction and task design; parameters such as the choice of modality in each task can influence observed cognitive load, leading to different findings between studies investigating similar qualities (Esmaeili Bijarsari, 2021). To ensure replicability of our results, clear definition of both tasks' modalities as well as correct definitions of assumptions on measurement of cognitive load is important. Additionally, future studies should compare these multitasking scenarios with non-multitasking conditions to isolate the specific contributions of concurrent task management to cognitive load.

6. CONCLUSION

In this work we explored attentional factors in industrial HRC. Through our experimental design, we observed the impact of attentional multitasking with two different levels of difficulty on productivity. We show that secondary tasks with increased attentional requirements may result in productivity decrease in the form of higher error rates and task duration. Our findings underscore the importance of considering attentional demands in the design and implementation of collaborative human-robot applications in manufacturing. Moving forward, our exploratory study aimed to address a gap in empirical research on human factors in HRC. We state our design recommendations for developing applications in order to mitigate potential productivity decrease and prevent increased cognitive demands from workers. We call for more empirical research on industrial HRC to further investigate this interesting field wand shape applications that benefit workers.

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Impact of work instruction difficulty on cognitive load and operational efficiency

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As industries progress toward integrating more complex technologies within Industry 4.0 frameworks, ensuring work instructions that balance cognitive load and performance is increasingly critical, especially under the human-centric principles of the 5th industrial revolution. Drawing on Cognitive Load Theory (CLT), this study compares two instructional methods-visual-based and code-based-to determine whether cognitive overload can be reduced without compromising task outcomes in a controlled, assembly-like scenario derived from industrial tasks. We recruited 30 participants from the academic field (students and researchers), who completed assembly tasks under both visual-based and code-based instructions. Cognitive load was measured objectively by (Galvanic Skin Response, Heart Rate Variability, and hand motion acceleration) and subjectively through (NASA Task Load Index, short Dundee Stress State Questionnaire). Operational efficiency was assessed via task completion time (TCT), number of task repetitions (NTR), and assembly precision based on the standard deviation. The findings demonstrated that visual-based instructions significantly reduced cognitive load with a $p - value < 0.001$. It also showed an improvement in two of the performance metrics during the use of visual-based instructions for the TCT and NTR with $p - values < 0.001$. However, although code-based instructions increased cognitive load, they showed better assembly precision with a $p - value < 0.001$. These results suggest that while simple and direct instructions facilitate task execution and reduce cognitive loads, deep thinking approaches may still hold value for tasks requiring high precision.

Keywords Work instruction, Assembly, Cognitive load, GSR, HRV, CLT

In modern industrial settings, the dynamic nature of the workforce and the rising costs of human labor necessitate implementing efficient and effective training and assembly procedures[1]. The introduction of Operator 4.0, a framework that integrates technological advancements with a human-centric approach, aims to enhance operational efficiency and worker well-being[2]. As industries evolve to embrace more advanced technologies and complex processes, there is a pressing need to ensure that human operators are not only efficient but also resilient and well-supported in their roles[3]. Human operators in these environments face multifaceted challenges, intensified by the rise in product variants that require precise cognitive engagement. Supporting these operators effectively involves not only enhancing the clarity and accessibility of work instructions but also customizing these instructions to reduce cognitive load-a concept grounded in Cognitive Load Theory (CLT)[4,5]. Given these escalating complexities and the imperative for human-centric approaches, re-assessing conventional work instructions emerges as a vital step to maintain productivity, reduce errors, and manage operator strain in increasingly dynamic manufacturing scenarios[4,6].

In the industrial setting, poorly designed instructions can significantly undermine productivity, increase the likelihood of errors, and lower overall job satisfaction. Moreover, the detrimental economic and social consequences of poor instruction have been extensively documented, resulting in reduced levels of customer satisfaction, increased operational costs, and inefficient decision-making processes[7]. This highlights the necessity for companies to prioritize high-quality information in their operational instructions[7–10]. Although numerous

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studies have explored the benefits of simplified or digital work instructions-such as textual guides or augmented reality (AR)-based solutions[11,12]-these approaches often do not systematically validate the objective metrics with the subjective experience of workers based on the utilized instructions. Furthermore, research that integrates subjective questionnaires and objective physiological metrics to comprehensively evaluate worker cognitive load and efficiency based on work instructions remains limited. This gap is particularly pressing in modern assembly environments, where rising task complexity calls for instruction designs that are both cognitively considerate and operationally effective.

To address this gap, the present study systematically compares two distinct instructional approaches-code-based and visual-based-within an assembly-like scenario. Specifically, we hypothesize that code-based instructions, which rely on alphanumeric codes to guide the assembly process, impose a higher subjective cognitive load due to the increased mental effort required to decipher the codes. By contrast, visual-based instructions are expected to reduce cognitive load by offering more intuitive, graphical representations of the same tasks. However, this simplified approach may induce more frequent hand movements and repeated task cycles-potentially resulting in more pronounced changes in physiological signals (Galvanic Skin Response GSR and Photoplethysmogram PPG) due to increased physical activity. In evaluating these hypotheses, we measure both subjective cognitive load (using the NASA Task Load Index 'NASA_TLX' and short Dundee Stress State Questionnaire 'short DSSQ') and objective indicators (physiological signals and task performance metrics) to capture a comprehensive view of how work instructions influence operator well-being and efficiency. We therefore pose the central question: *How do subjective perceptions of cognitive load and performance align with objectively measured changes in cognitive load and performance when different instructional methods are employed?*

The next subsections detail the theoretical and practical frameworks-Cognitive Load Theory and Worker Performance-to further contextualize our research.

Cognitive load theory (CLT)

CLT serves as the primary framework for assessing the effectiveness of work instructions in this study. Cognitive load refers to the amount of mental resources and effort required to process information and carry out a particular task. It represents the demand placed on working memory during task execution. CLT highlights that while our long-term memory has an expansive capacity, our working memory is significantly more limited. The theory defines three types of cognitive loads, each impacting the efficiency of our information processing. The first type, *"Intrinsic Cognitive Load"*, deals with the degree of complexity associated with the acquisition of new knowledge[5,13]. In this research, the intrinsic cognitive load is highlighted through the task of constructing specific patterns using "Make 'N' Break Extreme" pieces, which are intentionally designed to possess a consistent level of intrinsic complexity.

The second type within CLT is known as *"Extraneous Cognitive Load"*. This arises from the manner in which instructions are presented and the design of the instructional system itself. This type of load, which often results from less effective instructional designs, should preferably be reduced since it has the potential to improperly complicate the learning processes. Fortunately, instructors can manage extraneous cognitive load through careful planning and execution, thereby optimizing instructional delivery to reduce or eliminate its impact[5,13]. In our study, we have applied this concept by incorporating two different instructional methods: visual and code-based to examine their respective influences on cognitive load and performance. The last type defined by CLT is referred to as *"Germane Cognitive Load"*. This concept relates to the cognitive processes that motivate workers to engage actively and exert effort in the learning process. This type of load is crucial for facilitating knowledge acquisition[5,13]. However, in our experimental design, we did not specifically address Germane Cognitive Load as our focus was primarily on examining the effects of work instructions (Extraneous Cognitive Load) while controlling the other types of cognitive load.

In this study, we assess cognitive load both subjectively and objectively. Subjective measures are obtained using both the NASA_TLX[14] and the short form of the DSSQ[15], which together provide a comprehensive assessment of multidimensional cognitive workload and dynamic stress states. Short DSSQ focuses on three key psychological states: *engagement*, *distress*, and *worry*. Task *engagement* refers to the individual's energy level, personal concentration, and task motivation, indicating how strongly someone applies themselves toward achieving goals. Low task engagement is characterized by low energy, reduced motivation, and easy distraction, often manifesting as fatigue. *Distress*, on the other hand, is associated with negative emotional states; it reflects an overload of processing capacity that leads to feelings of lost control and reduced capability. Finally, *worry* involves negative self-assessments and intrusive thoughts that distract from task performance by shifting focus to the personal relevance of the task[16]. Objective cognitive load assessment is evaluated through multiple variables, including physiological indicators: GSR and Heart Rate Variability (HRV) derived from recorded PPG data, hand-motion acceleration, and performance measures like the number of task repetitions, task completion times, and assembly precision.

Worker performance

In evaluating the effectiveness of work instructions in industrial environments, the performance of workers emerges as a crucial metric. It provides tangible evidence of how well instructions support task execution. This study focuses on several key performance metrics to assess the effectiveness of different instructional methods. One of the primary indicators of effective work instructions is *Task Completion Time (TCT)*. It measures the amount of time required for workers to finish a given task. Successfully accomplishing the task within the designated timeframe, or even earlier, could indicate that the instructions are clear and promote efficient comprehension and implementation. Conversely, prolonged completion times could potentially signify cognitive overload or confusion[17].

