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Exploring Psychosocial, Cognitive, and Behavioural Factors in Supply Chain Operations: A Human-Centric Approach

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Thèse présentée en vue de l'obtention du diplôme de *Philosophiæ Doctor*

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Exploring Psychosocial, Cognitive, and Behavioural Factors in Supply Chain Operations: A Human-Centric Approach

présenté par **Mario PASSALACQUA**

en vue de l'obtention du diplôme de *Philosophiæ Doctor*

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RÉSUMÉ

L’industrie 4.0 (I4.0) transforme les lieux de travail industriels modernes grâce à l'adoption de technologies avancées telles que l'intelligence artificielle (IA), l'analyse de données en temps réel et l'automatisation. Ces technologies modifient de manière significative les rôles et les responsabilités des travailleurs, introduisant à la fois des opportunités et des défis. D'un côté, ces avancées peuvent améliorer la productivité et offrir aux travailleurs la possibilité de s'engager dans des tâches plus significatives et stimulantes. D'un autre côté, elles introduisent des défis tels que des exigences cognitives accrues, l'insécurité de l'emploi, des tâches standardisées et monotones, ainsi que le besoin de développement continu des compétences. Ces derniers peuvent impacter de façon significative le bien-être, la rétention, la performance, la motivation et la satisfaction au travail à moyen ou long terme. Malgré de nombreuses recherches sur les aspects techniques des technologies de l'I4.0, il y a un manque notable d'études abordant les impacts psychologiques, en particulier les dimensions psychosociales, cognitives et comportementales de ces technologies sur les travailleurs.

Ainsi, l'objectif général de cette thèse est d'évaluer l'impact des technologies de l'I4.0 sur les dimensions psychologiques de l'interaction humain-technologie au sein des opérations de la chaîne d'approvisionnement. Pour atteindre cet objectif, la thèse utilise une méthodologie multifacette, incluant des revues systématiques de la littérature, des études expérimentales et des études de terrain longitudinales. La première étape consistait en une revue systématique visant à identifier et caractériser les résultats psychosociaux, cognitifs et comportementaux liés aux technologies de l'I4.0, à analyser leurs antécédents et leurs conséquences et à développer un plan de recherche pour les futures recherches centrées sur l'humain. Cette revue a permis d’identifier plusieurs lacunes importantes ouvrant la voie aux études expérimentales et longitudinales subséquentes. Premièrement, il existe peu de recherche évaluant les composantes psychosociales de l'interaction humain-IA, telles que la motivation des travailleurs, l'autonomie et le sens du travail, sans compter l’absence d'études expérimentales sur ces variables. Deuxièmement, la recherche sur les aspects cognitifs de l'interaction humain-IA, en particulier en ce qui concerne l'attention et la prise de décision lorsque les opérateurs humains doivent intervenir, est rare. Enfin, il y a un manque significatif de recherches longitudinales sur l'impact global de la technologie sur les travailleurs.

Pour combler la première lacune, une étude expérimentale a été menée pour évaluer les impacts psychosociaux de différents niveaux de soutien à la décision par l'IA sur la motivation, l'autonomie, le sens du travail et l'engagement des travailleurs. Cette étude a révélé que l'automatisation partielle de la sélection des décisions, qui équilibre l'assistance de l'IA avec le contrôle humain, conduit à de meilleurs résultats psychosociaux par rapport à l'automatisation complète, améliorant la motivation, l'engagement, le sens du travail et l'autonomie des travailleurs. Pour combler la deuxième lacune, une autre étude expérimentale s'est concentrée sur l'automatisation par l'IA pendant la formation examinant comment différents niveaux de soutien à la décision par l'IA pendant la formation de travailleurs impactent l'acquisition de compétences, l'engagement, la motivation et les capacités de prise de décision. Les résultats ont indiqué que l'automatisation partielle de la sélection des décisions pendant la formation améliore significativement l'acquisition de compétences, la motivation et maintien des niveaux plus élevés d'engagement cognitif chez les travailleurs. Pour combler la dernière lacune, une étude de terrain longitudinale a été menée pour évaluer les impacts psychosociaux, cognitifs et comportementaux réels des technologies de l'I4.0 en examinant spécifiquement les facteurs de risque situationnels introduits par les technologies avancées dans la livraison du dernier kilomètre. En utilisant une approche multi-méthodes incluant des mesures physiologiques, perceptuelles et observationnelles, cette étude a révélé que les conditions de livraison telles que le secteur de livraison, la durée du quart de travail et la pression temporelle affectent significativement la fatigue, le stress, l'attention et le comportement de conduite à risque des conducteurs, soulignant ainsi l'importance de considérer comment les choix de conception technologique impactent les travailleurs.

En conclusion, l'exploration des facteurs humains dans l'intégration des technologies avancées dans les opérations de la chaîne d'approvisionnement a produit des résultats généralisables à d’autres contextes que ceux étudiés. Ces constats ont des implications pour l'avenir du travail, la conception technologique et la gestion organisationnelle, faisant progresser la vision d'une Industrie 5.0 centrée sur l'humain. En somme, les résultats démontrent que l'automatisation équilibrée et une conception réfléchie des systèmes d'IA peuvent améliorer de manière significative les dimensions psychosociales, cognitives et comportementales de l'interaction humain-technologie. Cet équilibre améliore non seulement le bien-être individuel, mais se traduit également par des niveaux plus élevés de motivation, d'engagement et de performance, entre autres. En favorisant des environnements qui priorisent le bien-être et le développement des travailleurs, l'Industrie 5.0 peut soutenir un avenir durable et inclusif où la technologie et l'humanité progressent ensemble.

Cette thèse souligne également l'importance critique de la recherche interdisciplinaire, multi-méthodes et intersectorielle pour comprendre les impacts multifacettes des nouvelles technologies sur les travailleurs humains. Intégrer des perspectives de domaines tels que l'ergonomie, la psychologie organisationnelle, les sciences cognitives et le génie industriel est essentiel pour développer une vue d'ensemble de la manière dont les travailleurs s'adaptent aux changements dans leur environnement de travail. Cette approche assure que la conception et la mise en œuvre des nouvelles technologies et des processus de travail soient informées par une compréhension profonde de la réalité des travailleurs, promouvant ultimement le bien-être humain et faisant avancer la vision d'une Industrie 5.0 centrée sur l'humain.

ABSTRACT

Industry 4.0 (I4.0) is reshaping modern industrial workplaces through the adoption of advanced technologies such as artificial intelligence (AI), real-time data analytics, and automation. These technologies significantly alter worker roles and responsibilities, introducing both opportunities and challenges. On the positive side, these advancements can improve productivity and create opportunities for workers to engage in more meaningful and stimulating tasks. However, they also introduce challenges such as increased cognitive demands, job insecurity, standardized monotonous tasks, and the need for continuous skill development. These dual-edged impacts of technology have significant medium- to long-term effects on the psychological dimensions of workers, including employee well-being, retention, performance, motivation, and job satisfaction. Despite extensive research on the technical aspects of I4.0 technology, there is a notable lack of studies addressing the psychological impacts—specifically the psychosocial, cognitive, and behavioral dimensions—of these technologies on workers.

As such, the general objective of this thesis is to assess the impact of I4.0 technology on the psychological dimensions of human-technology interaction within supply chain operations. To achieve this objective, the thesis employs a multifaceted methodology, including systematic literature reviews, experimental studies, and longitudinal field studies. The first step was a systematic review aimed at identifying and characterizing the psychosocial, cognitive, and behavioral outcomes related to I4.0 technology, analyzing their antecedents and consequences, and developing a roadmap for future human-centered research. This review identified several critical gaps, which paved the way for the subsequent experimental and longitudinal data collections. First, there is a lack of evaluation of the psychosocial components of human-AI interaction, such as worker motivation, autonomy, and job meaningfulness, compounded by the absence of experimental studies on these variables. Second, research on the cognitive aspects of human-AI interaction, particularly in attention and decision-making when human operators must intervene, is insufficient. Finally, there is a significant gap in longitudinal and field research on the overall impact of technology on workers.

To address the first gap, an experimental study was conducted to evaluate the psychosocial impacts of different levels of AI decision support on worker motivation, autonomy, job meaningfulness and engagement. This study found that partial automation of decision selection, which balances AI

assistance with human control, leads to better psychosocial outcomes compared to full automation, enhancing worker motivation, engagement, job meaningfulness, and autonomy. Addressing the second gap, another experimental study focused on AI automation during training, examining how different levels of AI decision support during training sessions impact skill acquisition, engagement, motivation, and decision-making capabilities. The findings indicated that partial automation of decision selection during training significantly improved skill acquisition and motivation and maintained higher levels of cognitive engagement among workers. To fill the final gap, a longitudinal field study was conducted to assess the real-world psychosocial, cognitive, and behavioral impacts of I4.0 technologies, specifically examining situational risk factors brought forward by advanced technology in last-mile delivery. Using a multi-method approach that included physiological, perceptual, and observational measures, this study revealed that delivery conditions such as delivery area, shift length, and time pressure significantly affect driver fatigue, stress, attention, and risky driving behavior, emphasizing the importance of considering how technology design choices impact workers.

The comprehensive exploration of human factors in the integration of advanced technologies in supply chain operations has yielded insights that extend beyond the immediate findings of the individual studies. These insights hold implications for the future of work, technological design, and organizational management, driving forward the vision of a human-centric Industry 5.0. In short, the findings demonstrate that balanced automation and the thoughtful design of AI systems can significantly enhance the psychosocial, cognitive, and behavioural dimensions of human-technology interaction. This balance not only improves individual well-being but also translates into higher levels of motivation, engagement, and performance, among others. By fostering environments that prioritize the well-being and development of workers, Industry 5.0 can achieve a sustainable and inclusive future where technology and humanity advance together, ensuring that as technology evolves, it does so in a way that uplifts and empowers humanity.

This thesis also underscores the critical importance of interdisciplinary, multi-method, and cross-domain research in comprehending the multifaceted impacts of new technologies on human workers. Integrating insights from fields such as ergonomics, organisational psychology, cognitive science, and industrial engineering is essential to develop a comprehensive view of how workers adapt to changes in their work environment. This approach ensures that the design and implementation of new technologies and work processes are informed by a deep understanding of workers' reality, ultimately promoting human well-being and driving the vision of a human-centric Industry 5.0.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ηp2 Partial Eta Squared

AI Artificial Intelligence

AIEDS Artificial Intelligence Error-Detection System

ANOVA Analysis of Variance

CBT Cognitive-behavioural theory

DSI Driver Stress Inventory

ECG Electrocardiogram

ECG Electrocardiogram

HCI Human-Computer Interaction

HF High Frequency

HRV Heart Rate Variability

I4.0 Industry 4.0

I5.0 Industry 5.0

IRB Institutional Review Board

JBI Joanna Briggs Institute

JCT Job Characteristics Theory

JD-R Job Demands-Resources Model

LF Low Frequency

NASA TLX NASA Task Load Index

PNS Parasympathetic Nervous System

PRISMA Preferred Reporting Items for Systematic Reviews and Meta-Analyses

PROSPERO International Prospective Register of Systematic Reviews

SD Standard Deviation

SDNN Standard Deviation of NN Intervals

SDT Self-Determination Theory

SNS Sympathetic Nervous System

SPIDER Sample, Phenomenon of Interest, Design, Evaluation, Research type

SPSS Statistical Product and Service Solutions

SPSS Statistical Product and Service Solutions

SSS Stanford Sleepiness Scale

TAM Technology Acceptance Model

UTAUT Unified Theory of Acceptance and Use of Technology

UWES Utrecht Work Engagement Scale

LIST OF APPENDICES

CHAPTER 1 INTRODUCTION

Industry 4.0 (I4.0) represents a transformative paradigm, emphasising the integration of advanced technologies to revolutionise products, services, and processes through seamless connectivity and agile decision-making (Moeuf et al., 2018; Usuga Cadavid et al., 2020). At the forefront of this transformative wave is artificial intelligence (AI), which acts as a catalyst, driving innovative breakthroughs reshaping manufacturing and operational landscapes (Cannas et al., 2024; Jackson et al., 2024; Luo et al., 2023). This technological evolution is reshaping human interactions with AI-driven systems integral to I4.0, reflecting a profound shift in human-technology interaction (Neumann et al., 2021; Reiman et al., 2023; Rožanec et al., 2023; Sitarević et al., 2023).

While AI plays a central role, I4.0 encompasses a broader range of technologies, including Internet of Things, robotics, and digital twins, that collectively create a connected, intelligent ecosystem. Each of these technologies contributes uniquely to the I4.0 landscape, but AI's ability to enhance decision-making and automate complex processes makes it particularly influential in transforming workplace interactions and task structures. Essentially, AI has the potential to alter worker roles, responsibilities, perceptions, attitudes, and behaviours, introducing both opportunities and challenges within the workplace (Flores et al., 2020; Gagné et al., 2022; Work, 2022).

For instance, at Siemens' electronics manufacturing facility, AI-driven systems are employed to predict equipment failures before they occur, leading to a decrease in unplanned downtime and a smoother production process (Siemens, 2024). Workers have transitioned from performing routine maintenance to focusing on more strategic and cognitively-demanding tasks that require problem-solving skills. While this shift can add a stronger perception of meaningfulness to their job by providing opportunities to exercise creativity in problem-solving, it can also impose high cognitive demands and increase stress levels due to the complexity of the issues they need to address, as well as job insecurity (Ghislieri et al., 2018; Y. Lu et al., 2022).

This situation exemplifies the dual-edged nature of AI systems in Industry 4.0. On the positive side, these technologies can offer significant improvements in productivity and create new opportunities for workers to engage in more meaningful and stimulating tasks (Gagné et al., 2022). However, they also introduce challenges such as increased cognitive demands, job insecurity, standardised monotonous tasks, and the need for continuous skill development (Alves et al., 2023;

Ghislieri et al., 2018; Grosse et al., 2023). Both the positive and negative impacts of technology have significant medium- to long-term effects on workers, including employee well-being, retention, performance, motivation, and engagement (Deci et al., 2017; Szalma, 2014). These factors, over time, profoundly influence the overall efficiency and profitability of a company. A workforce that is healthy, motivated, and skilled is essential for maintaining high levels of productivity and innovation, which in turn drive competitive advantage and financial success (Van den Broeck et al., 2021).

However, research in the context of Industry 4.0 has primarily focused on the technical aspects of technology and human performance while using technology (Passalacqua, Cabour, et al., 2024; Yahia et al., 2024). Numerous authors have noted the critical underrepresentation of human factors in this research (Kadir et al. 2019; Neumann et al. 2021; Sgarbossa et al. 2020; Reiman et al. 2021; Gagné et al. 2023; Grosse et al. 2023; Vijayakumar et al., 2022; Xu et al. 2022). Neumann et al. (2021) emphasise a significant neglect of psychosocial and perceptual aspects in current studies, calling for a systematic integration of these dimensions into Industry 4.0 systems. This gap is echoed by Reiman et al. (2021), who highlight that most research is heavily focused on technical details while insufficiently considering human-centred design principles. Gagné et al. (2023) and Grosse et al. (2023) further underline the necessity for future research to delve deeper into human-machine interactions and the psychosocial impacts of emerging technologies. Vijayakumar et al. (2022) also stress the significant gap in the evaluation of human factors in production and logistics systems, advocating for the development of tools and methods that specifically address these aspects.

Collectively, these perspectives underscore the lack of a balanced research agenda giving equal importance to technological advancements and human factors, thus jeopardising the successful adoption of Industry 4.0 technologies and human well-being at work. This predominant focus on technical and human performance aspects has often overshadowed other human-centric aspects, such as the psychosocial (how workers feel and relate to their work) and cognitive (mental and perceptual processes) dimensions of human factors, essential for a comprehensive understanding of the human-technology relationship. As such, there is a gap in our understanding when it comes to designing and implementing human-centred AI systems, i.e., systems that are safe, trustworthy, performant, and that account for human psychological needs (Calzavara et al., 2020; May et al., 2015; Rožanec et al., 2023).

In response to these limitations, the European Commission has introduced a progressive approach, termed Industry 5.0 (I5.0), marking a significant evolution to I4.0. I5.0's vision accentuates a more human-centric approach to technological design and integration in the workplace, emphasising a balance between technological progress and human welfare (European Commission, 2021; Ivanov, 2023). Fundamentally, the introduction of I5.0 aspires to rectify the gaps observed in I4.0, focusing on creating work environments that prioritise the human well-being and empowerment.

To fully embrace the potential of I5.0, we believe it is imperative to amalgamate and extend existing insights about interactions between humans and technology within I4.0 environments. Therefore, the general objective of this thesis is to **assess the impact of Industry 4.0 technology on the psychological dimensions of human-technology interaction in the context of supply chain operations, with the aim of designing and implementing supportive, efficient, and human-centred technological systems.**

To provide a foundation for this investigation, we will first begin by systematically reviewing the I4.0 and I5.0 literature, which is presented in Chapter 2. The specific objective of the review is to provide an in-depth examination of psychosocial, cognitive, and behavioural factors in I4.0 contexts, identifying their outcomes, antecedents, consequences, and the methodologies used to address them, to ultimately uncover gaps in the current literature. Using the identified gaps in the literature, Chapter 3 will then present the specific objective of the thesis, and the methodology used to achieve them.

As this is a thesis by articles, Chapters 4 to 6 will present Articles 1 to 3. Chapter 4 will present Article 1, titled *Safeguarding Worker Psychosocial Well-being in the Age of AI: The Critical Role of Decision Control*, which is under review in the *Journal of Organizational Behavior*. Chapter 5 will present Article 2, titled *Practice with less AI makes perfect: partially automated AI during training leads to better worker motivation, engagement, and skill acquisition*, which has been published in the *International Journal of Human-Computer Interaction*. Chapter 6 will present Article 3, titled *Assessing Risk Factors in Last-Mile Delivery Driving: A Multi-Method Longitudinal Field Study Accident*, which is currently under review in *Accident Analysis &*

Prevention. Finally, Chapter 7 will discuss the results of these articles and the overall contribution of the thesis.

CHAPTER 2 SYSTEMATIC LITERATURE REVIEW

The literature review is structured as follows. First, Section 2.1 will present the methodology used to conduct the review. Section 2.2 will present the development of our conceptual model, which is central to our exploration of human factors in I4.0/I5.0. Section 2.3 will present the bibliometric and descriptive results of the review its results; and Section 2.4 will synthesise and critically discuss the results, while presenting gaps within the literature.

2.1 Methodology

This review adhered to the PRISMA guidelines for systematic reviews, ensuring transparency, comprehensiveness, and ethical rigor throughout the process. The full methodology used to conduct the systematic review is presented in Appendix A[1]. The review was registered with PROSPERO and followed a pre-published PRISMA protocol. The SPIDER tool was employed to define eligibility criteria, focusing on studies examining human interaction with AI-based technology in manufacturing or logistics settings. A systematic search was conducted across multiple databases, including Web of Science, Engineering Village, and PsycInfo, using a carefully crafted search strategy. The search terms were iteratively refined to ensure the inclusion of relevant studies, following the Cochrane Handbook's recommendations.

Data extraction was managed using Zotero and Covidence, with two reviewers independently screening and extracting data to ensure accuracy and reliability. The final dataset was synthesized using a narrative synthesis approach, given the predominance of qualitative studies in the emerging field of human-centred AI in manufacturing. This method allowed for the integration of diverse data types, identifying patterns and themes across the included studies. The synthesis highlighted commonalities and variances in how human factors are addressed in Industry 4.0 contexts, providing a comprehensive overview of the current state of research in this area.

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[1] The content of this chapter has been accepted as a systematic review paper in the *International Journal of Production Research* (Passalacqua, M., Pellerin, R., Magnani, F., Doyon-Poulin, P., Del-Aguila, L., Boasen, J., & Léger, P.-M. (2024). Human-centred AI in industry 5.0: a systematic review. *International Journal of Production Research*, 1-32.)

2.2 Conceptual Model Development

The current section will review existing frameworks and conceptual models in production research used to understand the impact of technological and organisational factors on human factors and outcomes. We will then synthesise them and create a new conceptual model through the integration of theories and models from organisational and clinical psychology. This conceptual model will be used to structure the findings from the systematic review and to aid in the identification of research gaps.

Within the optic of I5.0, multiple frameworks and conceptual models within production research are proposed to examine the impact of I4.0 technologies on workers (De Lombaert et al., 2023; Grosse et al., 2023; Setayesh et al., 2022; Sgarbossa et al., 2020; van Oudenhoven et al., 2022; Vijayakumar et al., 2022). At their core, these frameworks indicate that the design and implementation of technological systems, as well as the organisational conditions in which work tasks are performed, both impact human factors. These impacts then cascade to affect operator behaviour and work performance, ultimately influencing overall system and organisational performance. For instance, consider an AI-driven production system that enforces high workloads and strictly dictates workflows, offering minimal decision-making flexibility for operators. The lack of variety and autonomy in their roles can leave workers feeling disengaged, while the overwhelming demands of the system lead to increased stress and mental exhaustion. Consequently, these factors contribute to negative outcomes, including high absenteeism, low productivity, and turnover. Ultimately, such a poorly designed system compromises overall organisational performance, resulting in unanticipated costs due to errors, dysfunction, and employee burnout.

In their conceptual models and frameworks, Grosse et al. (2023; 2015), Setayesh et al. (2022), Vijayakumar et al. (2021), Sgarbossa et al. (2020), and Longo et al. (2019) propose that the design, use, and implementation of technology can both positively and negatively impact human factors on a perceptual, cognitive, physical, and psychosocial level. In turn, this impact will directly affect operator performance and overall system performance. De Lombaert et al. (2023) add to this conceptual model by adding skills as an additional level of human factors affected by technology and work design. Van Oudenhoven et al. (2023) propose a similar model based on the Smith-Carayon Work System model (Smith & Sainfort, 1989). Specifically, they divide jobs into five domains, each of which can affect worker behaviour (e.g., technology acceptance) and thus their performance. These domains are technology (tools and systems used for tasks), individual (psychological and physical characteristics), tasks (specific activities performed), organisation (structural and cultural context), and environment (physical conditions of the workplace). The model emphasizes that changes in one domain can cascade to other domains, impacting worker behaviour and performance.

Building upon the strong foundation of these frameworks and models, we propose a conceptual model that firstly unites them, then expands them through the integration of psychological theories that have long been used to understand workers in a work environment. Figure 2.1 illustrates our proposed conceptual model, which aims to gain a comprehensive understanding of the psychological experience of workers within their work environment.

On the far left of Figure 2.1, we have technological and organisational characteristics (work environment), which mutually influence each other, as described in Sociotechnical Systems Theory (STS) (Emery & Trist, 1960). For example, the transparency of an AI-powered scheduling tool (technological) can change how teams communicate and collaborate (organisational). Conversely, a supportive organisational culture that encourages learning (organisational) can enhance the continuous improvement of the AI tool (technological). Technological factors refer to the design, implantation, and use of technology. Organisational factors refer to the structural and cultural elements of the workplace, including training opportunities, management support, and the overall organisational culture. Technological and organisational characteristics have a direct impact on human factors, as presented in all of the reviewed models and frameworks. Specifically, they impact the psychosocial and cognitive dimensions of human factors, with this relationship being moderated by individual factors such as personality and demographics. While physical factors may be impacted, they are outside the scope of this model and article, which deal only with psychological aspects. Psychosocial factors pertain to how workers feel and relate to their work environment, encompassing elements such as motivation, engagement, autonomy, work meaningfulness, and stress (Neumann et al., 2021). Cognitive factors relate to mental and perceptual processes, such as attention, cognitive workload, decision-making, learning, and fatigue (Longo et al., 2019). Psychosocial and cognitive factors both impact behavioural outcomes, such as technology acceptance and worker performance, which then affect organisational outcomes (van Oudenhoven et al., 2022).

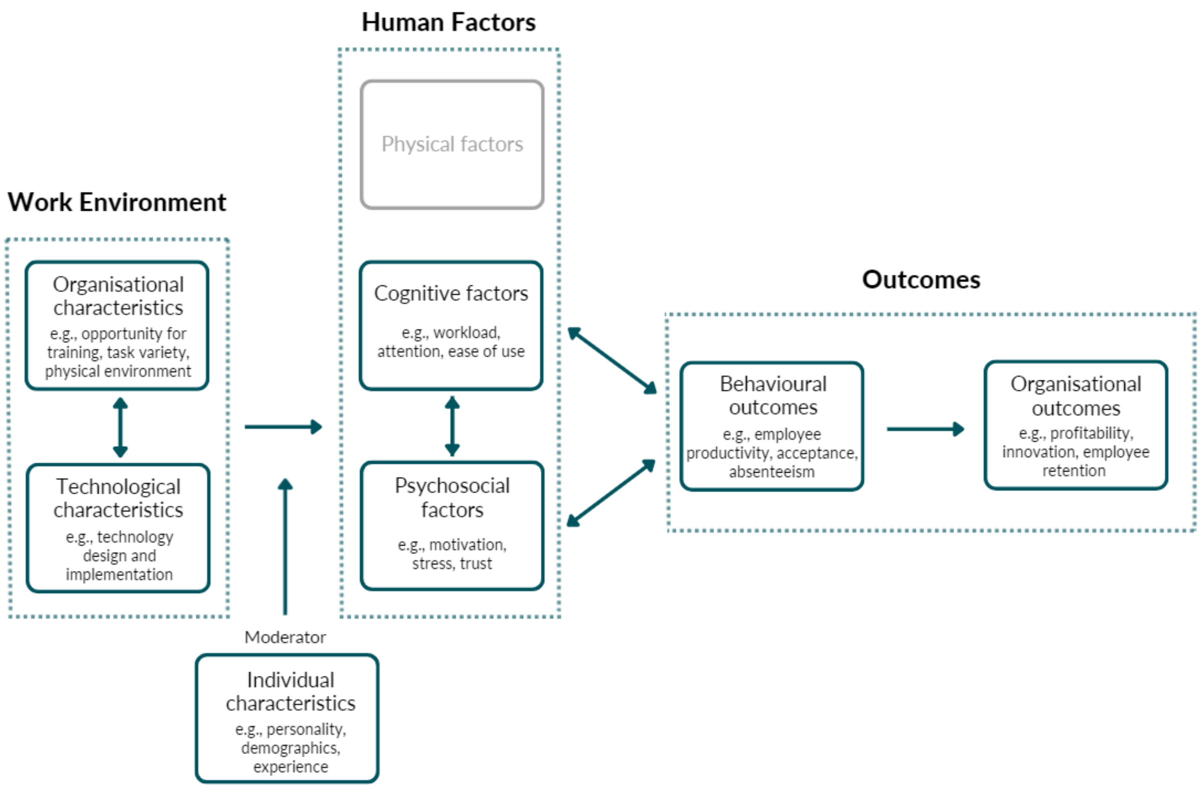

Figure 2.1: Proposed conceptual model

The effect of characteristics of the work environment on human factors has been extensively studied in the field organisational psychology through prominent theories such as the Job Characteristics Theory (Hackman & Oldham, 1976), the Job Demands-Resource Model (Demerouti et al., 2001), and Self-Determination Theory (Deci & Ryan, 1980), which we have used to enhance and solidify our proposed model.

Job Characteristics Theory (JCT) posits that certain aspects of the work environment affect a worker's psychological state, with this relationship being moderated by individual characteristics such as personality traits (e.g., growth need, desire for personal development). Psychological state then affects outcomes related to the worker and the organisation. Specifically, work characteristics such as skill variety, task identity, task significance, autonomy, and feedback affect the psychological states of experienced work meaningfulness, experience work responsibility, and knowledge of results, which in turn affect outcomes such as motivation, satisfaction, performance, absenteeism, and turnover. The relationship between work characteristics (technological, organisational), individual characteristics, psychological states (cognitive, psychosocial), and outcomes (behavioural, organisational) is directly integrated into our model.

The Job Demands-Resource (JD-R) Model presents a similar link between work characteristics, psychological states, and outcomes. This model posits that work characteristics can either be classified as job demands (requiring sustained effort or skill) or job resources (reduce job demands and associated psychological cost). A high amount of job demands (e.g., poorly designed technology leading to high cognitive workload), without sufficient job resources, can lead to stress, disengagement, burnout, and thus a reduction in well-being and performance. Whereas a high amount of job resources (e.g., worker autonomy, opportunities for training) can lead to high motivation, engagement, well-being, and performance. The relationship between job demands/resources and outcomes is moderated by individual characteristics such as resilience and self-efficacy.

Similarly, Self-Determination Theory (SDT) posits that work characteristics can positively or negatively impact workers' innate psychological needs of autonomy, competence, and relatedness, with this relationship being moderated by individual characteristics such as autonomy orientation and personality. The satisfaction of the three psychological needs is a direct antecedent of various psychosocial and cognitive factors, for example, self-determined motivation (drive to engage in activities based on intrinsic interest, personal values, and the inherent satisfaction derived from the activity itself, rather than external pressures or rewards), which itself is an antecedent of positive work outcomes such as high engagement, performance, and well-being.

It is important to note that, within our model, the relationship between psychosocial, cognitive, and behavioural factors/outcomes is bidirectional, indicating, for example, that behavioural outcomes can go on to affect psychosocial or cognitive factors, and vice-versa. This bidirectionality is a foundational component of Cognitive Behavioural Therapy/Theory (CBT) (Beck, 2012), which is widely used in psychotherapy to understand how thoughts, feelings, and behaviours are intertwined. CBT posits that cognitive processes, emotional responses (psychosocial factors) and behavioural responses are interconnected and influence each other. For example, consider the implementation of an AI tool in the workplace. This new technology can initially lead to a high cognitive workload and low trust (psychosocial) in the AI's recommendations. However, as employees use the AI tool effectively and begin to accept it (behaviour), their cognitive workload can decrease, and their trust in the technology can increase.

Overall, our conceptual model adds to the models and frameworks of Grosse et al. (2023; 2015), Setayesh et al. (2022), Vijayakumar et al. (2021), Sgarbossa et al. (2020), Longo et al. (2019), De Lombaert et al. (2023), and Van Oudenhoven et al. (2023) by adding specificity through interdisciplinary theoretical foundations, further contributing to the understanding of workers psychological experience within their work environment. First, we emphasise the bidirectionality of the relationship between technological and organisational characteristics of a work environment, as presented in STS. Second, we add individual characteristics as moderators between work environment and human factors, as detailed in the JCT, the JD-R model, and SDT. Third, we add a nuance to the relationship between the psychological dimensions of human factors (psychosocial and cognitive) and behavioural outcomes, emphasising its bidirectionality. Overall, our work bridges the gap between production research and organisational psychology by expanding existing models, thereby enabling a more comprehensive examination of human factors within production environments.

2.3 Results

This section will present the descriptive results of the systematic review. The bibliometric results are presented in Appendix B. For transparency, all raw and processed extracted data is available at https://doi.org/10.17632/ynptkr357k.1.

2.3.1 Results of the Search

A total of 1611 records were identified through the database search. After title and abstract screening, full text screening, and backward-forward citation search, 67 articles were retained for extraction. Figure 2.2 presents a flow diagram that details the process through which we obtained the retained articles.

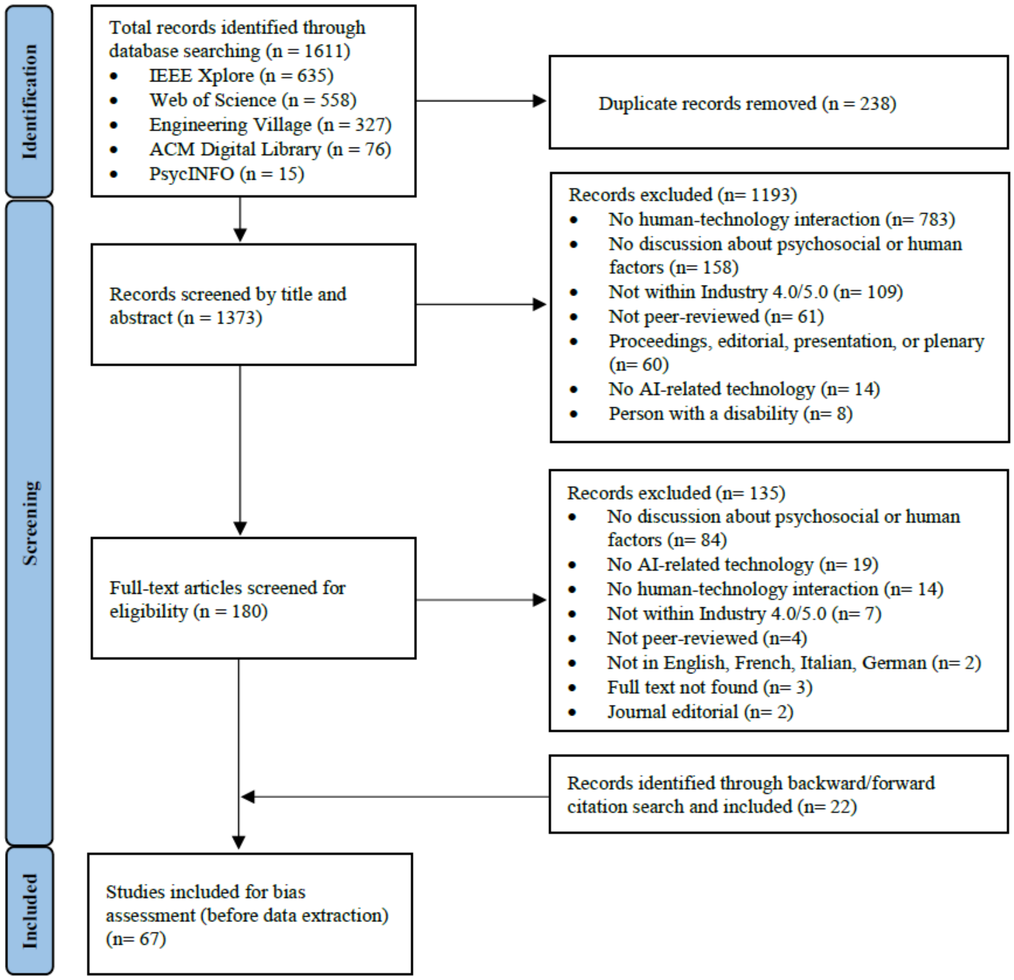

Figure 2.2: PRISMA Flow Diagram

There was substantial agreement between the reviewers for title and abstract screening (87% agreement rate, Cohen's kappa of 0.63). Similarly, there was substantial agreement for the full-text screening (90% agreement, Cohen's kappa of 0.76).

Through analysis of the 67 selected articles, we have derived 9 meta-topics, as shown in Table 2.1. Some articles appear in more than one category.

Table 2.1: Topics in All Articles

Topic (number of articles)	Article
Defining and transitioning to human-centred smart manufacturing (12)	(Alves et al., 2023; Bocklisch & Huchler, 2023; Cagliano et al., 2019; Enang et al., 2023; Ghislieri et al., 2018; Gladysz et al., 2023; Grabowska et al., 2022; Kadir et al., 2019; Kumar & Lee, 2022; Langer & Landers, 2021; Lindner & Reiner, 2023; van Oudenhoven et al., 2022; Xu et al., 2022)
Trust in AI and trustworthiness (7)	(Adadi & Berrada, 2018; Alexander et al., 2024; De Visser et al., 2018; Grigsby, 2018; Ismatullaev & Kim, 2022; Sassmannshausen et al., 2021; Shneiderman, 2020)
Organisational adoption of AI (5)	(Chatterjee et al., 2021; Ismatullaev & Kim, 2022; Malik et al., 2021; Marcon et al., 2021; van Oudenhoven et al., 2022)
Use of AI (11)	(Arana-Landín et al., 2023; Bechinie et al., 2024; Colombo et al., 2023; Fügener et al., 2022; Hertel et al., 2019; Jain et al., 2022; Klumpp et al., 2019; Lee et al., 2022; Passalacqua, Pellerin, Yahia, et al., 2024; Tortorella et al., 2024; Wellsandt et al., 2021)
Acceptance of AI (6)	(Del Giudice et al., 2023; Dimitrakopoulos et al., 2024; Ismatullaev & Kim, 2022; Klumpp et al., 2019; Molino et al., 2020; Molino et al., 2021; van Oudenhoven et al., 2022)
Work satisfaction and absenteeism (3)	(Ghislieri et al., 2018; Sitarević et al., 2023; Winkelhaus et al., 2022)

Table 2.1 (continued and end)

Algorithm aversion (3)	(Burton et al., 2019; Jain et al., 2022; Klumpp et al., 2019)
AI design and implementation guidelines/frameworks (13)	(Adattil et al., 2024; Angulo et al., 2023; Bednar & Welch, 2020; Cachada et al., 2019; De Visser et al., 2018; Kaasinen et al., 2022; Longo et al., 2020; Y. Lu et al., 2022; Neumann et al., 2021; Ngoc et al., 2021; Reiman et al., 2021; Sgarbossa et al., 2020; Shneiderman, 2020; Waschull & Emmanouilidis, 2023)
Evaluation of worker state (11)	(Bousdekis et al., 2022; Brunzini et al., 2021; Ciccarelli et al., 2022; Cohen et al., 2018; Diamantopoulos & Weitian, 2021; Grigsby, 2018; Longo et al., 2019; Papetti et al., 2020; Peruzzini et al., 2017, 2020; Vijayakumar & Sgarbossa, 2020)

2.3.2 Empirical Articles

This section will focus on the 17 empirical articles. Through analysis of the articles, we derived multiple topics, as shown in Table 2.2.

Table 2.2: Topics in empirical articles

Topic (number of articles)	Article
Identifying antecedents of AI adoption or use (3)	(Chatterjee et al., 2021; Jain et al., 2022; Marcon et al., 2021)

Table 2.2 (continued and end)

Examining how smart manufacturing affects work design (2)	(Cagliano et al., 2019; Winkelhaus et al., 2022)
Evaluating the impact of use of AI on task performance and human factors (6)	(Arana-Landín et al., 2023; Colombo et al., 2023; Hertel et al., 2019; Lee et al., 2022; Malik et al., 2021; Passalacqua, Pellerin, Yahia, et al., 2024; Tortorella et al., 2024)
Identifying the antecedents of AI acceptance and how it impacts work engagement (2)	(Molino et al., 2020; Molino et al., 2021)
Examining optimal delegation between human and AI for task performance (1)	(Fügener et al., 2022)
Identifying the antecedents of trust in AI (1)	(Sassmannshausen et al., 2021)
Identifying the antecedents of absenteeism (1)	(Sitarević et al., 2023)

Most empirical articles (11) used an observational, cross-sectional research design, meaning that data was collected at only one point in time and that no variables were manipulated. To collect data, nine articles used questionnaires, four used interviews, and one used a focus group.

Three articles used an experimental research design, implying the manipulation of independent variables and random assignment of participants to groups. Two articles used questionnaires and task performance measures as means of data collection. The other article used physiological data (heart rate, respiration), questionnaires, and performance measures.

Finally, three articles employed case study designs in diverse organisational settings, engaging employees, managers, and experts across industries including manufacturing, aerospace, and IT.

Within the empirical articles, the job demands-resource model (Demerouti et al., 2001; Karasek Jr, 1979), sociotechnical systems theory (Emery & Trist, 1960), and the technology acceptance model (TAM) (Davis, 1989) were most commonly used, appearing in four articles each. The unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003) and job characteristics theory (Hackman & Oldham, 1976) appeared twice.

Within the empirical article, multiple relationships between variables were examined. Table 2.3 outlines these relationships. Figure 2.3 then maps the statistically significant relationships onto each category of the proposed conceptual model (Figure 2.1). Notably, no two articles statistically tested the same relationship.