Moreover, evaluating the *Number of Task Repetitions (NTR)* experienced by workers across sessions will provide insight into their ability to efficiently execute and repeat the tasks based on the provided instructions. A higher number of task repetitions can indicate more effective work instructions that facilitate quicker familiarity and mastery of tasks[18,19]. We have utilized a video-based assessment as a method to measure the precision of the worker's assembly process. Specifically, we define precision as the degree of positional accuracy in placing the blocks, which is quantified by tracking the centers of the attached Aruco markers on each piece. The lower the variance or standard deviation of these positions, the higher the precision. This metric is critical for gauging the relationship between task execution quality and NTR under different instructional methods[7,20,21].

Related work

The transition toward Industry 4.0 and 5.0 has brought us to the end of Tayloristic industrial production, a system that breaks tasks into small, standardized steps to maximize efficiency. Modern industrial settings are now distinguished by higher complexity and greater flexibility[22]. Manual assembly is not exempt from these transitions through reducing production depth and increasing reliance on suppliers, and small and more diverse batches[22,23]. This shift leads to less predictability and routine for assembly workers. This uncertainty has increased workers' workloads and put more pressure on designers to design efficient assembly instructions.

One of the suggested scenarios that has received great attention in recent years is the digital management system, which includes digitally designing and delivering work instructions to individuals. A few examples of these digital techniques are extended reality (XR), augmented reality (AR)[11,24,25], mixed reality (MR)[26], digital work instruction supported by multiple video streams[27], visual contents of work instructions (pictures)[4] and an approach based on gesture recognition for a self-learning digital assistant system[28]. These techniques can help workers complete their tasks with higher productivity and fewer errors by continuously updating information on the current assembly product, including updates on parts, tools, and processes[22]. However, implementing these new technologies can increase cognitive demands[26]. Furthermore, a significant limitation of many studies is their reliance on subjective metrics, such as questionnaires, and basic performance metrics, like task completion time, without incorporating physiological signals to monitor workers' cognitive load and performance. While some studies have explored objective indicators using physiological signals, they often lack thorough validation of correlating these objective measures with subjective assessments of both cognitive load and worker performance.

Researchers have employed a wide range of physiological signals to assess cognitive load, including skin conductivity (GSR)[29–32], photoplethysmography (PPG)[33–35], electrocardiograms (ECG)[36], electrooculograms (EOG)[37], electromyograms (EMG)[38,39], speech signals[40], electroencephalograms (EEG)[36,41–43], acceleration[35,36], eye blinks, gaze, and movements[44–46], breathing rate[36,38,46], skin temperature[36,39], and blood volume pulse[36]. Most of the studies that utilized these physiological markers to monitor workers' cognitive load have ranged from standard lab tasks like mathematical problems[29], the Stroop test[33], IQ tasks[34], and constructing with LEGO bricks[37] to more industrially relevant scenarios such as pushing/pulling wagons and sorting tasks[31].

Within these contexts, GSR is frequently cited for its sensitivity to stress and arousal[47], whereas HRV has demonstrated distinct responsiveness to both mental and physical demands. For instance, a study by Taelman et al.[48] using the wavelet transform of HRV found that tasks involving both mental and physical effort showed similar trends in the High Frequency (HF) parameter as purely physical tasks. However, these tasks had Low Frequency (LF) values, similar to those seen in tasks that were only mentally demanding. In contrast, Garde et al.[49] found that adding mental challenges to a physical task did not significantly impact HRV parameters. Cheng et al. conducted a study on HRV in individuals engaged in cognitive activities under medium and high physical conditions. The study revealed substantial changes in HRV compared to situations without physical load[50,51]. Given that our experiment encompasses a code-based condition expected to impose significant mental effort yet involve fewer repetitive motions, alongside a visual-based condition anticipated to have lower mental demands but increased physical activity, we integrate HRV and GSR as complementary measures to monitor workers' cognitive load. Additionally, relatively few studies have systematically evaluated work instructions in assembly tasks while concurrently measuring both subjective (questionnaires) and objective (GSR, HRV) markers of cognitive load.

Following the model proposed by Eesee et al.[52], who recommended a strategy to manage cognitive load by adjusting workers' surroundings and the nature of the activity or providing supplementary aids, we designed our experiment that keeps intrinsic task complexity constant-through assembling collections with the same number of pieces each time- while manipulating extraneous load through code-based and visual-based instructions. By doing so, we are applying their criterion to explore how task difficulty management influences the extraneous cognitive load on workers.

This approach extends existing research on digital or simplified instruction methods[22,26] by explicitly contrasting two instructional formats and validating the outcomes with physiological and self-report data. By examining how workers respond differently in terms of mental effort, stress arousal, and operational efficiency, our study clarifies the balance between offering intuitive guidance and avoiding information overload. This integrated perspective addresses a critical gap in understanding how instructional design can optimize both cognitive and performance outcomes in modern, high-mix industrial environments.

Methodology

Given the gap identified in the literature, we designed a controlled experiment in which participants assembled "Make 'N' Break Extreme" blocks using two instructional methods: code-based and visual-based instructions. This protocol was chosen specifically to isolate extraneous load while maintaining consistent intrinsic load across tasks. The present study aims to investigate the impact of work instructions on operator cognitive load and performance within a controlled, assembly-like scenario. The experiment was carried out in the Industry

5.0 laboratory of the University of Pannonia[53]. In the following subsections of the methodology, we detail the participant recruitment, experimental procedure, data collection, and processing methods used to extract the features from the physiological responses and performance outcomes under each instructional approach.

Participants

This study recruited 30 participants from the academic field, a mix of university students and researchers with different demographic and ethnic backgrounds. Twelve of them were male and eighteen were female, with ages ranging from 19 to 39 years ($M = 24.733$, $SD = 5.252$). Ethical approval for this study was obtained from the Institutional Review Board of the University of Pannonia (Approval number: KEB_MK_FIT_2024_01). All methods were performed in accordance with the relevant guidelines and regulations. All participants provided written informed consent prior to participation. Since both the visual-based and the code-based instructions rely on colors, participants were required to fill out a vision questionnaire to make sure none of them had color blindness. Three of the participants were wearing contact lenses, and 17 of them had glasses. We also asked the participant to fill out an Edinburgh-handedness questionnaire[54]. Three of the participants were left-handed, and none of the participants had limited hand or finger movements.

Instructional design

The study involved the use of two instructional approaches for two distinct sessions: *Visual-based* instructions for the low cognitive load session and *Code-based* instructions for the high cognitive load session. In the visual-based session, the participants see a series of step-by-step images depicting exactly how each pair of blocks should connect. In other words, each image clearly shows which sides of the pieces should touch, allowing participants to visually align the blocks until they match the illustrated pattern. The visual instructions presented in this context are characterized by their clarity as they provide a straightforward and unambiguous representation of the final goal. This approach aims to minimize the need for interpretive effort from the participants.

On the other hand, we utilized a color-based coding system for the assembly instructions to increase the difficulty level in the code-based hard session. A code, usually consisting of the first two letters of its color, references each piece. For example, 'Re' signifies the red piece and appears in red text, while 'Gr' signifies the green piece and appears in green text. The instructional material provides participants with these codes, which they must use to determine the position and contact points between pieces. The representation of spatial relationships between pieces is denoted by 'A' for Above, 'B' for Below, 'L' for Left of, and 'R' for Right of. We denote the degree of contact between two adjacent pieces as 'T1' for a single contact region and progressively increase it to 'T4' for four contact regions. The codes require participants to translate abstract instructions into the concrete task of assembling the blocks, reflecting a cognitive challenge often encountered in real-life situations where such instructions can be difficult to interpret. Figure 1 shows the setup of the experiment in this study.

Experiment design and procedure

The experimental setup utilized a customized "Make 'N' Break Extreme Game" construction block set. This set comprises ten distinct blocks, each with a unique color and shape, which are used as the main tools for the work. We attached Aruco markers-square black and white barcode-like stickers-to each block. These stickers enable computer vision algorithms through video-based monitoring to track and verify the precision of the constructions made by the participants.

Each participant completed both visually based and code-based assembly tasks. To counterbalance task difficulty, half of the participants started with the visually-based assembly task, and the other half of the participants started with the code-based assembly task. We created four unique assembly patterns (labeled 1, 2, 3, and 4), each consisting of six distinct blocks. This is to make the tasks more varied and make sure that participants can be properly tested across both instructional approaches. Each participant went through all of them, two for visual-based and two for code-based instructions. To provide a counterbalance and control for the order effect in learning and performance, we further allocated the participants in these two main groups into two subgroups each. Table 1 shows the distributions of the participants for the sessions and the assembly of the patterns.

Before each session, participants engaged in a brief training that corresponds to the specific instructional format, visual, or code-based. The experiment commenced with a three-minute baseline physiological recording. Subsequently, the participants proceeded to complete the pre-DSSQ[15] to evaluate their stress levels before starting the experiment. Upon finishing the first session, participants completed the post-DSSQ and NASA_TLX questionnaires to evaluate their subjective cognitive load and stress post-task. The process of filling out the post-DSSQ and the NASA_TLX was then repeated at the end of the second session.

Physiological responses during task execution were monitored using the Shimmer3 sensor. Electrodes were attached to the index and middle fingers of the non-dominant hand to record the GSR signal, with its PPG electrode affixed to the earlobe or the thumb for HRV extraction. As physiological signals are sensitive to motion[55], participants were asked to use their dominant hands only during the assembly task. Furthermore, a Metamotion sensor was employed to track the acceleration of the hand, utilizing its capability as a wearable, wristwatch-like device strapped to the participant's dominant wrist.