Table 2.3: Relationships from empirical articles

Article	Relationship			Direction of effect	Statistical testing?
	Antecedent	Moderator/ mediator/ covariate	Outcome		
Arana-Landin et al., 2023	Type of application of AI	Surveillance by AI	Anxiety, Stress	Mediation	No
	Proper communication and pretraining to use AI		Anxiety, Stress	Negative	No
Cagliano et al., 2019	Technological complexity	-	Number of tasks performed, Job autonomy, Cognitive demand, Decentralised decision making	Positive effect	No

Table 2.3 (continued)

Chatterjee et al., 2021	Organisational complexity	-	Perceived usefulness, perceived ease of use	Negative effect	Yes
	Competitive advantage	-	Perceived ease of use, Perceived usefulness	Positive effect	Yes
	Organisational competency, Organisational readiness, Partner support, Perceived ease of use	-	Perceived usefulness	Positive effect	Yes
	Perceived ease of use, Perceived usefulness	Leadership support	Intention to adopt AI	Positive effect Moderation	Yes
Colombo et al., 2023	Automation technologies		Perceived autonomy	Positive	No
	Augmentation technologies		Task breadth/ enlargement	Positive	No
Fugener et al., 2022	AI-human teams (versus human or AI alone), AI delegates tasks to humans when uncertain (compared to AI alone)	-	Task performance	Positive effect	Yes

Table 2.3 (continued)

Hertel et al., 2019	Availability of decision-support system	-	Quality of decisions	Positive effect	Yes
	Availability of decision-support system	-	Strain	Negative effect	Yes
	Availability of decision-support system	High trust	Recall of single data point	Moderation	Yes
Jain et al., 2022	Effort expectancy, social influence to use AI, facilitating conditions to use AI	-	Use of AI	Positive effect	Yes
	Facilitating conditions, Social influence	-	AI aversion	Negative effect	Yes
	More performance expectancy	Less AI aversion	More use of AI	Moderation.	Yes

Table 2.3 (continued)

(Lee et al., 2022)	Adoption of AI		Work engagement, job satisfaction	Positive	Yes
	Adoption of AI	Employer-provided training (vs. self-paid)	Job insecurity	Positive (moderation buffers effect)	Yes
	Job insecurity	Self-paid training (vs. employer-provided)	Job satisfaction	Negative (moderation exacerbates effect)	Yes
	Job insecurity	Self-paid training (vs. employer-provided)	Work engagement	Negative (moderation exacerbates effect)	Yes
Malik et al., 2022	Adoption of AI	-	Job insecurity, Work flexibility, Worker autonomy, Performance, Creativity, Technostress, Work overload, Work complexity	Positive effect	No

Table 2.3 (continued)

Marcon et al., 2021	Development of company sociotechnical subdimensions (social, organisational, environmental)	-	Company adoption of I4.0 technology	Positive effect	Yes
Molino et al., 2020	Opportunities for information and training	Technology acceptance	Work engagement	Positive effect. Partial mediation	Yes
	Resilience	Technology acceptance	Work engagement	Positive effect. Full mediation	Yes
Molino et al., 2021	Supervisor support, Role clarity	Technology acceptance	Work engagement	Positive effect. Partial mediation	Yes
Passalacqua et al., 2024	Partial automation of decision selection during training (vs. full or no automation)	Trait engagement (covariate)	Skill acquisition, self-determined motivation (identified), autonomy, behavioural engagement	Positive effect	Yes
Sassmannshausen et al., 2021	Perceived ability of AI, Perceived comprehensibility of AI, Digital affinity	-	Trust	Positive effect	Yes

Table 2.3 (continued)

Sitarevic et al., 2023	Friendship, Skill variety, Human autonomy, Feedback, Work identity, Cooperation, Mental health	-	Absenteeism	Positive effect (less absenteeism)	Yes
(Tortorella et al., 2024)	Implementation/use of AI according to Lean principles		Employee engagement (physical, cognitive, and emotional dimensions), psychological conditions (safety, meaningfulness, and availability), and performance	Positive effect	No

Table 2.3 (continued and end)

(Winkelhaus et al., 2022)	Digitisation, automation	Reduced process complexity, performance measurement/display, and ergonomics for utilisation, task enlargement, task enrichment, increased efficiency, and social cooperation	Work satisfaction	Positive effect on work satisfaction. Mediation	No
	Digitisation, automation	Standardisation, process rigor, division of labour, equipment complexity, substitution of tasks, need for utilisation of automation equipment, substitution of knowledge, and limitation of tasks	Work satisfaction	Negative effect on work satisfaction. Mediation	No

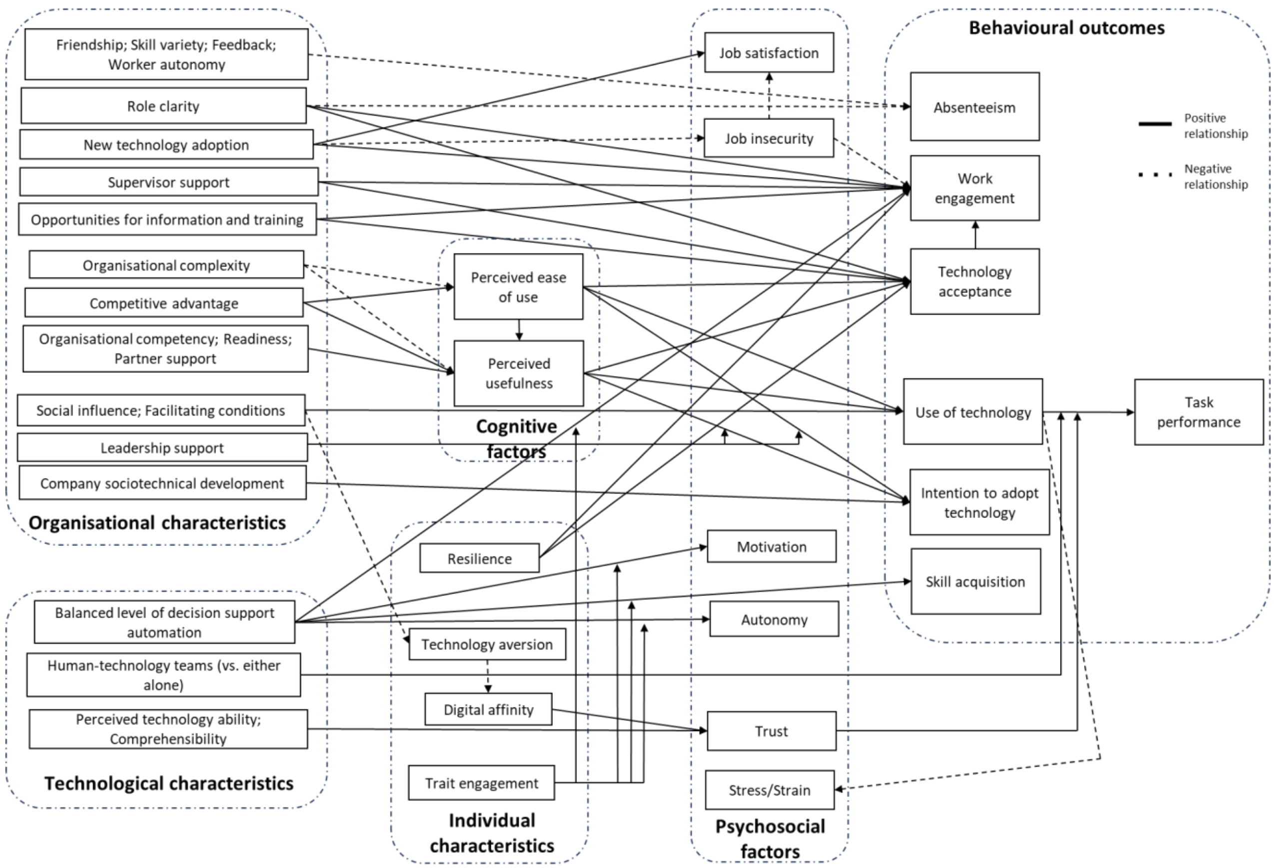

Figure 2.3: Map of Statistically-Significant Relationships

To enhance our analysis of the variables examined in the empirical articles, we have mapped all these variables, as well as their occurrence, onto our proposed conceptual model, as shown in Figure 2.4. This mapping includes both statistically analysed variables and those that were not, ensuring that all variables within the empirical articles are considered. Regarding the technological characteristics explored, technological complexity was the most frequently examined (three articles). For organisational characteristics, task variety and complexity were the most commonly studied (five articles), followed by opportunities for training/information and leadership/partner support (three articles each). In the realm of cognitive factors, cognitive workload was the most investigated (four articles). Among psychosocial factors, perceived autonomy and stress/strain were the most explored (three articles each). Lastly, in terms of behavioural outcomes, worker performance was the most frequently analysed (five articles), followed by work engagement (four articles).

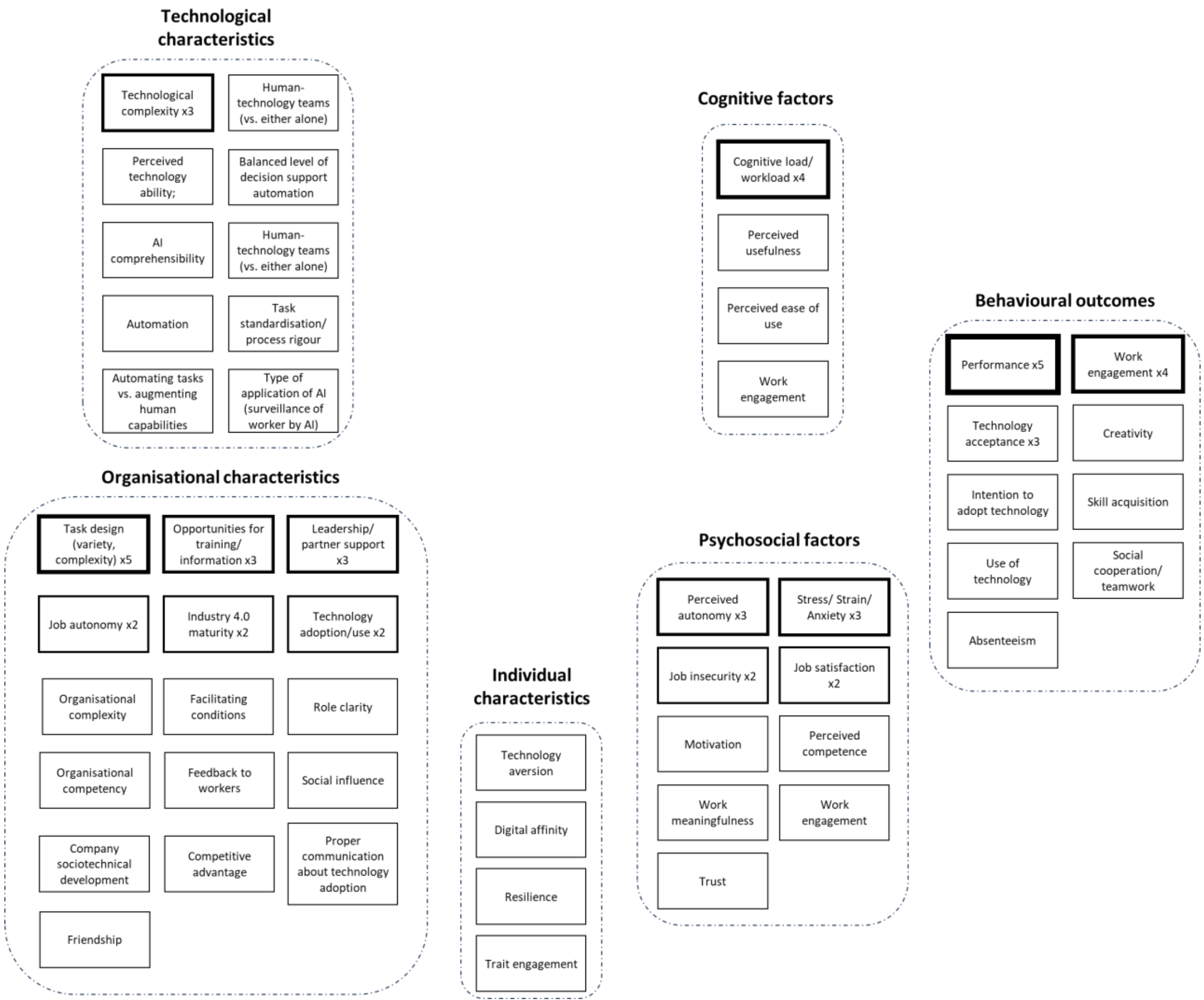

Figure 2.4: Variables Examined in All Empirical Articles

2.3.3 Conceptual Articles

This section will focus on the 21 conceptual articles. Table 2.4 presents the topics addressed in the conceptual articles. Most articles (12) are about integrating human factors in the design, implementation, and evaluation of AI.

Table 2.4: Tables in conceptual articles

Topic (number of articles)	Article
Considering human factors or human centricity in the design, implementation, or evaluation of AI systems (12)	(Angulo et al., 2023; Bechinie et al., 2024; Bednar & Welch, 2020; Bousdekis et al., 2022; Del Giudice et al., 2023; Kaasinen et al., 2022; Lindner & Reiner, 2023; Y. Lu et al., 2022; Shneiderman, 2020; van Oudenhoven et al., 2022; Vijayakumar & Sgarbossa, 2020; Waschull & Emmanouilidis, 2023)
Integrating operator and/or workstation state into AI systems (3)	(Cohen et al., 2018; Golan et al., 2019; Grigsby, 2018)
Designing serious games to (re)train workers (1)	(Brauner & Ziefle, 2022)
Developing a framework to integrate trust repair in the design of AI systems (1)	(De Visser et al., 2018)
Introducing guidelines for achieving trustworthy AI (1)	(Floridi, 2019)
Creating a human factors taxonomy and examining each factor's correlation with work performance (1)	(Longo et al., 2019)
Exploring the benefits of digital assistants (1)	(Wellsandt et al., 2021)

Within conceptual articles, the most common theoretical framework used is sociotechnical systems theory (five), followed by joint cognitive systems and TAM (two each), cognitive systems theory, unified theory of cognition, actor-network theory, and Maslow’s hierarchy of needs (each occurring once).

To investigate the variables discussed in the conceptual article, we have mapped them and their occurrences onto our proposed conceptual model, as shown in Figure 2.5. This mapping includes all variables that were significantly discussed, rather than simply mentioned. Concerning the technological characteristics explored, human-centred design (considering human factors) was the most frequently discussed (six articles), followed by human control/ decision-making authority and AI transparency (five articles each). For organisational characteristics, task variety and complexity were the most commonly studied (four articles), followed by social support, employee training, and social pressure to accept technology (three articles each). In terms of individual characteristics, personality was the most discussed (two articles). For cognitive factors, cognitive workload was the most investigated (five articles), followed by usability (three articles). Regarding psychosocial factors, trust was by far the most discussed variables (14 articles), followed by motivation (seven articles), emotion, worker autonomy/agency, and well being (five each). In terms of behavioural outcomes, worker performance was the most frequently discussed (eight articles), followed by technology acceptance (five articles). Lastly, for organisational outcomes, employee safety was the most discussed (two articles).

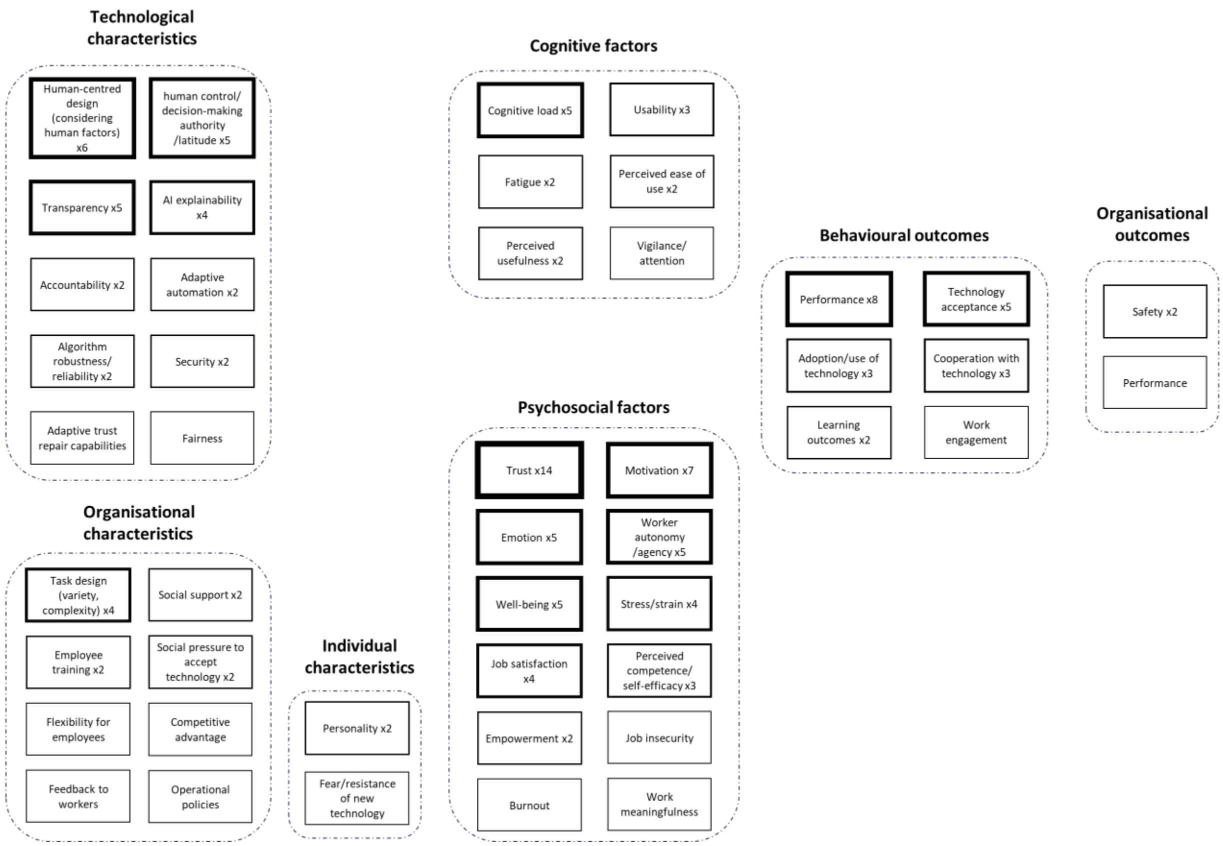

Figure 2.4: Variables examined in all conceptual articles

2.3.4 Review Articles

This section will focus on the 20 review articles. Table 2.5 presents the topics of the review articles. Similar to the conceptual articles, many review articles (six) discuss the importance of examining the human factors associated with I4.0.

Table 2.5: Variables examined in all conceptual articles

Topic (number of articles)	Article
Examining the measure, application, or importance of human factors in Industry 4.0 (6)	(Kadir et al., 2019; Kumar & Lee, 2022; Neumann et al., 2021; Ngoc et al., 2021; Reiman et al., 2021; Sgarbossa et al., 2020)

Table 2.5 (continued and end)

Exploring the transition between Industry 4.0 and human-centred 5.0 (4)	(Alves et al., 2023; Enang et al., 2023; Gladysz et al., 2023; Grabowska et al., 2022)
Multidisciplinary analysis of human-computer interaction in highly-automated environments (3)	(Bocklisch & Huchler, 2023; Klumpp et al., 2019; Xu et al., 2022)
Understanding the impact of Industry 4.0 technology on workers (2)	(Adattil et al., 2024; Ghislieri et al., 2018; Langer & Landers, 2021)
Identifying the factors that contribute to AI acceptance and adoption (2)	(Dimitrakopoulos et al., 2024; Ismatullaev & Kim, 2022)
Exploring the state of the art on explainable AI (2)	(Adadi & Berrada, 2018; Alexander et al., 2024)
Examining algorithm aversion and misuse (1)	(Burton et al., 2019)

2.3.5 System/Framework Design with User Test Articles

This section will focus on the eight articles including system/framework design with user tests. Table 2.6 presents the topics of the system/framework design with user test articles. Most articles (five) developed and tested a methodology to evaluate the operator's state. The user tests conducted in these eight articles are as follows. Questionnaires were the most used method (6), followed by heart rate sensors (5), eye-tracking (3), electrodermal activity (2), skin temperature (1), and emotion recognition (1).

Table 2.6: Topics discussed in system/framework design with user test articles

Topic (number of articles)	Article
Developing a methodology to assess operator state and/or factory environment to improve worker welfare (5)	(Brunzini et al., 2021; Ciccarelli et al., 2022; Papetti et al., 2020; Peruzzini et al., 2017, 2020)
Applying ISO guidelines to design ergonomic user interfaces in the context of cyber-physical systems (1)	(Cachada et al., 2019)
Developing a co-bot that recognise human emotions and adapt itself to aid human learning (1)	(Diamantopoulos & Weitian, 2021)
Providing guidelines for designing systems that consider human values and welfare in factories of the future (1)	(Longo et al., 2020)

2.4 Critical Review

In this section, we critically analyse the existing literature on human factors in I4.0/I5.0, with a focus on psychosocial, cognitive, and behavioral dimensions. Our goal is to examine the theoretical frameworks, variables, research designs, and data collection methodologies used in the reviewed studies. This section is organised as follows: first, we examine the theoretical frameworks employed across the literature and discuss their applicability and limitations. Next, we explore the choice of variables emphasized in both empirical and non-empirical studies. Following this, we critically assess the research designs and methodologies utilized, highlighting their strengths and weaknesses.

2.4.1 Theoretical Frameworks

Within the literature, there is a consensus that technological and organisational factors significantly influence various aspects of human factors, which in turn affect both employee and organisational outcomes. Multiple authors have noted the lack of examination of this relationship within the context of I4.0/I5.0, with particular emphasis on the underrepresentation of psychosocial factors, despite being flagged as the most significant risk factors for workers in I4.0/I5.0 (Bispo & Amaral, 2024). Consequently, several frameworks and models in production research have been developed to highlight the need for a comprehensive evaluation of all components for a holistic understanding of human-technology interaction (Grosse et al. 2023; Vijayakumar et al. 2022; Setayesh et al. 2022; De Lombaert et al. 2023; van Oudenhoven et al. 2022; Sgarbossa et al. 2020). Additionally, many authors of non-empirical articles advocate for integrating theoretical frameworks from organisational psychology to better understand human factors, particularly psychosocial factors (De Visser, Pak, and Shaw 2018; Ghislieri, Molino, and Cortese 2018; Lu et al. 2022; Sitarević et al. 2023; Gagné et al. 2022; Jain, Garg, and Khera 2022; Xu et al. 2022). While some empirical articles have begun utilising these theoretical frameworks (Passalacqua et al. 2024; Winkelhaus, Grosse, and Glock 2022; Lee et al. 2022; Tortorella et al. 2024; Molino, Cortese, and Ghislieri 2021; Molino, Cortese, and Ghislieri 2020), many have not. This gap indicates a substantial shortfall in connecting theoretical models with empirical evidence, which is crucial for informed decision-making and practical applications.

Recognising this gap, we identified the need to merge relevant theoretical frameworks and models into a cohesive, multi-disciplinary conceptual model (Figure 2.1) to guide the human-centred design and implementation of technology within production environments. This conceptual model integrates research from production and psychological (organisational and clinical) research. From production research, we incorporated frameworks designed to understand how technological and organisational characteristics influence human factors and individual and organisational outcomes (Grosse et al. 2023; Vijayakumar et al. 2022; Setayesh et al. 2022; De Lombaert et al. 2023; van Oudenhoven et al. 2022; Sgarbossa et al. 2020).

Guided by our conceptual model, we examined the key technological and organisational characteristics, as well as psychosocial and cognitive factors, and outcomes, that contribute to effective human-centred human-technology interaction. We then conducted a comparative analysis of the variables identified as important in non-empirical articles (Figure 2.6) against those addressed in empirical articles (Figure 2.5). This analysis uncovered a significant disconnect between the variables emphasised in theoretical discussions and those investigated in empirical studies. This disconnect is described in the following section.

2.4.2 Choice of Variables

Within our sample of non-empirical articles, there is a strong emphasis on specific technological, psychosocial, cognitive, and behavioural variables due to their significant impact on various outcomes related to worker well-being, organisational performance, and overall system performance in the context of human-technology interaction.

2.4.2.1 Technological Characteristics

Within non-empirical articles, many authors suggest the need to understand how technology and task design choices affect workers on a psychosocial and cognitive level (Shneiderman 2020; Langer and Landers 2021; Ngoc, Lasa, and Iriarte 2021; Lu et al. 2022; Angulo et al. 2023; Vijayakumar et al. 2020, Kaasinen et al. 2022; Bechinie et al. 2024). For example, examining the effects of various levels of automation, levels of human control, delegation strategies, task allocation, levels of system reliability, system complexity, or ways of presenting information on human perceptions of autonomy, empowerment, or stress.

However, within our sample of empirical articles, only one study experimentally manipulated characteristics of technology to evaluate the effect on human factors (Passalacqua, Pellerin, Yahia, et al., 2024). They manipulate the level of automation of AI decisional control to evaluate the impact on perception of autonomy, motivation, engagement, and skill acquisition. Rather, authors often focused on performance as an outcome variable (Fügener et al. 2022), focused on organisational factors (Chatterjee et al. 2021; Marcon et al. 2021; Jain, Garg, and Khera 2022), adopted a binary view of AI use (Hertel et al. 2019), or were unable to perform statistical analyses due to data type (Winkelhaus, Grosse, and Glock 2022; Malik et al. 2021; Cagliano et al. 2019; Arana-Landin et al. 2023; Colombo et al. 2023; Tortorella et al. 2024). This highlights a significant gap in the empirical investigation of how technological characteristics impact human factors, suggesting a need for more experimental studies in this area.

2.4.2.2 Individual Characteristics

As detailed in both non-empirical and empirical articles, considering individual differences is crucial for understanding how personality traits and prior experience with technology influence workers' responses to AI (Ghislieri et al., 2018; Molino et al., 2020; Molino et al., 2021; Passalacqua, Pellerin, Yahia, et al., 2024; Sassmannshausen et al., 2021). Personality traits such as resilience, self-efficacy, openness to experience, conscientiousness, and neuroticism can influence how workers perceive and interact with AI systems. For example, resilience and self-efficacy may help workers adapt to AI-driven changes, while traits like neuroticism could increase resistance and stress. Additionally, prior experience with technology and demographic factors such as age, education, and cultural background can shape workers' comfort with AI, impacting their attitudes and performance. Recognising these individual differences is key to developing AI systems and strategies that are tailored to diverse worker needs, ensuring a supportive and effective integration of AI in the workplace.

2.4.2.3 Psychosocial Factors

Trust and Trustworthiness: Non-empirical articles have emphasised the importance of AI trustworthiness and trust in AI for technology acceptance, efficient cooperation, and system performance, among others. In fact, as seen in Figure 2.6, trust was the most discussed variable, appearing in 14 articles. According to Floridi (2019), a trustworthy AI is defined as one that supports human autonomy, ensures security and robustness, maintains transparency, and upholds ethical standards. Thus, AI should be designed according to those principles. The level of workers' trust in AI is important, as exemplified in the concept of calibrated trust (Grigsby, 2018): it must not be too low to induce disuse, nor too high to prevent overuse. Adadi & Berrada (2018) further characterise trust as a measure that evolves through time. Antecedents to trust are AI transparency, explainability and interpretability which can be achieved through explainable AI (XAI) and Interpretable AI methods (Alexander et al., 2024; Bechinie et al., 2024; Gladysz et al., 2023; Lindner & Reiner, 2023). Additionally, individual characteristics, such as education and experience are antecedents (Adadi & Berrada, 2018; Ismatullaev & Kim, 2022).

Integrating these antecedents into AI design is crucial for creating systems that users feel comfortable relying upon. The three-layered model of trust (Hoff & Bashir, 2015), identifying dispositional, situational, and learned layers, serves as a guide for pinpointing these antecedents. This model informs AI design by emphasizing the importance of: (1) Tailoring user experiences to align with individual differences in trust propensity, which may involve personalized interfaces or adaptive levels of autonomy in AI systems (dispositional trust); (2) Ensuring that AI systems are transparent in operation and decision-making, providing clear context-specific information and appropriate responses to users' expectations and the environment they operate in (situational trust);

and (3) Designing AI systems with the capability to learn and adapt from user interactions, thereby demonstrating reliability and competency over time, which are key for users to develop a sustained trust in the system's capabilities (learned trust).

Despite its importance, trust was examined in only two empirical articles. Sassmannshausen et al. (2021) found that the situation predictability decreased, and error cost increased trust, with both relationships being mediated by the AI’s perceived ability and comprehensibility. Additionally, the authors found that workers’ digital affinity (attraction or interested in technology) is associated with higher trust in AI. Hertel et al. (2019) found that the use of AI led to better information recall, but only when participants had high trust in the AI.

Motivation: In non-empirical articles, multiple authors (seven) identified worker motivation as crucial for system long-term performance, worker well-being, worker engagement, and worker retention, among others (Bocklisch & Huchler, 2023; Ghislieri et al., 2018; Neumann et al., 2021; Sgarbossa et al., 2020; Vijayakumar et al., 2022; Xu et al., 2022). Authors stressed the importance of evaluating the impact of changing technological and organisational characteristics of the work environment, such as human control/decisional latitude, task variety, task complexity on worker motivation.

However, only one empirical article has addressed worker motivation (Passalacqua, Pellerin, Yahia, et al., 2024). In this study, we manipulated the level of automation of an AI’s decisional authority. We found that a balanced level of automation, one in which the AI assisted the human, but final decisional authority remained with the worker, led to the best outcomes in terms of motivation, perceived autonomy, and skill acquisition. In line with these findings, within the non-empirical articles, decision-making authority/control/latitude has been raised as an important technology design characteristics affecting human factors, specifically employee perception of autonomy, motivation, job satisfaction, performance, well-being, among others. (Y. Lu et al., 2022; Shneiderman, 2020; van Oudenhoven et al., 2022; Vijayakumar et al., 2022; Waschull & Emmanouilidis, 2023). As presented during the development of our conceptual model, both Job Characteristics Theory and Self-Determination theory also emphasise the importance of decision-making autonomy for similar outcomes, highlighting the need for further research on this technological characteristic.

Given the importance of worker motivation highlighted in non-empirical studies, further empirical research is needed to explore how technological and organisational changes impact this critical factor. While existing theories provide a solid foundation, there remains a lack of empirical evidence that directly examines how specific work environment characteristics influence motivation. Expanding research in this area will not only enhance our understanding of these dynamics but also guide the design of AI systems and work environments that better support worker motivation and overall well-being

Perceived Autonomy: In non-empirical articles, workers' perception of autonomy (sense of control) has been discussed in multiple papers, emphasising its importance for increasing worker well-being, performance, and reducing AI aversion/resistance (Burton et al., 2019; Floridi, 2019; Klumpp et al., 2019; Longo et al., 2020; Reiman et al., 2021). Others have raised the point that AI and automation could both enhance or reduce workers' perceptions of autonomy (Enang et al., 2023; Ghislieri et al., 2018; Langer & Landers, 2021; Wellsandt et al., 2021; Xu et al., 2022). The reduction of perceived autonomy is due to a decrease in task variety or an increase in task rigidity. Conversely, the enhancement of perceived autonomy can be attributed to the automation of monotonous, repetitive tasks, consequently allowing employees to engage in more meaningful and engaging activities.

In empirical articles, we also find that automation/AI can both increase and decrease perceived autonomy, depending on technological factors. Passalacqua, Pellerin, Yahia, et al. (2024) found that balanced levels of AI decision decisional authority led to higher levels of perceived autonomy, while high levels of decisional authority led to decreased autonomy. Cagliano et al. (2019) found that low levels of technological complexity are associated with low task variety, low worker autonomy, and low cognitive demand. Higher levels of technological complexity are associated with higher task variety and positively correlated with worker autonomy. Winkelhaus et al. (2022) found that automation is negatively correlated with autonomy. Conversely, Malik et al. (2021) found that the adoption of AI increases worker perceived autonomy. Lastly, Sitarević et al. (2023) found that higher perceived autonomy is associated with less absenteeism.

To deepen our understanding of perceived autonomy in AI-integrated workplaces, it's essential to investigate how specific design choices in AI systems influence this perception. Factors such as the degree of decision-making control, the transparency of AI decision-making processes, and the flexibility of task assignments could play pivotal roles in either enhancing or diminishing workers' sense of autonomy. Research should focus on identifying which AI design features most effectively support a positive perception of autonomy, and how these features can be integrated into various work environments to optimise worker satisfaction and performance.

Stress: In non-empirical articles, stress has been flagged as an important variable to evaluate due to its significant impact on both mental and physical well-being (Brunzini et al., 2021; Ciccarelli et al., 2022; Papetti et al., 2020). Authors emphasise that the increased prevalence of human collaboration with automated systems could increase stress by reducing worker autonomy, by reducing co-worker informal support (by reducing the number of human relationships), by increasing technology complexity, or by increasing job security concerns, among others (Ghislieri et al., 2018; Grigsby, 2018; Langer & Landers, 2021; Xu et al., 2022). To mitigate stress, Bispo and Amaral (2024) found, in their review, that adequately training employees, giving sufficient support systems, and allowing for a healthy work-life balance are effective solutions.

In empirical articles, three studies explored the effects of AI use/adoption on stress. Hertel et al. (2019) found that a decision-support system significantly reduced participant strain (stress). Contrarily, Malik et al. (2021) found that AI adoption can increase stress due to work overload, job insecurity, technology complexity, and role ambiguity. Providing a balanced perspective, Arana-Landín et al. (2023) found that the type of application of AI can affect stress differently. For instance, the study found, using interviews, that AI applications for voice recognition reduced stress by automating routine tasks for operators, whereas AI used in surveillance systems increased stress due to employees feeling monitored and privacy concerns.

Examining the factors contributing to worker stress in AI-integrated environments is crucial for promoting well-being. Stress can stem from the complexity of new technologies, the pace at which workers must acquire new skills, and concerns about job displacement. To address these issues, strategies such as adaptive automation, which adjusts the level of AI intervention based on the worker’s current state, and real-time feedback, offering continuous support and reassurance, can be effective. These approaches help manage cognitive demands and maintain a balanced work environment, ultimately enhancing both performance and well-being.

2.4.2.4 Cognitive Factors

Cognitive Workload: Non-empirical articles explore how AI impacts cognitive demands and propose strategies to manage them. Angulo et al. (2021) present a framework for AI-assisted cognitive support in manufacturing, focusing on reducing cognitive workload through human factors like trust and usability. Bednar and Welch (2017) advocate for a socio-technical approach, integrating social and cultural components to manage cognitive workload. Bousdekis et al. (2019) suggest an evaluation framework using the NASA TLX to assess and adapt systems to human cognitive limits. Brauner et al. (2020) recommend serious games for training to manage increased cognitive tasks from AI. Cohen et al. (2018) discuss adaptive automation that modulates cognitive workload based on real-time physiological data, enhancing well-being and efficiency. Strategies to alleviate high cognitive workload include comprehensive training, support systems, and work-life balance (Bispo & Amaral, 2024).

In empirical studies, cognitive load is well-represented. Cagliano et al. (2019) show that technological complexity in smart manufacturing increases cognitive demands, requiring enriched roles. Fugener et al. (2022) highlight the importance of efficient delegation and metaknowledge in managing cognitive workload during human-AI collaboration. Hertel et al. (2019) find that Decision Support Systems (DSS) improve decision quality and reduce cognitive strain when trusted. Malik et al. (2022) identify cognitive challenges and technostress from AI adoption, emphasizing strategic training to manage workload and highlighting job insecurity, work overload, and complexity as sources of technostress. Tortorella et al. (2024) reveal that AI can reduce cognitive demands by handling routine tasks, increasing meaningfulness and engagement as employees focus on more challenging, value-added tasks.

2.4.2.5 Behavioural Outcomes

Technology Acceptance: Non-empirical articles frequently discuss technology acceptance. Ismatullaev and Kim (2022) offer a framework categorizing factors into four domains:

- **Technology-Related Factors:** Transparency, reliability, complexity, and compatibility are key for user-friendly AI solutions (Ismatullaev & Kim, 2022).

- **Organisation-Related Factors:** Worker decision-making control, managerial motivations, and available resources/support are crucial for acceptance (Dimitrakopoulos et al., 2024; Van Oudenhoven et al., 2022).
- **Perception/Behaviour-Related Factors:** Perceived usefulness, ease of use, autonomy, trust, cognitive resources, and perceived risks influence acceptance, along with attitudes shaped by rational, emotional, and social factors (Dimitrakopoulos et al., 2024; Ismatullaev & Kim, 2022; Klumpp et al., 2019; van Oudenhoven et al., 2022).
- **Human-Factors:** Age, gender, education, and experience significantly impact AI acceptance (Ismatullaev & Kim, 2022).

In empirical studies, technology acceptance was well-represented. The TAM was used to examine acceptance, finding that perceived ease of use and usefulness are key antecedents. Organizational complexity negatively affects these, while competitive advantage and organizational readiness positively impact perceived usefulness (Chatterjee et al., 2021). Technology acceptance also mediates the relationship between work engagement factors like information, training, and supervisor support (Molino et al., 2020, 2021).

2.4.3 Research Designs

Non-empirical articles emphasize the need for experimental methodologies to explore human factors, especially psychosocial ones, in AI systems (Adadi & Berrada, 2018; Bispo & Amaral, 2024; Del Giudice et al., 2023; Ismatullaev & Kim, 2022; Kadir et al., 2019; Y. Lu et al., 2022; Peruzzini et al., 2020). Experimental designs allow researchers to systematically vary independent variables, like automation level or human oversight, and assess their effects on dependent variables such as trust, job satisfaction, and perceived autonomy. This controlled manipulation helps establish causal links and provides critical insights for designing AI systems that meet workforce needs.

The precision of experimental design also allows researchers to isolate specific aspects of human-AI interaction. For instance, manipulating AI feedback frequency and type can reveal its impact on stress, cognitive load, or decision-making efficacy. Controlling extraneous variables leads to a deeper understanding of how AI systems influence worker perceptions, attitudes, and behaviors. Experimental research can also support longitudinal studies, offering a dynamic view of how human factors, particularly psychosocial ones, evolve as workers interact with AI over time (Ghislieri et al., 2018).

In empirical studies, 11 used observational cross-sectional designs, and only three employed experimental designs. While observational studies aren't ideal for establishing causality, they provide quick, accessible insights into current human-AI interactions, identifying trends and associations crucial for hypothesis generation. These studies lay the groundwork for future research, offering a broad understanding of workplace dynamics.

By combining observational and experimental methods, researchers can achieve a comprehensive understanding of human-AI interactions. Observational studies reveal real-world complexities, while experimental studies test causal hypotheses, resulting in a balanced view that reflects workplace realities and supports rigorous causal conclusions.

2.4.4 Data Collection Method

Non-empirical articles emphasize the importance of a multi-method approach to evaluate human factors, using perceptual, psychophysiological, and observational measures for a comprehensive understanding of workers' states (Bousdekis et al., 2022; Brunzini et al., 2021; Ciccarelli et al., 2022; Cohen et al., 2018; De Lombaert et al., 2023; Diamantopoulos & Weitian, 2021; Golan et al., 2019; Grigsby, 2018; Papetti et al., 2020; Peruzzini et al., 2017, 2020; Vijayakumar & Sgarbossa, 2020). Perceptual measures involve assessing workers' subjective experiences via questionnaires or interviews. Adattil et al. (2024) suggest tools like the Work Design Questionnaire or the International Labor Organisation Stress Checkpoints to assess psychosocial factors. Psychophysiological measures use sensors to capture physiological data such as heart rate and galvanic skin response, providing objective evidence of stress and cognitive workload, which complements subjective perceptual data (Khairai et al., 2020; Peruzzini et al., 2020). Observational measures analyze worker behavior through performance metrics or video/audio recordings.

In the empirical studies reviewed, all used perceptual measures, with two experimental studies combining perceptual and observational measures. Only one study, our own, incorporated all three—perceptual, observational, and physiological measures (Passalacqua, Pellerin, et al., 2024).

The incorporation of psychophysiological measures significantly enhances the understanding of human-AI interaction by adding an objective layer to the inherently subjective self-reported data. For instance, while a questionnaire might capture perceived stress, galvanic skin response provides objective physiological evidence of this stress. Similarly, eye-tracking can reveal where attention is focused during AI interactions, and heart rate variability offers insights into cognitive workload and emotional states (Vasseur et al., 2023). Psychophysiological measures also help reduce mono-method bias, which can skew data or lead to false confirmations of hypotheses. By combining these measures with perceptual and observational metrics, researchers can validate findings across multiple evidence streams, leading to more robust and reliable results.

The inclusion of these various methods enriches research design, ensuring a comprehensive analysis of subjective experiences, observable behaviors, and objective physiological responses. While empirical studies predominantly used perceptual measures due to their methodological design, the move towards integrating psychophysiological measures would significantly deepen the research findings and enhance the understanding of human factors in human-AI interactions. This multi-method approach is especially valuable in experimental research, where the manipulation of variables allows for real-time observation and measurement of the complex interplay between perceptions, behaviors, and physiological responses.

2.5 Conclusion

In light of these findings, our review suggests several research avenues for developing human-centred AI systems, which guide the rest of this thesis. In short, studies should manipulate technological characteristics like automation levels, system reliability, and AI transparency to assess their impact on worker psychosocial, cognitive, and behavioural factors. Research should also examine how to train workers to use AI, with the goal of creating efficient human-AI collaboration. Additionally, research should consider individual differences, exploring how personality traits or demographic factors influence workers' responses to AI, providing insights into tailoring AI integration strategies. Investigating underexplored psychosocial variables, their relationships with cognitive and behavioural factors, as well as their antecedents and outcomes can be beneficial to designing and implementing human-centred systems. Lastly, a diverse data collection strategy integrating experimental or longitudinal research designs, along with perceptual, psychophysiological, and observational measure is essential for advancing our understanding of human-AI interactions and informing AI systems that support worker well-being and organisational effectiveness.

The insights gained from this review directly inform the empirical focus of the thesis. As we transition into Chapter 3, these identified gaps will be mobilised to formulate specific sub-objectives, guiding the design and methodology of the empirical studies (Articles 1-3) to follow.

CHAPTER 3 METHODOLOGY AND CONCEPTION OF EMPIRICAL INVESTIGATIONS

Building on the research gaps identified in the literature review, this chapter will outline the methodologies used to conduct the empirical investigations in this thesis. The goal is to provide an overview of the research design and methods employed to assess the impact of Industry 4.0 technologies on the psychological dimensions of human-technology interaction. This chapter will explain the rationale behind the chosen methodologies and how they address the specific research objectives.

This chapter is organised as follows. Section 3.1 provides an overview of the general methodology guiding the thesis, including the relationship between the general objective, sub-objectives, and associated thesis articles. Section 3.2 to 3.5 provide details on our sub-objectives, the addressed research gaps, and the specific methodologies employed to tackle these gaps. Finally, Section 3.6 concludes with a discussion of the overall research approach, summarizing the contributions of the empirical investigations to the thesis's broader aims.

3.1 General Methodology

The general objective of this thesis is to assess the impact of Industry 4.0 technology on the psychological dimensions of human-technology interaction, specifically the psychosocial, cognitive, and behavioral aspects, with the goal of designing and implementing supportive, efficient, and human-centered technological systems. To achieve this overarching goal, we have identified several sub-objectives that each address a critical aspect of this complex interaction. Figure 3.1 presents the relationship between the general objective, sub-objectives (SO), and thesis articles.

The first sub-objective was addressed through a systematic review of I4.0 and I5.0 research. The subsequent sub-objectives are crafted to address the specific gaps identified within it, thereby refining our research focus. SO2 and SO3 were addressed through a laboratory experiment, while SO4 was addressed through a longitudinal observational field study. In the following section, each sub-objective will be presented separately, illustrating how these gaps have informed our specific aims. Subsequently, the specific methodologies used to achieve each sub-objective will be detailed, demonstrating our comprehensive approach to assessing the psychological impacts of Industry 4.0.

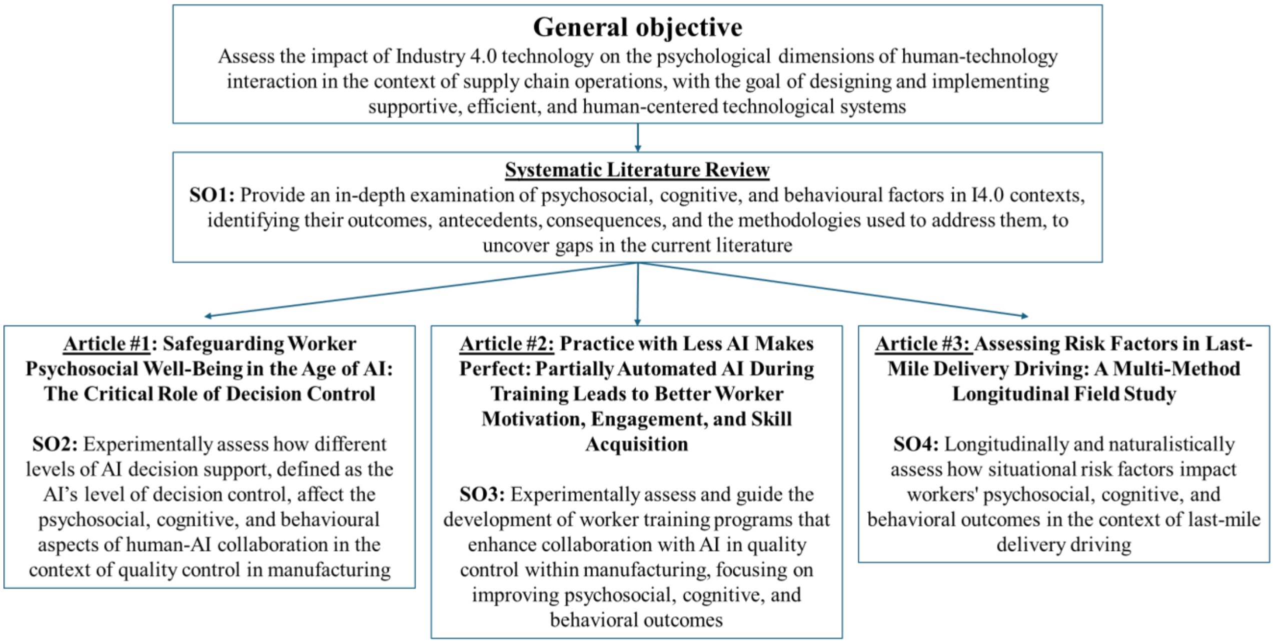

Figure 3.1: Relationship between the general objective, sub-objectives, and thesis articles

3.2 Sub-Objective 1

The primary, overarching gap identified is the lack of research taking a human-centered approach to evaluate the impact of technology on workers, including psychosocial, cognitive, and behavioral dimensions. This gap limits our understanding of how to design and implement technological systems that are aligned with human values, empowering worker well-being and performance. Thus, **sub-objective (SO) 1** is to provide an in-depth examination of psychosocial, cognitive, and behavioral factors in I4.0 contexts, identifying their outcomes, antecedents, consequences, and the methodologies used to address them, to uncover gaps in the current literature. This sub-objective is the basis for our empirical studies, as it allows us to better understand the existing literature and where it is lacking. We have chosen to focus on AI due to its central role in driving Industry 4.0 innovations, fundamentally reshaping work environments through automation, real-time data analytics, and intelligent decision-support.. AI's broad applicability and significant impact on various aspects of work necessitate a deep understanding of its effects on workers to ensure that its implementation not only boosts efficiency and productivity but also supports the psychological well-being of employees. SO1 was addressed through the systematic review of the AI literature presented in Chapter 2.

3.3 Sub-Objective 2

Through the systematic review, we identified several critical gaps. First, there is a notable lack of evaluation of the psychosocial components of human-AI interaction, such as worker motivation, autonomy, and job meaningfulness. This issue is compounded by the absence of experimental articles evaluating psychosocial variables; most existing literature is conceptual rather than empirical, resting strongly on predictions rather than causal inferences. A particular area of interest is the effect of decisional control, which discusses the balance of AI decision support. Some authors hypothesised that while AI providing some decisional support can positively impact psychosocial variables, too much decisional support could have adverse effects by reducing worker autonomy and engagement. Multiple types of AI exist, each performing different functions; in this thesis, AI refers broadly to algorithms and systems that aid in the decision-making of employees or organizational decision-makers. This encompasses various forms of AI, from machine learning models providing predictive analytics to decision-support systems that offer real-time recommendations, all of which directly influence the psychological and cognitive dynamics within the workplace.

As such, our **SO2** is to experimentally assess how different levels of AI decision support, defined as the AI's level of decision control, affect the psychosocial, cognitive, and behavioural aspects of human-AI collaboration in the context of quality control in manufacturing. We chose quality control in manufacturing due to the prominent role of AI in this sector. Quality control involves complex decision-making where AI can significantly aid human operators, making it an ideal setting to examine the balance of decisional control.

SO2 was addressed using experimental data collection within a laboratory that simulated a factory setting, which constitutes **Article 1**. The study was approved by HEC Montreal's institutional review board. The experiment involved 102 participants, recruited from engineering students with manufacturing experience, who were tasked with detecting errors in a snowshoe assembly line. The study employed a 3x2 mixed factorial design to assess how different levels of AI decision support (no automation, partial automation, full automation) affect psychosocial, cognitive, and behavioral aspects of human-AI collaboration. Participants completed the same task twice (within-subject factor), in the same condition.

Participants took on the role of the final operator in a four-operator assembly line, receiving snowshoes that were 90% complete and required final inspection and assembly. Errors were systematically introduced into specific snowshoes to test the participants' error-detection capabilities. The experimental setup included identical workstations and used a simulated AI decision support system to provide varying levels of assistance.

To measure the impacts, a combination of self-report questionnaires, behavioural observation, and physiological data was used. This multi-method approach, as recommended in the literature, allowed for a comprehensive assessment of the various dimensions of human-AI interaction. Using multiple methods helps limit mono-method bias, providing a more holistic understanding of participant experiences (De Guinea et al., 2013). Additionally, physiological measures allowed for continuous recording of participants' states throughout the experiment, offering real-time, objective data that complemented the subjective self-reports. Self-determined motivation, autonomy, competence, work meaningfulness were assessed using validated scales; engagement was measured using validated scales and physiological data; and performance was measured using task key performance indicators (time and error detection).

The statistical analysis included type-3 ANOVA for between-subject comparisons and paired samples t-tests for within-subject comparisons. Non-parametric tests were applied when assumptions were violated. An a priori power analysis determined that a sample size of 99 participants would be sufficient to detect meaningful differences with 90% power.

This comprehensive experimental setup allowed for a detailed examination of how varying levels of AI decision support impact worker psychosocial, cognitive, and behavioral outcomes in a controlled yet realistic manufacturing environment.

3.4 Sub-Objective 3

Another significant gap identified through the systematic review is the lack of research on the cognitive aspects of human-AI interaction, particularly in attention and decision-making when human operators must intervene. While automation of tasks through AI enhances performance during normal operations, it can drastically reduce worker performance when manual intervention is necessary. To address these challenges, workers need to be properly trained to use AI. This training must focus on skill acquisition, cognitive engagement, and maintaining motivation, preparing workers for supervisory roles where they stay engaged and ready to intervene. However, most training research has prioritized technology effectiveness over how training design influences motivation and engagement, highlighting the need for a comprehensive approach to improve human-AI collaboration. As such, our **SO3** is to experimentally assess and guide the development of worker training programs that enhance collaboration with AI in quality control within manufacturing, focusing on improving psychosocial, cognitive, and behavioral outcomes.

SO3 was addressed, in **Article 2,** using different data from the same experimental data collection as **SO2**, with a key modification. Instead of participants remaining in the same condition for both experimental tasks, AI decision support was removed for the second task for all participants to simulate an AI malfunction, requiring them to manually take over. Specifically, for task 1, participants were randomly assigned to one of three AI decision support conditions (no automation, partial automation, or full automation). For task 2, AI support was removed for everyone, creating a no automation condition. This design allowed us to evaluate how varying levels of AI support during training influenced worker skill acquisition, self-determined motivation, autonomy, competence, and engagement. Skill acquisition was measured using task key performance indicators, while self-determined motivation, autonomy, and competence were assessed with validated scales. Engagement was measured using both validated scales and physiological measures.

3.5 Sub-Objective 4

The final significant gap identified in the systematic review relates to the lack of longitudinal and field research on the psychosocial, cognitive, and behavioural impact of technology on workers. Most current studies are either cross-sectional or conducted as case studies, which limits the understanding of how advanced technologies affect workers over extended periods in real-world environments. This shortfall hampers the ability to develop technological systems that truly align with human needs and enhance long-term well-being and performance. As such, our **SO4** is to longitudinally and naturalistically assess how risk factors impact workers' psychosocial, cognitive, and behavioral outcomes in the context of last-mile delivery driving.

We chose the context of last-mile delivery due to its critical role in the supply chain and the unique challenges it presents, such as time pressure, long hours, and physical demands. Within this context, technology plays a significant role by incorporating advanced tools and systems like real-time tracking, automated routing, and digital communication platforms. These technologies directly influence situational variables such as delivery routes, shift lengths, and delivery timing. By shaping these situational variables, technology impacts the fatigue and stress levels of delivery drivers, which in turn affects their behaviour. Understanding how these technological influences affect drivers over time is essential for designing interventions that support their well-being and performance, ultimately leading to more sustainable and human-centric logistics operations.

SO4 will be addressed using a longitudinal field study conducted with a grocery delivery company. This study constitutes **Article 3.** The study, approved by HEC Montreal's ethics review board, involved three male participants. These participants were observed during their normal work activities without any experimental manipulation.

Data were collected over three full workdays for each participant, totaling nine shifts and 84.33 hours. Shift lengths ranged from 7 hours and 19 minutes to 10 hours and 49 minutes. Participants worked in two delivery areas: downtown and suburbs, with each participant having at least one shift in each area to avoid biases. Participants completed two shifts in the suburbs and one downtown. On the data collection day, the research team equipped the vehicles with an accelerometer and cameras, and the participants with physiological vests. The team monitored data collection from the passenger seat during the whole workday, administered hourly questionnaires verbally, and conducted a five-minute semi-structured interview at the end of each shift.

Similarly to Article 1 and 2, a multi-method approach was used for data collection. Situational variables, collected directly from company telematics, included delivery area (suburbs or downtown), shift length, delivery timing (on-time vs. late), and portion of the shift (first or second half). Fatigue (cognitive) and stress (psychosocial) were measured using physiological measures and validated scales. Risky driving behavior (behavioural) was quantified through an algorithm monitoring acceleration fluctuations, while attention (cognitive) was assessed using video footage and an algorithm developed to detect distracted driving.

Data were segmented to differentiate driving and delivery activities, focusing on the driving portion. Linear models assessed the direct effects of situational variables on physiological indicators of fatigue and stress, while Poisson regression handled count data for incidents of risky and inattention.

This longitudinal field study allowed us to longitudinally assess how situational risk factors impact workers' psychosocial, cognitive, and behavioral outcomes in the context of last-mile delivery driving, providing valuable insights into the real-world effects of advanced technologies in Industry 4.0.

3.6 Conclusion

In conclusion, the research methodology employed in this thesis combines a multifaceted approach, including systematic reviews, experimental studies within laboratory settings, and longitudinal field studies, to comprehensively address the identified gaps in the literature. Executed in multiple phases, this methodology ensures the collection of empirical data necessary to achieve the specific research objectives. This structured approach allows for a thorough investigation and validation of our findings, contributing to the development of more human-centered technological systems in the context of Industry 4.0.

The rest of this thesis is structured as follows. Chapter 3 will present an experimental study on the psychosocial impact AI decision support levels, addressing SO2. The chapter presents Article 1, titled "Safeguarding Worker Psychosocial Well-being in the Age of AI: The Critical Role of Decision Control," which is currently under review in the *International Journal of Human-Computer Studies*.

Chapter 4 will examine the effects of training programs for AI collaboration, addressing SO3. It will present Article 2, titled "Practice with Less AI Makes Perfect: Partially Automated AI during Training Leads to Better Worker Motivation, Engagement, and Skill Acquisition," which has been published in the *International Journal of Human-Computer Interaction*.

Chapter 5 will present a longitudinal field study on the impact of situational risk factors on delivery drivers, addressing SO4. It will present Article 3, titled "Assessing Risk Factors in Last-Mile Delivery Driving: A Multi-Method Longitudinal Field Study," which is currently under review in *Transportation Research Part F: Traffic Psychology and Behaviour*.

Finally, Chapter 8 will discuss the results of these articles and the overall contribution of the thesis, summarizing how the research findings advance the understanding of human-centered technological systems in the context of Industry 4.0.

CHAPTER 4 ARTICLE 1: SAFEGUARDING WORKER PSYCHOSOCIAL WELL-BEING IN THE AGE OF AI: THE CRITICAL ROLE OF DECISION CONTROL

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Abstract

Advancements in artificial intelligence (AI) have ushered in the era of the fourth industrial revolution, transforming workplace dynamics with AI's enhanced decision-making capabilities. While AI has been shown to reduce worker mental workload, improve performance, and enhance physical safety, it also has the potential to negatively impact psychosocial factors, such as work meaningfulness, worker autonomy, and motivation, among others. These factors are crucial as they impact employee retention, well-being, and organizational performance. Yet, the impact of automating decision-making aspects of work on the psychosocial dimension of human-AI interaction remains largely unknown due to the lack of empirical evidence. To address this gap, our study conducted an experiment with 102 participants in a laboratory designed to replicate a manufacturing line. We manipulated the level of AI decision support—characterized by the AI's decision-making control—to observe its effects on worker psychosocial factors through a blend of perceptual, physiological, and observational measures. Our aim was to discern the differential impacts of fully versus partially automated AI decision support on workers' perceptions of job meaningfulness, autonomy, competence, motivation, engagement, and their performance on an error-detection task. The results of this study suggest the presence of a critical boundary in automation for psychosocial factors, demonstrating that while some automation of decision selection can nurture motivational needs, meaningfulness, self-determined motivation, and engagement, there is a pivotal point beyond which these benefits can decline. This insight is particularly significant in the context of automating the decision-making process, where

maintaining a balance between AI assistance and human control is essential for preserving worker psychosocial well-being.

Keywords: Human-centered AI · Motivation · Engagement · Industry 4.0 · Industry 5.0

4.1 Introduction

Advancements in technology, particularly in artificial intelligence (AI), have profoundly transformed the dynamics of the modern workplace, marking the dawn of the fourth industrial revolution, or Industry 4.0 (I4.0). This era is characterized by AI's enhanced capacity for intricate decision-making processes, significantly expanding its role within industrial operations (Rosin et al., 2022). The implications of this shift are underscored by reports from the World Economic Forum (2020) and Deloitte (2023), which highlight AI's growing implementation across various manufacturing dimensions, including operations, product development and supply chain management. AI's integration into manufacturing processes symbolizes a broader trend within I4.0, emphasizing the evolving dynamics between humans and highly automated, AI-driven systems. As detailed in the European Agency for Safety and Health at Work's report, this evolution extends beyond technological innovation, significantly influencing various aspects of workforce perceptions, attitudes, and behavior (European Agency for Safety and Health at Work, 2023).

Automation through AI brings substantial advantages to the workplace, including increased efficiency, improved safety protocols, and a reduction in the mental workload for human employees (Gagné et al., 2022; Xu et al., 2022). However, it is crucial to acknowledge the challenges automation poses to psychosocial factors within the workplace. As AI systems increasingly handle higher-level decision-making responsibilities once reserved for humans, concerns arise about the potential erosion of worker autonomy, motivation, and overall engagement (Bankins et al., 2023; Gagné et al., 2022). When employees feel their decision-making authority is reduced, it can diminish their sense of meaning in their work and motivation, among other factors (Deci et al., 2017; Van den Broeck et al., 2021). This has far-reaching consequences, impacting various facets of worker well-being and organizational performance. In fact, the issue of employee retention has become a critical concern for manufacturing executives, with nearly

75% identifying it as their primary upcoming business challenge (Deloitte, 2023; National Association of Manufacturers, 2023).

Nonetheless, the focus within I4.0 research has predominantly been on technical efficiency (e.g., algorithm optimization), often overlooking the psychosocial dimensions of human-AI collaboration, i.e., the interaction between the work environment and worker's psychological experience (Grosse et al., 2023; Neumann et al., 2021; Vijayakumar & Sgarbossa, 2020). This overemphasis on technical aspects has catalyzed the advent of Industry 5.0 (I5.0), recognized as a manufacturing paradigm utilizing technology to enhance worker well-being and empowerment, advance societal development, and ensure environmental sustainability (Commission et al., 2021; Enang et al., 2023; Grosse et al., 2023; Ivanov, 2023). Its primary objective is to address the challenges identified in Industry 4.0 by fostering research that prioritizes human-centric outcomes, emphasizing the importance of human well-being and empowerment.

In line with these principles, this paper aimed to experimentally examine to what extent different levels of AI decision support, defined as the AI's level of decision control, affect the psychosocial aspect of human-AI collaboration (autonomy, competence, job meaningfulness, motivation, and engagement), and worker performance. Through an experimental approach, we manipulated the level AI decision support within a quality control task in manufacturing and assessed its impact on employees through physiological, perceptual, and observational measures.

The rest of the article is structured as follows: Section 2 will present the literature review and hypothesis development, Section 3 will present the experimental methodology, Section 4 will present the results, and Section 5 will discuss our findings.

4.2 Literature Review and Hypothesis Development

The following section will review the relevant literature on automation and psychosocial factors. Also, the hypothesis development process will be explained.

4.2.1 Industry 4.0 and the Advent of Advanced Automation

The emergence of I4.0 signifies a pivotal transformation in the manufacturing sector, fundamentally altering work dynamics and enhancing the role of human workers (Gagné et al., 2022; Neumann et al., 2021). This era is characterized by a shift towards oversight and strategic management roles within highly automated environments (Ghislieri, Molino, & Cortese, 2018;

Kumar & Lee, 2022). Central to this transformation is the advancement of AI, which has reached levels of automation previously unattainable. AI systems are now capable of executing complex information processing tasks, including those requiring high-level decision-making that was once solely done by human operators (Rosin et al., 2022). These systems can manage vast datasets, recognize intricate patterns, and make informed decisions in real-time, thereby enabling faster, more precise decision-making processes (Rosin et al., 2021). This capability is crucial across various industries, notably in manufacturing, where AI can monitor production lines in real-time, identify and rectify bottlenecks, and optimize output, significantly enhancing operational efficiency and effectiveness (Jéssica de Assis et al., 2021).

The progression of automation, facilitated by AI, can be delineated into four key **stages** of information processing in the context of manufacturing (Kaber & Endsley, 2004; Parasuraman, 2000; Wickens, 2018). In each stage, the level of automation can range from manual operations (no automation) to fully automated systems.

Stage 1 is information acquisition, which involves, in a manufacturing setting, data collection from the production environment. In a fully manual scenario (no automation), this may consist of operators conducting inspections and recording measurements of materials or components. A fully automated scenario could involve the use of sensors and computer vision systems to continuously monitor production quality and environmental conditions, seamlessly uploading data for real-time analysis.

Stage 2 is information analysis, which involves the interpretation and integration of collected data. Manually, operators might analyze production data using spreadsheets to identify trends or anomalies. Automated systems, however, could utilize AI algorithms to instantaneously analyze large datasets, identifying patterns and predicting potential issues without human intervention.

Stage 3 is decision and action selection. In this stage, decisions are made, and appropriate responses are selected based on the analysis from the previous stage. In a manual process, this might involve production managers reviewing analysis reports to decide on adjustments to production parameters. In contrast, AI-driven systems can automatically adjust machine settings in real-time or redirect resources to optimize production flow, often without any human input.

Stage 4 is action implementation, where the selected responses are executed. Manually, this could involve workers adjusting machinery or changing production lines based on earlier decisions.

Automated systems, however, directly interface with machinery to implement changes, such as adjusting temperatures or speeds, with precision and efficiency far beyond human capabilities. Recent advancements have seen AI systems particularly excel in the latter stages of decision/action selection and implementation (Stages 3 and 4); areas traditionally dominated by human expertise.

4.2.2 Advanced Automation, Worker Performance, and Psychosocial Factors

Automating the later stages—decision and action selection, and action implementation—has significant implications for human performance and psychosocial factors. The impact on human performance is clear due to decades of research in human factors (Onnasch et al., 2014; Wickens, 2018). Its impact is often described as a double-edged sword. The higher the automation, the greater the performance when the automated system is working as planned. However, higher levels of automation for stages 3 and 4 (decision selection and action implementation) exacerbate performance decrements when automation fails, compared to high automation of stages 1 and 2. In short, extensive automation in processes involving decision-making and action implementation can lead to significant performance problems when manual intervention becomes necessary, indicating a tradeoff between human performance in routine versus non-routine situations (Liu, 2023; Passalacqua, Pellerin, Yahia, et al., 2024). Consequently, it is recommended to maintain a level of human involvement in decision-making and action implementation processes. This ensures that workers remain engaged and prepared to intervene, balancing the efficiency of automated systems with the necessity for human oversight in non-routine situations (Wickens, 2018). This can be achieved by assigning the tasks of decision-making and action implementation to the worker instead of an AI, or by maintaining a moderate level of automation for these stages. (Onnasch et al., 2014).

While human performance in the context of high automation within manufacturing has been widely studied, little empirical research has examined the psychosocial impact on workers, as echoed by the scientific community (Briken et al., 2023; Commission et al., 2021; De Lombaert et al., 2023; Ghislieri et al., 2018; Grosse et al., 2023; Kadir et al., 2019; Neumann et al., 2021; Peruzzini et al., 2017; Reiman et al., 2021; Sgarbossa et al., 2020). This inhibits our comprehension of optimal design and implementation of AI systems in relation to psychosocial factors. Academic and industrial literature alike have pinpointed specific individual-level psychosocial factors that can be significantly affected by automation and that significantly contribute to worker well-being, safety, turnover, performance, and technology acceptance in the workplace. Some of these factors are the perceived meaningfulness of one's work, the perceived autonomy to execute one's work, worker motivation, and worker engagement (European Agency for Safety and Health at Work, 2023; Gagné et al., 2022; Deloitte, 2023; Molino et al, 2021; Bankins et al., 2024; Mazarakis et al., 2023).

Similarly to its effects on human performance, numerous authors suggest that high automation also represents a double-edged sword concerning psychosocial factors. (Ghislieri et al., 2018; Heer, 2019; Shneiderman, 2022; Ueda et al., 2021; Wellsandt et al., 2021; Winkelhaus et al., 2022). For example, highly automating decision making within a task may free up workers to complete higher-level strategic tasks, increasing their perception of job meaningfulness and autonomy (Staaby et al., 2021); on the other hand, highly automated decision making may render tasks standardized and rigid, reducing worker's decision latitude, and therefore their perceived meaningfulness and autonomy (Perez et al., 2022). However, empirical evidence remains scarce, particularly concerning the impact of task automation on work meaningfulness, autonomy, motivation, and engagement (Y. Lu et al., 2022). To our knowledge, no study has experimentally evaluated the impact of AI on workers' perception of work meaningfulness, perception of autonomy, competence, motivation, or engagement in a manufacturing setting. The empirical studies primarily addressed topics like AI adoption, AI acceptance, smart manufacturing's effect on work design, and the impact of AI use on task performance. For example, Chatterjee et al. (2021), Jain et al. (2022), and Marcon et al. (2021), focused on the antecedents of AI adoption or use, Cagliano et al. (2019) and Winkelhaus et al. (2022) examined how advanced technology affects work design, and Molino et al. (2020; 2021) examined the organizational antecedents of work engagement and technology acceptance.

Outside of manufacturing, we observe a similar pattern. There is a consensus that high automation can positively and negatively affect psychosocial factors, but there exists little empirical work, with most research papers being conceptual (Grosse et al., 2023; Passalacqua et al., 2022; Xu et al., 2022). In a conceptual paper, Szalma (2014) brings forward the idea that highly automated systems could reduce workers' sense of control of the task, their skill development, and the meaning of the task, among others. This could negatively impact workers' perceptions of autonomy, competence, motivation, and engagement. Similarly, in another conceptual paper, Bankins and Formosa (2023) discuss how automating decision-making aspects of work may reduce worker autonomy and thus, the meaningfulness they attribute to their job. Lastly, in a systematic review of the human-computer interaction literature, Bennett et al. (2023) found a general consensus regarding the importance of supporting human autonomy. They found that autonomy is discussed as being central to positive and meaningful user experience, human dignity, well-being, and empowerment.

Empirically, Berberian et al. (2012) have begun to test the impact of automating decision selection. In an aircraft supervision task, they found that participants felt the most agency/autonomy when they were in charge of decision making. Similarly, with a simple laboratory task, Ueda et al. (2021) found that participant sense of agency/autonomy was increased by automation but declined after a 90% level automation. Essentially, participants had to have some control over the decision making to maintain their perceptions of agency/autonomy. Lastly, in a qualitative case study with three companies, results from semi-structured interviews generally showed that automating routine tasks allowed employees to focus on more complex tasks, increasing their perceptions of autonomy and work meaningfulness (Staaby et al., 2021). However, in this case study, only lower stages of information processing were automated; decision selection and action implementation were not automated at any level.

In summary, the state of the literature regarding the effects of automation, particularly on decision-making tasks, reveals a critical gap in our knowledge: a pronounced lack of empirical studies investigating its psychosocial impacts. Although conceptual discourse suggests that automation could both enable and restrict workers, the empirical evidence needed to substantiate these claims is currently insufficient, especially within manufacturing.

4.2.3 Exploring the Psychosocial Dynamics of Automation Through Self-Determination Theory

Against this backdrop, Self-Determination Theory (SDT) offers a robust theoretical framework to deepen our understanding of automation's impact on worker psychosocial well-being (Deci & Ryan, 1980; Gagné et al., 2022; Passalacqua, Léger, et al., 2020). Fundamentally, SDT provides insights into human motivation, which can help us shed light on how the automation of decision selection or action implementation influences workers' sense of meaning, autonomy, motivation, and engagement. Central to SDT is the principle that a worker's environment plays a crucial role in shaping their motivation levels and engagement by either meeting or neglecting their fundamental psychological needs. These needs are competence, or the perceived capability to successfully complete tasks; autonomy, or the perception of being in control of their actions and decisions; and relatedness, or the need to have meaningful social interactions (Deci & Ryan, 2008). When automation is thoughtfully applied to support these psychological needs, it can significantly enhance worker motivation, leading to heightened engagement, increased work meaningfulness (significance of work), better performance, and greater retention (reduction of turnover intention) (Deci et al., 2017; Martela & Riekki, 2018; Rigby & Ryan, 2018). Conversely, automation that diminishes the complexity of tasks or restricts workers' involvement in decision-making can have adverse effects, potentially reducing job satisfaction and overall well-being, among others (Legaspi et al., 2024; Nazareno & Schiff, 2021).

The degree to which these needs are satisfied determines the level of self-determined motivation workers experience. This kind of motivation stems from the internalization of the underlying reasons for performing an action. Motivation can be viewed as a continuum or spectrum, with intrinsic motivation at one end, extrinsic motivation in the middle, and amotivation at the other end, as depicted in Figure 4.1.

Intrinsic motivation involves undertaking an activity for its inherent pleasure and alignment with values, and interests. It is the most self-determined form of motivation and is a strong antecedent of worker well-being and reduced absenteeism (Sitarević et al., 2023; Van den Broeck et al., 2021). Extrinsic motivation, on the other hand, is driven by external demands such as rewards or avoidance of punishment. It can be subdivided into four types based on the degree of internalization, which is the extent to which the motive aligns with the individual's values and interests. Identified motivation, a subtype of extrinsic motivation that is more self-determined, is particularly important. It involves doing an action/task because a person perceives it as meaningful and is the strongest predictor of workplace performance, sustained effort, and organizational citizenship behaviors (Van den Broeck et al., 2021).

Amotivation is characterized as a lack of motivation to complete an activity. According to Self-Determination Theory (SDT), fulfilling workers' psychological needs for competence, autonomy, and relatedness promotes greater internalization of their reasons for engaging in work tasks. This internalization leads to more intrinsic motivation and regulation, resulting in higher engagement, innovation, happiness, job retention, and technology acceptance (Gagné, 2014; Molino et al., 2020; Ryan & Deci, 2008).Conversely, when these needs are unmet, workers are less intrinsically motivated, which is associated with burnout, stress, and disengagement, negatively impacting their well-being (Deci & Ryan, 2008; Peters et al., 2018; Szalma, 2020). Unsurprisingly, their performance at work also suffers significantly.

A worker's engagement in a task stems directly from their motivation and is linked with similar outcome variables, such as well-being, performance, and technology acceptance. Task engagement is a complex concept, comprising three dimensions: dispositional/trait engagement, psychological state engagement, and behavioral engagement (Macey & Schneider, 2008; Meyer & Gagne, 2008; Meyer et al., 2010). Dispositional engagement, or trait engagement, is characterized as a worker's inherent propensity to experience work positively, actively, and energetically, and to adaptively behave (Macey & Schneider, 2008; Meyer et al., 2010). Within the theoretical framework of SDT, this implies that some individuals are more naturally inclined to perceive, act, and think in ways that may fulfill their psychological needs (Deci et al., 2017). Essentially, personality traits influence how workers evaluate situations as either controlling or autonomy-promoting, which in turn affects their intrinsic or extrinsic motivation and subsequent engagement levels (Deci & Ryan, 1985)

Psychological state engagement includes cognitive and emotional components (Kahn, 1990; Schaufeli et al., 2002). Cognitive engagement is characterized by intense concentration and mental absorption in a task, while emotional engagement involves emotional investment and activation. Behavioral engagement is the willingness to exert effort, evidenced by observable signs of engagement in work activities (Macey & Schneider, 2008). State and behavioral engagement are seen as results of need satisfaction, leading to more intrinsically motivated behavior (Meyer & Gagne, 2008; Meyer et al., 2010). When workers' psychological needs are fulfilled, they tend to exhibit higher levels of engagement across all dimensions, resulting in positive outcomes in their work-related activities.

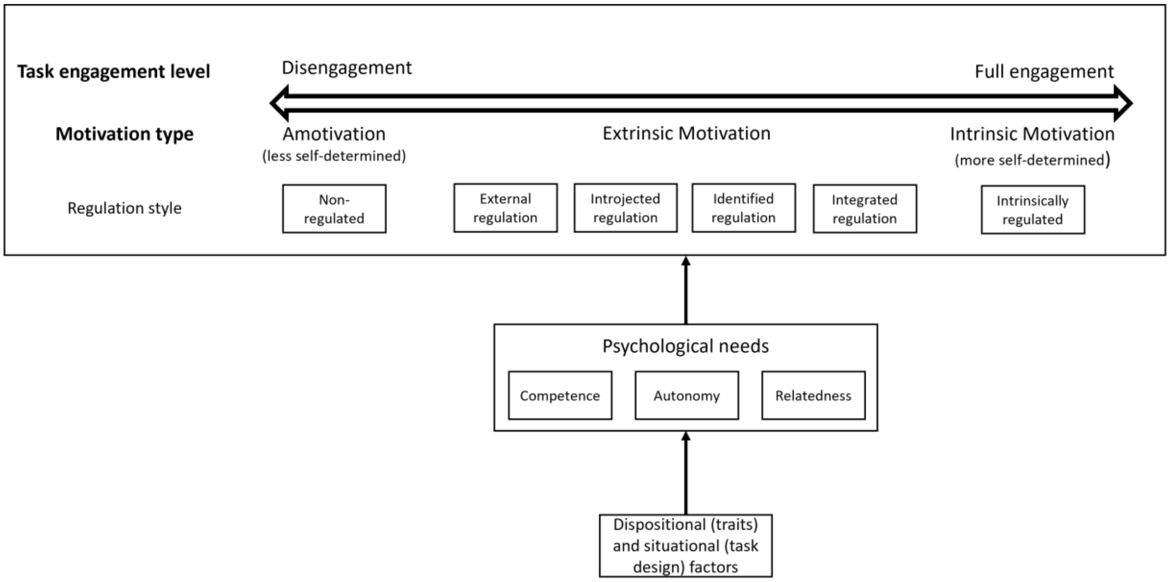

Figure 4.1: Continuum of motivation and engagement (adapted from Passalacqua et al., 2024; Meyer et al. (2010); Ryan and Deci (2000); Szalma (2014))

In summary, SDT emphasizes the integration of AI in the workplace should be navigated with a careful awareness of its impact on worker well-being. SDT not only underscores the necessity of aligning automation with the psychological needs of workers—competence, autonomy, and relatedness—but also highlights how such alignment can significantly enhance job satisfaction, motivation, and overall organizational performance. This theoretical foundation sets a critical stage for the practical examination of the human-AI relationship, emphasizing the importance of designing automated systems that support, rather than undermine, the worker's needs.

4.2.4 Guidelines for the Experimental Examination of the Human-AI Relationship

Building on the conceptual groundwork laid by SDT, there arises a compelling need for empirical research that directly explores the interactions between humans and AI systems. Despite the lack of empirical evidence with regard to the human-AI relationship, there is some consensus within the I4.0 literature on how to experimentally examine it. First, numerous authors emphasize the importance of understanding how choices in technology and task design impact workers on a psychosocial level (Langer & Landers, 2021; Y. Lu et al., 2022; Ngoc et al., 2021; Shneiderman, 2020). This can be done through experimental manipulation of the automation levels, the degree of human control, strategies for delegation, or the allocation of tasks on dependent variables (Goujon et al., 2024). Concerning the choice of dependent variables, it is recommended that researchers look beyond performance metrics and include perceptions, attitudes, and behaviors to gain a deeper understanding of the psychosocial dynamics of the human-AI relationship (Ghislieri et al., 2018; Neumann et al., 2021; Reiman et al., 2021; Sgarbossa et al., 2020; Vijayakumar & Sgarbossa, 2020).

Second, researchers recommend that the chosen variables be situated within a well-defined theoretical context, allowing researchers to more effectively discern their roles, interactions, and overall significance in the human-AI relationship, leading to more insightful and accurate interpretations of research findings (De Visser et al., 2018; Gagné et al., 2022; Ghislieri et al., 2018; Jain et al., 2022; Y. Lu et al., 2022; Sitarević et al., 2023; Xu et al., 2022). Many authors have recommended integrating theories from organizational psychology (e.g., self-determination theory, job demands-resources model, job characteristics model).

Third, there is a clear emphasis, within the literature, for researchers to use experimental methodologies when evaluating psychosocial factors that affect workers interacting with AI systems (Adadi & Berrada, 2018; Del Giudice et al., 2023; Goujon et al., 2024; Ismatullaev & Kim, 2022; Kadir et al., 2019; Y. Lu et al., 2022; Peruzzini et al., 2020). By using experimental designs in controlled settings like a simulated factory within a laboratory, can manipulate independent variables, such as the level of automation or the amount of human oversight, and control confounding and extraneous variables. This control is crucial as it helps in accurately observing the variables' effects and strengthens the potential to draw causal links. Controlling these variables in real-world settings is significantly more challenging, due to the complex and dynamic nature of such environments. Therefore, conducting studies initially in controlled laboratory settings is a vital first step, establishing a foundational understanding, which should then be tested and validated in real-world settings to assess their applicability and generalizability.

Lastly, concerning evaluation of psychosocial factors, many authors recommend a multi-method approach, integrating perceptual, psychophysiological, and observational measures (Peruzzini, Grandi, & Pellicciari, 2017; Passalacqua et al., 2024; Papetti et al., 2020; Brunzini et al., 2021; Ciccarelli et al., 2022; Diamantopoulos & Weitian, 2021; Khairai et al., 2020; Vijayakumar & Sgarbossa, 2020; Bousdekis et al., 2022; Golan, Cohen, & Singer, 2020). This approach combines subjective experiences (e.g., questionnaires, interviews) with objective physiological data (e.g., heart rate), and observable behaviors (e.g., performance metrics) to gain a more complete understanding of worker states. Additionally, incorporating psychophysiological measures can mitigate mono-method bias associated with using only perceptual measures, thus enhancing the reliability of research findings (De Guinea et al., 2013). Physiological measures also allow uninterrupted, real-time data collection while participants engage in tasks.

4.2.5 Hypothesis Development

We have integrated the four above-stated recommendations into the creation of an experiment that manipulated the level of decision-selection automation and evaluated its impact on psychosocial factors through the lens of SDT, using perceptual, physiological, and observational measures. More specifically, through an experimental data collection within a laboratory designed to replicate a manufacturing line, we aimed to understand how an AI's decision selection (stage 3) level of automation affected operator meaning, autonomy, competence, motivation, engagement, and task performance during an error-detection task. Automation of Stage 3 of the information processing model represents a critical boundary, where over-automation may negatively impact human performance (Onnasch, 2015; Onnasch et al., 2014). For our studied psychosocial factors, this critical boundary has been vaguely hypothesized by others but not tested. Specifically, Ghislieri et al. (2018), Wellsandt et al. (2021), and Winkelhaus et al. (2022), among others, have argued that automation may be beneficial for psychosocial factors up to a certain degree of automation. We thus manipulated the automation of decision selection along three levels to begin to find a critical boundary: no automation, partial automation, and full automation. Figure 4.2 shows these three levels (our experimental conditions) within the four-stage information processing model (Parasuraman, 2000). To ensure a focused comparison, we maintained a consistent level of automation for Stage 4 (action implementation) across all conditions, thereby reducing the potential for confounding effects.