Each session was limited to a total duration of five minutes, during which participants were required to create each specified pattern a minimum of three times for the purpose of learning curve analysis. The duration of the sessions could be longer than five minutes, just in the cases where the participant has not met the minimum number of task repetitions (NTR). Time-stamped data from each session was captured to track progress and performance.

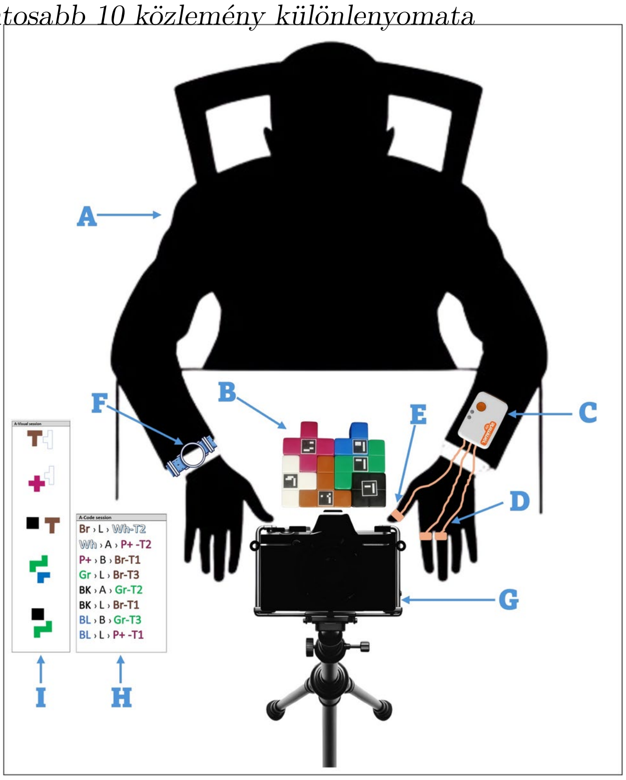


Fig. 1. This figure illustrates the comprehensive setup used in our experiment: **Participant (A)**: The participant sits on a chair facing a table where the tasks take place. **Building Blocks (B)**: Displayed on the table are the building blocks used in the experiment, each tagged with an Aruco marker to identify them during the tasks. **Shimmer3 Sensor (C)**: This sensor is attached to the arm of the participant's non-dominant hand to monitor the physiological signals (GSR and PPG). **GSR Electrodes (D)**: These electrodes are fixed to the proximal phalanx of the index and middle fingers of the non-dominant hand to measure skin conductance. **PPG Electrode (E)**: Positioned on the thumb's distal phalanx of the non-dominant hand, this electrode monitors the PPG signal. **Metamotion Sensor (F)**: an accelerometer worn on the dominant hand's wrist; this sensor tracks the participant's physical motion while engaging in the tasks. **Video Camera (G)**: This camera is mounted on a stand to capture a top-view of the task area. It records the activities during the experiment. **Code-based Instructions (H)**: A sample of code-based instructions provided to participants for task guidance. **Visual-based Instructions (I)**: This is a sample of visual instructions used to direct participants in the experiment.

Groups	Sub_Groups	Baseline	Questionnaires	1st Session	Questionnaires	2nd Session	Questionnaires
G1	Sub_G1.1	3 minutes	Pre-DSSQ	Code-based (1 , 2)	Post-DSSQ +NASA_TLX	Visual-based (3 , 4)	Post-DSSQ +NASA_TLX
	Sub_G1.2	3 minutes	Pre-DSSQ	Code-based (3 , 4)	Post-DSSQ +NASA_TLX	Visual-based (1, 2)	Post-DSSQ +NASA_TLX
G2	Sub_G2.1	3 minutes	Pre-DSSQ	Visual-based (1, 2)	Post-DSSQ +NASA_TLX	Code-based (3 , 4)	Post-DSSQ +NASA_TLX
	Sub_G2.2	3 minutes	Pre-DSSQ	Visual-based (3 , 4)	Post-DSSQ +NASA_TLX	Code-based (1 , 2)	Post-DSSQ +NASA_TLX

Table 1. Participants distribution and session sequencing in the study of visual and code-Based assembly tasks.

Data preprocessing

In this experiment, we set the sampling frequency of the Shimmer3 sensor to 250 Hz to capture the physiological signals GSR and PPG. Low-frequency trend noise accompanies most of the recorded PPG signals, which complicates direct HRV extraction. We started with mean correction by removing the DC level offset to make sure that the signals are oscillating around the zero baseline. Following this step, we implemented the Savitzky-Golay filter to remove the low-frequency trend noise. We then implemented the peak detection technique to extract the distances between the peaks and obtain the HRV. Figure 2 shows a sample of a 60-second PPG signal before and after removing the DC offset and low-frequency trend.

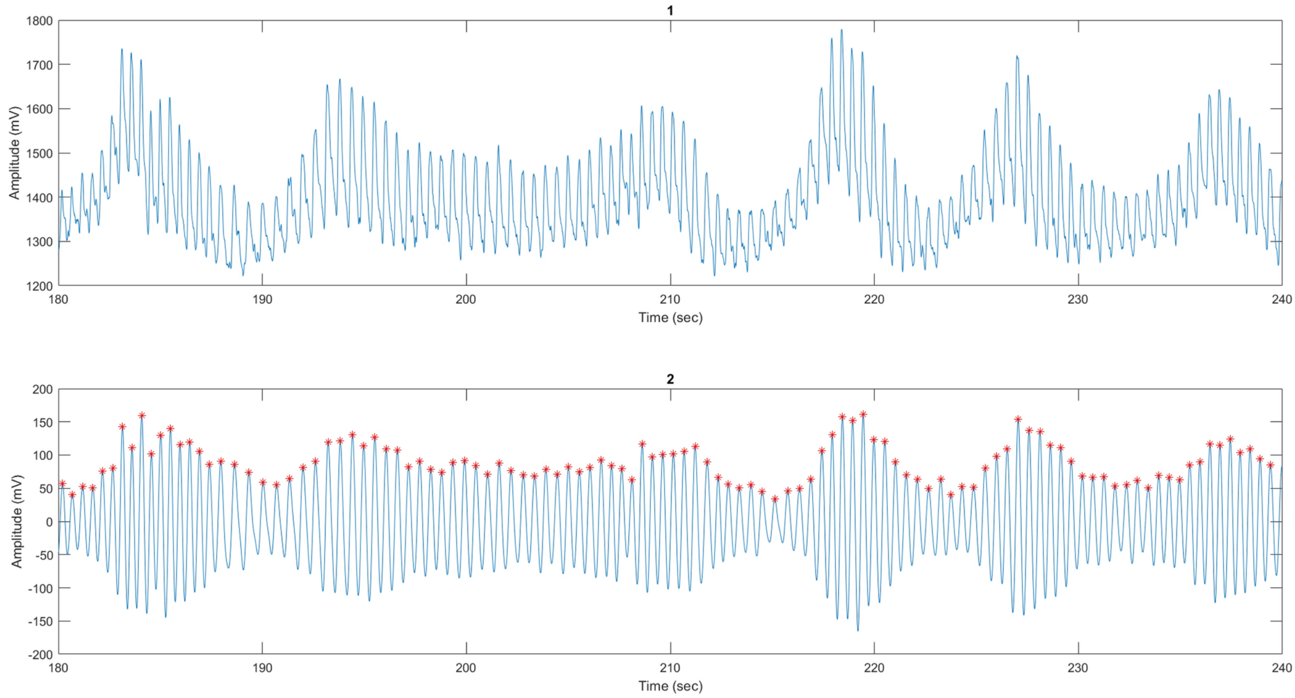


Fig. 2. (1) A sample of Raw PPG signal for 60 seconds, (2) The same sample of the PPG signal after being filtered and removing the DC offset and low-frequency trend with its detected peaks.

HRV acronyms	Description
RMSSD	The square root of the average of the squared differences between consecutive intervals:
	$\sqrt{\frac{\sum_{i=1}^{N-1}(RR_{i+1}-RR_{i})^{2}}{N-1}}$, RR is the interval between the peaks[56].
MEAN	The mean of the RR intervals.
MEDIAN	The median of the RR intervals.
SDRR	Standard Deviation of the RR intervals.
SDSD	Standard deviation of the differences between consecutive RR intervals.
SDRR_RMSSD	Ratio of SDRR to RMSSD.
HR	Heart Rate (beats per minute).
PNN25	Percentage of consecutive RR intervals differing by more than 25 ms.
PNN50	Percentage of consecutive RR intervals differing by more than 50 ms.
SD1	Descriptor of short-term HRV from the Poincaré plot.
SD2	Descriptor of long-term HRV from the Poincaré plot.
KURT_RR	Kurtosis calculated from all RR intervals.
SKEW_RR	Skewness calculated from all RR intervals.
VRL	Power spectrum of the Very low frequency band (0.003 Hz to 0.04 Hz) of the HRV.
LF	Power spectrum of the low frequency band (0.04 Hz to 0.15 Hz) of the HRV.
HF	Power spectrum of the high frequency band (0.15 Hz to 0.4 Hz) of the HRV.
TP	Total power spectrum of the HRV.
LF_HF	The ratio of the LF to HF.
HF_LF	The ratio of HF to LF.

Table 2. The list of the extracted HRV features and their description.

To increase the data size, we applied a 60-second segmentation window to the filtered signals. We extracted HRV signals for each 60-second window by calculating the variation between consecutive detected peaks on the time axis. We extracted 19 features from the HRV signals for each window. The summarized HRV features extracted in this study are presented in Table 2.

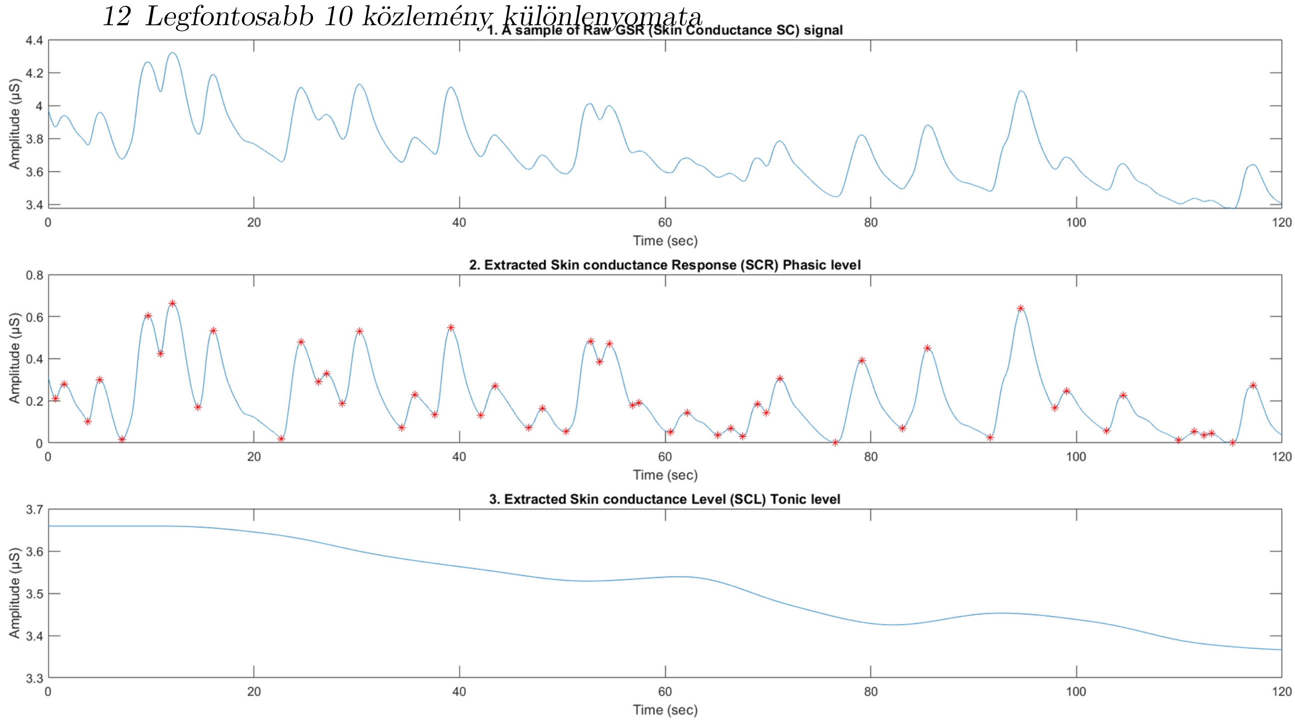


Fig. 3. (1) A sample of the recorded GSR for 120 seconds; (2) The extracted SCR through continuous decomposition analysis (CDA) with extracted peaks and bottoms that are utilized for feature extraction; and (3) The extracted SCL through the same CDA analysis.

GSR acronyms	Description
AreaSCR	Total area under the SCR curve
AreaGSR	Total area under the SC curve
No_Peakes	Number of the detected peaks in the SCR
AvgRiseTime	Average of the rising time of the peaks
AvgDecayTime	Average of the decaying time of the peaks
Entropy	Measured entropy of the SC signal
STDGSRdata	Standard deviation of the SC
STDSCRdata	Standard deviation of the SCR
BandPower	Summation of the power spectrum of the SCR

Table 3. The list of the extracted GSR features and their description.

The GSR signal (also known as the skin conductance SC) is formed by superimposing the phasic SC, also called the skin conductance response (SCR), on the tonic SC (also called the skin conductance level SCL), which is slowly changing[57]. This concept dictates that $SC = SC_{\text{tonic}} + SC_{\text{phasic}}$. Monitoring SCR is a simple way to detect sympathetic activity in response to an event[58]. Based on these facts, using the SC as a monitor for the change in sympathetic activity requires a technique to separate the signal into its phasic and tonic levels. We have utilized the Matlab-based Ledalab software V3.4.9, which uses a standard deconvolution algorithm to separate the SC into its two components[58]. Before starting the separation process, we applied a built-in adaptive smoothing filter to the signals to remove their noise. We initiated the separation process by applying continuous decomposition analysis (CDA).

We also employed a 60-second segmentation on the extracted signals, ensuring consistency in sample size with previous HRV measurements. From the GSR and its two components, SCR and tonic SC, we extracted 9 features. Personal differences in skin conductivities influenced the amplitudes of both SC components (SCR and tonic SC). As our study focuses on the effects of work instructions, we manually checked the processing steps during feature extraction. This approach enhanced the robustness of our methods, helping us avoid irrelevant details and preserve critical and subtle features. Figure 3 shows a sample of 2 minutes of GSR recording with its two components (SCR and SCL). Table 3 shows the list of the extracted GSR features.

For acceleration data recorded from the sensor on the dominant hand's wrist, we captured three data axes: *X*, *Y*, and *Z*. Consistent with previous physiological data, we applied 60-second segmentation on the acceleration signals. We calculated the resultant of these three axes and extracted six features from each axis, resulting in 24 features. These features included mean, median, standard deviation, minimum, and maximum. All the signal processing steps, including filtration, feature extraction, and segmentation for GSR, HRV, and acceleration data, were conducted using MATLAB 2024b[59].

Finally, the precision of each constructed pattern was evaluated through a customized algorithm. This algorithm processes video-captured images and analyzes the placement and orientation of each piece via Aruco markers. It calculates the Euclidean distance between the centers of the markers in the constructed pattern and compares it against a reference, whereby variances are determined as a measure of standard deviation. A higher value of the standard deviation indicates lower assembling precision, while a lower value suggests higher precision. This analysis was implemented using Python within the Spyder 5 environment[60]

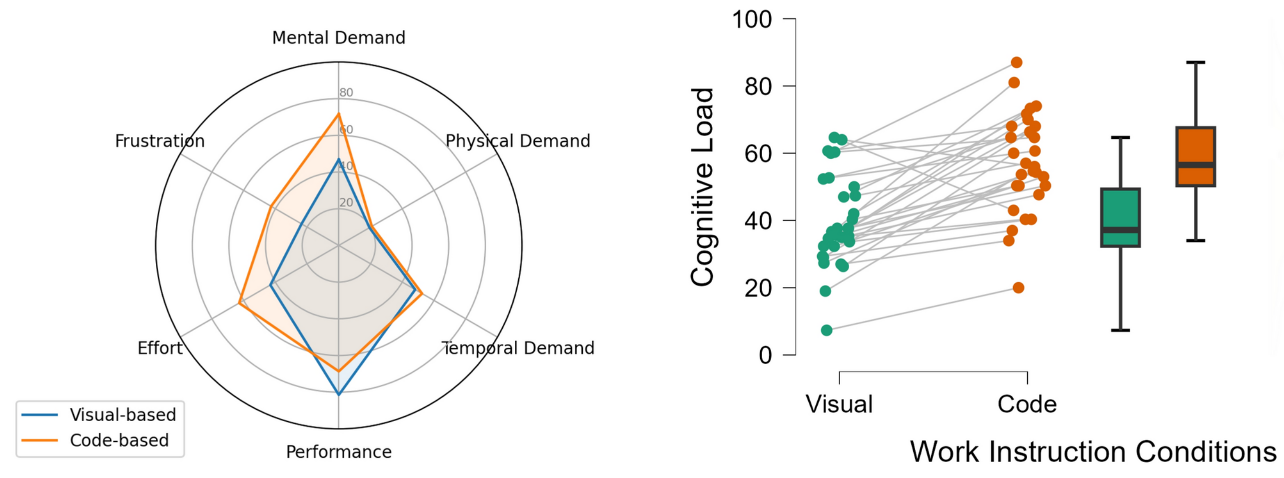
Results
Subjective data analyses
In this subsection, we analyze the subjective data collected from participants during the three sessions of the experiment. We utilized two questionnaires, the NASA_TLX and the short version of the DSSQ. These questionnaires capture the perceptions of the participants after each session of the experiment.