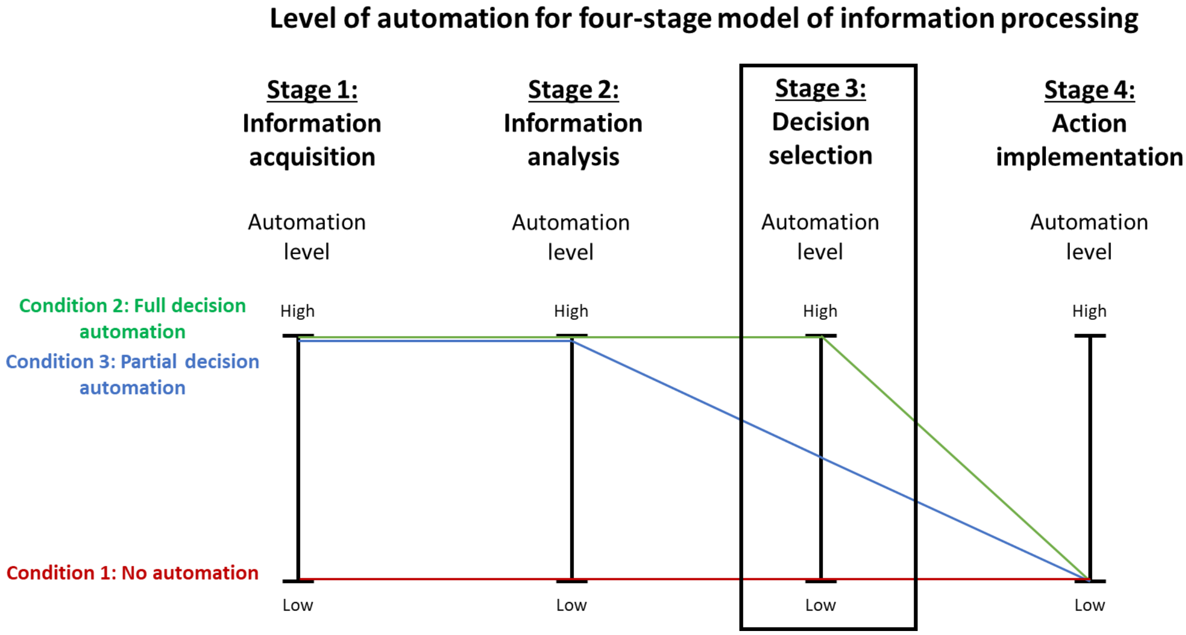

Figure 4.2: Experimental condition shown within the information processing model (Parasuraman, Sheridan. & Wickens, 2000; Passalacqua et al., 2024)

Full automation of decision selection meant that participants had to simply execute the task (completing or discarding snowshoe), without taking any decisions, thus resulting in limited room for decision-making latitude (autonomy) or opportunities for workers to experience a sense of self-efficacy (competence). This may thwart participants' motivational needs, and lead to less perceived work meaningfulness, self-determined motivation, and engagement. In terms of task performance, we expect that full automation will lead to the best result. The negative effects of full automation of decision selection on human performance have been shown to occur only when automation malfunctions or fails. In our experiment, no such failure or malfunction occurred.

In the partial automation condition, the decision support system suggested a decision, which had to be approved or denied by the participant. This approach can give participants a sense of decisional freedom (autonomy) while also offering sufficient support to help them feel competent. As such, participants should view their job as more meaningful, be motivated in a more self-determined manner, and be more engaged. In terms of task performance, we expect partial automation to yield the second-best results, after full automation, because it provides the operator with some decision-making support.

Similarly, in the no automation condition, participants are likely to experience high levels of need satisfaction, self-determined motivation, and engagement because they retain complete control over their work processes. This autonomy allows them to tackle tasks in ways that align with their personal skills and preferences, fostering a sense of competence and achievement. As such, we expect that both partial automation and no automation will lead to better outcomes for the motivational needs, meaning, self-determined motivation, and engagement, compared to full automation. Additionally, we expect partial automation and no automation to be equal for these variables.

In our experiment, participants sequentially completed two identical tasks. Participants remained in the same experimental condition for both tasks, enabling us to collect questionnaire data between the tasks, and thus allowing us to examine the temporal evolution of our dependent variables longitudinally. We expect the differential effects of partial automation and full automation to be further exacerbated over time. For the partial automation and no automation conditions, we expect motivational need satisfaction, meaning, self-determined motivation, and engagement to increase or remain the same (but not decrease) over time. For the fully automated condition, we expect our dependent variable to decrease or remain the same (but not increase) over time. In terms of task performance, we expect performance to improve over time for all conditions due to the learning effect.

Table 4.1 presents all hypotheses. Hypotheses are separated by the level of analysis. Between-subject analyses involved comparing participants across the three levels of decision-selection automation (no automation, partial automation, and full automation). Figure 4.3 shows the statistical model for the between-subject analyses. Within-subject analyses involved comparing participants through time. Figure 4.4 shows the statistical model for the within-subject effects. We have opted not to investigate the interaction effects between these factors due to the expected learning effect, a common feature of within-subject designs. This effect arises because participants, who undergo both tasks in sequence, are likely to improve on the second task simply through familiarity, not because of the automation level. While we strived to reduce it by training participants before the start of the experimental tasks, such a learning effect could obscure any genuine interaction effects, making it challenging to determine whether changes over time are the result of the automation level or simply due to participants getting better at the task. Therefore, to avoid conflating these effects and to ensure clarity in our findings, our analysis will exclusively focus on the main effects. This approach allows us to isolate the impact of the level of decision-selection automation on our variables of interest while still recognizing the influence of learning across the Time points.

Table 4.1: Hypotheses for motivational needs, meaningfulness, motivation, and engagement

Variables	Level of analysis	Hypothesis number	Hypothesis
Motivation needs (autonomy and competence)	Between-subject (decision automation level)	H1a	Motivational needs will be most supported in the partial automation and no automation conditions, compared to full automation
	Within-subject (Time)	H1b	Motivational need support will remain stable or increase with partial or no automation, whereas it will remain stable or decrease with full automation over time
Work meaningfulness	Between-subject (decision automation level)	H2a	Meaningfulness will be higher in the partial automation and no automation conditions, compared to full automation
	Within-subject (Time)	H2b	Meaningfulness will remain stable or increase with partial or no automation, whereas it will remain stable or decrease with full automation over time

Table 4.1 (continued and end)

Self-determined motivation	Between-subject (decision automation level)	H3a	Self-determined motivation will be higher for participants in the partial automation and no automation conditions, compared to full automation
	Within-subject (Time)	H3b	Self-determined motivation will remain stable or increase with partial or no automation, whereas it will remain stable or decrease with full automation over time
Task Engagement	Between-subject (decision automation level)	H4a	Task engagement will be higher for participants in the partial automation and no automation conditions, compared to full automation
	Within-subject (Time)	H4b	Task engagement will remain stable or increase with partial or no automation, whereas it will remain stable or decrease with full automation over time
Performance (time and error detection	Between-subject (decision automation)	H5a	Performance will be best for fully automated AI, followed by partially automated, then no automation.
	Within-subject (Time)	H5b	Performance will improve over time for all conditions

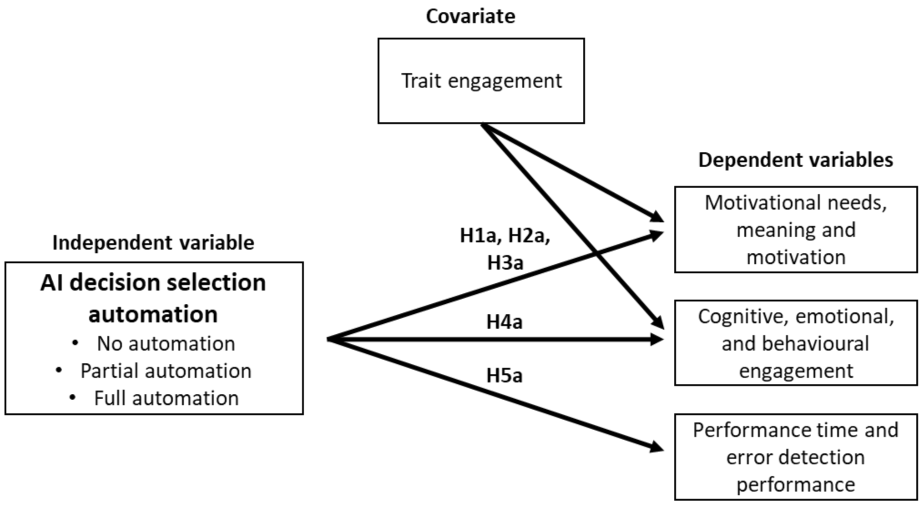

Figure 4.3: Statistical model for between-subject effects

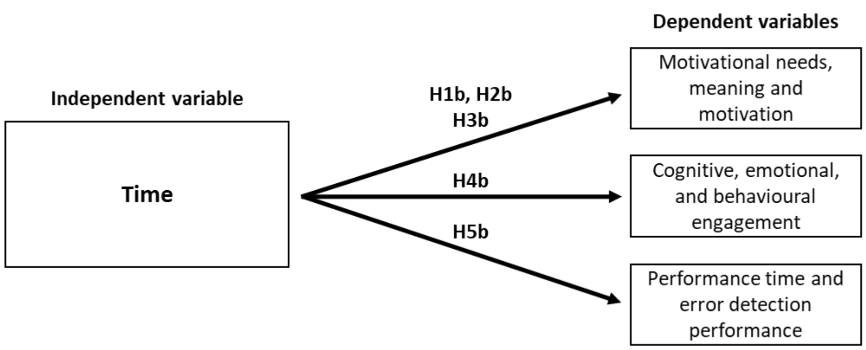

Figure 4.4: Statistical model for within-subject effects

4.3 Materials and Methods

The following section presents the setup, sample, task, design, and procedure of the experiment. It also presents the variable operationalization, apparatus, statistical analysis, and a priori statistical power analyses. The current study builds upon one of our previous studies, employing a very similar methodology (Passalacqua et al., 2024).

4.3.1 Sample and experimental setup

A total of 102 participants, all engineering students in training, completed the laboratory experiment (67 men and 35 women). The average age of the participants was 21.97 years (SD=2.69). Researchers recruited these novice engineers from two universities in France using mass emails. Despite having some general manufacturing experience, none of the participants had any previous experience with the experimental task selected. The experiment was approved by our university's research ethics board (certificate #2023-5058). Each participant provided their written informed consent before the experiment and was given 40€ after their participation. Since the study was conducted in France, French was used to carry out the experiment.

The experiment was conducted at the [university and laboratory name masked]. The space was equipped with two identical workstations (see Fig. 4.5), each separated by a divider to ensure participants could not see one another. The following video shows the experimental setup: https://youtu.be/xtcpxqcyz8k.

4.3.2 Experimental task

Participants took the role of the fourth (final) operator on a four-operator snowshoe assembly line. Their objective was to identify possible errors made by previous operators on the assembly line and to complete the assembly of the snowshoe if no errors were found. Figure 4.6 shows the snowshoe. Participants received snowshoes that were 90% assembled. Each of the two tasks involved 30 snowshoes, which were placed on shelves next to the participant (see Fig. 4.5). For each snowshoe, participants scanned the barcode using a scanner, placed the snowshoe on the workstation, verified for errors, and used the computerized system (Fig. 4.8) to indicate whether they detected an error. They then completed the remaining 10% of the assembly and returned the snowshoe to its original place. The researchers artificially introduced errors into specific snowshoes. Six out of the 30 snowshoes contained these errors, each one unique and consistently present in the same snowshoe for all participants. These six errors were randomly distributed among the 30 snowshoes, for each task, in the planning phase of the experiment. In short, the only difference between Time 1 and Time 2 is the order of the errors and the snowshoes in which they appeared.

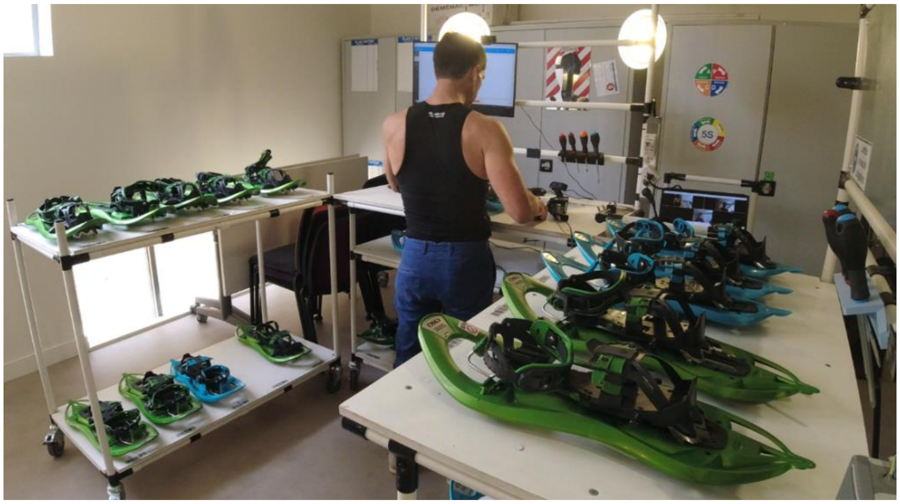

Figure 4.5: Participant workstation

Figure 4.6: Snowshoe used

To create this task, we travelled to the factory where these snowshoes were assembled. We monitored and recorded the employees as they carried out their tasks. Each worker on the production line had the responsibility of assembling a particular part of the snowshoe and inspecting it for any defects or errors made by prior operators. On average, employees took around 20 seconds to work on each snowshoe before passing it along to the next person. To maximize the study's ecological validity, we designed the experimental task to reflect the activities observed in the factory. Snowshoes, which are made up of various components with different levels of assembly complexity, were the ideal product for this study.

4.3.3 Experimental design

A 3x2 mixed factorial design was used. Participants were randomly assigned to one of **three** conditions, which differed in terms of the level of AI decisional support to detect snowshoe defects (no automation, partial automation, or full automation), which represented our between-subject factor. Our dependent variables were measured at **two** time points (Time 1 and Time 2), representing our within-subject factor. Figure 4.7 illustrates the experimental design.

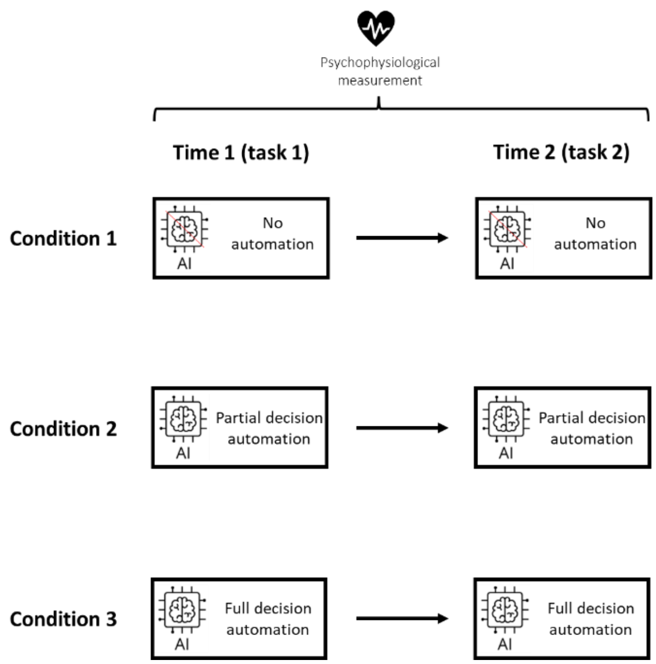

Figure 4.7: 3x2 mixed factorial design

In the **no automation condition**, participants completed the task without being helped by the AI decision support system. In the **partial decision automation condition**, decision selection (stage 3 of information processing), specifically determining whether or not an error was present, was partially automated by the AI. Specifically, this meant the AI recommended a decision and the participant chose whether or not to accept it. When no errors were detected, the remaining 10% of the snowshoe was assembled. However, when an error was detected, this step was skipped. Within this condition, the AI's recommendation was erroneous in 1 out of 30 snowshoes (97% reliability), meaning that the AI was wrong once per task. This information was communicated to participants during their training. In the **full decision automation condition**, the AI fully automated the decision selection. This meant that participants simply followed the AI's decision. In this condition, the AI's decision was always correct, which was communicated to the participants. Figure 4.8 illustrates the computer interface both when the AI found an error and when no error is found. Appendix C provides a list of detectable errors.

Figure 4.8: AI decision support system when error is detected (left) and no error detected (right)

Note: The translation of the green button is "next snowshoe", while that of the red button is "validation of the detected error"

4.3.4 Procedure

Participants were informed that the objective of the experiment was to assess their ability to identify manufacturing defects in snowshoes. They were instructed that they needed carry out two identical error-detection and assembly tasks, each comprising 30 snowshoes. After signing the consent form, physiological instruments were installed on the participants. They then went through training, in which the task and the six possible defects were presented. Within the training, participants also completed the error-detection/assembly of six snowshoes, to become familiar with the task and the computer's interface, and to learn the skills necessary to manually detect all errors. Participants did not proceed to the next step until they demonstrated adequate error-detection skills. Participants then filled out a pre-experiment questionnaire that included demographic information and trait engagement (personality) assessments before proceeding to the two experimental tasks. Both tasks were followed up with a questionnaire.

4.3.5 Variable operationalization and measures

Table 4.2 provides an overview of how the variables were defined and measured. Wherever feasible, constructs were assessed using a multi-method approach, incorporating both perceptual and physiological evaluations. Physiological measures offer a continuous and objective assessment of a participant's state, minimizing biases inherent in sole reliance on perceptual measures. Unlike self-reported data, susceptible to subjective interpretation and recall bias, physiological data provide real-time, quantifiable insights. This consistent and objective monitoring ensures an complementary representation of the participant's experience, capturing subtle and unconscious responses that may elude perceptual measures (De Guinea et al., 2013, 2014).

4.3.5.1 Motivational needs, meaning, and motivation

Motivational needs and meaning were assessed using the meaning, competence, and autonomy (self-determination) subscales from Spreitzer’s (1995) empowerment scale. A French version was used, which was created and validated by Boudrias et al. (2010). Each subscale consists of three items rated on a five-point Likert scale. This study did not address relatedness, another psychological need crucial for self-determined motivation, as it pertains to positive social interactions within the workplace, which were beyond the scope of this research.

We utilized the French version of the situational motivation scale to evaluate motivation, which has developed and validated by Guay et al. (2000). This scale includes 16 items rated on a seven-point Likert scale, divided into four subscales, each representing a different type of motivational regulation: intrinsic regulation, identified regulation, external regulation, and amotivation.

4.3.5.2 Cognitive task engagement

We utilized the absorption subscale from the Utrecht Work Engagement Scale to evaluate cognitive engagement (Schaufeli et al., 2003). The French version of this questionnaire, validated by Zecca et al. (2015), consists of 9 items rated on a seven-point Likert scale.

Cognitive engagement was also inferred using heart rate variability (HRV) frequency measures (Léger et al., 2014). By applying the Fast Fourier Transform to inter-beat intervals (RR intervals), we calculated the power for both the low frequency (LF) (0.04-0.15 Hz) and high frequency (HF) (0.15-0.4 Hz) bands of HRV. The LF band of HRV is influenced by both the parasympathetic (PNS) and sympathetic nervous systems (SNS), while the HF band is primarily influenced by the PNS (Shaffer et al., 2014). The SNS is responsible for "fight-or-flight" responses, whereas the PNS controls "rest-and-digest.” LF and HF measures have been demonstrated to be indicators of cognitive engagement during tasks (Gao et al., 2020). Past literature has shown that low LF coupled with balanced HF is an indicator of cognitive absorption (Tozman et al., 2015).

4.3.5.3 Emotional task engagement

To evaluate emotional engagement, the dedication subscale from the French version of the Utrecht Work Engagement Scale was utilized (Schaufeli et al., 2003; Zecca et al., 2015). Emotional engagement was also inferred using respiration rate, which has been validated as an indicator of emotional arousal (Bradley & Lang, 2007). Emotional arousal is an indicator of emotional engagement (Lang, 1995; Macey & Schneider, 2008). Higher respiration indicates higher emotional arousal, and thus higher emotional engagement.

4.3.5.4 Behavioral task engagement

Behavioral engagement was assessed using the vigor subscale from the French version of the Utrecht Work Engagement Scale (Schaufeli et al., 2003; Zecca et al., 2015). Additionally, behavioral engagement was inferred from the variability in the intensity of physical effort during the task, measured in g-force. A lower standard deviation in this measurement indicates higher behavioral engagement (Gao et al., 2020).

4.3.5.5 Trait task engagement

To evaluate trait task engagement, the French version of the General Causality Orientation Scale was utilized (Deci & Ryan, 1985; Meyer et al., 2010), validated by Vallerand et al. (1987). This scale includes 12 vignettes that describe achievement-oriented scenarios, each accompanied by three questions. Participants respond to these questions using a seven-point Likert scale. The questions are categorized into three subscales: autonomy, control, and impersonal.

Participants who score higher on the autonomy subscale tend to view tasks as promoting autonomy and are more likely to experience intrinsic, integrated, or identified motivation, leading to higher engagement. Those scoring higher on the control subscale perceive tasks as being externally controlled, making them more prone to experiencing introjected or external motivation and resulting in lower engagement compared to those with high autonomy scores. Participants with higher scores on the impersonal subscale often feel ineffective in influencing or controlling tasks, leading to feelings of helplessness and a higher likelihood of experiencing amotivation and lack of engagement (Deci et al., 2017; Ryan & Deci, 2008; Szalma, 2020).

Variations in individuals' tendencies to experience specific types of motivation and levels of engagement create intra-group variability within our conditions (Passalacqua, Sénécal, et al., 2020). This variability can impact how different AI types (independent variable) influence our dependent variables. To mitigate this confounding effect, we included trait engagement as a covariate in our statistical model (see Fig. 4.3).

4.3.5.6 Performance measures

Two primary performance indicators were used in this study. The first is the time taken by a participant to complete the task, referred to as performance time. A shorter performance time signifies better performance. The second indicator is the accuracy of participants in detecting errors, expressed as a percentage of correctness, termed error detection performance. This percentage decreases when participants either fail to identify an actual error or incorrectly identify a non-existent error. With 30 items per task, each mistake reduces the percentage of correctness by 1/30. For instance, one error results in a correctness percentage of 96.67%, two errors bring it down to 93.33%, and so forth. Thus, a higher percentage indicates superior performance.

Table 4.2: Summary of variable operationalization and measurement

Variable	Measure	Measure type	Operationalization
Motivational needs	Psychological empowerment scale	Self-report	Meaning, competence, and autonomy scores
Motivation	Situational motivation scale	Self-report	Intrinsic, identified, external, and amotivation score
Cognitive engagement	Absorption subscale of UWES	Self-report	Cognitive absorption score
	Hexoskin vest	Physiological	Low and high frequency (HRV)

Table 4.2 (continued and end)

Emotional engagement	Dedication subscale of UWES	Self-report	Emotional arousal score
	Hexoskin vest	Physiological	Respiration rate
Behavioral engagement	Vigor subscale of UWES	Self-report	Vigor score
	Hexoskin vest (accelerometer)	Physiological	Physical effort shown during a task
Trait engagement	General causality orientation scale	Self-report	Autonomy, control, and impersonal score
Task performance time	Video recording	Observational	Time taken for a participant to complete the task (lower = better)
Task error detection performance	Excel output file	Observational	Percentage of correctness (higher = better)

4.3.6 Apparatus

All participants were equipped with a Hexoskin smart vest (Carré Technologies, Montreal, Canada). This physiological vest captured heart rate, respiration, and movement data. The vest recorded data at various frequencies: 256 Hz for 1-lead electrocardiogram using an integrated electrode, 128 Hz for respiration using two embedded respiratory inductive plethysmography sensors, and 64 Hz for acceleration/activity via an internal 3-axis accelerometer. Numerous studies have assessed and validated the effectiveness of the Hexoskin smart vest (Cherif et al., 2018; Jayasekera et al., 2021; Smith et al., 2019).

A touchscreen desktop computer (Dell, Round Rock, USA) was used to display the AI decision support system interface at the participant's workstation. More specifically, Excel (Microsoft, Redmond, USA) was used to create and display the interface. The same Excel document automatically collected data related to participant error detection performance. The AI decision support system was a simulated error detection system. This system emulated an AI-driven product scanning technology that is meant to help operators identify and report defects on snowshoes. However, the system employed a Wizard of Oz (Kelley, 2018) approach instead of having actual AI scanning functionality. It depended on operators scanning barcodes attached to the snowshoes to display an image on the computer interface, as shown in Figure 4.8. A webcam (Logitech, Newark, USA) was connected to the computer and used to record participants. We used the video recordings to accurately measure the time it took to complete the task (performance time).

4.3.7 Statistical analysis

When comparing between-subject levels (no automation, partial automation, and full automation), a type-3 analysis of variance was performed to determine the main effect of AI condition on each dependent variable. For motivational needs, motivation, cognitive engagement, emotional engagement, and behavioral engagement, we controlled for trait engagement (covariate). A natural logarithmic transformation was applied to the relevant data when assumptions were violated. For performance time and error detection performance, normality was violated, but applying a logarithmic transformation would hinder proper interpretation of the values. Thus, we opted for the Kruskal-Wallis non-parametric test for those two dependent variables.

When we found globally significant effects, we used pairwise t-tests, which have been adjusted for multiple comparisons using the Bonferroni method. When comparing within-subject levels (Time 1 and Time 2), paired samples t-tests were used. When assumptions were violated, we applied a natural logarithmic to the corresponding data. We used R (programming language) and Statistical Product and Service Solutions (SPSS) version 26 to carry out our analyses.

4.3.8 A priori statistical power calculation

To estimate the necessary sample size for achieving adequate statistical power, a priori calculations were conducted. Statistical power indicates the likelihood of correctly identifying differences within the sample (Cohen, 1992). The G*Power software (Faul et al., 2009) was employed for these calculations during the experiment's planning phase. Due to the inability to estimate the effect size from previous studies, a conservative small effect size (f=0.15) was chosen. A power level of 0.90 was selected, although a minimum of 0.80 is generally recommended (Cohen, 1992). A correlation of 0.80 among repeated measures was obtained from pilot tests. Based on these power calculations, a sample size of 99 participants was determined to be sufficient to reject the null hypothesis with 90% certainty.

4.3.9 Transparency and openness

All raw data, processed data, and statistical outputs are available at [stable masked link to repository]. In the preparation of this article, we used Chat GPT-4o (OpenAI, 2024) to optimize the readability of sentences throughout the text.

4.4 Results

Three participants were excluded from the study due to technical equipment issues, leaving a final sample of 99 participants for analysis. All graphs display error bars representing the standard error of the mean. Table 4.3 summarizes all results related to our hypotheses.

4.4.1 Autonomy

1.1.1.1 Time 1

A type-3 ANOVA showed a significant main effect of AI condition on autonomy when controlling for trait engagement, $F(2, 94) = 3.79$, $p = .026$, $\eta_p^2 = .08$. Post-hoc pairwise linear regressions revealed that autonomy was significantly lower using fully automated AI compared to no automation ($t = 2.70$, $p = .024$). However, no differences were observed between partial automation and full automation ($t = 1.72$, $p = .266$), or between partial automation and no automation ($t = -0.98$, $p = .992$). Figure 4.9 shows these results.

1.1.1.2 Time 2

A type-3 ANOVA showed no significant main effect of AI condition on autonomy after controlling for trait engagement, $F(2, 25) = 1.28$, $p = .295$.

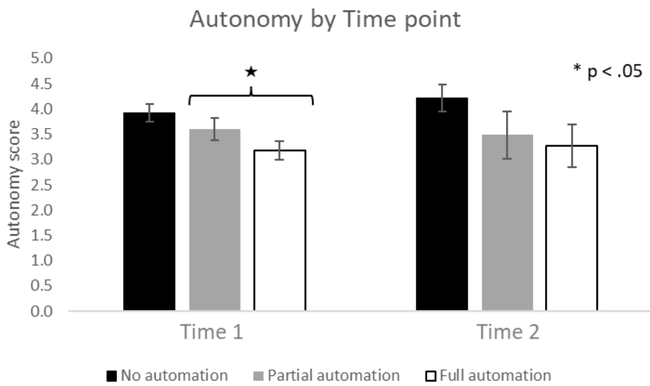

Figure 4.9: Comparison of autonomy between conditions within each Time point

1.1.1.3 Delta between Time 1 and Time 2

A paired samples t-test was performed to evaluate whether there was a difference in autonomy between Time 1 and Time 2 for each condition. Within the no automation condition, results revealed no significant differences between Time 1 (M = 4.22, SD = 0.65) and Time 2 (M = 4.22, SD = 0.80). Within the fully automated condition, results revealed no significant differences between Time 1 (M = 3.36, SD = 1.52) and Time 2 (M = 3.27, SD = 1.56). Within the partially automated condition, results revealed no significant differences between Time 1 (M = 3.33, SD = 1.17) and Time 2 (M = 3.48, SD = 1.39).

4.4.2 Competence

1.1.1.4 Time 1

A type-3 ANOVA showed no significant main effect of AI condition on competence when controlling for trait engagement, $F(2, 94) = 1.61$, $p = .206$.

4.4.3 Time 2

A type-3 ANOVA showed no significant main effect of AI condition on competence after controlling for trait engagement, $F(2, 25) = 0.45$, $p = .640$.

1.1.1.5 Delta between Time 1 and Time 2

A paired samples t-test was performed to evaluate whether there was a difference in competence between Time 1 and Time 2 for each condition, as shown in Figure 4.10. Within the no automation condition, results revealed no significant differences between Time 1 (M = 1.41, SD = 0.12) and Time 2 (M = 1.47, SD = 0.11). Within the fully automated condition, results revealed no significant differences between Time 1 (M = 1.49, SD = 0.12) and Time 2 (M = 1.45, SD = 0.23). Within the partially automated condition, competence was significantly higher in Time 2 (M = 1.53, SD = 0.10) compared to Time 1 (M = 1.48, SD = 0.11), t(10) = 3.01, p = .013).

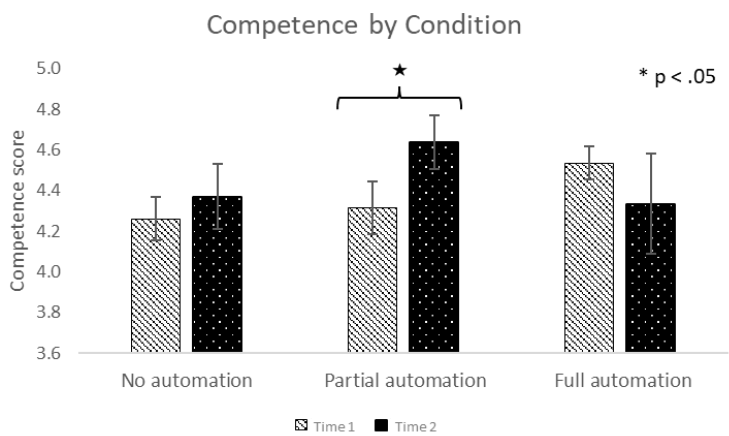

Figure 4.10: Comparison of competence through time by condition

4.4.4 Meaning

Time 1

A type-3 ANOVA showed a significant main effect of AI condition on meaning after controlling for trait engagement, $F(2, 94) = 3.40$, $p = .038$, $\eta_p^2 = .07$. Post-hoc pairwise linear regressions revealed that meaning was significantly higher using partially automated AI compared to fully automated AI (t = 2.44, p = .05). However, we found no significant differences between partial automation and no automation (t = 0.43, p = 1) or between full automation or no automation (t = -2.01, p = .149). Figure 4.11 illustrates these results.

Time 2

A type-3 ANOVA showed no significant main effect of AI condition on meaning when controlling for trait engagement, $F(2, 25) = 3.08$, $p = .064$.

Delta between Time 1 and Time 2

A paired samples t-test was performed to evaluate whether there was a difference in meaning between Time 1 and Time 2 for each condition. Figure 4.12 shows these results. Within the no automation condition, results revealed no significant differences between Time 1 (M = 0.82, SD = 0.42) and Time 2 (M = 0.70, SD = 0.39). Within the fully automated condition, meaning was significantly higher in Time 1 (M = 0.62, SD = 0.29) compared to Time 2 (M = 0.31, SD = 0.36), t(10) = 3.18, p = 0.10). Within the partially automated condition, results revealed no significant differences between Time 1 (M = 0.43, SD = 0.25) and Time 2 (M = 0.39, SD = 0.34).

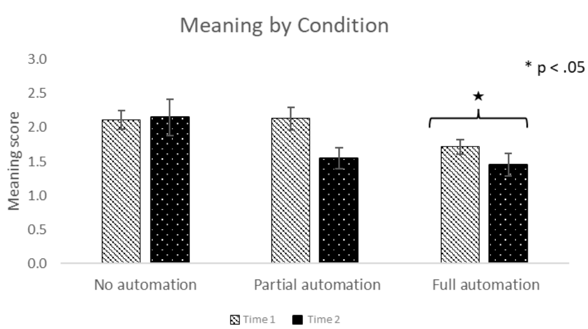

Figure 4.11: Comparison of meaning through time by condition

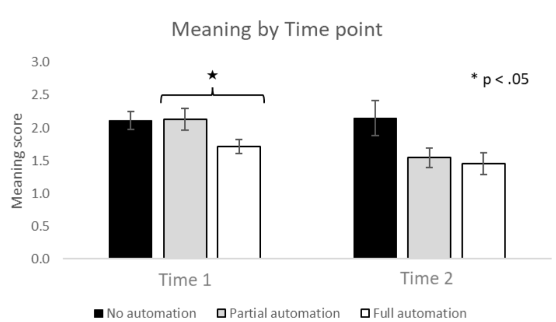

Figure 4.12: Comparison of meaning between conditions within each Time point

4.4.5 Motivation

Time 1

A type-3 ANOVA showed a significant main effect of AI condition on identified regulation when controlling for trait engagement, F(2, 94) = 3.62, p = .031, η_p^2 = .07. However, no significant main effect was found for intrinsic motivation ($F(2, 94) = 1.47$, $p = .236$), external regulation ($F(2, 94) = 1.16$, $p = .317$), or amotivation ($F(2, 94) = 1.03$, $p = .363$)

Post-hoc pairwise linear regressions revealed that identified regulation was significantly higher using the partially automated AI versus fully automated AI ($t = 2.64$, $p = .029$). However, no differences were observed between partial automation and no automation ($t = 1.80$, $p = .224$) or between full automation and no automation ($t = -0.84$, $p = 1$), as shown in Figure 4.13.

Time 2

A type-3 ANOVA showed no significant main effect of AI condition on identified regulation when controlling for trait engagement, $F(2, 25) = 1.13$, $p = .339$. Additionally, no significant main effect was found for intrinsic motivation ($F(2, 25) = 0.02$, $p = .984$), external regulation ($F(2, 25) = 1.19$, $p = .322$), or amotivation ($F(2, 25) = 1.80$, $p = .186$).

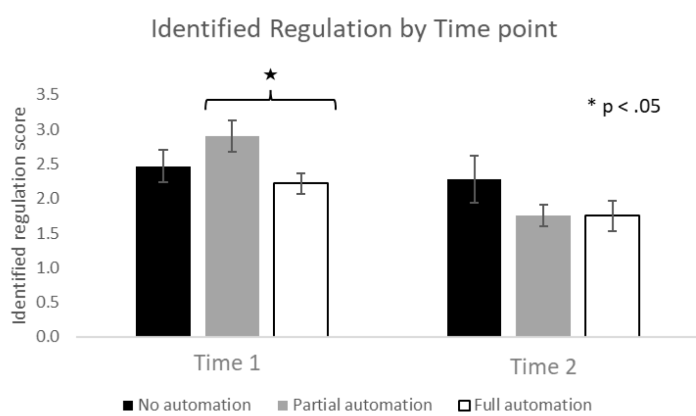

Figure 4.13: Comparison of identified regulation between conditions within each Time point

Delta between Time 1 and Time 2

A paired samples t-test was performed to evaluate whether there was a difference in motivation between Time 1 and Time 2 for each condition. Figure 4.14 and Figure 4.15 show these results.

Within the no automation condition, intrinsic motivation was significantly higher in Time 1 ($M = 0.97$, $SD = 0.48$) compared to Time 2 ($M = 0.77$, $SD = 0.44$), $t(8) = 4.03$, $p = .004$). However, no differences were observed between Time 1 and Time 2 for identified regulation ($M = 0.78$, $SD = 0.54$; $M = 0.74$, $SD = 0.44$), external regulation ($M = 1.26$, $SD = 0.40$; $M = 1.18$, $SD = 0.59$), or amotivation ($M = 0.71$, $SD = 0.49$; $M = 0.82$, $SD = 0.41$).

Within the fully automated condition, identified regulation was significantly higher in Time 1 (M = 0.79, SD = 0.37) compared to Time 2 (M = 0.48, SD = 0.42), t(10) = 2.77, p = 0.020). However, no differences were observed between Time 1 and Time 2 for intrinsic motivation (M = 0.85, SD = 0.55; M = 0.75, SD = 0.61), external regulation (M = 1.20, SD = 0.43; M = 1.22, SD = 0.55), or amotivation (M = 1.07, SD = 0.66; M = 1.15, SD = 0.57).

Within the partially automated condition, no differences were observed between Time 1 and Time 2 for intrinsic motivation (M = 0.88, SD = 0.37; M = 0.78, SD = 0.35), identified regulation (M = 0.67, SD = 0.38; M = 0.52, SD = 0.31), external regulation (M = 1.47, SD = 0.45; M = 1.47, SD = 0.58), or amotivation (M = 0.90, SD = 0.53; M = 0.92, SD = 0.54).

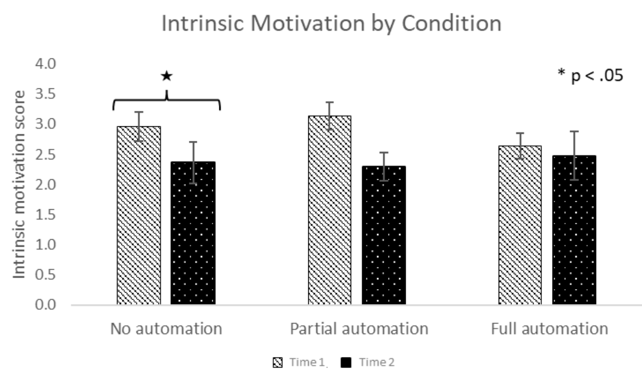

Figure 4.15: Comparison of intrinsic motivation through time by condition

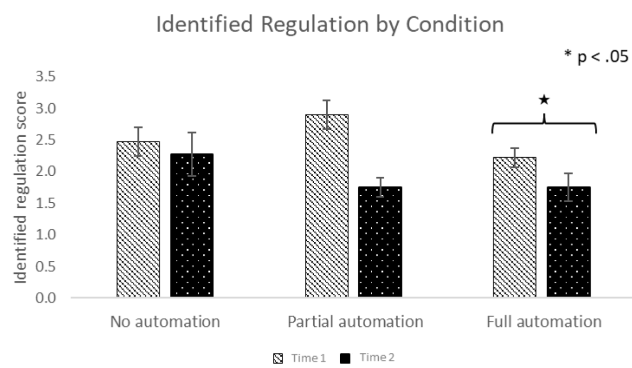

Figure 4.14: Comparison of identified regulation through time by condition

4.4.6 Cognitive engagement

Time 1

A type-3 ANOVA showed no significant main effect of AI condition on absorption when controlling for trait engagement, F(2, 94) = 2.88, p = .061. A type-3 ANOVA showed no significant main effect of AI condition on LF (HRV) after controlling for trait engagement, F(2, 91) = 0.81, p = .450. Similarly, we found no significant main effect of AI condition on HF (HRV) after controlling for trait engagement, F(2, 91) = 0.45, p = .640.

Time 2

A type-3 ANOVA showed no significant main effect of AI condition on absorption after controlling for trait engagement, $F(2, 25) = 1.16$, $p = .330$. A type-3 ANOVA showed no significant main effect of AI condition on LF (HRV) after controlling for trait engagement, $F(2, 25) = 0.24$, $p = .786$. Similarly, we found no significant main effect of AI condition on HF (HRV) after controlling for trait engagement, $F(2, 25) = 0.24$, $p = .790$.

Delta between Time 1 and Time 2

A paired samples t-test was performed to evaluate whether there was a difference in cognitive engagement (absorption, LF, and HF) between Time 1 and Time 2 for each condition. Figure 4.16 and Figure 4.17 show these results.

Within the no automation condition, results revealed no significant differences in absorption between Time 1 ($M = 1.28$, $SD = 0.41$) and Time 2 ($M = 1.12$, $SD = 0.37$). However, LF was significantly higher in Time 2 ($M = 5.32$, $SD = 1.47$) compared to Time 1 ($M = 5.06$, $SD = 1.42$), $t(7368) = 13.84$, $p < .001$). Additionally, HF was significantly higher in Time 2 ($M = 5.89$, $SD = 1.41$) compared to Time 1 ($M = 5.61$, $SD = 1.28$), $t(7368) = 15.02$, $p < .001$).

Within the fully automated condition, absorption was significantly higher in Time 1 ($M = 1.06$, $SD = 0.47$) compared to Time 2 ($M = 0.78$, $SD = 0.57$), $t(10) = 2.72$, $p = .021$). However, LF was significantly higher in Time 2 ($M = 5.67$, $SD = 1.78$) compared to Time 1 ($M = 5.15$, $SD = 1.43$), $t(6801) = 21.48$, $p < .001$). Additionally, HF was significantly higher in Time 2 ($M = 6.29$, $SD = 1.83$) compared to Time 1 ($M = 5.72$, $SD = 1.33$), $t(6801) = 22.75$, $p < .001$).

Within the partially automated condition, results revealed no significant differences between Time 1 and Time 2 for absorption ($M = 1.18$, $SD = 0.27$; $M = 1.13$, $SD = 0.34$), LF ($M = 5.26$, $SD = 1.40$; $M = 5.30$, $SD = 1.39$), and HF ($M = 5.83$, $SD = 1.30$; $M = 5.83$, $SD = 1.29$).

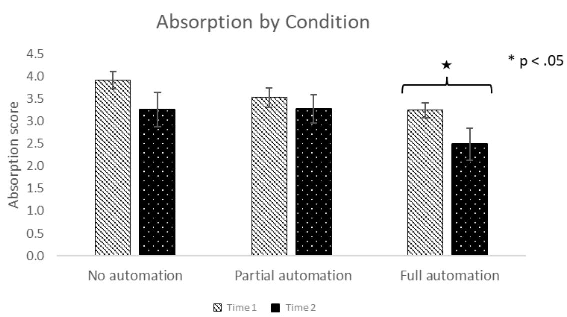

Figure 4.17: Comparison of absorption through time by condition

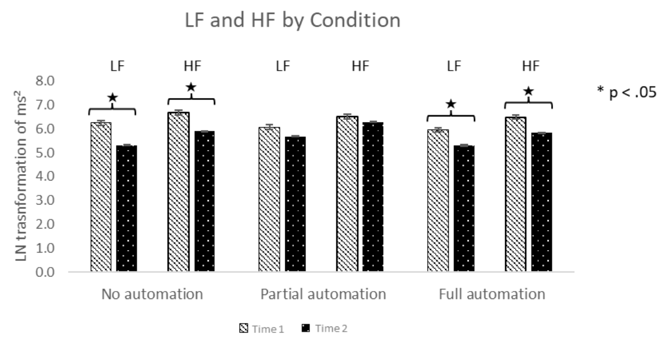

Figure 4.17: Comparison of LF and HF through time by condition

4.4.7 Emotional engagement

Time 1

A type-3 ANOVA showed no significant main effect of AI condition on dedication after controlling for trait engagement, $F(2, 94) = 1.53$, $p = .222$. A type-3 ANOVA showed no significant main effect of AI condition on respiration rate after controlling for trait engagement, $F(2, 86) = 2.09$, $p = .130$.

Time 2

A type-3 ANOVA showed no significant main effect of AI condition on dedication after controlling for trait engagement, $F(2, 25) = 0.22$, $p = .805$. A type-3 ANOVA showed a significant main effect of AI condition on respiration rate when controlling for trait engagement, $F(2, 23) = 3.46$, $p = .048$, $\eta_p^2 = .23$. Post-hoc pairwise linear regressions showed that respiration rate was higher using the partially automated AI compared to no automation ($t = 2.73$, $p = .036$). However, no significant differences were observed between partial automation and full automation ($t = 0.55$, $p = .589$), or between no automation and full automation ($t = -2.27$, $p = .066$). Figure 4.18 shows these results.

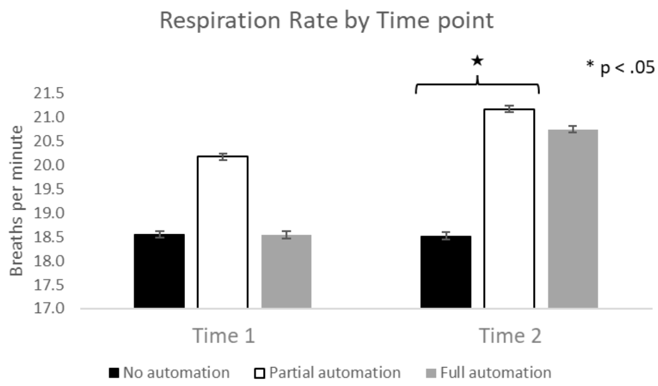

Figure 4.18: Comparison of respiration rate between conditions within each Time point

Delta between Time 1 and Time 2

A paired samples t-test was performed to evaluate whether there was a difference in emotional engagement (dedication, respiration rate) between Time 1 and Time 2 for each condition.

Within the no automation condition, results revealed no significant differences in dedication between Time 1 (M = 2.96, SD = 1.11) and Time 2 (M = 2.63, SD = 0.70). However, the breathing rate was significantly higher in Time 2 (M = 18.52, SD = 6.42) compared to Time 1 (M = 18.05, SD = 6.49), $t(7368) = 6.19$, $p < .001$).

Within the fully automated condition, results revealed no significant differences in dedication between Time 1 (M = 2.58, SD = 1.22) and Time 2 (M = 2.61, SD = 1.09). However, breathing rate was significantly higher in Time 2 (M = 20.75, SD = 5.22) compared to Time 1 (M = 18.54, SD = 5.22), $t(6801) = 22.64$, $p < .001$).

Within the partially automated condition, results revealed no significant differences in dedication between Time 1 (M = 2.55, SD = 0.37) and Time 2 (M = 2.48, SD = 0.58). However, breathing rate was significantly higher in Time 2 (M = 21.17, SD = 5.28) compared to Time 1 (M = 20.14, SD = 5.84), $t(5930) = 13.91$, $p < .001$).

4.4.8 Behavioral engagement

Time 1

A type-3 ANOVA revealed no significant main effect of AI condition on vigor after controlling for trait engagement, $F(2, 94) = 0.362$, $p = .697$. However, a type-3 ANOVA indicated a significant main effect of AI condition on the SD of the intensity of physical effort after controlling for trait engagement, $F(2, 91) = 15.34$, $p < .001$, $\eta_p^2 = .25$. Post-hoc pairwise linear regressions showed that the SD of the intensity of physical effort was significantly higher for fully automated AI compared to partially automated AI ($t = 5.18$, $p < .001$) and no automation ($t = 2.86$, $p = .010$). Additionally, the SD of the intensity of physical effort was higher for no automation compared to partial automation ($t = 2.29$, $p = .024$). These results are illustrated in Figure 4.19.

Time 2

A type-3 ANOVA showed no significant main effect of AI condition on vigor after controlling for trait engagement, $F(2, 25) = 0.41$, $p = .667$. A type-3 ANOVA showed no significant main effect of AI condition on the standard deviation of the intensity of physical effort after controlling for trait engagement, $F(2, 25) = 0.45$, $p = .643$.

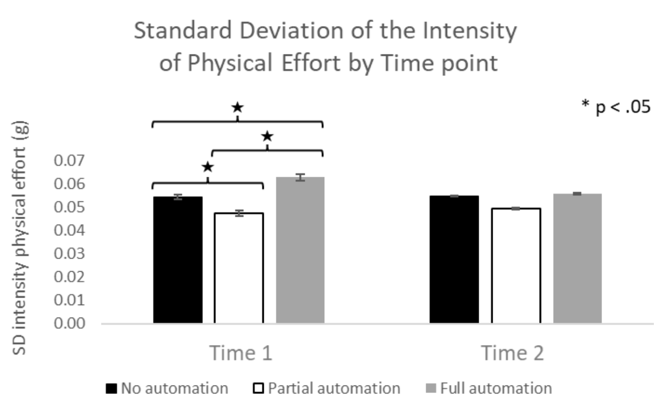

Figure 4.19: Comparison of SD of intensity of physical effort between conditions within each Time point

Delta between Time 1 and Time 2

A paired samples t-test was performed to evaluate whether there was a difference in cognitive engagement (vigor and standard deviation of the intensity of physical effort) between Time 1 and Time 2 for each condition.

Within the no automation condition, results revealed no significant differences in vigor between Time 1 ($M = 2.81$, $SD = 0.94$) and Time 2 ($M = 2.59$, $SD = 0.60$). However, the standard deviation of the intensity of physical effort was significantly higher in Time 2 ($M = 0.054$, $SD = 0.032$) compared to Time 1 ($M = 0.047$, $SD = 0.033$), $t(7368) = 14.60$, $p < .001$).

Within the fully automated condition, results revealed no significant differences between Time 1 and Time 2 for vigor ($M = 2.73$, $SD = 1.08$; $M = 2.61$, $SD = 1.08$) and standard deviation of the intensity of physical effort ($M = 0.056$, $SD = 0.031$; $M = 0.056$, $SD = 0.029$)

Within the partially automated condition, results revealed no significant differences in vigor between Time 1 ($M = 2.33$, $SD = 0.73$) and Time 2 ($M = 2.39$, $SD = 0.79$). However, the standard deviation of the intensity of physical effort was significantly higher in Time 2 ($M = 0.049$, $SD = 0.028$) compared to Time 1 ($M = 0.046$, $SD = 0.031$), $t(5930) = 7.27$, $p < .001$).

4.4.9 Performance time

Time 1

A Kruskal-Wallis H test showed a significant main effect of AI condition on performance, $H(2) = 49.22$, $p < .001$, $\eta_p^2 = .50$. Post-hoc analysis using Dunn's test revealed that performance time was significantly better using the fully automated AI compared to partially automated AI ($p < .001$) and no automation ($p < .001$). However, no difference was observed between partial automation and no automation ($p = 1$).

Time 2

A Kruskal-Wallis H test showed a significant main effect of AI condition on performance, $H(2) = 13.33$, $p = .001$, $\eta_p^2 = .43$. Post-hoc analysis using Dunn's test revealed that performance time was significantly better using the fully automated AI compared to no automation ($p = .001$). However, no differences were observed between full automation and partial automation ($p = .291$), or between partial automation and no automation ($p = .127$), as illustrated in Figure 4.20.

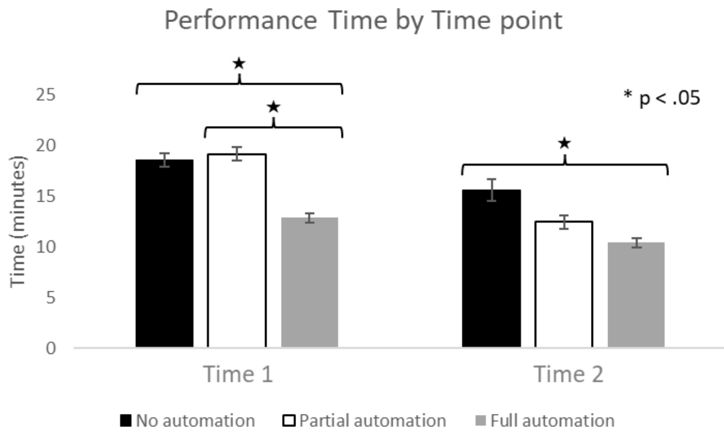

Figure 4.20: Comparison of performance time between conditions within each Time point

Delta between Time 1 and Time 2

A paired samples t-test was performed to evaluate whether there was a difference in performance time between Time 1 and Time 2 for each condition. Within the no automation condition, performance time was significantly higher (worse performance) in Time 1 (M = 21.20, SD = 5.22) compared to Time 2 (M = 15.56, SD = 3.37), t(9) = 5.39, $p < .001$). Within the fully automated condition, performance time was significantly higher (worse performance) in Time 1 (M = 12.54, SD = 1.94) compared to Time 2 (M = 10.39, SD = 1.63), t(10) = 6.43, $p < .001$). Within the partially automated condition, performance time was significantly higher (worse performance) in Time 1 (M = 17.25, SD = 2.59) compared to Time 2 (M = 12.44, SD = 2.26), t(10) = 12.91, $p < .001$).

4.4.10 Error detection performance

Time 1

A Kruskal-Wallis H test showed a significant main effect of AI condition on performance, H(2) = 37.88, $p < .001$, $\eta_p^2 = .38$. Post-hoc analysis using Dunn's test revealed that performance was significantly better using the fully automated AI compared to partially automated AI ($p < .001$) and no automation ($p < .001$). Results also showed that partial automation was significantly better than no automation ($p = .044$).

Time 2

A Kruskal-Wallis H test showed a significant main effect of AI condition on performance, H(2) = 10.99, p = .005, η_p^2 = .35. Post-hoc analysis using Dunn's test revealed that performance was significantly better using the fully automated AI compared to no automation (p = .003). However, no differences were observed between full automation and partial automation (p = 0.566), or between no automation and partial automation (p = .13). These results are shown in Figure 4.21.

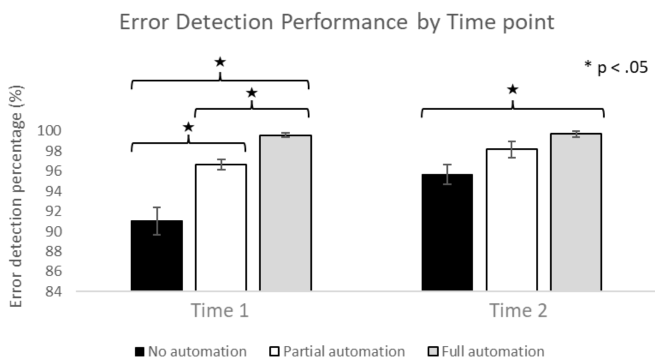

Figure 4.21: Comparison of error detection performance between conditions within each Time point

Delta between Time 1 and Time 2

A paired samples t-test was performed to evaluate whether there was a difference in error detection performance between Time 1 and Time 2 for each condition. Within the no automation condition, results revealed no significant differences between Time 1 (M = 4.51, SD = 0.10) and Time 2 (M = 4.56, SD = 0.03). Within the fully automated condition, results revealed no significant differences between Time 1 (M = 4.60, SD = 0.01) and Time 2 (M = 4.60, SD = 0.01). Within the partially automated condition, results revealed no significant differences between Time 1 (M = 4.57, SD = 0.04) and Time 2 (M = 4.59, SD = 0.03).

Table 4.3: Summary of results

Measure	**Variable**	**Hypothesis**	**Time**	**Result**	**Hypothesis support?**
Motivational needs	Autonomy	H1a	1	No automation > full automation	Partial
			2	-	No
		H1b	1→2	-	Yes
	Competence	H1a	1 & 2	-	No
		H1b	1→2	Partial: More competence in Time 2 Full: Equal competence between time points No automation: Equal between Time points	Yes
Meaning	Meaning	H2a	1	Partial automation > Full automation	Yes
			2	-	No
		H2b	1→2	Partial: Equal meaning between Time points Full: Less meaning in Time 2 No automation: Equal between Time points	Yes

Table 4.3 (continued)

Motivation	**Identified**	**H3a**	**1**	**Partial automation > full automation**	**Yes**
			2	-	No
	Intrinsic, external, and amotivation		1 & 2	No differences	No
	Identified	H3b	1→2	Partial: Equal between Time points Full: Less identified regulation in Time 2 No automation: Equal between Time points	Yes
	Intrinsic	H3b	1→2	Partial: Equal between Time points Ful: Equal between Time points No automation: Less intrinsic in Time 2	No

Table 4.3 (continued)

Cognitive engagement	**Absorption** LF and HF	**H4a**	**1 & 2**	**-**	**No**
	Absorption	H4b	1→2	Partial: Equal between Time points Full: Absorption lower in Time 2 No automation: Equal between Time points	Yes
	LF and HF			Partial: Equal between Time points Full: LF and HF higher in Time 2 No automation: LF and HF higher in Time 2	
Emotional engagement	Dedication	H4a	1 & 2	-	No
	Respiration rate		1	-	
			2	Partial automation > No automation	No
	Dedication	H4b	1→2	-	No
	Respiration rate			All conditions: Higher in Time 2	No

Table 4.3 (continued and end)

Behavioral engagement	**Vigor**	**H4a**	**1 & 2**	**-**	**No**
	SD of the intensity of physical effort		1	Partial < No automation < Full	Yes
			2	-	No
	Vigor	H4b	1→2	-	No
	SD of intensity of physical effort			Partial: Higher in Time 2 No automation: Higher in Time 2	No
Performance	Performance time and Error detection	H5a	1	Full > Partial > No automation	Yes
			2	Full > No automation; Full = Partial	Partial
	Performance time	H5b	1→2	All conditions: Better in Time 2	Yes
	Error detection	H5b	1→2	-	No

4.5 Discussion

The current study aimed to examine the effect of decision selection automation on worker motivational needs, meaning, motivation, engagement, and performance. We primarily sought to compare the effects of full and partial automation of decision selection on the psychosocial aspects of human-AI interaction. This allowed us to take a first step in examining whether a critical boundary exists after which automation negatively impacts psychosocial variables, as is well-documented for human performance. Specifically, our research was designed to identify at what point the balance between human involvement and AI control in decision-making processes shifts from being beneficial to detrimental psychosocially. By focusing on the intersection of technological efficiency and human psychological needs, we aimed to contribute to a more nuanced understanding of how varying levels of automation in decision-making can influence not just operational outcomes but attitudes, perception, and behavior of workers, which are crucial for long-term organizational success and employee retention.

4.5.1 Effect of Decision Support Level on Psychosocial Variables

Our results show a significant difference between conditions in Time 1 for the motivational need of autonomy (sense of control in one's work). Specifically, participants perceived themselves as more autonomous when decision selection was only partially automated, compared to full automation. This finding aligns with both conceptual and limited empirical evidence within the literature, which indicates that the automation of decision selection could negatively impact worker autonomy (Bankins & Formosa, 2023; Berberian et al., 2012; Perez et al., 2022; Szalma, 2014; Ueda et al., 2021). However, this difference did not persist over time. Additionally, no differences between conditions were observed for the perception of competence (sense of effectiveness). Thus, our results show limited support for H1a.

However, participants interacting with partial automation show a significant increase in perceived competence over time, indicating that partial automation may foster a growing sense of mastery and effectiveness in their tasks. This suggests that while the initial introduction of automation does not immediately impact feelings of competence, continuous interaction with a system that still requires human input and decision-making may enhance an individual's confidence and proficiency in their role over time. This finding aligns with the idea that partial automation, which balances AI assistance with human control, can contribute positively to a worker's development and fulfillment of their need for competence (Szalma, 2014). We see no such improvement in competence for participants who used full automation or no automation, thus providing additional evidence supporting H1b.

We see important differences between conditions regarding participants' perceived significance of their work (meaning). At Time 1, we observe that partial automation leads to a greater sense of meaning than full automation. Additionally, we observe that meaning degrades over time for full automation, whereas no such degradation occurs for partial automation or no automation, thus supporting H1a and H1b.

Similarly, we found that self-determined motivation within Time 1, specifically identified regulation, is higher for partial automation compared to full automation. Identified regulation is a form of motivation where individuals engage in an activity because they feel it is important or meaningful, even if it is not inherently enjoyable. It is a more autonomous form of extrinsic motivation and a significant indicator of job performance, sustained effort, and various organizational citizenship behaviors (Van den Broeck et al., 2021). In addition, we observe that identified regulation degrades over time for full automation, whereas it remains stable for partial automation and no automation, thus showing some support for H3a and H3b. These findings indicate that when workers retain a degree of control and active involvement in tasks, it contributes to a stronger perception of their work being meaningful and thus enhances their self-determined motivation. In contrast, when tasks are fully automated, the sense of personal contribution and significance in the work diminishes over time. Additionally, we found that intrinsic motivation degrades over time in the no automation, while it remains stable for the other conditions. This result goes against H3b and implies that no automation may lead to a reduction in worker well-being, job satisfaction, proactivity, and performance over time (Van den Broeck et al., 2021).

We found no differences in cognitive engagement between conditions. Conversely, when looking at the delta between Time 1 and Time 2, we found that both low and high-frequency heart rate variability significantly increased (Time 2) in the full automation and no automation conditions but remained stable in the partial automation condition. Cognitive absorption is associated with lower levels of LF and balanced levels of HF (Peifer et al., 2014; Tozman et al., 2015). As such, heightened LF and HF, as seen in the full automation and no automation, are less compatible with cognitive absorption. However, we interpret these findings cautiously since participants' perceived cognitive engagement (absorption) did not reveal any differences between conditions or Time points.

In terms of emotional engagement, we found within Time 2 that participants were more engaged with partial automation compared to no automation, as indicated by a heightened respiration rate. Concerning behavioral engagement, we found within Time 1 a lower standard deviation of movement intensity for partial automation compared to full automation and no automation. A standard deviation that is lower indicates heightened behavioral engagement (Gao et al., 2020). However, for partial automation, the standard deviation of movement intensity significantly increased in Time 2, signifying a lowered behavioral engagement. No differences were observed between conditions in Time 2.

Overall, our results show partial support for H4a and H4b. While our results suggest that full automation does not immediately influence certain facets of worker engagement, the effects observed by looking at the delta between Time points indicate potential challenges in maintaining an adequate level of cognitive engagement. Specifically, the increase in both low and high-frequency heart rate variability under full automation and no automation may signal a cognitive disengagement from the task. As outlined by SDT, engagement is a direct consequence of the satisfaction of motivational needs and self-determined motivation. As such, the decreasing cognitive engagement in the full automation condition could be explained by the declining sense of meaning and self-determined motivation, as well as the stagnant perception of competence. While the decreasing cognitive engagement in the no automation condition could be explained by the declining intrinsic motivation through time. Conversely, partial automation shows a more favorable impact on worker engagement. This is evident in the stability of cognitive engagement observed, in contrast to the decline seen in other conditions. Such engagement patterns suggest that partial automation better aligns with fulfilling psychological needs and nurturing self-determined motivation. As such, results suggest that the balance between AI assistance and human control in the partial automation condition is more conducive to engagement through time.

In terms of performance, full automation led to the best outcomes in Time 1 for both performance time and error detection, suggesting that when tasks are fully automated, they are completed more quickly and with fewer errors. Partial automation followed closely, indicating that the system was still highly effective even with some level of human involvement. The no automation AI condition lagged behind, due to the absence of any AI assistance, placing the entire burden of error detection on human participants.

Interestingly, the dynamics changed in Time 2. While the no automation condition continued to perform relatively poorly, there was no significant difference between full and partial automation. This shift suggests that participants in the partial automation condition were able to adapt and improve their performance over time, matching the efficiency of the fully automated AI. It is important to note that performance in partial automation increased for Time 2, and that performance in full automation did not decrease. This improvement could be due to participants in the partial automation condition learning to better interact with and utilize the AI system, enhancing their efficiency and accuracy. The overall improvement in performance time across all conditions in Time 2 indicates a general adaptation to the task, regardless of the level of automation. However, the stability in error detection performance across Time points for all conditions suggests that while participants became faster at completing the tasks, their accuracy did not significantly change.

4.5.2 Practical Implications

Our results reveal that partial automation, striking a balance between AI assistance and human control, optimally supports psychosocial outcomes like perceived work meaningfulness, competence, self-determined motivation, and cognitive engagement. This contrasts with the scenario of full automation, where AI's complete takeover of decision-making precipitates a noticeable decrease in these psychosocial factors. It becomes apparent that when automation encroaches upon the worker's sense of control and efficacy in their role, it detrimentally affects their perception of job meaningfulness and self-determined motivation. In essence, our findings suggest that just as there is a critical level of automation beyond which human performance degrades, a similar boundary may exist for psychosocial well-being.

Furthermore, our research underscores that the optimal level of AI automation is not solely a technical consideration but also a psychosocial one. In light of these findings, it becomes evident that the design of AI systems should not solely prioritize maximal automation but should also carefully consider the optimal level of human involvement. This means that AI implementation should aim to augment humans' ability to carry out their work rather than aim to replace them (Jarrahi, 2018; Jiang et al., 2023; Mazarakis et al., 2023; Newman et al., 2020; Rosin et al., 2021). This vision aligns with the emerging paradigm of Industry 5.0, which emphasizes the integration of human-centric values in automated systems (Enang et al., 2023; Goujon et al., 2024; Sitarević et al., 2023). It also aligns with the concept of human-centered AI, which focuses on designing systems that amplify human abilities, enhance human decision-making, and foster collaboration between humans and machines (Shneiderman, 2020, 2022).

Essentially, system and business process analysts must exercise caution in the determination of the level of automation provided by technological systems. When possible, steps should be taken to nurture motivational needs by increasing worker decisional power, job variety, and performance feedback while simultaneously reducing excessive workload, job insecurity, and controlling leadership (Gagné et al., 2022; Peters et al., 2018). This approach can have a positive effect not only on the worker, but also the organization. Workers will find their jobs more meaningful, self-actualizing, and enjoyable, leading to improved self-determined motivation, engagement, and well-being in the workplace. In turn, organizations will benefit from heightened productivity, increased acceptance of new technology, reduced turnover, fewer safety incidents, and decreased absenteeism (Mann & Harter, 2016).

4.5.3 Theoretical Implications

Our investigation into the psychosocial impacts of AI automation, guided by SDT, offers insight into the relationship between technology and worker well-being. It demonstrates that partial automation—merging AI support with human control—can enhance workers' autonomy, competence, and job meaningfulness, validating SDT's principle that well-balanced automation nurtures psychological needs. However, the study also exposes the potential downsides of excessive automation, particularly within the decision-making aspects of work, which can undermine the meaning of work, autonomy, self-determined motivation, and engagement. This revelation points to the necessity of a balanced automation approach that supports worker psychosocial well-being.

Our findings underscore the utility of SDT in the realm of AI research, especially as industries grapple with the implications of increasingly automated decision-making. SDT emerges as a solid framework for the design and implementation of AI systems, advocating for a balance that enhances psychosocial well-being. This approach ensures AI acts as an enabler rather than a replacement for human expertise, promoting a synergy that can lead to more fulfilling and productive work environments. Therefore, integrating SDT principles into AI system design is essential for fostering a transition to Industry 5.0, which emphasizes human-centric approaches in technological advancement. Our study not only highlights SDT's applicability in evaluating the psychosocial dimensions of AI-driven automation but also illustrates its importance in guiding the development of automation strategies that enhance, rather than undermine, human work experiences.

4.5.4 Limitations

The limitations of our study provide essential context for interpreting the findings and suggest directions for future research. One limitation is the applicability of our results to life-critical systems. Our study focused on manufacturing contexts where performance degradation, while potentially impacting efficiency and productivity, does not pose immediate risks to human life or cause environmental harm. This distinction is crucial as the dynamics of human-AI interaction and the psychosocial impacts of AI automation in life-critical systems, such as aviation or healthcare, may differ significantly due to the higher stakes involved. In such settings, the balance between automation and human control, as well as the psychological impacts of this balance, may have different implications for safety, decision-making, and well-being.

Another notable limitation is the short-term measurement of our dependent variables. Although self-determination theory allows for long-term predictions, a longitudinal study would be the most effective approach. This type of research design is necessary to understand how workers' perceptions, motivations, and engagement with AI evolve as they gain more experience with these systems. Such studies could reveal whether the initial impacts of AI automation on psychosocial factors intensify, diminish, or stabilize over time, offering deeper insights into how to design AI systems that support sustained employee well-being and productivity.

Furthermore, the generalizability of our results is limited by the composition of our sample, which consisted of novice engineers with manufacturing experience rather than expert factory workers. While this specific population provides a useful proxy for examining human-AI interaction dynamics, their experiences and responses may not fully capture the complexities of expert workers' interactions with AI in real-world manufacturing settings. The difference in prior experience, technological proficiency, and psychological responses to AI between novice and experts could influence the study's outcomes. To address this limitation, we endeavored to enhance ecological validity by selecting an experimental task mirroring actual factory work and conducting the experiment in a laboratory that was designed to mimic a manufacturing line environment.

4.5.5 Future Research Directions

Future research directions in the context of AI's impact on psychosocial factors in the workplace could explore several pertinent areas highlighted by the findings of our study. One promising avenue is to delve deeper into the effects of varying levels of AI decision automation on employee well-being and organizational outcomes. The identification of a critical boundary beyond which the benefits of automation begin to diminish offers a fertile ground for further investigation. Future studies could aim to pinpoint more precisely where this boundary lies across different industries and job roles, examining the conditions under which partial automation enhances or detracts from worker satisfaction, motivation, and engagement.

Another direction could involve longitudinal studies to observe the long-term impacts of AI integration on employee psychosocial factors. Our research provides a snapshot of these effects. However, understanding how workers' perceptions and experiences evolve over time with sustained AI interaction is crucial for designing systems that support long-term well-being and productivity.

Exploring the interplay between AI automation and organizational culture and leadership practices could also yield valuable insights. Research could examine how leadership styles and organizational policies influence the effectiveness of AI in supporting or undermining psychosocial outcomes. This includes investigating the role of training, support, and communication strategies in facilitating a positive human-AI interaction experience.

Additionally, developing and testing intervention strategies to mitigate the potential negative effects of full automation on worker psychosocial well-being is a critical area for future work. This could include designing AI systems that are adaptable to individual worker preferences, implementing team-based approaches that leverage AI to enhance collaboration, or developing training programs that empower workers to effectively partner with AI.

Finally, expanding the scope of research to include diverse populations and settings can enhance our understanding of the generalizability of the findings. Different demographic groups may experience the psychosocial impacts of AI in the workplace differently, influenced by factors such as age, gender, educational background, experience, and job type. Investigating these variations can inform the design of AI systems that are inclusive and supportive of all workers.

4.6 Conclusion

In the quest to understand the impact of AI on workers in the manufacturing sector, this study explored how varying levels of AI decision support affect key psychosocial factors, including workers' sense of autonomy, competence, meaning, motivation, and engagement. This study contributes to the evolving discourse on the integration of AI, particularly through the lens of SDT. By exploring how different levels of AI decision support influence psychosocial factors, this research sheds light on the complex dynamics of human-AI interaction. The findings support the existence of a critical boundary in the degree of decision automation that, once crossed, leads to diminishing returns on psychosocial outcomes. This boundary delineates a threshold beyond which the automation benefits, in terms of enhancing workers' psychosocial well-being, begin to deteriorate.

From a theoretical standpoint, our study extends the application of Self-Determination Theory (SDT) into the realm of AI and work. It empirically demonstrates that while partial automation can support and even enhance workers' basic psychological needs (competence, autonomy), full automation tends to undermine these needs, leading to reduced motivation, meaningfulness, and engagement. This finding enriches our understanding of SDT by illustrating how technological interventions, specifically AI, interact with the fulfillment of psychological needs in the workplace. It suggests that the design and implementation of AI systems must consider not only technical efficiency but also their capacity to support or hinder the satisfaction of these fundamental human needs.

Practically, our research offers insights for organizations and AI system designers. It highlights the importance of designing AI with a human-centric approach, ensuring that systems support workers' psychological needs and foster an environment conducive to meaningful and engaging work. This involves creating AI systems that augment human capabilities without completely removing decision-making authority, allowing for a symbiotic relationship where both human and AI contributions are valued. The study's results suggest that businesses should carefully consider how they deploy AI technologies, aiming to strike a balance that enhances operational efficiency without compromising the psychosocial well-being of their workforce. This balance is crucial for maintaining high employee engagement, motivation, and retention levels and overall job satisfaction, which are key drivers of organizational performance and innovation.

In conclusion, this study not only advances our theoretical understanding of the interplay between AI and worker psychosocial factors but also offers practical guidance for leveraging AI to create more supportive, engaging, and human-centric work environments. As we move forward into an increasingly automated future, it will be imperative for organizations to heed these insights, ensuring that technological advancements serve to enhance, rather than detract from, the human elements of work.

CHAPTER 5 ARTICLE 2: PRACTICE WITH LESS AI MAKES PERFECT: PARTIALLY AUTOMATED AI DURING TRAINING LEADS TO BETTER WORKER MOTIVATION, ENGAGEMENT, AND SKILL ACQUISITION

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Abstract

The increased prevalence of human-AI collaboration is reshaping the manufacturing domain, fundamentally changing the nature of human work and training needs. While high automation improves performance when functioning correctly, it can lead to problematic human performance (e.g., defect detection accuracy, response time) when operators are required to intervene and assume manual control of decision-making responsibilities. As AI capability reaches higher levels of automation and human-AI collaboration becomes ubiquitous, addressing these performance issues is crucial. Proper worker training, focusing on skill-based, cognitive, and affective outcomes, and nurturing motivation and engagement, can be a mitigation strategy. However, most training research in manufacturing has prioritised the effectiveness of a technology for training, rather than how training design influences motivation and engagement, key to training success and longevity. The current study explored how training workers using an AI system affected their motivation, engagement, and skill acquisition. Specifically, we manipulated the level of automation of decision selection of an AI used for the training of 102 participants for a quality control task. Findings indicated that fully automated decision selection negatively impacted perceived autonomy, self-determined motivation, behavioral task engagement, and skill acquisition during training. Conversely, partially automated AI enhanced motivation and engagement, enabling participants to better adapt to AI failure by developing necessary skills. The results suggest that involving workers in decision-making during training, using AI as a decision aid rather than a decision selector, yields more positive outcomes. This approach ensures that the human aspect of manufacturing work is not overlooked, maintaining a balance between technological advancement and human skill development, motivation, and engagement. These findings can be applied to enhance real-world manufacturing practices by designing training programs that better develop operators' technical, methodological, and personal skills, though companies may face challenges in allocating substantial resources for training redevelopment and continuously adapting these programs to keep pace with evolving technology.

Keywords: Human-centered AI · Training curriculum · Motivation · Self-determination Theory · Industry 5.0

5.1 Introduction

Advances in technological interconnectivity, decision-making speed, and automation have greatly improved the capability of artificial intelligence (AI)-based manufacturing work systems, thus changing the nature of the work being done by workers in the manufacturing domain. AI is becoming more integrated and pervasive in industrial processes due to this technological advancement, also known as Industry 4.0 (I4.0) or the fourth industrial revolution (Jan et al., 2022). The main objective is to support human workers rather than replace them. This focus on supporting rather than replacing human workers is driven by the recognition that the complete replacement of humans by AI could lead to several detrimental outcomes and be unfeasible in many manufacturing contexts.

Firstly, it risks losing the critical thinking, creative problem-solving, and adaptability that human workers bring, which are essential for handling unpredictable situations and innovations that AI cannot yet replicate (Kolade & Owoseni, 2022; Strenge & Schack, 2021). Secondly, many organizations, particularly those embracing Lean Management principles (Rosin et al., 2020), place a high value on worker autonomy. They aim for a transition from a technology-centered to a value-centered vision, where AI tools are designed to support rather than replace human decision-making processes (Enang et al., 2023; Kumar et al., 2021). This approach is aligned with the findings of Rosin et al. (2021, 2022), who demonstrated various ways to support decision-making in manufacturing with Industry 4.0 tools, including AI, suggesting that complete automation is not always desirable. Indeed, research has shown that automating decision-making aspects of work may reduce workers' perceptions of autonomy/agency, and thus their subjective well-being, characterized by lower motivation and sense of meaningfulness at work (Legaspi et al., 2024; Nazareno & Schiff, 2021).

Thirdly, the full automation of tasks without human oversight might lead to systemic vulnerabilities, where AI systems may fail to adapt to novel scenarios or detect nuanced anomalies, potentially compromising safety and efficiency. Indeed, AI tools, vary greatly in performance depending on the complexity of the task and data quality (Usuga Cadavid et al., 2020). Particularly notable are the challenges arising from the adoption of personalised product strategies seen in I4.0. The inherent variability in data associated with customised approaches, frequently hinders the development of robust and reliable AI systems, necessitating more advanced and adaptable technological solutions (Neumann et al., 2022). Lastly, manufacturing environments frequently undergo changes, as new products are continuously developed and brought to market. This necessitates regular adjustments in manufacturing and assembly processes, including shifts in raw materials (Martínez-Olvera & Mora-Vargas, 2019; Zhou et al., 2022). These regular changes can lead to decreases in AI tool reliability and even obsolescence in cases of significant technological shifts (Mellal, 2020).

Recognizing the strengths and limitations of both AI and humans leads to the acknowledgment that both have distinct but complementary roles to play in modern manufacturing. Humans, with their versatility, creativity, and problem-solving capabilities, complement AI's proficiency in performing repetitive tasks quickly, accurately, and consistently. In contrast to humans or AI acting alone, it is anticipated that both working together would increase efficiency, productivity, and cost-effectiveness (Klumpp et al., 2019; Wilson & Daugherty, 2018). Because of this, human-AI collaboration in manufacturing systems is becoming more common in the age of I4.0. The nature of the human's work is fundamentally altered by this partnership in terms of job responsibilities and skill/training requirements (Avril et al., 2022; Da Silva et al., 2022; Gagné et al., 2022; Magnani, 2021; Parker & Grote, 2022; Soo et al., 2021). For example, the automation of repetitive manual tasks shifts human work towards a higher-level supervisory role which involves manual takeover, troubleshooting, or problem-solving when automation malfunctions.

This role requires workers to have the capabilities to detect a malfunctioning/failing automation and manually take over efficiently. Research has shown this to be a challenging aspect of human-automation collaboration, noting that the increased automation of AI systems is a double-edged sword with regards to human task performance. As levels of automation increase, so does worker performance during routine system operation. On the other hand, when automation fails or malfunctions, higher levels of automation lead to worse performance (Bainbridge, 1983; Onnasch et al., 2014). Essentially, workers may become complacent and over-rely on automation, leaving them unable to adequately respond, resulting in precarious performance (Liu, 2023).

As human-AI collaboration becomes more prevalent and the capability of AI increases, it is necessary to find ways to mitigate worker task performance issues in the inevitable situation of automation malfunction. One such mitigation, brought forward by many, is proper worker training (Büth et al., 2018; Cazeri et al., 2022; Da Silva et al., 2022; Molino et al., 2020; Parker & Grote, 2022; Saniuk et al., 2021). Indeed, providing workers with problem-solving, analytical and decision-making skills, as well as the motivation to learn and improve, can help them adapt to the growing capability of AI, fostering an efficient human-AI collaboration (Bell et al., 2017; Hecklau et al., 2016; Zirar et al., 2023). Despite its noted importance, training workers using highly-automated AI systems has received relatively little research attention in the manufacturing domain. Rather, most of the research has focused on operational, or technical aspects, as opposed to a human-centred focus, which values the worker as an indispensable resource to the success of I4.0 work systems in which humans and AI collaborate.

This issue has been echoed by the scientific community (European Commission et al., 2021; Gagné et al., 2022; Kaasinen et al., 2018; Kadir et al., 2019; Neumann et al., 2021; Rauch et al., 2020). Indeed, in their systematic review, Kadir et al. (2019) found that less than 2% of all papers about I4.0 had a human-centred focus. Generally speaking, this limits our understanding regarding the design and implementation of AI systems. More specific to the current study, this limits our understanding regarding the creation of training that would give workers the necessary capabilities to adequately adapt when AI systems malfunction. The European Commission has raised the lack of human-centric research and has brought forward the concept of Industry 5.0 (I5.0), defined as a manufacturing paradigm that leverages technology to promote worker well-being and empowerment, societal development, and environmental sustainability (European Commission et al., 2021; Humayun, 2021; Leng et al., 2022). Essentially, I5.0 aims to alleviate issues within I4.0 research by stimulating human-centric research in which human empowerment and augmentation is paramount.