NASA_TLX questionnaire

The NASA_TLX expresses six categories as percentages: mental demand, physical demand, temporal demand, performance, effort, and frustration. Figure 4a is a radar chart to visually compare these categories between the code-based and visual-based work instructions sessions. It shows that the code-based instructions induced higher levels of mental demand, frustration, and effort compared to the visual-based instructions. The statistical paired t-test confirmed significant differences between them, with $p-values < 0.001$ and effect sizes of −1.522 for mental demand, −0.788 for frustration, and −0.913 for effort. These findings indicate that code-based instructions were more mentally demanding and frustrating, requiring more effort to decipher than visual-based instructions. Additionally, the results showed slightly higher levels of both physical and temporal demand for the code-based instructions compared to the visual-based instructions. However, these differences were not statistically significant. The $p-value$ for physical demand was 0.775 with an effect size of −0.082, and for temporal demand, the $p-value$ was 0.339 with an effect size of −0.177. This suggests that participants did not feel rushed by time constraints, but they were more challenged by aspects related to their limited working memory.

Finally, the nature of the NASA_TLX scale interprets the "performance" dimension in the opposite direction of the other five categories, yet assigns its weight in the same direction as the others. This means that a higher perceived performance results in a lower NASA_TLX score, contributing to a lower overall cognitive load. For visual clarity in our radar chart, we assigned the performance weight in the reverse direction to the other categories to reflect each participant's self-perceived performance. According to the radar chart and the paired t-test, participants reported higher perceived performance with the visual-based instruction compared to the code-based instruction, with a significant difference ($p-value < 0.001$ and Effect Size = −0.852).

The cognitive loads (CLs) for the visual-based (Visual) and code-based (Code) sessions were compared in Fig. 4b. These CLs were calculated from the NASA_TLX categories. The figure presented a combination of individual data points (personal CLs) with paired lines and box plots. The lines connecting the dots across the two sessions indicate the shift in CL for each participant from "Visual" to "Code", highlighting a general increase in CLs in the code-based session.



(a) Comparative Radar Chart of NASA_TLX categories average scores across code-based and visual-based sessions.

(b) Comparison of Cognitive Load between visual-based (Visual) and code-based (Code) sessions

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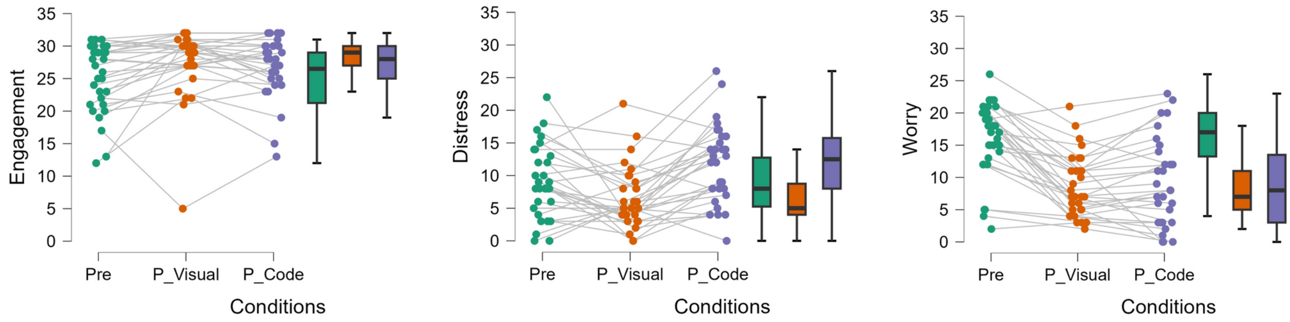
Fig. 4. Comparative analysis of subjective Cognitive Load and NASA_TLX dimensions across visual-based and code-based sessions.

Measure 1 Visual-session	Measure 2 Code-session	Shapiro-Wilk *p*-value	Test	Z	Effect size	t-test *p*-value
Cognitive load	Cognitive load	0.208	Student	N/A	−1.182	<0.001
Mental demand	Mental demand	0.150	Student	N/A	−1.522	<0.001
Physical demand	Physical demand	<0.001	Wilcoxon signed-rank	−0.305	−0.082	0.775
Temporal demand	Temporal demand	0.575	Student	N/A	−0.177	0.339
Performance	Performance	0.114	Student	N/A	−0.852	<0.001
Effort	Effort	0.942	Student	N/A	−0.913	<0.001
Frustration	Frustration	0.125	Student	N/A	0.788	<0.001

Table 4. Statistical comparison of NASA_TLX Cognitive Load and its dimensions between visual-based and code-based instruction sessions.



(a) Changes in the Engagement levels from pre-experiment (Pre) to post-visual (P_Visual) and post-code (P_Code) sessions.

(b) Changes in the Distress levels from pre-experiment (Pre) to post-visual (P_Visual) and post-code (P_Code) sessions.

(c) Changes in the Worry levels from pre-experiment (Pre) to post-visual (P_Visual) and post-code (P_Code) sessions.

Fig. 5. Engagement, distress, and worry psychological states derived from the short DSSQ across three different conditions.

The box plot shows the distribution of CLs in both sessions, with a higher median and wider interquartile range in the code-based session. This suggests more variability and a higher overall CL. The mean values of the two sessions align with these box plots, where the visual-based session gave a *Mean* of 39.84 with an *SD* of 13.74 compared to the code-based session, which gave a *Mean* of 57.24 with an *SD* of 14.71. An analysis using a paired t-test supported these observations. It showed that CL increased significantly from the visual-based session to the code-based session ($P < 0.001$), with an effect size of −1.182. This indicates that code-based instructions, compared to visual-based ones, place a significantly higher cognitive demand on participants. The statistical results for the comparisons of cognitive load and each NASA_TLX dimension between the visual-based and code-based sessions are summarized in Table 4.

Short DSSQ questionnaire

The second questionnaire we utilized in this experiment was the short version of DSSQ. Participants in this study completed the DSSQ three times under the following conditions: pre-experiment, post-visual-based session, and post-code-based session. The scores for each of the three psychological states were in the range of $(0 - 32)$. Figure 5a displays the engagement scores of each individual, connecting them across the sessions to illustrate changes in engagement for each participant. Boxplots summarize the distribution of scores within each condition, providing a clear visual comparison.

The descriptive statistics for the engagement scores revealed variations across the three sessions. Prior to the experiment (Pre), the *Mean* engagement score was 25.06, with an *SD* of 5.33. Following the visual-based session (P_Visual), the *Mean* engagement score increased to 27.43, accompanied by a *SD* of 5.21. Following the code-based session (P_Code), the *Mean* engagement score decreased slightly to 26.83, with a *SD* of 4.75.

To check if study sessions had a significant effect on task engagement, we decided to implement the Repeated Measures RM ANOVA. To check the assumption of sphericity, we applied Mauchly's test, which revealed a violation of assumptions with a $p - value$ of 0.043. Therefore, we applied the Huynh-Feldt correction to account for this violation. The corrected repeated measures ANOVA identified significant differences in engagement scores across the conditions, with a significant $p - value$ of 0.012.

Following the main RM ANOVA test, we also applied the Post-Hoc analysis. We observed a significant increase in engagement from the pre-experiment to the post-visual-based session, as evidenced by a significant $p - value$ of 0.041 and an effect size of −0.464. Although the increase in engagement from the pre-experiment to the post-code-based session had a *p*-value of 0.059 with effect size of −0.346, it did not meet the conventional significance threshold of 0.05. Finally, a *p*-value of 0.323 and an effect size of 0.118 indicated no significant differences between the post-visual-based and post-code-based sessions. This suggests that both types of instructions managed to sustain similar levels of engagement (see Fig. 5a). These results indicate that while both instructional methods effectively boosted engagement compared to the baseline, the visual-based instructions proved particularly effective, as reflected in higher mean engagement scores.

We further looked into the distress scores of participants across three different sessions. There was a notable variation in these scores. Initially, before the experiment (Pre), the *Mean* distress score was 9.00, with an *SD* of 5.52. After the visual-based session (P_Visual), the distress scores decreased to a *Mean* of 6.56 with an *SD* of 4.76. However, following the code-based session (P_Code), the *Mean* distress score increased to 11.83, with an *SD* of 6.02 (see Fig. 5b).

To figure out if these changes in distress scores were statistically significant, we applied the RM ANOVA test, followed by the Post-Hoc tests. As before, for robust analysis, we applied Mauchly's test to check for sphericity. The test results showed no violations ($p - value = 0.792$), which meant that we could use a standard repeated measures ANOVA without any adjustments. The ANOVA results indicated that there were indeed significant differences in distress scores across the conditions, with a highly significant $p - value$ of less than 0.001.

In the Post-Hoc tests of the ANOVA results, we took a closer look at the changes in distress scores between the sessions. We found a significant decrease in distress from the pre-experiment to the post-visual-based session, with a $p - value$ of 0.030 and an effect size of 0.446. Furthermore, the transition from the pre-experiment to the post-code-based session revealed a similar significant increase in distress, with a $p - value$ of 0.030 and an effect size of −0.519. Most notably, the transition from the post-visual-based session to the post-code-based session marked a substantial increase in distress levels, with a $p - value < 0.001$ and a high effect size of −0.964.