Within the optic of I5.0, the current paper presents an experiment which explores an under-researched aspect of human-AI collaboration that plays a pivotal role in the long-term success of work system, i.e., worker training in a highly-automated manufacturing environment. More specifically, we aim to investigate the impact of AI decision-selection level of automation during training for a quality control task on worker skill acquisition, motivation, and engagement. We intend to answer two research questions: (1) Does AI level of automation during training affect a worker's ability to perform when AI fails? (2) Does AI level of automation affect worker motivation and engagement during training?

The rest of the article is structured as follows. First, the next section presents a literature review of worker competencies in relation to automation and worker training within I4.0. We then discuss our experimental methodology and results before concluding the paper a with a discussion on this research's main contribution and limitations.

5.2 Literature Review

The following section will review the relevant literature on I4.0, automation, worker competencies, training, motivation, and engagement.

5.2.1 Industry 4.0, Automation, and the Impact on Work and Workers

I4.0 is characterised by technological advancement such as decentralised decision-making, real-time data, and technology interconnectivity (Danjou et al., 2017). These advancements have led to the increased capability of AI-based systems, allowing more cognitive complex tasks to now be automated. Humans will not be completely replaced by AI, as whole jobs cannot be automated (Brynjolfsson et al., 2018; Parker & Grote, 2022). Additionally, AI and humans each have their strengths. For example, humans are better at complex decision-making requiring contextual understanding, while AI is better at collecting and processing a large amount of data (Bainbridge, 1983). Rather than whole jobs, tasks within jobs are being automated, meaning that humans and AI are working collaboratively more than ever.

Increased automation comes with both benefits and drawbacks, as is well-documented within human factors research. For example, automated systems can improve worker safety by taking over dangerous tasks and can improve company profitability through better process efficiency (Parker & Grote, 2022). On the other hand, higher automation is associated with significant human performance issues when AI systems malfunction, as they inevitably do (Bindewald et al., 2020; Onnasch et al., 2014; Wickens, 2018). This issue, commonly known as the out-of-the-loop performance problem, is due to an overreliance on automation, complacency, and/or cognitive overload (Endsley & Kiris, 1995; Onnasch et al., 2014). Automation can be classified according to one of four **stages** of information processing that it acts on: (1) information acquisition; (2) information analysis; (3) decision and action selection; (4) action implementation) (Kaber & Endsley, 2004; Parasuraman, 2000; Wickens, 2018). Within each of these stages, the **level** of automation can vary from no automation to full automation. In a meta-analysis performed by

Onnasch et al. (2014), they found that the performance issues when automation fails are exacerbated when higher levels of automation are present for stages 3 and 4 (decision selection and action implementation), compared to stages 1 and 2. Essentially, high levels of automation of processes involving decision making and action implementation can cause important performance issues when manual takeover is required. It is thus recommended that workers be kept in the loop when it comes to decision selection and action implementation (Wickens, 2018). This can be done by allocating the function of decision selection and/or action implementation to the worker rather than an AI, or by keeping the level of automation to a maximum of medium for these two stages of information processing (Onnasch et al., 2014).

As the capability and ubiquity of AI are increasing, so too is the level of automation for the later stages of information processing. AI systems are increasingly capable of processing complex information, resulting in a greater capacity to perform tasks involving higher-level decision-making, which used to be performed exclusively by workers. AI systems can now recognise patterns, handle a large amount of data, and make real-time decisions. This increased capability of automation in the advanced stages of information processing leads to quicker and more accurate decision-making when all is well but leads to problematic performance when a human takeover is required due to malfunction, as demonstrated by the out-of-the-loop performance problem (Onnasch et al., 2014).

It is necessary to find ways to mitigate this issue, thus improving overall system performance specifically when automation malfunctions. One such mitigation is the development of competencies through worker training (Bahner et al., 2008; Dattel et al., 2023; Parasuraman & Riley, 1997). I4.0 and the resulting increased prevalence of human-AI collaboration have changed the necessary worker competencies, i.e., the skills, abilities, knowledge, and attitudes needed to effectively do one's job (Armstrong & Taylor, 2020; Da Silva et al., 2022; Hecklau et al., 2016; Oberländer et al., 2020). Indeed, different categories of competencies that are changing in the context of I4.0 have been identified: technical, methodological, and personal (Hecklau et al., 2016; Kowal et al., 2022). Here, we present only competencies relevant to human-AI interaction. For a complete description of all competencies, refer to Hecklau et al. (2016). Technical competencies include a greater and deeper understanding of processes due to a increased complexity of work systems, as well as more comprehensive technical skills for manual takeover in case of AI malfunction (Gehrke et al., 2015; Pacher et al., 2023). Methodological competencies include greater analytical and problem-solving capability to detect the source of an error within complex systems (World Economic Forum, 2016; Morgan, 2014; Pacher et al., 2023). Personal competencies include motivation to learn and ability to work under pressure to be able to adapt to changing technology and shorter product life cycles (Employment & Skills, 2014; Pacher et al., 2023).

5.2.2 Worker Training

Proper training is necessary for workers to develop these competencies. Training research has a century-long history, which provides "evidence-based recommendations and best practices for maximising training effectiveness" (Bell et al., 2017; Salas et al., 2012, p. 80). Four research themes have emerged, each contributing to the effectiveness of training: (1) training criteria, (2) trainee characteristics, (3) training context, and (4) training design and delivery. A short description of each theme will be presented, focusing on the relevant findings; for a comprehensive description, refer to Bell et al. (2017) and Salas et al. (2012).

5.2.2.1 Training criteria

Evaluating the effectiveness of training should be done using multi-dimensional outcomes (Bell et al., 2017; Kraiger et al., 1993). Specifically, skill-based outcomes, cognitive outcomes, and affective outcomes should be considered. Skill-based outcomes include performance metrics and related outcomes. Cognitive outcomes refer to knowledge organisation and cognitive state. For example, task engagement represents a cognitive state that facilitates knowledge acquisition. Affective outcomes relate to trainee motivation and related constructs. Considering all three dimensions will provide a better understanding of a training's success since it can affect multiple individual and organisational factors directly affecting a company's well-being (Salas et al., 2012).

5.2.2.2 Trainee characteristics

Individual characteristics that affect trainees' motivation to learn should be considered. This includes personality traits, such as trainee trait engagement (general causality orientation), which refers to one's perception of control over actions and events (Deci & Ryan, 1985). Trainee skills should also be taken into consideration so that the training can be adequately adapted.

5.2.2.3 Training context

The success of training depends not only on the training itself but on a variety of other factors related to the organisational context. Training effectiveness is heavily influenced by supervisor and peer support, as well as organisational learning culture. Additionally, it is essential to understand that skill decay occurs over that and that refresher training may be needed (Bell et al., 2017; Salas et al., 2012). Training context is not in the scope of the current experiment since our focus is on the short-term outcomes of training.

5.2.2.4 Training design and delivery

Training should focus on active rather than passive learning. Active learning should involve hands-on practice with the work system, allowing trainees to practice decision-making. Additionally, errors should be incorporated into training, allowing trainees to be better when errors happen during actual work (Salas et al., 2012; Sauer et al., 2016). Active learning techniques, such as problem-based learning or simulation-based learning, allow trainees to develop flexible and adaptive skills necessary to deal with complex work systems, such as those seen in I4.0 (Bell et al., 2017; Kozlowski et al., 2001; Léger et al., 2012). Active learning also promotes trainee motivation and engagement during learning. It is essential to design training in a way that promotes trainee motivation and engagement, as they are crucial determinants of training effectiveness and sustainment (Bell et al., 2017; Lazzara et al., 2021; Salas et al., 2012; Van der Klink & Streumer, 2002). Additionally, they are strong predictors of employee performance, turnover, absenteeism, innovation, organisational learning culture, and technology acceptance, among others (Akhlaq & Ahmed, 2013; Deci et al., 2017; Gerhart & Fang, 2015; Molino et al., 2020; Salas et al., 2012; Schmid & Dowling, 2020). The following sections will present the concepts of motivation and engagement within the context of employee training.

5.2.3 Worker motivation

Through meta-analytic evidence, theories of human motivation and work engagement were created. One of these theories, self-determination theory (SDT), provides a robust theoretical framework that can be leveraged to understand how elements of training design affect trainee motivation and engagement. At its core, SDT aims to explain how situations and environments impact a worker's motivation and engagement (Deci & Ryan, 2008). SDT states that workers have innate and universal needs, such as the need to feel a sense of self-efficacy (competence), to feel in control of their actions and decisions (autonomy), and to have meaningful social interactions (relatedness). The satisfaction of these needs dictate to what extent workers experience more self-determined motivation, i.e., motivation resulting from a greater internalisation of the motive for completing an action. Motivation lies on a continuum, starting from intrinsic on one end, to extrinsic at the center, to amotivation on the other end. Figure 5.1 illustrates this continuum. Intrinsic motivation relates to performing an action for its inherent enjoyment and because it is in line with the individual's values, interests, or aspirations. Intrinsic motivation represents the most self-determined type and is the strongest predictor of worker well-being and absenteeism (Van den Broeck et al., 2021). Extrinsic motivation relates to performing a task because of some external demand, such as an external reward or punishment avoidance. Extrinsic motivation is further divided into four types that vary in terms of internalisation, i.e., the degree to which the motive for performing an action is in line with their values, interests, or aspirations. A more self-determined subtype of extrinsic motivation, identified motivation, is of particular importance. This type of motivation represents completing a task because it is perceived as meaningful. Identified motivation is the strongest predictor of workplace performance, continuous effort investment, and other organisational citizenship behaviour (Van den Broeck et al., 2021). Amotivation represents a complete lack of motivation to perform an action. SDT's main premise is that satisfying workers' psychological needs of competence, autonomy, and relatedness leads to a greater internalisation of the motive for learning, which is synonymous with a more intrinsic type of motivation and regulation. In turn, motivation that is more intrinsically regulated will lead to workers being more engaged, innovative, generally happier, less likely to change jobs, and greater acceptance of technology (Deci et al., 2017; Meyer & Gagne, 2008; Venkatesh et al., 2002). When these needs are thwarted, workers are less intrinsically motivated, which is associated with burnout, stress, and disengagement, all of which affect their well-being (Deci et al., 2017). Unsurprisingly, training effectiveness, skill acquisition, and work performance are also negatively affected.

5.2.4 Worker engagement

A worker's engagement during training or a task is a direct consequence of their motivation and is associated with the same outcomes as motivation (e.g., well-being, performance, technology acceptance). Task engagement is a multi-dimensional concept consisting of a (1) dispositional (trait) dimension, a (2) psychological state dimension, and a (3) behavioural dimension (Macey & Schneider, 2008; Meyer et al., 2010). Trait engagement is defined as a worker's predisposition "to experience work in positive, active, and energetic ways and to behave adaptively" (Macey & Schneider, 2008, p. 21). Within the context of SDT, this means that some workers are more likely than others to perceive, behave, and think in ways that will satisfy their psychological needs (Deci & Ryan, 1985; Meyer et al., 2010). In essence, a worker's personality traits impact how they cognitively evaluate a situation as being more controlling or autonomy-inducing, which affects whether they will experience more intrinsic or extrinsic motivation and, consequently more engagement (Ryan & Deci, 2008; Szalma, 2020). State engagement is composed of a cognitive and an emotional component (Kahn, 1990; Schaufeli et al., 2002). Cognitive engagement is characterised by full concentration and mental absorption within a task. Emotional engagement encompasses positive and negative affect (valence), and emotional arousal/activation (Lang, 1995; Macey & Schneider, 2008). Behavioural engagement refers to observable indicators of engagement within a work task (Macey & Schneider, 2008). Both state and behavioural engagement are viewed as consequences of need satisfaction, i.e., a more intrinsically regulated type of motivation (Meyer et al., 2010).

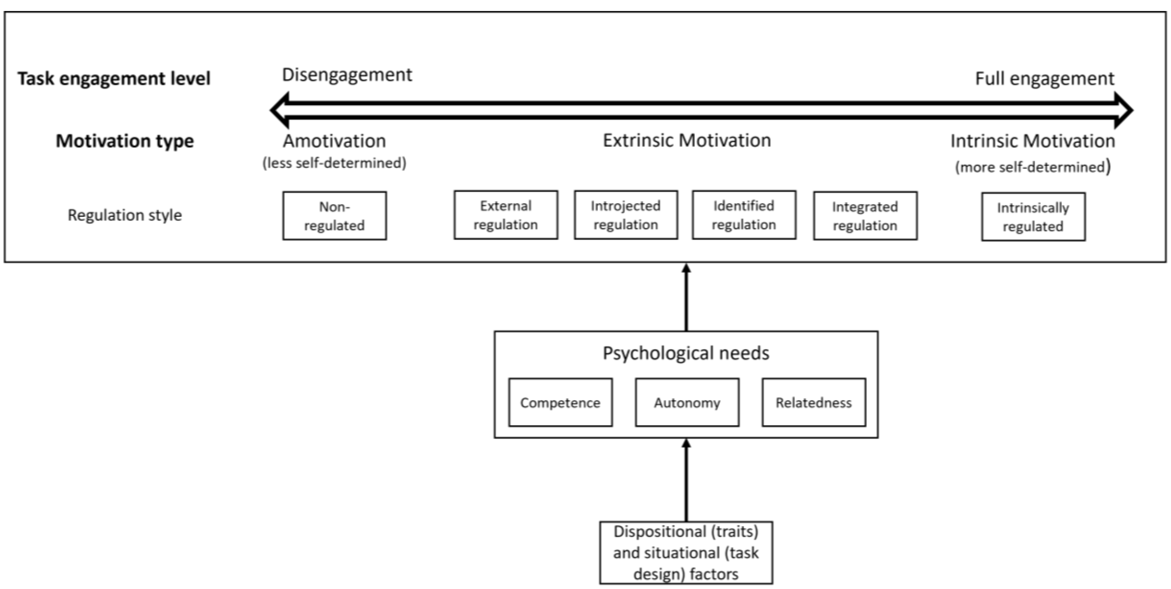

Figure 5.1: Motivation and Engagement Continuum (adapted from Meyer et al. (2010); Ryan and Deci (2000); Szalma (2014))

5.2.5 Worker training in Industry 4.0

Training workers to develop the competencies to be motivated and performant within I4.0 work systems has been consistently raised as a main concern for researchers and practitioners alike (Cazeri et al., 2022; Employment & Skills, 2014; World Economic Forum, 2016; Ivaldi et al., 2022; Pacher et al., 2023; Saniuk et al., 2021). Nevertheless, I4.0 research has focused mainly on technical and operational aspects rather than human-centric issues such as worker training (European Commission et al., 2021; Gagné et al., 2022; Kaasinen et al., 2018; Kadir et al., 2019; Neumann et al., 2021; Rauch et al., 2020). Some authors have taken a step forward by assessing how I4.0 technology can be used to aid in worker training, with a strong focus on virtual, augmented, and mixed reality (Carretero et al., 2021; Dhalmahapatra et al., 2021; Lopez et al., 2021; Simões et al., 2021; Ulmer et al., 2020; Vidal-Balea et al., 2020; Zawadzki et al., 2020). For example, Dhalmahapatra et al. (2021) evaluated the effectiveness of a virtual reality training to improve the safety of crane operators; Zawadzki et al. (2020) also assessed the effectiveness of virtual reality training to improve operational performance; in a similar vein, Casillo et al. (2020) evaluated the effectiveness of training using chatbots in a manufacturing setting. This research generally adopts an active learning approach, as recommended by training literature. In other words, workers are able to practice their decision-making skills and make errors safely with the help of virtual, augmented, or mixed reality. However, it does not seem to account for the importance of worker motivation and engagement, as main drivers of training effectiveness and other positive outcomes related to worker and company well-being (e.g., turnover, technology acceptance, worker performance). This hinders our ability to design training that enables workers to effectively collaborate with highly automated AI systems. To our knowledge, no paper has experimentally evaluated, using a multi-dimensional approach recommended in the training literature, the impact of using AI as a tool to train workers. In other words, no paper has used trainee performance, cognitive state, and affective/motivational state in conjunction to better understand how an AI can impact training effectiveness.

5.2.6 Hypothesis development

In the current study, we aim to understand how training design, in the context of highly-automated AI, impacts worker training effectiveness, motivation, and engagement. Specifically, we aim to understand how levels of automation of an AI system used to train workers impacts their motivation and engagement during training, as well as their ability to perform when AI malfunctions. Within the literature, it can be seen that full automation of decision selection (Stage 3 of information processing) represents the critical boundary after which human performance is strongly impacted when automation fails (out-of-the-loop performance effect) (Onnasch et al., 2014). Logically, it can be expected that workers being trained with an AI error-detection system (AIEDS) that fully automated the decision selection stage will not acquire the technical, methodological, and personal competencies to properly respond to a malfunctioning AI. On the other hand, being trained with an AIEDS that only partially automates decision selection should mitigate the out-of-the-loop performance effect. Indeed, partial automation during training is more aligned with an active learning approach, allowing workers to practice their decision-making and build the necessary competencies and motivation. Thus, partial automation of decision selection should lead to trainees gaining a deeper understanding of the work process being learned, more comprehensive technical skills, and better problem-solving capabilities, among others, which translates to better overall performance after training. As such, we hypothesise that:

- H1: Training completed with an AI system that partially automates decision selection (compared to full automation) will lead to better performance after training

Using a fully automated AI system during training also has implications for trainee motivation and engagement. Not having the decision-making aspect of the training present can have deleterious effects on worker autonomy and self-efficacy, two drivers of self-determined motivation and engagement. Indeed, full automation leaves participants no choice but to agree with the AI's recommendation, leaving little room for decisional latitude or opportunities for them to feel a sense of self-efficacy. On the other hand, the partially automated decision-selection merely suggests a decision, allowing participants to override the AI's recommendation. This may provide participants with a sense of decisional freedom while providing enough error-detection support for participants to feel competent. Thus, partial automation of decision selection should better motivate and engage trainees by satisfying their psychological needs, leading to greater skill acquisition. As such, we hypothesise that:

- H2: Training completed with an AI system that partially automates decision selection (compared to full automation) will lead to more self-determined motivation during training

- H3: Training completed with an AI system that partially automates decision selection (compared to full automation) will lead to more engagement during training

5.3 Materials and Methods

The following section will present the experimental design, sample, task, setup, procedure, as well as variable operationalisation, statistical analysis, and a priori power analysis.

5.3.1 Experimental design and sample

A total of 102 participants completed the laboratory experiment (67 men, 35 women). Gender was self-reported. Participants were recruited using a mass email sent to all undergraduate students. The average participant age was 21.97 (SD=2.69). No participant had any prior experience with the task chosen for this experiment. This experiment was reviewed and approved by HEC Montreal's research ethics board (certificate #2023-5058). Informed consent was obtained, and each participant was given 40€ for their participation at the end of the experiment. The experiment was conducted in French.

This study used a between-subject design. We have devised an experiment based on findings from worker training literature, i.e., considering the importance of training criteria (multi-dimensional evaluation of training effectiveness), of trainee characteristics (personality factors affecting motivation to learn), and of training design (active learning with a strong focus on motivation and engagement). Also, we have incorporated theoretical knowledge from SDT, which allows us to better understand how elements of training affect trainee motivation and engagement. To this end, we manipulated the level of automation of decision selection of the AIEDS during training (Part A), resulting in three conditions (1. No automation, 2. Full automation, 3. Partial automation). During the experimental task itself (Part B), automation was removed to simulate a failure of the AIEDS and thus evaluate skill acquisition (see Figure 5.2). Figure 5.3 shows the level of automation for each condition based on the four stages of information processing (Parasuraman et al., 2000). Refer back to section 2.1 for more details about this model and stages of information processing. Participants were randomly assigned to one of three conditions. This experiment was part of a larger experiment which consisted of nine conditions after the training.

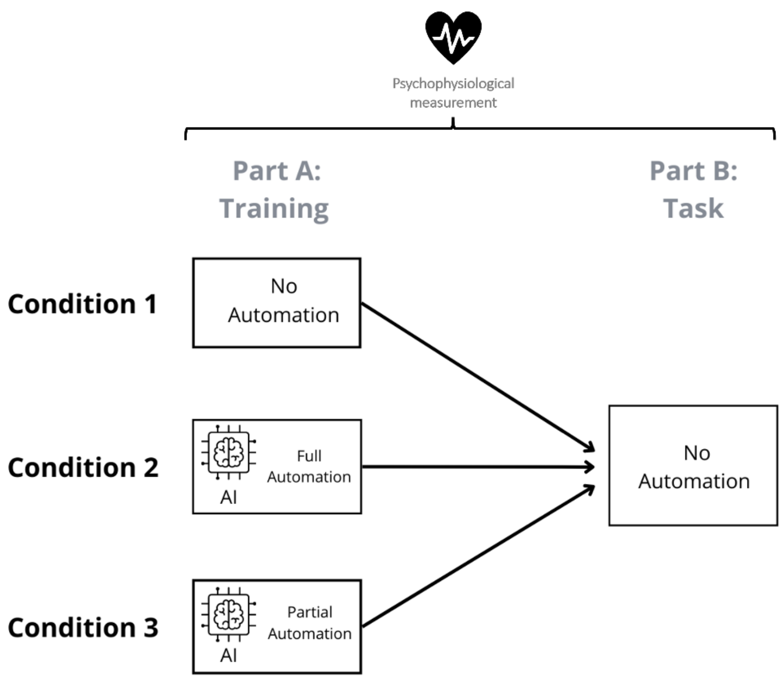

Figure 5.2: Experimental Design and Procedure

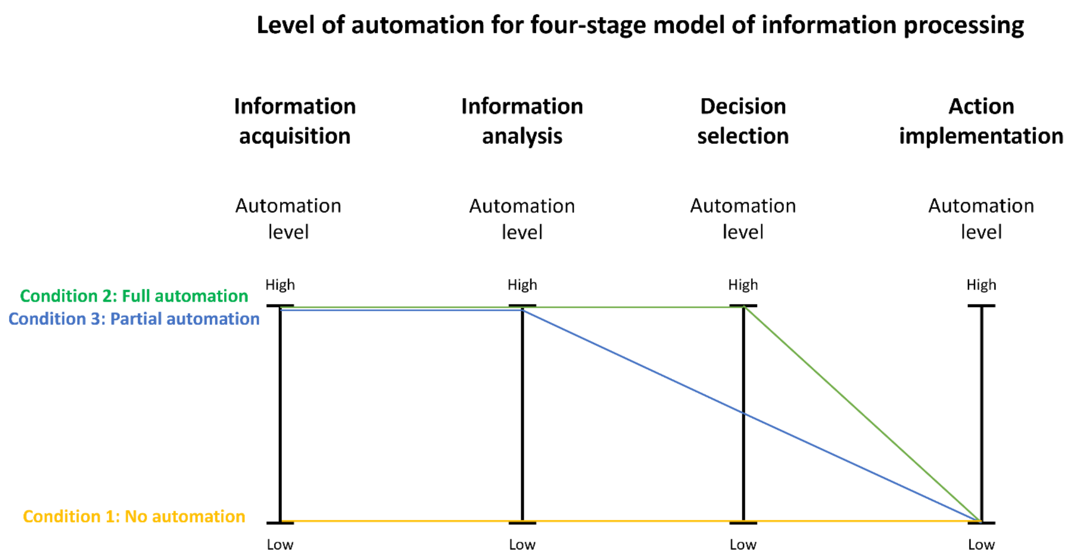

Figure 5.3: Level of automation for each condition (adapted from Parasuraman et al. (2000))

5.3.2 Training, experimental task, and setup

To create the experimental task (Part B), members of the research team went to the factory in which the product used (snowshoe) was built. We observed and filmed the employees completing their work tasks. We ascertained that each employee on the production line was responsible for assembling one component of the snowshoe and checking for defects/errors that previous employees may have committed. Employees spent approximately 20 seconds on each snowshoe before passing it on to the next worker. To maximise the study's ecological validity, we designed the experimental task in accordance with what was observed in the factory. Snowshoes (Figure 5.4), composed of many pieces that vary in terms of assembly difficulty, were an ideal product because they allowed us to completely control the presence of errors.

Figure 5.4: Snowshoe Used in the Experiment

To create the training, we based ourselves on the training literature. We took an active learning approach, in which participants were trained (Part A) with the exact same work system (interface) as the experimental task (Part B). Additionally, errors were incorporated, allowing participants to practice their decision-making and develop their technical, methodological, and personal competencies. The training task (Part A) was identical to the experimental task they had to perform afterwards (Part B).

Participants were instructed that they were the fourth worker on a four-worker snowshoe assembly line, i.e., the final worker. Their goal was to detect any possible errors made by the previous three workers and to finish assembling the snowshoe if no error was detected. Participants received snowshoes that were 90% assembled. Both tasks in Part A and Part B consisted of 30 of these snowshoes, which were placed on racks (120cm x 71cm x 103cm) next to the participant (see Figure 5.5 for workstation). For each snowshoe, participants scanned the barcode associated with it using a barcode scanner, placed it on the workstation, checked it for errors, indicated using the computer interface (Figure 5.6) whether or not they detected an error, assembled the remaining 10%, then put it back in its original place. Errors were artificially and systematically introduced into specific snowshoes by the researchers. Six snowshoes out of 30 contained these errors. Each error was unique and always appeared in the same snowshoe across participants. Each of the six errors was randomly assigned to one of the 30 snowshoes in the planning phase of the experiment. The order of the appearance of errors was different for Part A and Part B of the experiment.

The experiment was conducted at the DynEO learning factory in Aix-en-Provence (France). The room contained two identical workstations (see Figure 5.5), separated with a room divider so that participants could not see each other. The experimental setup can be seen in the video in the supplementary material or by following this link: https://youtu.be/xtcpxqcyz8k.

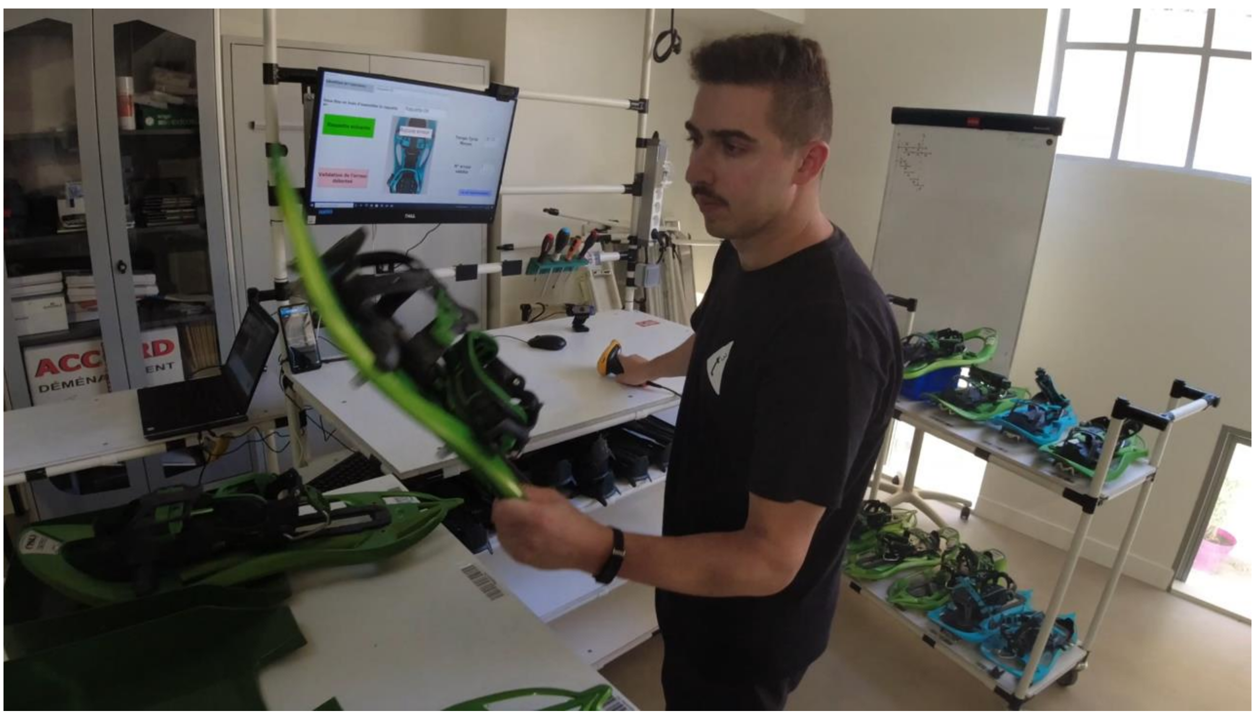

Figure 5.5: Participant Workstations

5.3.3 Procedure

Participants were told that the experiment involved evaluating their ability to detect production errors in snowshoes. They were told that they would be trained to complete error-detection and assembly tasks, comprising 30 snowshoes. They were told that the task they must complete during the training (Part A) and the experimental task (Part B) were identical; only that the AI would be removed for Part B. After signing the consent form, participants put on physiological vests under their clothes. They were then shown the workstation and the AI interface was explained to them, Additionally, the task was explained, and the six possible errors were shown. Participants then completed a pre-experiment questionnaire consisting of demographics and personality (trait engagement) questionnaires before moving on to Part A and Part B of the experiment. Both parts of the experiment were followed up with a questionnaire. See Figure 5.2 for the full experimental procedure.

In the *no automation* condition, participants were trained without any help from an artificial intelligence error-detection system (AIEDS). In the *fully automated AI* condition, decision selection (stage 3 of information processing), i.e., error versus no error, is fully automated by the AIEDS. The decision made by the AIEDS is always correct. Figure 5.6 shows the computer interface when the AIEDS detected an error and when no error was detected. Appendix C shows all possible errors that can be detected. In the *partial automation AI* condition, decision selection was partially automated by the AIEDS. Participants had to make the final decision about the presence of an error. The AIEDS acted like a decision-support tool by suggesting a decision to the participants. The AIEDS was correct in its error detection 83% of the time. Since each task contained six errors, this simply means that one of these errors was missed by the AIEDS (false negative). False positives, i.e., when the AIEDS detects an error without the presence of one, were not possible. Participants were informed beforehand of the AIEDS' percentage of reliability since prior studies have found that providing participants with accurate information about a system's reliability percentage improves their performance when using that system (Avril, 2022). The percentage itself was chosen based on past research. Reliability levels under 70% have been found to not be beneficial in terms of performance (Onnasch, 2015; Wickens & Dixon, 2007). Therefore, we opted to approximately split the difference between 100% and 70%. Additionally, a reliability percentage of approximately 85% has been commonly used in past studies (e.g., Avril et al., 2022; Wickens & Dixon, 2007).

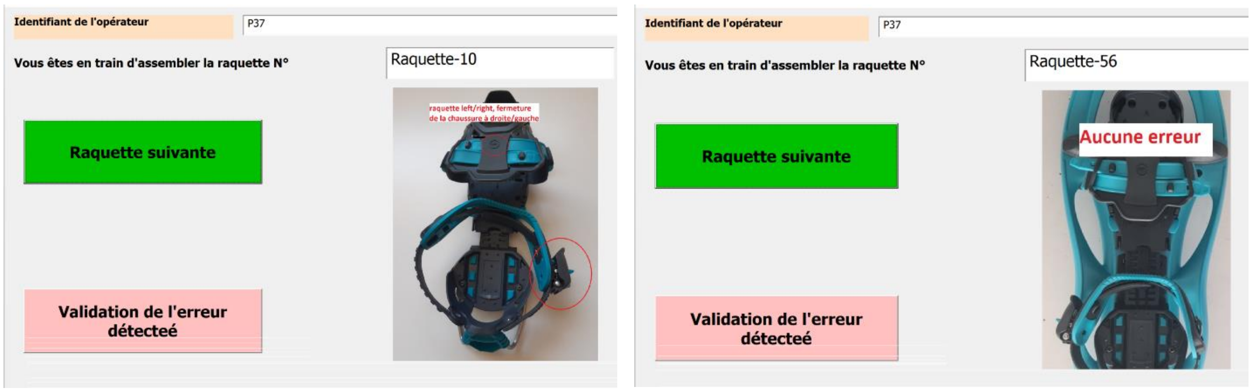

Figure 5.6: AIEDS When Error is Detected (Left) and No Error Detected (Right)

5.3.4 Variable operationalisation and measures

As recommended, the efficacy of training was evaluated using skill-based, cognitive, and affective outcomes (Bell et al., 2017; Salas et al., 2012). See Table 5.1 for a summary of variable operationalisation and measurement. Whenever possible, constructs were evaluated using a multi-method approach (perceptually and psychophysiologically). Psychophysiological measures allowed us to measure a participant's state without interruption throughout the whole task, thus limiting biases associated with using only perceptual measures.

The Hexoskin smart vest (Carré Technologies, Montreal, Canada) was used to capture the psychophysiological data, i.e., heart rate and respiration data. This vest captured 256 Hz 1-lead electrocardiogram data using a built-in electrode, 128 Hz respiration data using two built-in respiratory inductive plethysmography sensors, and 64 Hz acceleration/activity data using a built-in 3-axis accelerometer. The use of the Hexoskin smart vest has been evaluated and validated by a multitude of studies (Cherif et al., 2018; Jayasekera et al., 2021; Smith et al., 2019)

5.3.4.1 Performance

Time

The first of two key performance indicators is the amount of time taken for a participant to complete the task (hereinafter performance time). A lower time indicates better performance

Error detection

The second is the participants' error detection mistakes, operationalised as a percentage of correctness (hereinafter error detection performance). Percentage of correctness is negatively affected when participants fail to detect an error and when they falsely detect an error. Each mistake reduces the percentage of correctness by 1/30 since there are a total of 30 items per task. For example, one mistake in the whole task would produce a percentage of correctness of 96.96%, while two mistakes would lead to 93.33%, and so on. Therefore, a higher percentage indicates better performance.

5.3.4.2 Motivational needs

Motivational needs were measured using the autonomy (self-determination) and competence subscales of the empowerment scale (Spreitzer, 1995). Each subscale is composed of 3 items on a five-point Likert scale. The third psychological need, relatedness, was not addressed in this study because it relates to positive social interactions within the workplace. The scope of this study did not include any social interactions.

5.3.4.3 Motivation

Motivation was assessed using the French version of the situational motivation scale, created and validated by Guay et al. (2000). This questionnaire is composed of 16 items scored on a seven-point Likert scale. It is divided into four subscales, each of which represents a type of motivational regulation: intrinsic regulation, identified regulation, external regulation, and amotivation.

5.3.4.4 Cognitive task engagement

Self-reported

Cognitive engagement was measured using the absorption subscale of the Utrecht Work Engagement Scale (Schaufeli et al., 2003). The French version of the questionnaire was used, which has been validated (Zecca et al., 2015). This questionnaire is composed of 9 items scored on a seven-point Likert scale.

Psychophysiological

Using the Fast Fourier Transform on interbeat intervals (RR intervals), we derived the absolute power for the low frequency (LF) 0.04-0.15 Hz) and high frequency (HF) (0.15-0.4 Hz) bands of heart rate variability (HRV). The LF band of HRV is produced by both the parasympathetic (PNS) and sympathetic nervous system (SNS). On the other hand, the HF band of HRV has been shown to be produced mainly by the PNS (Shaffer et al., 2014). The SNS mainly controls “fight-or-flight” responses, while the PNS mainly controls the “rest-and-digest” responses. The LF/HF ratio is intended to estimate the ratio between SNS and PNS activity and has been shown to be an indicator of cognitive engagement during a task (Gao et al., 2020).

5.3.4.5 Emotional task engagement

Self-reported

The emotional component of state task engagement can be further subdivided into two sub-components: valence (happiness/sadness) and arousal (interest/boredom) (Lang, 1995; Macey & Schneider, 2008; Passalacqua, Léger, et al., 2020). We used Betella and Verschure’s (2016) affective slider, which consists of two sliders measuring valence and arousal on a scale of 0 to 100. The valence slider has sadness on one end and happiness on the other end, while the arousal slider has boredom on one end and interest on the other.

Psychophysiological

We have used respiration rate as an indicator of emotional arousal. This measure has been validated as an indicator of sympathetic and emotional arousal (Bradley & Lang, 2007). Respiration rate was measured using the two built-in respiratory inductive plethysmography sensors within the Hexoskin vest. Respiration data have been baselined at the participant level using a period of idle standing as the baseline.

5.3.4.6 Behavioural task engagement

Self-reported

Behavioural engagement was measured using the vigor subscale of the French version of the Utrecht Work Engagement Scale (Schaufeli et al., 2003).

Psychophysiological

Behavioural engagement is operationalised as the standard deviation of the intensity of movement (physical effort) during a task, measured in g-force (Gao et al., 2020). This is measured by the 3-axis accelerometer of the Hexoskin vest. A smaller standard deviation in movement intensity suggests that individuals are maintaining a consistent level of movement, reflecting sustained engagement, while a larger standard deviation indicates variability in movement, reflecting fluctuations in engagement (Gao et al., 2020).

5.3.4.7 Trait task engagement

Trait task engagement was measured using the French version of the general causality orientation scale (Deci & Ryan, 1985; Meyer et al., 2010). The French version has been validated by Vallerand et al. (1987). It consists of 12 vignettes depicting an achievement-oriented situation, about which the participant must answer three questions for each using a seven-point Likert scale. Each of the three questions represents a subscale of the questionnaire: autonomy, control, and impersonal. Participants scoring higher in autonomy are more likely to perceive situations or tasks as being autonomy-promoting and, thus are more likely to experience intrinsic, integrated, or identified motivation and higher engagement. Participants scoring higher in control are more likely to perceive situations or tasks as controlled by an external source and, thus are more likely to experience introjected or external motivation and less engagement compared to those who score higher in autonomy. Participants scoring higher in impersonal are more likely to feel unable to have an effect or control situations or tasks. They may experience a sense of helplessness and are more likely to experience amotivation and lack of engagement (Deci et al., 2017; Ryan & Deci, 2008; Szalma, 2020).

Table 5.1: Summary of variable operationalisation and measurement

Variable	Measure	Measure type	Operationalisation
Task performance time	Video recording	Observational	Time taken for a participant to complete the task (lower = better)
Task error detection performance	Excel output file	Observational	Percentage of correctness (higher = better)
Motivational needs	Psychological empowerment scale	Self-report	Competence and autonomy score
Motivation	Situational motivation scale	Self-report	Intrinsic, identified, external, and amotivation score
Cognitive engagement	Absorption subscale of UWES	Self-report	Cognitive absorption score
	Hexoskin vest	Psychophysiological	LF/HF ratio
Emotional engagement (arousal)	Affective slider	Self-report	Emotional arousal score
	Hexoskin vest	Psychophysiological	Baselined respiration rate
Emotional engagement (valence)	Affective slider	Self-report	Emotional valence score

Table 5.1 (continued and end)

Behavioural engagement	Vigor subscale of UWES	Self-report	Vigor score
	Hexoskin vest (accelerometer)	Psychophysiological	Standard deviation of the intensity of physical effort shown during a task
Trait engagement	General causality orientation scale	Self-report	Autonomy, control, and impersonal score

5.3.5 Statistical Analysis and Research Model

A type-3 analysis of variance (ANOVA) was conducted to determine the global effect of AI level of automation on each dependent variable. As recommended by both the training and motivation literature, trait engagement (individuals' predisposition to experience certain types of motivation and a certain level of engagement) was controlled for. Not controlling for these personality traits could introduce intragroup variability within our experimental conditions that can influence how AI type (independent variable) affects our dependent variables. Therefore, we attempted to reduce the confounding effect of trait engagement by entering it as a covariate in our statistical model. Figure 5.7 presents the research model. When we found globally significant effects, we used linear regressions to compare the pairwise least square means. These tests have been adjusted for multiple comparisons using the Holm method.

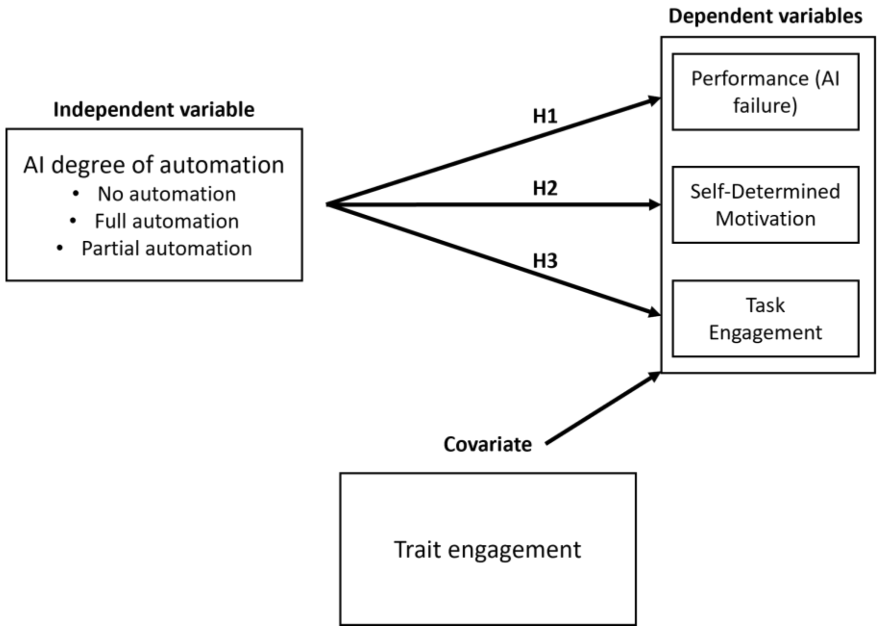

Figure 5.7: Statistical Model

5.3.6 A Priori Statistical Power Calculation

A priori statistical power calculations allow us to estimate the sample size necessary to achieve a sufficient level of statistical power. Statistical power refers to the probability of correctly detecting differences within the sample (Cohen, 1992). G*Power software (Faul et al., 2009) was used to calculate power in the planning phase of the experiment with the following parameters. The effect size was unable to be estimated from past studies, therefore we selected a small value (f=0.15) to be as conservative as possible. A power of 0.90 was selected; a minimum of 0.80 is recommended (Cohen, 1992). A 0.80 correlation among repeated measures was derived from pilot tests. In short, power calculations informed us that a sample size of 99 participants was deemed sufficient to correctly reject the null hypothesis with 90% certainty.

5.3.7 Transparency and Openness

All raw data, processed data, and statistical outputs on which the study's conclusions are based are available at https://data.mendeley.com/datasets/7njpg3g33g/2. Feel free to contact the corresponding author should you have any questions. This study's design and its analysis were not preregistered. We used R version 4.3.1 (Team, 2021) and Statistical Product and Service Solutions (SPSS) version 26 to conduct our analyses.

5.4 Results

Two participants were excluded due to technical issues with the equipment. A total of 100 participants were retained for analysis. Error bars on all graphs represent the standard error of the mean. No significant gender differences were observed.

5.4.1 H1: Training completed with an AI system that partially automates decision selection (compared to full automation) will lead to better performance after training

5.4.1.1 Performance time

A type-3 ANOVA showed no significant main effect of AI level of automation on performance time in the experimental task after controlling for trait engagement, $F(2, 27) = 1.74$, $p = .195$.

5.4.1.2 Error detection performance

A type-3 ANOVA showed a significant main effect of AI level of automation on error detection performance in the experimental task 2 after controlling for trait engagement, $F(2, 27) = 5.65$, $p = .009$, $\eta_p^2 = .30$. Post-hoc pairwise linear regressions revealed that error detection performance was significantly worse when being trained with the fully automated AI compared to starting to partial automation ($t = -3.02$, $p = .022$) or no automation ($t = -2.80$, $p = .052$). However, there were no significant differences between participants were trained with partial automation and no automation ($t = 0.22$, $p = 1$). Figure 5.8 shows these results. The x-axis show the condition participants were assigned to during training, while the y-axis show the participants' percentage of error detection correctness during the experimental task.

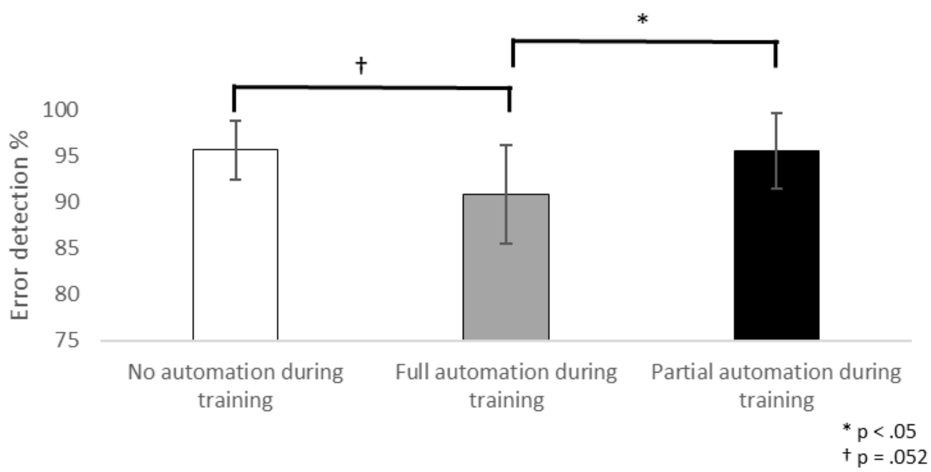

Figure 5.8: Error Detection During the Experimental Task

5.4.2 H2: Training completed with an AI system that partially automates decision selection (compared to full automation) will lead to more self-determined motivation during training

5.4.2.1 Motivational needs

Autonomy

A type-3 ANOVA showed a significant main effect of AI condition on autonomy after controlling for trait engagement, $F(2, 94) = 3.80$, $p = .026$, $\eta_p^2 = .08$. Post-hoc pairwise linear regressions revealed that autonomy was significantly higher using the partially automated AI compared to Full automation AI ($t = 2.67$, $p = .024$). However, no differences were observed between partial automation and no automation ($t = 0.97$, $p = .992$) or between Fully automated AI and No automation ($t = -1.72$, $p = .266$). Figure 5.9 shows these results. The x-axis shows the condition to which participants were assigned, while the y-axis shows the questionnaire score of the autonomy subscale of the empowerment scale during training (5-point Likert scale).

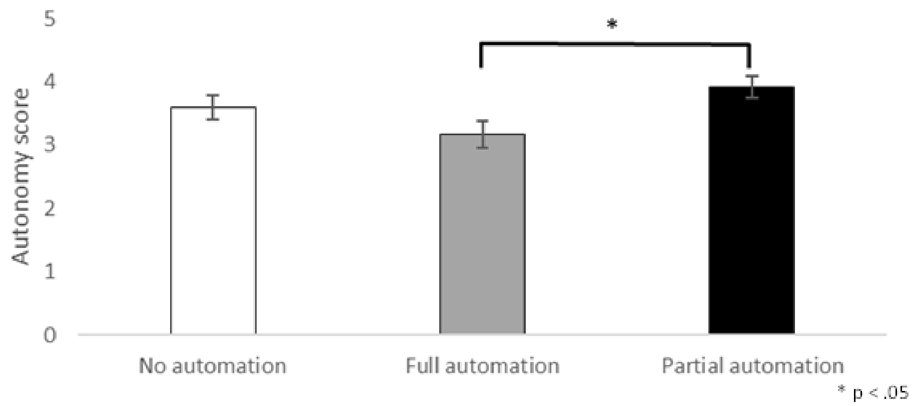

Figure 5.9: Perceived Autonomy During Training

Competence

A type-3 ANOVA showed no significant main effect of AI condition on competence after controlling for trait engagement, $F(2, 94) = 1.61$, $p = .206$.

5.4.2.2 Motivation

A type-3 ANOVA showed a significant main effect of AI condition on identified regulation after controlling for trait engagement, $F(2, 94) = 3.62$, $p = .031$, $\eta_p^2 = .07$. However, no significant main effect was found for intrinsic motivation ($F(2, 94) = 1.47$, $p = .236$), external regulation ($F(2, 94) = 1.164$, $p = .317$), or amotivation ($F(2, 94) = 1.03$, $p = .363$)

Post-hoc pairwise linear regressions revealed that identified regulation was significantly higher using partially automated AI compared to full automation AI ($t = 2.64$, $p = .029$). However, no differences were observed between partial and no automation ($t = 1.80$, $p = .224$) or between full automation and no automation ($t = -0.84$, $p = 1$). Figure 5.10 shows these results. The x-axis shows the condition to which participants were assigned, while the y-axis shows the questionnaire score of the identified regulation subscale of the situational motivation scale during training (7-point Likert scale).

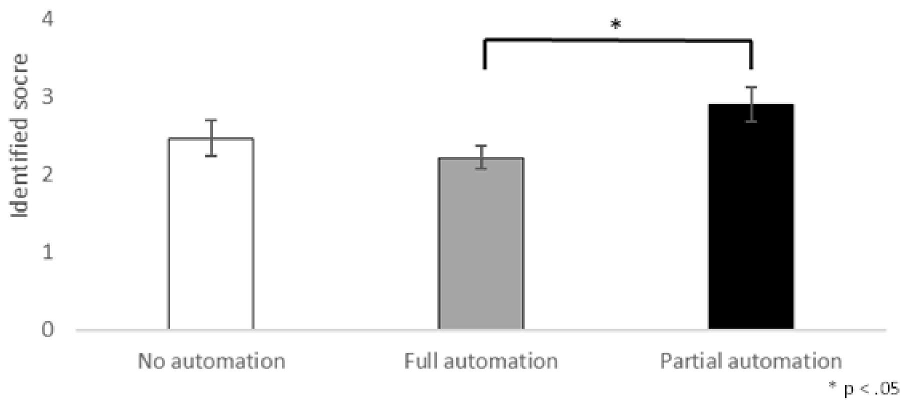

Figure 5.10: Identified Motivation During Training

5.4.3 H3: Training completed with an AI system that partially automates decision selection (compared to full automation) will lead to more engagement during training

5.4.3.1 Cognitive (state) engagement

Self-report

A type-3 ANOVA showed no significant main effect of AI condition on self-reported absorption after controlling for trait engagement, $F(2, 94) = 2.88$, $p = .061$.

Psychophysiological

A type-3 ANOVA showed no significant main effect of AI condition on LF/HF ratio (HRV) after controlling for trait engagement, $F(2, 91) = 0.06$, $p = .944$.

5.4.3.2 Emotional (state) engagement

Self-report

A type-3 ANOVA showed a significant main effect of AI condition on self-reported arousal after controlling for trait engagement, $F(2, 94) = 1.37$, $p = .260$.

A type-3 ANOVA showed no significant main effect of AI condition on self-reported valence after controlling for trait engagement, $F(2, 94) = 0.23$, $p = .796$.

Psychophysiological

A type-3 ANOVA showed no significant main effect of AI condition on respiration rate after controlling for trait engagement, $F(2, 86) = 2.09$, $p = .130$.

5.4.3.3 Behavioural engagement

Self-report

A type-3 ANOVA showed no significant main effect of AI condition on self-reported vigor after controlling for trait engagement, $F(2, 94) = 0.362$, $p = .697$.

Psychophysiological

A type-3 ANOVA showed a significant main effect of AI condition on standard deviation of the intensity of physical effort after controlling for trait engagement, $F(2, 91) = 15.34$, $p < .001$, $\eta_p^2 = .25$. Post-hoc pairwise linear regressions revealed the SD of the intensity of physical effort was significantly lower using the partially automated AI compared to full automation AI ($t = -5.18$, $p < .001$) and compared to No automation ($t = -2.29$, $p = .024$). Also, the intensity of physical effort was lower for No automation compared to Full automation AI ($t = -2.86$, $p = .01$). Figure 5.11 shows these results. The x-axis shows the condition to which participants were assigned, while the y-axis shows the standard deviation of movement intensity (G-force) during training, measured using a 3-axis accelerometer. A lower standard deviation indicates a higher behavioural engagement.

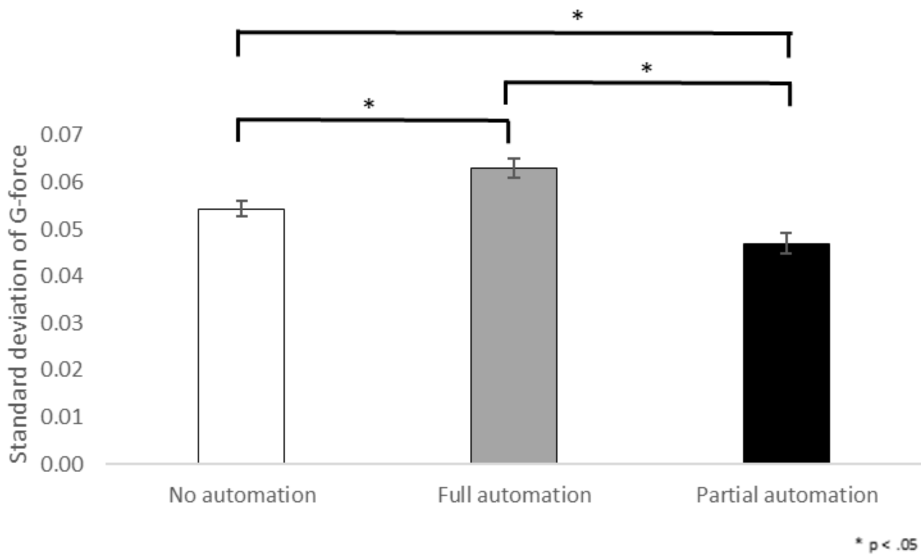

Figure 5.11: Intensity of Movement (Behavioural Engagement) During Training

Note. A lower standard deviation is indicative of higher behavioural engagement (Gao et al., 2020)

5.5 Discussion

The following section will discuss the results pertaining to each hypothesis, as well as the practical contributions and limitations.

5.5.1 H1: Training completed with an AI system that partially automates decision selection (compared to full automation) will lead to better performance after training

Results indicate that training with full automation of decision selection proved to be problematic when the AI was removed. Indeed, participants who were trained with the fully automated version of the AIEDS had a significantly worse error-detection performance in the experimental task (AIEDS malfunction) compared to participants who were trained with partial or no automation. Using a fully automated AI during training has hindered participants' acquisition of competencies, i.e., the skills, abilities, and knowledge necessary for manual takeover of the error-detection task. No such effect was found when participants were trained with partial automation since their error-detection performance was equivalent to that of participants who were trained without automation, thus confirming H1. These results are in line with previous research on automation, indicating that full automation of decision selection (stage 3) represents a critical boundary, at which point humans are very vulnerable to automation failure. Whereas when humans select the final decision (partial automation of stage 3), manual performance when automation malfunctions is less affected (Onnasch et al., 2014; Parasuraman et al., 2000). Our results build upon these findings, indicating that the level of automation matters during training as well. Indeed, the critical boundary of automation affects worker skill acquisition, suggesting that training with high automation may impede the development of the technical, methodological, and personal competencies necessary to manually takeover for a malfunctioning AI. Full automation of decision selection keeps trainees out of the decisional loop, not allowing them to practice decision-making and make errors, creating a passive learning approach, rather than an active one. Practitioners creating training should avoid automation past the critical boundary, even though the capabilities of AI are increasing. They should focus on creating training curricula that employee an active learning approach, i.e., problem- or simulation-based learning in which trainees could experiment with decision-making and with errors. As such, they will be able to better comprehend and manage I4.0 work systems, which are growing in complexity with every advance in technology.

5.5.2 H2: Training completed with an AI system that partially automates decision selection (compared to full automation) will lead to more self-determined motivation during training

5.5.2.1 Motivational needs

Participants felt the strongest sense of autonomy when being trained with the partially automated AIEDS. To put this result into context, it is necessary to break down the participant/worker role in each AI condition. Within the no automation condition, participants were responsible for examining each snowshoe and deciding whether an error was present. While they had complete decision-making freedom, error-detection without the AIEDS is repetitive in nature, resulting in very low task variety, which may have negatively affected their perception of autonomy during training. In the fully automated, the AI made the decisions, and the worker simply had to implement them, i.e., assembling or discarding the snowshoe, without much leeway in terms of decision-making. Participants may have felt that the AI was in control of the training rather than themselves, negatively affecting their perception of autonomy. In the partial automation condition, participants were monitoring the AI's decisions, with the freedom to decide whether to accept or reject those decisions. While the AI was doing most of the repetitive work (error detection), participants were left with a supervisory role, characterised as more meaningful and gratifying, which positively affected their perception of autonomy.

Regarding participants' perception of competence during training, we observed no differences between the three conditions. When looking at the mean values for each condition, we see that all values are above 4.25 on a five-point Likert scale, indicating that participants felt a rather strong sense of self-efficacy or capability to successfully complete the training. A lack of differentiation between conditions could be due to the training not being difficult enough. A higher degree of difficulty could have put participants' feeling of competence to the test, which could have resulted in significant variability between conditions. Nevertheless, equally high competence between conditions indicates that participants did not feel less supported or empowered by partially automated compared to fully automated AI.

5.5.2.2 Motivation

From most self-determined/internalised to least self-determined/internalised, four types of motivation were measured: intrinsic regulation, identified regulation, external regulation, and amotivation (see Fig. 5.1). Results indicate that identified regulation was higher when participants used partially automated AI compared to fully automated AI. No differences were found within the other types of motivation. Identified regulation represents performing a task because it is perceived as meaningful. It implies a significant internalisation, meaning that the motive for completing the task has been integrated into the self and has a certain means-to-end value for the participant. Putting this into context, the results indicated that participants in the partial automation condition attributed a greater meaning to the completion of the training, compared to the other conditions. This can be explained by higher levels of perceived autonomy due to participants in this condition having decision authority over the AI. Identified motivation has been shown to be the strongest predictor of performance and organisational citizenship behaviours (e.g., continuous effort investment, commitment) (Van den Broeck et al., 2021). These results indicate that partial automation should lead to the best long-term outcomes for organisations. Overall, results show support for H2. The partial automation condition led to the most self-determined motivation, which is crucial for the success and sustainment of any training (Bell et al., 2017; Lazzara et al., 2021; Salas et al., 2012; Van der Klink & Streumer, 2002). As such, maximizing the level of automation may not be the ideal solution for successful skill acquisition. As the prevalence of human-AI collaboration is increasing, it is more important than ever for practitioners to strive for a balanced level of automation and design trainings to allow trainees to feel in control of their decisions/action rather than being controlled by an automated system.

5.5.3 H3: Training completed with an AI system that partially automates decision selection (compared to full automation) will lead to more engagement during training

5.5.3.1 Cognitive, emotional, and behavioural engagement

No significant differences were observed when looking at self-reported cognitive engagement, i.e., mental absorption during a task, or cognitive engagement measured psychophysiologically (LF/HF HRV ratio).

We observed no differences for emotional arousal measured perceptually or psychophysiologically (respiration rate). For self-reported emotional valence, no differences were observed. When looking at the mean values for each condition, values are between 52-61 (scale is 0-100). This indicates a neutral valence, not positive nor negative. The lack of significant differences may be due to the training being unable to produce any significant affective response from participants.

We observe no significant differences between conditions for self-reported behavioural engagement, i.e., the perceived investment of physical energy into the task. For psychophysiological measurement of behavioural engagement (standard deviation of the intensity of movement), partial automation led to the highest engagement, while full automation led to the lowest. This means that participants were more behaviourally engaged during the training when in the partial automation condition.

Overall, results show some support for H3. The partial automation condition seems to lead to the best outcomes only in terms of behavioural engagement (psychophysiological). This means that participants were the most physically engaged in the training when decision selection was only partially automated. As seen in SDT, this is most likely due to stronger feelings of autonomy and more self-determined motivation (Deci et al., 2017). Indeed, autonomy and self-determined motivation are antecedents of task engagement. Task engagement itself lead to better skill acquisition, which could have contributed to the best performance being in the partial automation condition. For all other variables, we observe no significant differences between the conditions, indicating that one does not lead to better or worse outcomes than the others.

5.6 Conclusion

Using skill-based, cognitive, and affective criteria to evaluate the effectiveness of training, we found that partial automation led to the most positive outcomes. Indeed, workers retaining decision-selection authority during training led them to feel a stronger sense of decisional latitude (autonomy), self-determined motivation, and behavioural engagement during training. In turn, this better allowed workers to develop their technical, methodological, and personal skills, which led to them being able to better adapt to AI failure, as indicated by better error-detection performance. Within the context of worker training in Industry 5.0, these results imply that AI may have more value as a decision aid rather than a decision selector during training.

From a practical perspective, those responsible for creating training should be mindful when deciding the level of automation an AI system provides at the decision-selection stage of information processing. Care should be taken to nurture trainee perceptions of autonomy, i.e., their perception of being in control of their behaviours and actions, through increased worker decisional power, for example (Gagné et al., 2022). These considerations will positively impact both the worker and the organisation. Workers will be more motivated and engaged during training and perceive it as more meaningful, improving their competency acquisition. Positive effects are also seen after training through improved performance, technology acceptance, and well-being (Bell et al., 2017; Deci et al., 2017; Molino et al., 2020). Organisations will benefit from improved productivity, reduced turnover, safety incidents, and absenteeism, among others (Lazzara et al., 2021; Mann & Harter, 2016; Schmid & Dowling, 2020). From a societal perspective, policymakers can use these insights to guide regulations and initiatives that support workforce development in the face of rapid technological advancement. By promoting training programs that balance AI capabilities with human skill and decision-making, policies can foster a workforce that is adaptable and competent in an increasingly automated world. Socially, this research contributes to a narrative that values the human element in the age of AI. By ensuring that technological advancements do not diminish human importance in manufacturing systems or in operations but rather complement them, we can influence public attitudes towards technology in the workplace, enhancing overall quality of life.

Our study has two main limitations. First is that our dependent variables were measured in the short term. While extrapolation to the long-term can be done through the lens of our theoretical framework (SDT), a longitudinal study would be ideal to test skill retention, motivation, and engagement over time. A second limitation is that our sample consisted of university students, not actual factory workers. University students may have different levels of familiarity with AI systems, varying motivation levels due to the experimental context, and less experience in a manufacturing setting. Factory workers may have more practical experience, pre-existing skills specific to manufacturing environments, and resistance to change. These differences could influence how each group interacts with AI systems, their learning curve, and how they perceive and adapt to AI-assisted training. As such, skill acquisition, motivation, and engagement could be different between groups. Acknowledging this, our results necessitate further validation with actual factory workers to enhance their applicability in real-world manufacturing settings. Nevertheless, we attempted to maximise ecological validity through the selection of an experimental task that was identical to one of those in the actual factory. Additionally, the experiment was conducted within a learning factory setting.

The current research reinforces the need to gain a deeper understanding of the impact of new technology on manufacturing workers. More research applying self-determination theory to the training of workers using highly-automated AI systems should be conducted to explore how to effectively support workers' motivational needs. Additionally, future research should validate our current findings longitudinally and with a sample of actual factory workers. Lastly, future research could experimentally evaluate the use of other I4.0 technologies for worker training (e.g., augmented/virtual reality, digital twin) using the multi-method, multi-dimensional, and human-centered approach used in this paper.

CRediT author statement

Mario Passalacqua: conceptualisation, methodology, validation, investigation, writing - original draft, visualisation, project administration. **Robert Pellerin:** conceptualisation, methodology, resources, writing - review & editing, supervision, funding acquisition. **Esma Yahia:** conceptualisation, methodology, software. **Florian Magnani:** conceptualisation, methodology, investigation, writing - review & editing. **Frédéric Rosin:** conceptualisation, methodology, resources. **Laurent Joblot:** conceptualisation, methodology, resources, writing - review & editing. **Pierre-Majorique Léger:** conceptualisation, methodology, resources, writing - review & editing, supervision, funding acquisition.

Funder information

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Declaration of interest statement

We have no known conflicts of interest to disclose.

CHAPTER 6 ARTICLE 3: ASSESSING RISK FACTORS IN LAST-MILE DELIVERY DRIVING: A MULTI-METHOD LONGITUDINAL FIELD STUDY

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Abstract

In the fast-paced world of logistics and delivery, the role of a delivery driver is both vital and perilous, critically supporting global commerce yet facing inherent risks that can compromise safety and health. Occupational hazards such as stress, fatigue, and inattention are prevalent among drivers, exacerbated by high-traffic conditions, tight schedules, and long shifts. These factors contribute to a high and increasing incidence of transportation-related accidents and health issues. In this longitudinal field study, we aimed to assess how situational variables such as shift length, delivery area, and delivery lateness affect drivers' physiological and psychological states, and consequently, their driving behaviors. The objective was to fill the gap in understanding the real-world impacts of these phenomena on driver safety and to provide a data-driven basis for targeted occupational health interventions. Employing a multi-method approach, this study integrated physiological measures (heart rate variability and respiration), self-reported data on stress and fatigue, and behavioral observations of driving practices (e.g., attention, hard braking, sharp turning). This methodology was applied in a naturalistic driving study involving three delivery drivers over three full shifts, capturing data that reflects the complexities of their work environment. Key findings indicated significant physiological and psychological impacts associated with different driving conditions, which correlate with specific risky driving behaviors. Specifically, we found that situational variables significantly influence drivers' stress and fatigue, affecting their driving behavior and attention. These results underline the importance of considering environmental and operational factors in developing interventions aimed at reducing occupational risks for delivery drivers.

Keywords: Delivery driving; Stress; Fatigue; Attention; Risky driving behavior; Occupational health

6.1 Introduction and Literature Review

In the fast-paced world of logistics and delivery, the role of a last-mile delivery driver emerges as both vital and perilous. In 2021, transportation incidents were the leading cause of work-related fatalities, accounting for 37.3% of all occupational deaths in the USA (Labor, 2023). Furthermore, from 2021 to 2022, there was an 8% increase in fatalities among driver/sales workers and truck drivers, rising from 1,032 to 1,115 (Labor, 2023). Focusing specifically on delivery drivers, they faced a substantial 40% increase in injuries from 2020 to 2021, with one in five drivers affected in 2021, highlighting the growing hazards in the profession (Center, 2022). As urban populations expand and the demand for quick delivery escalates, delivery drivers will be increasingly exposed to occupational hazards. From 2021 to 2023, global e-commerce sales surged from $4.98 trillion to $5.82 trillion, marking a 17% increase (Shopify, 2024). Projections indicate an annual increase of 8.8%, reaching nearly $8 trillion by 2027, which represents a cumulative increase of about 60% from 2021 (Shopify, 2024). This rapid growth in e-commerce directly contributes to the increase in the number of delivery vehicles on the road, with the number of delivery vehicles in major cities expected to grow by 36% by 2030. The rise in the number of delivery drivers means more workers are exposed to the risks inherent in this profession, increasing the likelihood of incidents.

These trends underscore the need to understand and mitigate the inherent dangers faced by delivery drivers and to delve into the occupational hazards, along with the psychological and physical challenges delivery drivers face.

6.1.1 Occupational Hazards, Fatigue, Stress, Inattention, and Risky Driving Behavior

The occupational hazards faced by delivery drivers are numerous and varied. Drivers routinely navigate and park in high-traffic environments, manage tight delivery schedules, and handle the physical demands of loading and unloading packages, often over long shifts. These conditions are conducive to elevated levels of occupational stress, fatigue, and inattention, which are significant contributors to both minor and severe accidents. In fact, within the literature, fatigue and inattention are consistently identified as two of the most prominent factors that cause accidents, with fatigue leading the way, being the cause of approximately 30% of accidents (Dahlman et al., 2024; Loew et al., 2024; Salmon et al., 2019). The three other prominent factors are driving under the influence of alcohol or drugs, failure to wear a seatbelt, and risky driving behavior, such as harsh driving and speeding (Cendales et al., 2023; Loew et al., 2024).

Fatigue, often used synonymously in the literature with drowsiness and sleepiness, is defined as a state of reduced mental and physical performance resulting from prolonged mental or physical activity (Hecht et al., 2019; K. Lu et al., 2022; Warwick et al., 2015). Fatigue manifests as decreased alertness, slower reaction times, impaired judgment, and difficulty concentrating – all critical factors for safe driving (Vogelpohl et al., 2019). According to May and Baldwin (2009), fatigue can emerge from two causes: sleep-related or task-related. Sleep-related refers to the circadian rhythm, sleep duration, and quality of sleep, while task-related refers to task load (overload or underload), time spent driving, or other factors inherent to driving.

Stress is defined as a transition from a state of calm to a state of excitement, which serves to maintain a person's equilibrium (Healey & Picard, 2005; Kopin et al., 1988). While stress can have a positive dimension (e.g., excitement, joy), this article will focus on the negative dimension (e.g., distress). It can manifest in various ways, impacting both psychological well-being (anxiety, frustration) and physiological responses (increased heart rate, blood pressure). Stress is closely linked to fatigue; when the body remains under stress for extended periods, it depletes its resources, leading to fatigue and hindering its ability to cope with additional challenges (Cendales et al., 2023; Hancock, 1989). This can significantly impact activities requiring sustained focus and alertness, such as driving, where fatigue and stress together significantly increase the risk of accidents (Shamsul et al., 2014). Both fatigue and stress have been shown to significantly impact a driver's attention on the road and their driving behavior (Ge et al., 2014; Useche et al., 2017). Indeed, fatigue and stress have been found to reduce a driver's ability to remain alert and maintain attention (Chen et al., 2017; Lal & Craig, 2001). Additionally, fatigue and stress have been found to increase risky driving behaviour, such as speeding and harsh driving (Cendales et al., 2023; Öz et al., 2010). Overall, both a lack of attention on the road and risky driving behaviors are causal factors of road accidents (Cardoso et al., 2019; Labbo et al., 2024; Singh & Kathuria, 2021).

The following section covers the methods used in the literature to measure these factors.

6.1.2 Measuring Fatigue, Stress, Inattention, and Risky Driving Behavior

In the literature, driver fatigue has most often been measured using self-report scales or observer ratings (K. Lu et al., 2022). The scales include the Standford Sleepiness Scale (SSS) and the Karolinska sleepiness scale (Åkerstedt & Gillberg, 1990; Hoddes et al., 1973). Observer ratings involve an external observer assessing the fatigue levels of drivers based on visual observations, often through video monitoring. Other measures of fatigue include camera-based, neurophysiological, and physiological measures (Loew et al., 2024; K. Lu et al., 2022; Sikander & Anwar, 2018). These other methods offer a continuous and more objective assessment of fatigue without relying on self-report or external observers, thereby enhancing the accuracy and reliability of fatigue detection.

Camera-based fatigue detection systems have become increasingly common in the trucking industry. These systems measure fatigue by monitoring behavioral indicators such as eye movements, blink rate, eye closure duration, gaze direction, head position, and facial expressions (Sikander & Anwar, 2018; Soliani et al., 2023). Advanced algorithms process these data in real-time to detect signs of drowsiness and inattention, providing immediate feedback to the driver and potentially alerting fleet managers (Loew et al., 2024).

Neurophysiological measures refer to brain activity monitoring techniques such as electroencephalography (EEG). EEG has been used to measure fatigue by analyzing changes in brain wave patterns, particularly increases in theta waves and decreases in alpha wave activity, which are indicative of drowsiness and reduced alertness (Correa et al., 2014; Sanjaya et al., 2016; Trejo et al., 2015). Physiological measures, such as heart rate variability (HRV) and respiration, have also been employed to infer fatigue by monitoring the autonomic nervous system's responses (Dahlman et al., 2024; He et al., 2024; K. Lu et al., 2022). HRV is the variation in time intervals between heartbeats, indicating changes in autonomic nervous system balance as a result of mental or physical states (e.g., fatigue, stress) (Cacioppo et al., 2007).

Similarly, the measurement of driver stress often relies on self-reported measures. Tools such as the Driver Stress Inventory (DSI) and the Driver Coping Questionnaire (DCQ) are commonly used to gauge drivers' perceived stress levels during driving tasks, as highlighted in studies by Cardoso et al. (2019), Öz et al. (2010), and Matthews et al. (1996). Physiological measures, such as HRV and respiration are also used as more objective way of inferring driver stress (Chen et al., 2017; Healey & Picard, 2005; Jung et al., 2014; Kiashari et al., 2018).

HRV indices such as SDNN (Standard Deviation of NN intervals), LF (Low Frequency) HRV and HF (High Frequency) HRV serve as markers of autonomic nervous system function, reflecting the body's response to stress and fatigue (Kim et al., 2018; Passalacqua, Pellerin, Yahia, et al., 2024). Specifically, SDNN represents the variability in the time intervals between successive heartbeats. A decrease in SDNN suggests heightened stress, indicating reduced variability between heartbeats and a diminished capacity to adapt to stressors (Healey & Picard, 2005; Kiashari et al., 2018). An increase in SDNN, on the other hand, is indicative of greater drowsiness/fatigue (Ishaque et al., 2021). Additionally, LF, ranging from 0.04 to 0.15 Hz, is associated with both sympathetic and parasympathetic activities, and often rises with increased sympathetic activation due to stress (Ishaque et al., 2021). Conversely, HF, which spans 0.15 to 0.4 Hz, correlates with parasympathetic activity and usually increases as fatigue sets in, reflecting the body's attempt to maintain balance (Miyaji et al., 2009; Warwick et al., 2015). Moreover, respiratory rate is another physiological indicator used to infer fatigue; specifically, a decreased respiratory rate can indicate increased fatigue (Kiashari et al., 2018; Tateno et al., 2018).

Attention in driving research is primarily gauged through behavioral observations, self-reports, and neurophysiological measures (Hecht et al., 2019; Kotseruba & Tsotsos, 2022; Trick et al., 2004). Behavioral observations in driving simulators often include tracking eye movements and response accuracy to unexpected road events, providing direct insights into a driver's focus and situational awareness. Self-reported measures involve drivers assessing their own levels of alertness or concentration, offering subjective data on their perceived attention states. Additionally, neurophysiological techniques like EEG measure brain activity patterns related to attention, where changes in specific brain waves such as alpha and beta indicate varying levels of cognitive engagement (Léger et al., 2014; Passalacqua, Léger, et al., 2020). Lastly, recent approaches have utilized camera-based systems to monitor the three-axis movement of the head as a proxy for attention on the road (Chen et al., 2017). These systems can robustly capture head orientation and motion, offering insights into driver alertness and focus without the intrusiveness or technical limitations of EEG and eye-tracking systems.

Risky driving behaviors such as hard acceleration, hard braking, and sharp turning are often quantified using accelerometers installed in vehicles (Freidlin et al., 2018; Singh & Kathuria, 2021). These accelerometers measure g-force events along the x (lateral), y (vertical), and z (longitudinal) axes, capturing moments that exceed a specific threshold, often set at 0.45 g, to distinguish normal driving actions from potentially dangerous ones (Freidlin et al., 2018). Hard acceleration is detected when the vehicle's speed suddenly increases, generating forward g-forces that surpass the 0.45 g threshold. Hard braking is characterized by intense deceleration, resulting in negative g-forces that also exceed this threshold. Similarly, sharp turning involves lateral g-forces significantly higher than those observed in regular turning maneuvers, indicating a rapid change in direction that could pose a risk to vehicular control.

Overall, research shows that a multi-method approach in driving research is crucial to thoroughly understand the effect of risk factors on drivers. This approach integrates self-reported measures, observational techniques, and neurophysiological or physiological data to provide a comprehensive analysis of driver behavior and safety. Each method addresses limitations inherent in the others, enhancing the overall validity of the findings through methodological triangulation (De Guinea et al., 2013). This integrated approach ensures a comprehensive assessment of the driver’s state, shedding light on the complex interplay of various factors affecting driver behavior and safety. For example, questionnaires like the DSI for stress and the SSS for sleepiness yield subjective insights, while accelerometers and cameras offer observational data on risky behaviors and attention levels. Neurophysiological tools like EEG and physiological indicators like heart rate and respiration provide objective data on drivers' attention, stress, and fatigue.

However, the application of this multi-method approach has predominantly occurred within laboratory or simulator settings (He et al., 2024). While these controlled environments allow for precise manipulation of variables and direct observation of driver behavior under varied conditions, they pose significant challenges in translating findings to real-world settings (Bowen et al., 2020; Cao et al., 2022; Sutantio & Widyanti, 2022). The primary drawback of relying heavily on laboratory and simulator studies is that they may not accurately reflect the dynamic and often unpredictable conditions drivers face on the road (Singh & Kathuria, 2021). This discrepancy can lead to over-simplified models of driver behavior that fail to account for the complexities of real driving environments.

The preference for controlled settings stems from several challenges associated with implementing a multi-method approach in naturalistic driving studies (He et al., 2024). For example, eye-tracking faces important issues outside of laboratory settings due to calibration drifts and the difficulty in maintaining accuracy in varying lighting conditions (Hecht et al., 2019). Also, neurophysiological measures such as EEG are impractical in real-world scenarios due to the cumbersome nature of the equipment, which is unsuitable for the dynamic environment of a vehicle, particularly in delivery driving where constant movement in and out of the vehicle is required (Fu & Wang, 2014). Although physiological measures are less intrusive than neurophysiological measures, they still present challenges. These include limited battery life, the complexity of data synchronization between physiological and other types of measures, and considerable variability in results across different studies, influenced by variations in study design and the multifaceted nature of fatigue and stress (K. Lu et al., 2022). This can affect the reliability of data collected in uncontrolled settings, necessitating careful calibration and potentially complex setups to ensure data integrity without interfering with the driver's natural behavior or the vehicle's operation.

Nevertheless, physiological measures, such as heart rate and respiration data, have emerged as viable alternatives to neurophysiological measures. In general, they are less intrusive and do not restrict movement, making them more suitable for continuous monitoring in real-world driving scenarios (Bowman et al., 2021; Chen et al., 2017; Lal & Craig, 2001; Vicente et al., 2016; Zhou et al., 2020). Advances in wearable technology have further enhanced the accessibility and non-intrusiveness of these methods, allowing for real-time, objective assessments of fatigue and stress that circumvent the subjectivity of self-reports and observer ratings.

In summary, most existing studies are constrained to laboratory or simulator settings, which do not fully capture the dynamic interactions and complexities of real-world driving environments. By focusing solely on controlled environments, prior research often fails to account for the real-time, situational variables that significantly influence driver behavior. This limitation reduces the ecological validity of the findings and restricts their applicability to actual driving scenarios. To address the current gap in naturalistic driving studies, this research proposes a different approach that combines self-reported, observational, and physiological data.

6.1.3 Research Objectives

The paper's general objective is to depict the dynamic interactions and complexities found in real-world driving environments. Our primary objective is to assess how situational factors influence drivers' levels of fatigue, stress, attention, and engagement in risky driving behaviors. Additionally, the study examines the relationships between drivers' fatigue and stress and their impact on attention and risky driving behaviors and aims to offer deeper insights into how specific elements of drivers' work environments contribute to critical safety outcomes, thereby informing targeted interventions to enhance driver well-being and safety.

The proposed methodology consists of an observational longitudinal case study within a grocery delivery company, where three drivers were monitored over three complete shifts across a single week. The application of the methodology provided a detailed view of the drivers' experiences in a real-world context, capturing data on various situational factors such as the area of delivery, shift length, delivery timing, and portion of the shift. This approach allows for a holistic understanding of the multifaceted influences on driver behavior, enhancing the relevance and application of research findings to real-world contexts.

The rest of the article is structured as follows. Section two will present how we developed our hypotheses and the rationale behind them. Section three will present the methodology and its application to the grocery delivery case study. Section four will present the results of the case study, while section five will dissect these results in the form of a discussion.

6.2 Hypothesis Development

Building on the outlined research objectives, this section proposes specific hypotheses to explore the dynamics within the naturalistic driving environment. We focus on situational factors such as delivery area, shift length, shift portion, and delivery timing, as well as driver stress, fatigue, attention, and driving behavior. These hypotheses aim to provide a comprehensive understanding of the multifaceted influences that various driving conditions exert on delivery drivers. Figure 6.1 illustrates our research model and the associated hypotheses.