Distress, which is linked to negative emotional states, was initially high, as demonstrated by the pre-experiment mean scores, indicating significant initial stress among participants. However, after using visual instructions, there was a noticeable drop in distress levels, indicating a sense of relief. In contrast, the distress levels increased sharply after the code-based sessions, suggesting that these instructions significantly heightened negative emotional states which is related to the overload of processing capacity. This pattern demonstrates the substantial impact that different instructional designs can have on participants' psychological stress. The marked differences between the visual and code-based sessions highlight the need to carefully consider the type of instructional material used and its potential psychological effects on learners. (Refer to Fig. 5b for a visual representation of these results.)

Next, we looked into the final psychological state, Worry. The worry scores changed notably across sessions. At the pre-experiment (Pre), the *Mean* worry score was quite high, at 15.86, with an $SD = 5.85$. After the visual-based session (P_Visual), this score significantly dropped to 8.60 ($SD = 4.86$), showing a large reduction in worry. However, after the code-based session (P_Code), the *Mean* worry score increased slightly to 9.23, with an $SD = 6.88$ (see Fig. 5c). To validate these observations, we first looked at the assumption of sphericity using Mauchly's test. It showed a violation ($p - value = 0.037$). Consequently, we applied the Huynh-Feldt correction before proceeding with a RM ANOVA. This analysis confirmed that there were significant differences in worry scores across the sessions, with a highly significant $p - value < 0.001$.

In the Post-Hoc tests of the ANOVA, worry greatly decreased from the pre-experiment to the post-visual-based session, with a $p - value < 0.001$ and a large effect size of 1.226. Similarly, worry significantly decreased from the pre-experiment to the post-code-based session, with a $p - value < 0.001$ and an effect size of 1.120. However, the worry scores did not significantly change from the post-visual-based to the post-code-based session ($p - value = 0.397$, effect size = −0.107). This suggests that the code-based session did not negatively affect the initial reduction in worry. These statistics for the DSSQ's three variables-engagement, distress, and worry-along with the Post-Hoc analysis, are presented in Table 5.

These findings show that the way instructions are designed can greatly affect worry, which is linked to negative self-assessments. The large decrease in worry scores after the visual-based session suggests that this method can effectively reduce worry, helping participants focus better and feel more comfortable. On the other hand, the slight increase in worry after the code-based session, although not significant compared to the visual session, shows that certain instructional methods might make anxiety worse under specific conditions. The

DSSQ states	Sphericity test Mauchly *p*-value	Sphericity Correction	RM ANOVA *p*-value	ANOVA Post-Hoc		
				Cases	*p*-value	Effect size
Engagement	0.043	Huynh-Feldt	0.012	Pre vs. P_Visual	0.041	−0.464
				Pre vs. P_Code	0.059	−0.346
				P_Visual vs. P_Code	0.323	0.118
Distress	0.792	None	<0.001	Pre vs. P_Visual	0.030	0.446
				Pre vs. P_Code	0.030	−0.519
				P_Visual vs. P_Code	<0.001	−0.964
Worry	0.037	Huynh-Feldt	<0.001	Pre vs. P_Visual	<0.001	1.226
				Pre vs. P_Code	<0.001	1.120
				P_Visual vs. P_Code	0.397	−0.107

Table 5. Statistical analyses of DSSQ variables (Engagement, Distress, and Worry) with Post-Hoc comparisons. Pre: Pre-experiment, P_Visual: Post Visual-based session, and P_Code: Post Code-based session.

visual representation of these results is shown in Fig. 5c. All statistical analyses, including t-tests, RM ANOVA, and Post-Hoc comparisons, were conducted using JASP statistical software (version 0.19.2)[61].

Objective data analyses

In this subsection, we present the results of the analyses based on the captured objective data. Starting with the recorded physiological data, we extracted 19 HRV features, and nine GSR features listed before respectively in Tables 2 and 3. Feeding all of these physiological features for classification purposes or even statistical analyses can lead to poor accuracy and precision because some of these features could be highly correlated while others may not show a high contribution to predicting the target. Based on this criterion, it is inevitable to implement the feature selection technique prior to classification processes. Wrapper methods are the most effective for feature selection, according to Rezaei and Jabbari[62]. We implemented a feature selection technique that belongs to the wrapper methods: backward elimination. This technique is based on employing the entire set of features in the first step and gradually iterating and removing the features. Each iteration removes the feature that contributes the least to the target. This process continues as long as the model improves with feature removal.

Due to the nature of our experiment design, the data from the three sessions is not equally sized. Repeated analyses with varying sizes contravene standard statistical analyses such as the ANOVA and paired t-test. However, we can use logistic regression analysis for this purpose. The rationale for utilizing logistic regression lies in its ability to provide classification properties, in addition to displaying the contribution of each feature to the target along with its p-value. We have utilized SPSS statistical software for this purpose. We fed the 29 extracted features into the model, using the backward elimination method to iterate over them and select the most significant ones. Following the designed sessions of this experiment (refer to Table 1), we will compare the whole three sessions and each session with the other two sessions separately, similar to the Post-Hoc tests in the subjective analyses.

We aim to provide a comprehensive overview of the impact of the type of work instruction on physiological features. We used a multinomial logistic regression model, setting the baseline session as the reference category for the visual and code-based sessions. This means that the features of both sessions of work instructions will be compared to the baseline session. The fitness of the model was assessed using the Chi-Square test, which revealed a significant improvement over the null model with Chi-Square = 270.503, $d = 30$, and a $p - value < 0.001$.

The backward elimination method removed 14 features and selected the top 15 contributing features, resulting in the optimal model classification parameters. Table 6 presents a list of the selected features, as well as their coefficient magnitudes and p-values. We also implemented three binary logistic regression models to compare each session with the others and see which features had contributed significantly to the target. We once again assessed the models' fitness using the Chi-Square test. The results revealed a significant improvement in the models compared to the null models without predictors. The visual-based vs. baseline model has shown Chi-Square = 140.358, $d = 12$, and a $p - value < 0.001$, the code-based vs. baseline model has shown Chi-Square = 176.691, $d = 13$, and a $p - value < 0.001$, and the code-based vs. visual-based model has shown Chi-Square = 91.401, $d = 14$, and a $p - value < 0.001$. Table 7 presents the results of the selected features with their coefficient magnitudes and significance evaluation parameter, p-values. Negative coefficients suggest that as the predictor (a specific feature) increases, the likelihood of the outcome being in the respective condition (target) decreases compared to the reference category.

By comparing the three conditions in our study, we calculated and presented the average of the models' performance parameters-*accuracy*, *precision*, and *recall*-in Table 8. We used the following abbreviations for each condition, B: Baseline (Pre-experiment) session, V: Visual-based instruction session, and C: Code-based instruction session. The high-performance classification metrics (B-C, B-V) showed that the models found a

Condition	Features	B	p-value	Condition	B	p-value
	AreaGSR	0.007	< 0.001		0.007	< 0.001
	NoPeakes	0.295	< 0.001		0.133	0.049
	avgRiseTime	0.238	0.11		0.338	0.017
	avgDecayTime	− 0.0001	0.957		−0.228	0.006
	STDGSRdata	−17.15	< 0.001		−13.008	< 0.001
	STDSCRdata	29.078	< 0.001		27.274	< 0.001
	spectralEnergy	−0.215	< 0.001		−0.389	< 0.001
Visual-based	MEAN_RR	−0.018	0.006	Code-based	−0.028	< 0.001
	SDRR	−0.147	< 0.001		−0.015	0.634
	SDSD	0.139	< 0.001		0.049	0.114
	SDRR_RMSSD	2.708	0.028		0.068	0.953
	HR	−0.218	0.01		−0.344	< 0.001
	pNN25	−0.019	0.301		−0.059	< 0.001
	LF_HF	−0.004	0.034		−0.006	0.001
	HF_LF	0.544	0.784		1.809	0.362

Table 6. Estimated parameters for selected features using multinomial logistic regression with baseline session as reference. The reference category is: Baseline session. B: Coefficient Magnitudes

Condition 1	Features	B	*p*-value	Condition 2	Features	B	*p*-value	Condition 3	Features	B	*p*-value
Visual-based vs Baseline	AreaGSR	0.006	0.003	Code-based vs Baseline	AreaSCR	0.465	< 0.001	Code-based vs Visual-based	NoPeakes	−0.158	< 0.001
	NoPeakes	0.164	0.005		NoPeakes	0.165	0.010		avgDecayTime	−0.200	0.032
	STDGSRdata	−13.921	0.001		STDGSRdata	−9.952	0.006		STDGSRdata	8.201	0.001
	STDSCRdata	22.950	< 0.001		spectralEnergy	−3.746	0.005		STDSCRdata	−8.528	0.016
	spectralEnergy	−0.177	0.006		bandPower	7.032	0.018		spectralEnergy	−1.177	0.016
	RMSSD	0.091	< 0.001		MEAN_RR	−0.031	< 0.001		bandPower	2.152	0.036
	MEDIAN_RR	−0.011	0.027		SDSD	0.092	< 0.001		MEAN_RR	−0.078	0.008
	SDRR	−0.054	0.003		HR	−0.753	0.003		SDSD	−0.056	< 0.001
	HR	−0.129	0.025		pNN25	−0.047	0.034		SDRR_RMSSD	−2.664	< 0.001
	pNN25	−0.048	0.023		pNN50	−0.095	0.020		HR	−0.546	0.005
	KURT_RR	−0.072	0.087		KURT_RR	−0.093	0.007		pNN50	−0.051	0.003
	LF_HF	−0.003	0.117		VLF	0.000	0.048		SD2	0.076	< 0.001
					LF_HF	−0.005	0.029		LF	0.000	0.015
									HF_LF	1.543	0.002

Table 7. Estimated parameters for selected features using three binary logistic regression models. Baseline is the reference category for Conditions 1, and 2, while Visual-based is the reference in the Condition 3. B: Coefficient Magnitudes

Classifier	Conditions	Accuracy	Precision	Recall
Multinomial Logistic Regression	B–V–C	78.04	67.79	63.12
Binary Logistic Regression	B–V	83.88	82.99	82.2
	B–C	**90.42**	**89.97**	**85**
	V–C	75.51	74.92	71.95

Table 8. Average of performance metrics of logistic regression models under various conditions based on the physiological features (GSR and HRV). B: Baseline (Pre-experiment), V: Visual-based session, and C: Code-based session

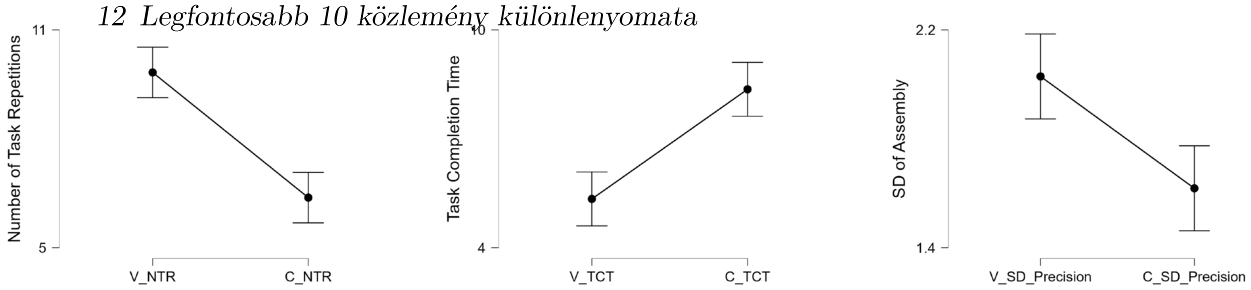
Measure 1	Measure 2	Shapiro-Wilk *p*-value	Test	Z	Effect size	t-test *p*-value
V_NTR	C_NTR	0.027	Wilcoxon signed-rank	4.286	1.00	< 0.001
V_TCT	C_TCT	0.018	Wilcoxon signed-rank	−4.573	−0.972	< 0.001
V_SD_Precision	C_SD_Precision	0.3	Student	N/A	0.709	< 0.001

Table 9. Comparison of participant performance metrics between Visual- and Code-based sessions using paired t-tests. V_NTR and C_NTR are the Number of Task Repetitions in the visual- and code-based sessions respectively, V_TCT and C_TCT are the Task Completion Time (in minute) of the visual- and code-based sessions respectively, and V_SD_Precision and C_SD_Precision are the SDs that reflect the precision of the assembly process for the visual- and code-based sessions respectively

clear boundary between the baseline condition (Pre-experiment) and both the visual-based and code-based conditions. This pattern aligns with the trends observed in the ANOVA and Post-Hoc tests of the DSSQ psychological states: engagement, distress, and worry. Although all selected features of condition 3 (Code based vs. Visual based) in Table 7 demonstrated significant differences, model V-C in Table 8 exhibited the lowest performance metrics when compared to the other binary classifier models. This is somewhat consistent with the previous statistical tests that compare these two conditions within the subjective DSSQ states.

To analyze participants' performance, we analyzed three key metrics: the Number of Task Repetitions (NTR), Task Completion Time (TCT) (a minimum of five minutes), and the precision of the assembly process. We represented this precision by the average of the standard deviation (SD) of Euclidean distances between the centers of the building pieces, derived from video-captured images; the lower the SD value, the better the assembly process. We calibrated the camera setup and averaged the trials within each instruction session to minimize potential algorithmic inaccuracies. We conducted Shapiro-Wilk tests to assess the normality of the data, followed by paired t-tests to evaluate differences between sessions.

Table 9 shows the main parameters extracted from these tests. We observed significant differences in the three parameters between the two sessions, with p-values < 0.001. In Fig. 6, we present the descriptive plots



(a) Average of Number of Task Repetitions by session type: Visual-based (V_NTR) vs. Code-Based (C_NTR).

(b) Avrage of task completion times (in minute) by session type: Visual-based (V_TCT) vs. Code-Based (T_TCT).

(c) Standard deviation (Precision indicator) by session type: Visual-based (V_SD_Precision) vs. Code-Based (C_SD_Precision) .

Fig. 6. Comparative analysis of task performance across visual and code-based instruction sessions.

Visual-based	Code-based	Test	Z	*p*-value
meanX	meanX	Wilcoxon signed-rank	2.411	0.016
meanY	meanY	Student	N/A	0.002
meanZ	meanZ	Wilcoxon signed-rank	2.038	0.042

Table 10. Results of t-test analyses comparing the mean accelerometer values across the three coordinates (X, Y, Z) during two work instruction sessions: visual-based and code-based. meanX, meanY, and meanZ are the mean values of the accelerometer data at the three coordinates X, Y, and Z respectively

of these three parameters as means with their confidence intervals 95%. Figure 6a presents the means of the NTR during the two sessions of the work instructions. In the code-based session, most of the participants found themselves stuck at the minimum number of iterations ($Mean = 6.379$), whereas they showed a greater capability to repeat the task in the visual-based session ($Mean = 9.828$).

Despite the higher number of repetitions in the visual-based session, the majority of participants did not exceed the allocated time for this session and showed a mean of 5.342 minutes compared to 8.363 minutes in the code-based session (refer to Fig. 6b). These results are aligned with the subjective results from NASA_TLX, where participants showed a significant increase in the cognitive load from visual-based instructions to code-based instructions. Figure 6c, however, showed intriguing results with lower SD values for code-based instructions (which means better precision) compared to visual-based instructions. This does not align with the subjective results of the NASA_TLX performance category, where participants evaluated themselves as having better visual instructions performance.

The higher number of task repetitions NTR and lower task completion time TCT in the visual-based session indicate that participants made more hand movements in this session compared to the code-based session. Table 10 shows the t-test analyses of the hand movements in the three coordinates (X, Y, Z) during two work instructions. The *p*-values from these analyses (< 0.05) indicate significant differences in hand movement across the three coordinates during the visual-based session compared to the code-based session, highlighting variations in NTR and TCT between the two sessions.

The accelerometer data in the three coordinates provided 24 features as already explained in the Data Preprocessing subsection. Combining these features with 29 features that were previously extracted from the physiological signals (GSR and PPG) will establish a clear boundary between the two instruction sessions. Feeding these 53 features into the binary logistic regression model with the backward elimination method has produced promising results. We again assessed the fitness of the model using the Chi-square test, revealing a significant improvement over the null model with Chi-square = 368.234, $d = 27$, and a $p - value < 0.001$. The model showed excellent performance metrics with average $accuracy = 92.91$, $precision = 92.67$, and $recall = 92.35$. These values outperform the model performance in Table 8 V-C condition. All statistical analyses related to the logistic regression modeling were conducted using IBM SPSS Statistics software (version 29)[63].

Discussion

This study investigated the impact of work instruction methods on the human cognitive load and their operational efficiency. In a controlled, assembly-like scenario inspired by industrial tasks, the study used two work instructions-visual-based and code-based-and a range of subjective and objective assessment methods. The study also examined the alignment between subjective and objective evaluation methods, in order to enhance the accuracy of conclusions by providing context for physiological responses and validating our experimental conditions. The findings revealed that code-based instructions imposed a higher subjective cognitive load on participants compared to visual-based instructions. This aligns with Cognitive Load Theory (CLT), which posits that extraneous cognitive load-stemming from the way information is presented-can hinder learning and performance[13].

The results are also consistent with previous studies indicating that visual aids can enhance comprehension and reduce cognitive load in assembly tasks. For instance, Li et al. (2018) found that supporting the work instructions with pictures can reduce the cognitive load and improve task performance compared to the traditional text instructional methods[4]. Similarly, our study suggests that visual-based instructions lead to faster task completion and higher task repetition rates. This is likely due to the reduced mental effort required to interpret the instructions, as visual-based instructions are less abstract and easier to interpret than code-based instructions. Furthermore, Vanneste et al. (2024) demonstrated that augmented reality (AR) visual instructions led to lower assembly times and a lower perceived physical effort compared to traditional methods[11]. This supports the idea that technologically advanced visual aids can further enhance the effectiveness of work instructions, which aligns with our findings on the superiority of visual-based instructions in most cases.

Taking each of the six categories in the NASA_TLX and comparing them between the two instructional sessions has produced profound results. The t-test analyses of each pair of the six categories within the NASA_TLX have shown a significant increase in mental demand, frustration, and effort in the code-based session. While there was a slight increase in physical demand in the code-based session, there was no significant increase. Conversely, the t-test analyses of hand movements in the X, Y, and Z coordinates, as well as the NTR, indicated higher means and significant differences in the visual-based session compared to the code-based session. As the hand movements were not exertive, participants focused on their goal of repeating the task during the visual-based session, where a higher repetition rate was intended to lead to better outcomes. Consequently, they did not perceive the task as physically demanding when filling out the Physical Demand category of NASA_TLX.

However, body movement significantly impacts physiological signals due to the alterations in autonomic sympathetic arousal resulting from increased energy expenditure[64]. Subjectively, the code-based instructions were more cognitively demanding. We also expected these instructions to influence the objective physiological data. On the other hand, although visual-based instructions posed subjectively lower cognitive demands, their straightforward nature objectively led to a higher number of hand movements. We expect the higher hand movements to impact the objective physiological data. These were clearly reflected in the performance metrics of the logistic regression models in Table 8. Classifying the code-based instruction session from the baseline session yielded the highest performance metrics, with the visual-based instruction session from the baseline session following closely behind. Both cognitively demanding tasks and tasks involving body movements significantly influence the physiological signals, justifying this. Simultaneously, when we attempted to classify the code visual-based sessions, the logistic regression models displayed relatively low-performance metrics because both tasks were objectively influencing the physiological signals.

The low-performance metrics for classifying the two sessions based on physiological data do not necessarily indicate a lack of alignment between the subjective and objective data metrics. However, they do imply that differentiating operators' conditions using the objective physiological data may not be entirely reliable, especially in scenarios combining cognitive and physical tasks. On the other hand, supporting the features extracted from the physiological signals (GSR and HRV) with the features extracted from the accelerometer has provided a clear boundary between the two instruction sessions. This is due to the higher levels of hand movements in the visual-based session. This supports the use of these kinds of signals in conjunction with other objective data to support operator condition analyses.

This study also used performance as a metric. We informed the participants about the criteria for evaluating their performance prior to the experiment. We analyzed this metric in two ways: subjectively using the NASA_TLX, and objectively using the parameters in Table 9: the number of task repetitions (NTR) within the given time, the task completion time (TCT), and the precision of the assembly process, as indicated by the standard deviation SD of the Euclidean distances between the assembled pieces. Participants subjectively rated their performance significantly higher in the visual-based instruction session. Participants seem to prioritize the possibility of repeating the task beyond its lower limit, disregarding the precision of their work. This higher repetition number gave them a sense of achieving their task with high performance in the visual-based session compared to the code-based session. The objective performance metrics aligned the subjective rate with respect to the NTR and TCT, as shown in Table 9 and Fig. 6a and b. In most cases, participants repeated the task significantly more during the visual-based session without exceeding the allocated time.

However, while the industry aims to increase production batches with short production times, it does not overlook the importance of product quality. In this study, the SD of the assembly process represented this metric. Due to their increased focus on the NTR, participants did not pay as much attention to their assembly precision. This resulted in a higher SD for the visual-based session, indicating lower precision compared to the code-based instruction session, where participants thoughtfully assembled each assembly piece without rushing through the process (See Fig. 6c). This suggests that while visual instructions may enhance speed and reduce perceived effort, they may inadvertently encourage less attention to detail. This objective metric is primarily not aligned with the subjective performance in the NASA_TLX. This contrast highlights the strengths and limitations of each measurement approach: subjective tools, such as NASA_TLX, can capture perceived workload or satisfaction, but they might miss more complex aspects of actual task performance. Objective measures like assembly precision provide quantifiable outcomes but do not fully account for internal states such as confidence or perceived effort.

The mismatch between objective metric and the subjective metric of performance might be understood within the framework of the Dynamic Model of Sustained Attention and Stress[65]. According to this model, individuals adjust their attention and effort allocation dynamically based on perceived task demands, available cognitive resources, and stress level. Thus, when task demands decrease, attention can become less focused, leading to a drop in task performance. Therefor, while the visual-based instruction optimize speed and effort, it may not sufficiently maintaine the level of attention needed for precision. These findings highlight the impratnce

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of achieving the optimal cognitive load during tasks. Although visual instruction can reduce cognitive load and increase assembly speed, it may not result in optimal cognitive performance in terms of precision. This indicates that while visual instruction may lower cognitive load and enhance efficiency, it might compomise attention and precision. Thus, in high-stakes or precision-demanding tasks, a certain level of cognitive load might be necessary to ensure attention and accurate performance. Therefore, instruction design should consider not just reducing cognitive load but also achieve optimal cognitive load that supports both efficiency and precision, optimizing overall task performance.

Future research can explore hybrid or modified methods to mitigate this trade-off. For instance, adaptive or context-sensitive instructions could primarily use visual aids for most assembly steps, yet incorporate code-based details during critical high-precision tasks. Alternatively, layered instructions-where a simple visual overview is supplemented by optional, more detailed code-based guidance-could preserve the clarity of visual methods while ensuring precision where it is needed. Such approaches might achieve a more optimal balance between efficiency and precision without overstressing the operator's cognitive resources.

Limitations and future research

This study faced several limitations that suggest directions for future research. One key limitation of this study is that the experiment was conducted in a controlled laboratory environment, which does not fully mirror the complexity of real-world industrial settings. In actual production lines, factors like noise, teamwork, multitasking, and real-time pressures can substantially influence the operators' cognitive load and performance. Consequently, the results presented here should be interpreted as foundational insights rather than direct predictions of on-site outcomes. Nonetheless, our findings highlight the importance of minimizing extraneous cognitive load in designing effective work instructions. Future research may further validate these insights by integrating realistic workplace parameters-such as time constraints, loud machinery, and group-based tasks-into experimental protocols.

Another limitation of this study is the sample representativeness, where the participant pool was restricted to university students and researchers. While this homogeneous sample allowed for consistent baseline characteristics, it may not adequately represent the demographic and experiential diversity of industrial workers. Therefore, caution is warranted in generalizing our findings to actual industrial environments. In future work, we plan to broaden our sample to include operators from various industrial settings. This expanded approach will help validate our current results and further refine guidelines for optimal instructional design.

Additionally, physiological sensor placement on the non-dominant hand limited task execution to one-handed, which was another limiting factor in this study. This constraint potentially affected both the pace and strategies used, reducing the ecological validity of our findings. In future studies, we plan to adopt less intrusive sensor placements (e.g., wearable wristbands, arm and chest straps, or forehead sensors) to enable two-handed operation and better replicate industrial conditions.

Moreover, the study utilized a limited set of physiological signals (GSR and PPG). Incorporating a broader array of biosignals, such as eye tracking, body motion or posture tracking, electromyography (EMG), electroencephalography (EEG), and electrooculography (EOG), can provide deeper insights into the cognitive and physical states of workers, offer more robust support for the study's hypotheses, or even provide a different point of view. Furthermore, while the sample size of 30 participants was substantial, future studies can expand it to enhance the statistical power and generalizability of the findings.

Finally, the five-minute time limit for the instruction sessions, which could only be extended if the specific pattern was not repeated three times, restricted most participants to completing the code-based session only three times. This prevented us from examining the full learning curve. It is possible that with more practice, participants could become more efficient with code-based instructions, potentially improving task performance over time.

Conclusion

In this study, we found that visual-based instructions significantly reduce cognitive load and improve some operational aspects, such as shorter TCT and higher NTR compared to code-based instructions. However, our findings show a clear divergence between participants' subjective ratings of performance through the NASA_TLX and the objective performance metric, assembly precision. While subjective measures are valuable for gauging perceived workload and emotional states, they can be influenced by factors like self-efficacy and momentary satisfaction. Conversely, the objective precision metric provides a direct measure of actual task outcomes but may overlook internal experiences of strain. As a result, high subjective performance scores did not always correspond to high objective precision.

Our study suggests that simple and direct instructions (visually based in this study) can enhance some of the operational aspects and reduce cognitive load, demonstrating that these kinds of instructional strategies are particularly beneficial in environments where quick task execution is critical. On the other hand, for tasks that require high precision and meticulous attention to detail, instructions that require deep thinking (code-based in this study) may be more appropriate. This discrepancy underscores the importance of a multi-method approach. Future research should explore more granular correlations between subjective and objective measures-perhaps by collecting in-task self-reports or by utilizing continuous physiological monitoring that can be compared against real-time performance logs. These insights can aid in developing customized training and operational protocols that improve productivity and enhance worker satisfaction.

Data availability

Data available upon request to Tamás Ruppert.

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Author contributions

A.K.E. contributed to every step of this study, including experiment design, data recording, data processing and analysis, and manuscript writing and V.V. contributed to the development of the experiment design and manuscript writing and G.E. contributed to the data analyses and T.R. contributed to the development of the experiment design, manuscript writing, data processing and analyses and data recording. All authors reviewed the manuscript.

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Declarations

Competing interests

The authors declare no competing interests.

Additional information

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