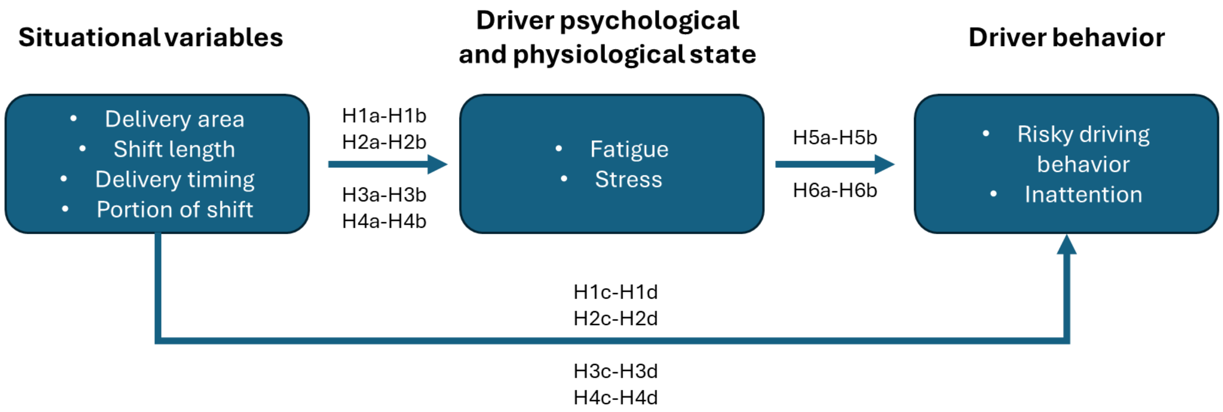

Figure 6.1. Research model and hypotheses

6.2.1 Delivery Area

For the delivery area, research supports the notion that driving in downtown areas (compared to the suburbs) is more demanding. For instance, urban delivery drivers experience higher levels of stress due to factors such as traffic congestion, frequent stops, high-density parking, traffic noise, and tight schedules (Bluhm et al., 2004; Fuller, 2005; Lu et al., 2021). These stressors contribute to fatigue, which is a well-documented risk factor for decreased attention and risky driving behavior (Cardoso et al., 2019; Williamson et al., 2011).

H1a – H1d: Delivering downtown versus the suburbs will be associated with greater (a) fatigue, (b) stress, (c) inattention, and (d) risky driving behaviour

6.2.2 Shift Length

Extended shift length naturally elevates fatigue and stress due to prolonged cognitive and physical exertion, impairing alertness, reaction time, and decision-making, and increasing accident risks (OSHA, 2023; Ren et al., 2023). Similarly, the Federal Motor Carrier Safety Administration (FMCSA) reports that driver fatigue significantly contributes to motor vehicle crashes, with impairment levels comparable to alcohol intoxication (Administration, 2015). These factors lead to greater inattention and risky driving behaviors (Ge et al., 2014; Useche et al., 2017).

H2a – H2d: Longer shifts will be associated with greater (a) fatigue, (b) stress, (c) inattention, and (d) risky driving behavior

6.2.3 Portion of Shift

Similarly, for the portion of the shift, fatigue and stress naturally accumulate, leading to a significant decline in drivers' cognitive and physical performance (OSHA, 2023; Ren et al., 2023). In the initial stages of a shift, drivers might be more alert and capable of managing the job demands. However, as the hours extend, the continuous cognitive load and physical exertion contribute to increasing levels of fatigue and stress. This gradual build-up can impair reaction times and diminish overall attention. By the later stages of a shift, these effects are likely to become pronounced, making it more challenging for drivers to maintain the same level of vigilance and precision in their tasks. The reduced ability to stay attentive increases the probability of risky behaviors, such as speeding, abrupt lane changes, or misjudging distances.

H3a – H3d: The second half of shifts will be associated with greater (a) fatigue, (b) stress, (c) inattention, and (d) risky driving behavior.

6.2.4 Delivery Timing

For delivery timing, late deliveries create a cycle of heightened stress due to the urgency to meet delivery deadlines. This urgency elevates stress levels, compelling drivers to work more intensively and for longer periods (Chen, 2023). The increased stress contributes to accelerated fatigue, impairing cognitive functions such as alertness, reaction time, and decision-making abilities (Useche et al., 2017).

As stress leads to fatigue, drivers' ability to maintain attention diminishes (Cendales et al., 2023; Hancock, 1989; Useche et al., 2017). This fatigue can result in lapses in concentration, making drivers more susceptible to errors. Consequently, the heightened state of stress-induced fatigue increases the likelihood of engaging in risky driving behaviors, compromising safety as drivers try to meet delivery demands.

H4a – H4d: More instances of late deliveries will be associated with greater (a) fatigue, (b) stress, (c) inattention, and (d) risky driving behavior.

6.2.5 Driver Fatigue and Stress

Research shows that delivery drivers working long hours were significantly more likely to experience high-risk fatigue, impairing their driving performance (Ren et al., 2023). As previously stated, fatigue impairs critical cognitive functions for driving, such as alertness and rapid information processing. This impairment leads to inattention and slower reaction times, increasing the likelihood of risky behaviors on the road (Soliani et al., 2023; Zhou et al., 2020).

Additionally, extended working hours increase stress levels, further diminishing cognitive functions important for safe driving (Afonso et al., 2017). Specifically, stress depletes the mental resources essential for maintaining focus, leading to inattention and exacerbating risky driving behaviors (Shamsul et al., 2014; Useche et al., 2017).

H5a – H5b: Greater fatigue will be associated with greater (a) risky driving behavior and (b) inattention.

H6a – H6b: Greater stress will be associated with greater (a) risky driving behavior and (b) inattention.

6.3 Materials and Methods

The following section will present the participants, the research design, the experimental procedure, variable operationalization, the measures, the equipment, and statistical analysis.

6.3.1 Participants and Case Study Design

This study was reviewed and approved by our institution's ethics review board (2021-4340).

Three participants were recruited by way of an internal email, from an online grocery delivery company in Canada. Participants self-identified as male, and their age ranged from 30 to 62 (M = 43.33, SD = 16.65). Participants' experience at the company as delivery drivers ranged from 14 to 17 months (M = 15, SD = 1.73). Their job consisted of driving a vehicle and delivering groceries to customer dwellings.

We used a correlation field study design, meaning that we observed participants going through their normal workplace activities without any experimental manipulation. Data were collected for three full workdays for each participant over the span of five days, totaling nine shifts and 84.33 hours. Shift length ranged from 10 hours and 49 minutes to seven hours and 19 minutes (M = nine hours and 22 minutes, SD = one hour and 0.5 minutes). During each of their three shifts, participants worked in one of two delivery areas for the entirety of the shift: downtown or in the suburbs. Downtown shifts mainly involved delivering in condo buildings, while suburb shifts involved delivering mainly to houses. To avoid the introduction of extraneous variables related to the interaction between participant characteristics and delivery area, each participant had a least one shift in each delivery area. In total, each participant completed two shifts in the suburbs and one downtown.

6.3.2 Procedure

Participants were first informed about the possibility of participating in the study by their managers in the weeks prior to the data collection. At that time, they also received a consent form explaining the goals of the study and the tools/measures that will be installed in their vehicle and on their body. On the day of the data collection, the research team travelled to the warehouse where all vehicles would leave from. At that point, the consent form was explained by the researchers, and signed by the participants. The research team then proceeded to equip the vehicle with sensors and cameras. During this time, participants answered a demographic questionnaire and were equipped with a physiological vest. Participants then began their workday as they normally would. Participant #2 always had afternoon shifts, starting approximately at 1:00 PM. Participants #1 and #3 always had morning shifts, starting approximately at 5:30 AM. Throughout the whole workday, a member of the research team was sitting in the passenger seat to monitor the data collection equipment, note down behaviours or situations of importance, and administer questionnaires. Hourly questionnaires were administered verbally (3 items) throughout the shift, starting at the beginning of the shift. Participants ended their shift at the warehouse where they began. At that point, the researcher administered a five-minute semi-structured interview.

6.3.3 Variable Operationalization and Measures

6.3.3.1 Situational Variables

Situational variables consist of delivery route characteristics and environmental factors that may affect the driver throughout their workday. **Delivery area** represents the location in which deliveries occurred. Delivery area was either suburbs or downtown, with the participant staying in the same area for the whole shift. **Shift length** represents the total length of the workday, from the departure to the return to the warehouse. **On-time versus late delivery (delivery timing)** represents whether the driver was running late or on time while driving to drop off a delivery to a customer. **Portion of the shift** represents either the first or second half of the workday.

6.3.3.2 Fatigue

The current study focused on task-related fatigue, which was measured using both physiological indicators and self-reported measures. Data on heart rate can be evaluated based on frequency (measured in Hertz, Hz) to assess the condition of a driver, such as their level of stress or fatigue. Studies have indicated that an increased HF band of HRV, ranging from 0.15 to 0.4 Hz, can be indicative of heightened fatigue levels (Warwick et al., 2015). Consequently, a decrease in the LF/HF ratio, indicative of greater parasympathetic activation, also indicates greater fatigue. Heart rate data can further be dissected into the time domain, where metrics such as SDNN are used to assess variability over time. The SDNN metric represents the variability in the time intervals between successive heartbeats. Generally, a higher SDNN, indicative of greater HRV, is associated with heightened states of drowsiness/fatigue (Ishaque et al., 2021). Finally, respiration rate was used as a marker of fatigue. Specifically, studies indicate that a deceleration in the pace of breathing correlates with enhanced fatigue or drowsiness (Chen et al., 2021; Kiashari et al., 2018; Wu et al., 2015). Concerning self-reported fatigue, the Stanford Sleepiness Scale was employed (Hoddes et al., 1973). This instrument is composed of a single question, which participants respond to using a seven-point Likert scale to reflect their current state of sleepiness.

Camera-based measures of fatigue were not used in this study because physiological measures such as heart rate variability and respiration rate provide direct, objective indicators of a driver's physiological state. These measures can detect subtle changes in the autonomic nervous system that are directly associated with fatigue, offering a more precise assessment of the driver's condition compared to behavioral indicators captured by cameras. Additionally, physiological measures are less susceptible to external factors that can affect camera-based systems, such as lighting conditions, driver facial features, and the use of accessories like glasses or hats. By focusing on physiological metrics, the study aims to provide a more reliable and consistent measure of fatigue that directly correlates with the driver’s internal state.

6.3.3.3 Stress

Stress was also measured using both physiological indicators and self-reported measures. Research has identified that an elevated LF band of HRV and an elevated LF/HF ratio is linked to increased stress levels (Ishaque et al., 2021; Kim et al., 2018; Sloan et al., 1994). For SDNN, a lower SDNN (lower HRV) is indicative of heightened stress (Kiashari et al., 2018). Lastly, a heightened respiration rate was also used as an indicator of heightened stress (Kiashari et al., 2018). For self-reported stress, a visual analog scale was employed (Lesage & Berjot, 2011). This measurement consists of a single item rated on a ten-point Likert scale.

6.3.3.4 Risky Driving Behavior

Risky driving behaviors are quantified through an algorithm that monitors acceleration fluctuations exceeding 0.45g across all axes (Freidlin et al., 2018). This method is frequently employed by insurance companies to identify risky driving incidents. Specifically, a lateral acceleration greater than 0.45g on the x-axis suggests sharp turning, whereas a similar acceleration on the y-axis signals hard acceleration or hard braking.

6.3.3.5 Attention

Attention levels are assessed by analyzing video footage captured by a camera mounted on the windshield (Chen et al., 2017). Initially, manual coding was employed to identify the range of 3-axis head orientation coordinates that signified attentive driving (as shown in Figure 6.2) compared to distracted driving (as depicted in Figure 6.3). From these identified coordinates, an algorithm was developed to detect instances of distracted driving. A higher frequency of detected distracted driving correlates with reduced attention levels.

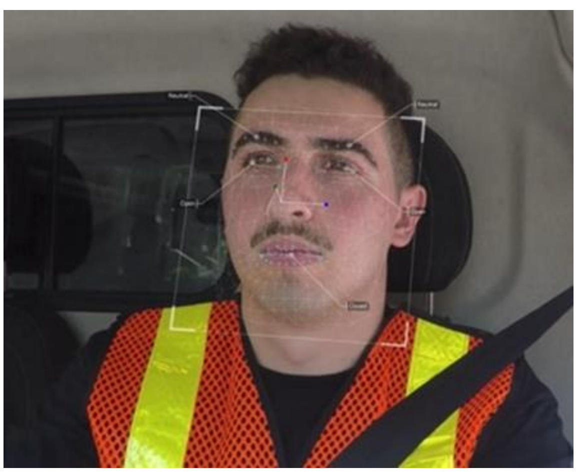

Figure 6.2: Example of attentive driving (head oriented towards the road)

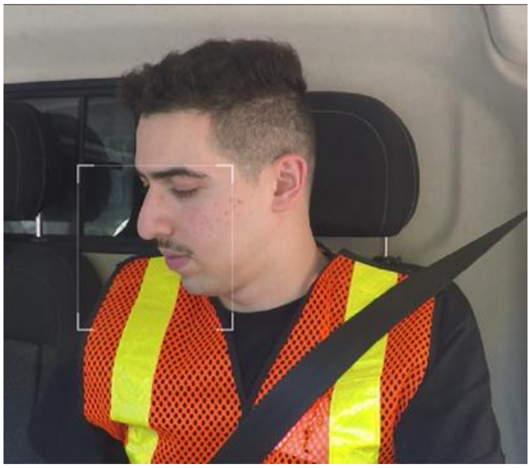

Figure 6.3: Example of distracted driving (head oriented away from the road)

6.3.4 Apparatus

Participants were outfitted with a Hexoskin physiological vest, depicted in Figure 6.4 (Carré Technologies inc., Montréal, Canada). This vest was designed to record various types of physiological data: it captured heart rate data at a frequency of 256 Hz using a single-lead electrocardiogram with an integrated electrode, measured respiration at 128 Hz through two built-in respiratory inductive plethysmography sensors, and monitored acceleration/activity at 64 Hz via a built-in 3-axis accelerometer.

Figure 6.4: Hexoskin physiological vest

A webcam (Logitech, Newark, USA) was mounted in the center top section of the windshield and connected to a computer to track the participant’s head orientation. Additionally, a second camera

(DJI, Shenzhen, China) was positioned at the bottom left of the windshield to serve the same purpose and act as a contingency in case of any malfunction with the primary webcam. A third camera (GoPro, San Mateo, USA) was installed in the center bottom of the windshield to capture the road ahead using an ultra-wide-angle lens, as illustrated in Figure 6.5. Moreover, a Cobalt device, which records three-axis accelerometer and GPS data, was strategically placed on the dashboard, as detailed in Figure 6.6 (Courtemanche et al., 2022; Léger et al., 2019).

The researcher utilized a laptop from Hewlett Packard (Spring, USA) to operate Observer XT (Noldus, Wageningen, the Netherlands), a software that allowed the synchronization of some of the data sources (physiological vest, webcam, and Cobalt accelerometer. This software also enabled the researcher to insert real-time event markers visible across all data streams. Additionally, Media Recorder (Noldus, Wageningen, the Netherlands), a video-recording application, was employed to capture footage from the webcam.

Figure 6.5: Camera setup in vehicle

Figure 6.6: Cobalt device (blue) on dash of vehicle

When preparing to gather data for a continuous 11-hour period, several technical factors required evaluation. Initially, the battery endurance of all devices was scrutinized. Apart from the Hexoskin vest, which boasts a 30-hour battery life, none of the other devices could sustain 11 hours on their own. For the DJI camera, GoPro camera, and the Cobalt Bluebox, a single portable charger with a 20,100mAh capacity sufficed. However, the laptop running Observer XT and the webcam needed two portable AC outlet power banks, each with a 31,200mAh capacity.

Another critical technical consideration was the storage capacity required for data collection. Recording video continuously for 11 hours from three cameras generated substantial data volume. Consequently, both the DJI and GoPro cameras were equipped with 128-gigabyte micro-SD cards to accommodate the entire duration of the experiment. Additionally, the laptop was connected to a 256-gigabyte external SSD drive, which was preferred over an HDD due to its faster data storage speed and reduced risk of mechanical failure.

The placement of three cameras with accompanying wires on the windshield also raised concerns about potentially obstructing the driver's view. After various adjustments, an optimal setup was achieved to minimize any visual blockage: one camera was positioned at the bottom left, another at the top middle, and a third at the bottom middle of the windshield, with all wires neatly taped down.

The final technical challenge involved synchronizing the data collected from all devices (Cobalt Bluebox, Hexoskin vest, webcam, DJI camera, GoPro camera, and Observer XT), which lacked an automatic synchronization feature. We opted for synchronization using the coordinated universal time (UTC). The Cobalt Bluebox and Hexoskin vest already included UTC timestamps in their data outputs, and we adjusted the laptop's local time to UTC to align with Observer XT. For the cameras, we used them to record a phone screen displaying a UTC clock, enabling us to manually align all recordings accurately.

6.3.5 Statistical Analysis

Data was segmented to differentiate driving and delivery activities. Our analyses focused on the driving potion. Data was then aggregated by delivery. For example, Participant 01 had 17 deliveries on their first day of data collection. Therefore, data was aggregated for each driving portion of each delivery, resulting in 17 averaged data points. This segmentation was particularly useful for examining the effects of delivery timing—whether late or on-time—on fatigue, stress, attention, and risky driving. It allowed us to extract and analyze data at the precise moments when a driver was on route to a late delivery.

To explore the relationships between situational variables, fatigue, stress, attention, and risky driving, our study utilized a combination of statistical methods tailored to the nature of the data collected. We applied linear models to assess the direct effects of situational variables on physiological indicators of fatigue and stress. In addition, we employed cumulative logistic regression to model the probability of higher-ordered values for self-reported fatigue and stress. This method was particularly suited to handling the ordinal nature of self-reported data. For the outcomes involving count data, specifically incidents of risky driving and distracted driving (attention), we used Poisson regression, accommodating the variability within and between participants. Where applicable, we adjusted for multiple comparisons using the Bonferroni method. Given the small sample size, we deliberately avoided more complex statistical analyses, such as mediation analysis. This decision was influenced by several factors: the limited statistical power, which constrains our ability to detect and accurately estimate indirect effects; the heightened risk of overfitting models to such a small dataset, potentially leading to non-generalizable conclusions; and the minimal variability among participants, which limits the robustness required for more sophisticated analytical techniques.

To address the challenges posed by the small sample size of this case study, we set our significance level at an alpha of 0.1 rather than the more traditional 0.05. This adjustment was made to reduce the risk of Type II errors—failing to detect an effect when one actually exists—thereby providing a more sensitive measure of the effects under study while acknowledging that this increases the possibility of Type I errors. These considerations led us to adopt a straightforward analytical approach, ensuring the clarity and accuracy of our interpretation of the direct relationships observed in the data.

6.4 Results

This section will present results related to (1) the descriptive statistics; (2) the effect of situational variables on fatigue and stress; (3) the effect of situational variables on risky driving behavior and attention; and (4) the effect of fatigue and stress on risky driving behavior and attention. Due to technical issues with the synchronization and a hard drive malfunction, no physiological, attention, or risky driving data is available for participant 2 day 3, and participant 3 day 1. Also, no physiological data is available for participant 3 day 2. Table 6.1 presents a synthesis of the results of the hypothesis testing. All raw and processed data are available at: doi.org/10.17632/c9kgj9b7fx.1 . Appendix A presents all descriptive data.

6.4.1 Descriptive Statistics

The mean shift length was 9.27 hours (SD = 1.16 hours) with a range of 7.32 to 10.82 hours. The number of late deliveries per shift had a mean of 3.67 (SD = 3.17) with a range of 0 to 14 late deliveries. Participants had 2 shifts in the suburbs and 1 downtown. When downtown, the percentage of condo deliveries had a mean of 74.50% (SD = 7.93%) with a range of 69% to 83%. In the suburbs, the percentage of condo deliveries had a mean of 8.00% (SD = 5.83%) with a range of 0% to 14%.

The number of deliveries per shift averaged 17.44 (SD = 4.27), ranging from 12 to 23 deliveries. For instances of risky driving behaviors, the mean number of hard accelerations per shift was 23.85 (SD = 13.80) with a range of 9 to 49; the mean number of hard braking events was 21.00 (SD = 8.68) with a range of 15 to 37; and the mean number of sharp turns was 52.5 (SD = 27.11) with a range of 9 to 91. Attention metrics, measured by distracted driving incidents, had a mean of 6.33 (SD = 7.60) with a range of 0 to 21 incidents.

6.4.2 Effect of Situational Variables on Fatigue and Stress

6.4.2.1 Breathing Rate

A Poisson regression analysis revealed that longer shifts were associated with a lower breathing rate ($t(114) = -1.84$, $p = .0689$). Breathing rate was higher downtown ($t(115) = 5.42$, $p < .0001$) and lower for late deliveries ($t(115) = -3.19$, $p = .002$). The second half of the shift showed higher breath rates compared to the first half ($t(115) = 2.39$, $p = .018$).

6.4.2.2 Low Frequency (LF)

A Poisson regression analysis showed that longer shifts were associated with higher LF ($t(92) = 2.02$, $p = .046$). Delivery area also affected LF, with higher values downtown ($t(93) = 3.97$, $p = .0001$). Neither the portion of the shift nor delivery timing significantly affected LF ($t(93) = -0.17$, $p = .869$ and $t(93) = 1.40$, $p = .164$, respectively).

6.4.2.3 High Frequency (HF)

A Poisson regression analysis showed that longer shifts were associated with an increase in HF ($t(92) = 2.29$, $p = .0241$), while HF was downtown ($t(93) = 3.84$, $p = .0002$). Both the portion of the shift and delivery timing showed no significant effects on HF ($t(93) = -0.07$, $p = .946$ and $t(93) = 0.68$, $p = .500$, respectively).

6.4.2.4 Ratio of Low to High Frequency HRV

A Poisson regression analysis revealed that a longer shift length was associated with a lower LF/HF ratio ($t(92) = -1.73$, $p = .0865$). The delivery area had no significant impact ($t(93) = 1.02$, $p = .311$). The second half of the shift was associated with a lower LF/HF ratio ($t(93) = -1.86$, $p = .067$). Late deliveries resulted in a higher LF/HF ratio ($t(93) = 2.15$, $p = .034$).

6.4.2.5 Standard Deviation of NN Intervals (SDNN)

A Poisson regression analysis showed positive correlation between shift length and SDNN ($t(92) = 2.45$, $p = .0162$). Also, higher SDNN values were observed downtown ($t(93) = 3.29$, $p = .001$). The second portion of the shift was associated with a lower SDNN ($t(93) = -1.77$, $p = .081$). However, no significant differences were found for delivery timing ($t(93) = -1.14$, $p = .259$).

6.4.2.6 Self-Reported Fatigue

A cumulative logistic regression showed that shift length did not have a significant effect on fatigue, $t(73) = -1.07$, $p = .289$. Regarding the influence of delivery area on self-reported fatigue, no significant results were found, $t(73) = -0.15$, $p = .881$. However, participants perceived themselves as more fatigued in the second half of the shift (Figure 6.7), $t(75) = 2.51$, $p = .0142$. Concerning delivery timing, no significant association was found, $t(84) = -1.26$, $p = .207$.

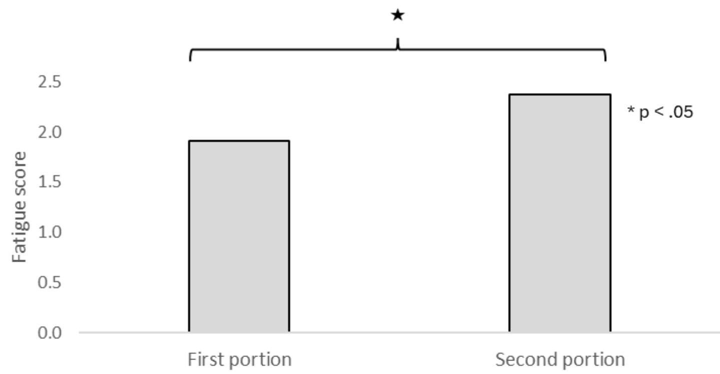

Figure 6.7: Self-reported fatigue by shift portion

6.4.2.7 Self-Reported Stress

A cumulative logistic regression analysis revealed that working downtown was associated with a significant increase in stress levels (Figure 6.8), $t(73) = 2.03$, $p = .046$. Shift length was not a significant predictor of stress, $t(73) = -1.59$, $p = .117$. Portion of shift was also not a significant predictor of stress, $t(75) = 0.95$, $p = 0.3457$. Concerning delivery timing, being late was associated with greater self-reported stress (Figure 6.9), $t(84) = 3.17$, $p = .002$.

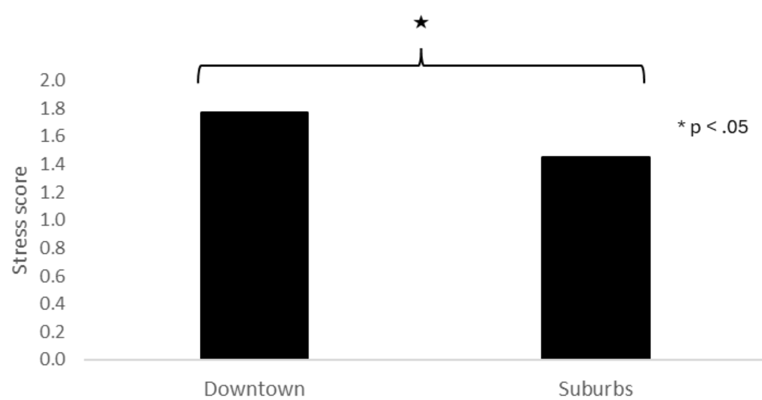

Figure 6.8: Self-reported stress by delivery area

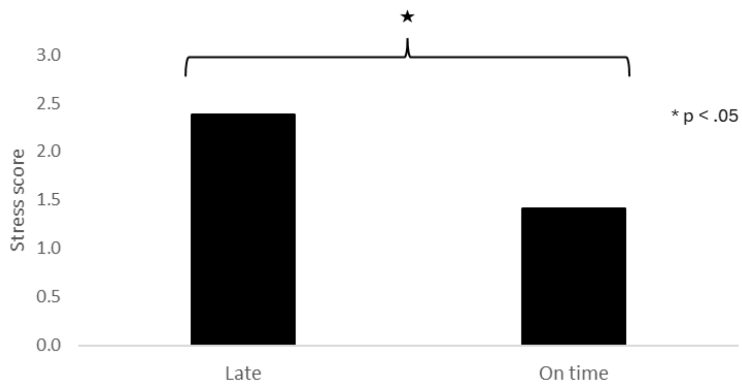

Figure 6.9: Self-reported stress by delivery area

6.4.3 Effect of Situational Variables on Driving Behaviour and Attention

6.4.3.1 Hard Acceleration

A Poisson regression analysis showed no significant differences found between the suburbs and downtown (t(108) = 1.59, p = .114). However, the second half of the shift was significantly associated with more hard accelerations than the first half (t(108) = 2.50, p = .0138). No significant differences were found with regard to delivery timing (t(108) = 1.62, p = .1092).

6.4.3.2 Hard Braking

A Poisson regression analysis showed that driving downtown significantly increased the number of hard brakes (t(108) = 1.72, p = .0879). Additionally, the second half of the shift showed a significantly higher number of hard brakes compared to the first half (t(108) = 1.78, p = .0787). However, no significant differences were found for delivery timing (t(108) = 1.05, p = .4928)

6.4.3.3 Sharp Turning

A Poisson regression analysis indicated that the suburbs experienced a significantly higher number of hard turns than downtown (t(108) = 3.52, p = .0006). The timing of the turns was also significant; there were significantly fewer hard turns when drivers were late compared to when they were on-time (t(108) = -5.42, p < .0001). Moreover, the second half of the shift had significantly more hard turns than the first half (t(108) = 3.87, p = .0002).

6.4.3.4 Attention (Distracted Driving)

A Poisson regression analysis revealed significant relationships for shift length ($t(117) = 5.572$, $p < .001$) and area ($t(117) = -7.489$, $p < .001$). Longer shift lengths (Figure 6.10) and downtown delivery (Figure 6.11) were associated with more distracted driving events. No significant effects were observed for delivery timing($t(117) = -0.616$, $p = 0.538$) and portion of the shift ($t(117) = -0.584$, $p = 0.559$).

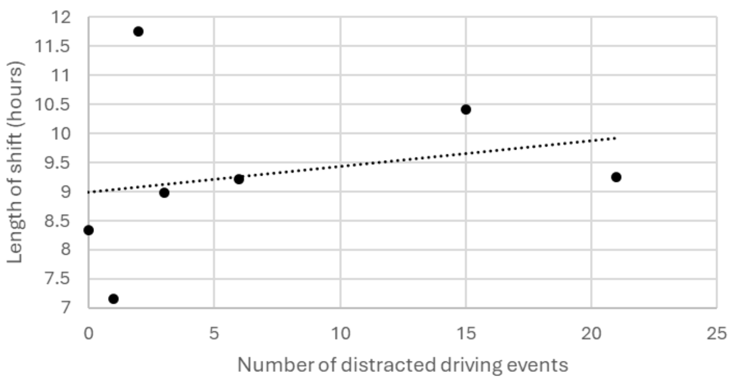

Figure 6.10: Distracted driving by shift length

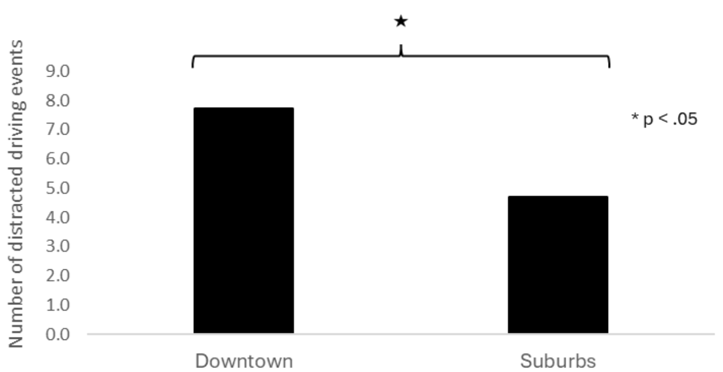

Figure 6.11: Distracted driving events by delivery area

6.4.4 Effect of Fatigue and Stress on Driving Behavior and Attention

6.4.4.1 Hard Acceleration

A Poisson regression analysis showed that higher breathing rate ($t(114) = 3.06$, $p = .0028$) and higher SDNN ($t(92) = 2.07$, $p = .0413$) were associated with more instances of hard acceleration.

There were no significant associations for changes in LF ($t(92) = 1.45$, $p = .1497$), HF ($t(92) = 1.22$, $p = .2265$), or the LF/HF ratio ($t(92) = 1.24$, $p = .2196$). Self-reported fatigue ($t(65) = 1.459$, $p = 0.578$) and self-reported stress ($t(65) = -1.882$, $p = 0.239$) did not show significant effects on acceleration.

6.4.4.2 Hard Braking

A Poisson regression analysis showed no significant association between hard braking and changes in breathing rate ($t(114) = -1.59$, $p = .1149$). No significant association was found with SDNN ($t(92) = 1.22$, $p = .227$). However, hard braking was significantly associated with an increased LF ($t(92) = 1.87$, $p = .0645$) and HF ($t(92) = 1.79$, $p = .0762$). Additionally, hard braking was associated with an increase in the LF/HF ratio ($t(92) = 1.70$, $p = .0921$). Increased self-reported fatigue significantly predicted more frequent braking ($t(65) = 2.912$, $p = 0.014$). Increased self-reported stress was significantly associated with fewer braking events ($t(65) = -3.222$, $p = 0.005$).

6.4.4.3 Sharp Turning

A Poisson regression analysis revealed no significant associations were found between sharp turning and changes in breathing rate ($t(114) = -0.42$, $p = .6724$), SDNN ($t(92) = 0.51$, $p = .6115$), LF ($t(92) = -1.24$, $p = .2173$), HF ($t(92) = -1.09$, $p = .2764$), or the LF/HF ratio ($t(92) = -0.71$, $p = .4772$). Increased self-reported fatigue was significantly associated with more frequent sharp turning events ($t(65) = 4.520$, $p < 0.001$). Increased self-reported stress was significantly associated with fewer sharp turning events ($t(65) = -2.777$, $p = 0.022$).

6.4.4.4 Attention (Distracted Driving)

A Poisson regression analysis revealed significant relationships for the LF/HF ratio ($t(101) = 7.68$, $p < .001$) and breathing rate ($t(101) = 18.42$, $p < .001$), which were both positively associated with the number of distracted driving events. Significant effects were found for HF ($t(101) = 2.52$, $p = .059$), suggesting a positive association. However, no significant effects were observed for the SDNN ($t(101) = -2.06$, $p = .199$) and LF ($t(101) = -1.76$, $p = .393$). Increased self-reported stress significantly predicted a decrease in distracted driving events ($t(65) = -7.688$, $p < 0.001$). The relationship between self-reported fatigue and distracted driving events was not significant ($t(65) = -1.792$, $p = 0.292$).

Table 6.1: Summary of hypothesis support

Hypothesis	Support?
H1a: Delivering downtown versus the suburbs will be associated with greater fatigue	Partial
H1b: Delivering downtown versus the suburbs will be associated with greater stress	Yes
H1c: Delivering downtown versus the suburbs will be associated with greater inattention	Partial
H1d: Delivering downtown versus the suburbs will be associated with greater risky driving behavior.	Yes
H2a: Longer shifts will be associated with greater fatigue	Partial
H2b: Longer shifts will be associated with greater stress	Partial
H3a: The second half of shifts will be associated with greater fatigue	Partial
H3b: The second half of shifts will be associated with greater stress	Partial
H3c: The second half of shifts will be associated with greater inattention	Yes
H3d: The second half of shifts will be associated with greater risky driving behavior	No
H4a: More instances of late deliveries will be associated with greater fatigue	Partial
H4b: More instances of late deliveries will be associated with greater stress	Partial

Table 6.1 (continued and end)

H4c: More instances of late deliveries will be associated with greater inattention	No
H4d: More instances of late deliveries will be associated with greater risky driving behavior.	No
H5a: Greater fatigue will be associated with greater risky driving behavior	Partial
H5b: Greater fatigue will be associated with greater inattention	Partial
H6a: Greater stress will be associated with greater risky driving behavior.	Partial
H6b: Greater stress will be associated with greater inattention	Partial

6.5 Discussion

This section will explore the obtained results in detail. We will begin by examining the impact of situational variables on driver fatigue, stress, driving behavior, and attention. Following this, we will explore how driver stress and fatigue influence driving behavior and attention. Finally, we will address the practical implications of our findings, discuss the limitations of the study, and suggest directions for future research.

6.5.1 Effect of Situational Variables on Fatigue, Stress, Driving Behavior, and Attention

6.5.1.1 Delivery Area

Our results indicated that the delivery area significantly impacted delivery drivers. Concerning fatigue, results showed a higher HF and higher SDNN downtown, indicating greater physiological fatigue. However, no significant differences were found in terms of self-reported fatigue, indicating partial support for H1a. Stress was found to be higher downtown, as indicated by higher LF, LF/HF ratio, breathing rate, and self-reported stress, thus supporting H1b.

To understand why the delivery area significantly impacts drivers, particularly in terms of physiological responses to fatigue and stress, it is essential to consider the inherent differences between downtown and suburban driving environments. Downtown areas typically exhibit higher traffic density, more frequent stops, and greater navigation challenges due to congested streets and complex road layouts. This increases drivers' cognitive and physical demands as they need to maintain high levels of vigilance and rapid decision-making. This environmental complexity is likely why we observed higher HF and SDNN downtown, indicating greater physiological fatigue. HF is associated with parasympathetic activity, which can increase as a response to the stress of managing these more challenging driving conditions, thus attempting to maintain autonomic balance under increased fatigue.

Interestingly, while physiological markers showed significant variation, self-reported fatigue did not differ significantly between downtown and suburban areas. This discrepancy might suggest that drivers are not always consciously aware of their fatigue levels or that they normalize the fatigue associated with downtown deliveries. The absence of significant differences in self-reported fatigue could also be attributed to individual differences in perception or reporting biases where drivers may underreport fatigue due to expectations about their endurance and job requirements.

Stress responses were also more pronounced in downtown areas, as evidenced by higher levels of LF, and the LF/HF ratio, which suggests a predominance of stress responses over parasympathetic recovery processes. These findings are complemented by increased breathing rates and higher self-reported stress levels, highlighting the physiological and subjective stress burden experienced by drivers in these high-demand environments. The elevated stress in downtown settings can be tied back to the continuous navigation and vigilance required to safely operate in unpredictable and congested traffic conditions, which can heighten sympathetic activation as the body responds to these acute stressors.

In terms of driving behavior and attention, driving downtown was associated with more instances of hard braking and distracted driving. However, suburb driving was associated with more instances of sharp turning. No significant results were found for hard acceleration. Overall, we see partial support for H1c and full support for H1d.

As discussed previously, the observed variations in driving behavior and attention between downtown and suburban areas can be influenced by the differing driving conditions inherent to these environments but are also likely exacerbated by fatigue and stress, which were found to be more pronounced in downtown settings.

In downtown areas, the increased frequency of hard braking and distracted driving incidents aligns with the higher traffic density, frequent intersections, and pedestrian activity, as well as with the elevated levels of fatigue and stress identified among drivers. These conditions necessitate frequent stops and adjustments in driving behavior, which can lead to more instances of hard braking as drivers respond to sudden changes in traffic flow or to avoid potential hazards. Higher stress levels and fatigue could impair drivers' ability to maintain sustained attention, leading to a higher incidence of distracted driving. The constant need to navigate complex urban environments while managing fatigue and stress may reduce drivers' capacity to process and react to traffic conditions effectively.

Conversely, the presence of more instances of sharp turning in the suburbs could be influenced by the typically less congested but more winding roads, which often require more frequent and pronounced maneuvers. The reduced traffic density may allow drivers to operate at higher speeds, contributing to the observed increase in sharp turning events. Moreover, while fatigue and stress levels were found to be lower in suburban settings compared to downtown, the cumulative effects of these factors over long shifts could still impact driving behavior, particularly in terms of the precision and safety of maneuvers like turning.

6.5.1.2 Shift Length

Our results indicated that longer shifts were associated with significantly more physiological fatigue, as evidenced by lower breathing rates, a lower LF/HF ratio, higher HF, and higher SDNN. However, no association was found between shift length and self-reported fatigue, indicating partial support for H2a. Longer shifts were also significantly associated with greater stress, as indicated by greater LF. No significant differences were found in terms of self-reported stress, indicating partial support for H2b.

The association of longer shifts with increased physiological fatigue and stress, as shown in our results, highlights the cumulative burden of extended periods of driving on the physiological state of drivers. The evidence of more physiological fatigue from longer shifts, marked by lower breathing rates and a lower LF/HF ratio, suggests a progressive depletion of the body's adaptive resources over time. Higher HF and SDNN levels further indicate an increased parasympathetic response, likely a compensatory mechanism to counteract the fatigue accumulated over the duration of long shifts. This physiological response could be the body's attempt to maintain homeostasis despite ongoing fatigue.

However, the lack of a significant association between shift length and self-reported fatigue might suggest a discrepancy between drivers' perceptions of their fatigue and the actual physiological changes occurring within their bodies. As previously mentioned, this could be due to drivers becoming habituated to the symptoms of fatigue over time, thus underreporting their fatigue levels, or potentially a lack of awareness about the signs of physiological fatigue.

Similarly, the increased stress associated with longer shifts, evidenced by greater LF, aligns with the understanding that prolonged driving involves sustained mental and physical exertion, which elevates stress levels. This stress response directly results from the prolonged focus and vigilance required by driving tasks. However, the absence of significant differences in self-reported stress might indicate a similar trend of underreporting or habituation to stress, where drivers might not perceive or report the gradual increase in stress that accompanies longer shifts.

6.5.1.3 Portion of Shift

Results showed a lower LF/HF ratio and higher self-reported fatigue in the second half shifts, indicating greater fatigue. However, no significant differences were observed in terms of HF, thus showing only partial support for H3a. Concerning stress, the second half of shifts was associated with higher stress, as shown by an increase in breathing rate and a decrease in SDNN. No significant differences were found in terms of LF or self-reported stress, indicating partial support for H3b.

The findings regarding the impact of the second half of shifts on fatigue and stress reflect the effect of prolonged driving. A lower LF/HF ratio in the second half of shifts indicates a shift towards parasympathetic dominance, suggesting that drivers are experiencing physiological fatigue as their shifts progress. This change, coupled with higher self-reported fatigue, points to an increasing awareness among drivers of their fatigue as the shift wears on. However, the absence of significant changes in HF could indicate that while the overall balance between sympathetic and parasympathetic activity shifts, the specific markers of parasympathetic activity may not show uniform increases.

In terms of stress, the increase in breathing rate and the decrease in SDNN during the second half of shifts highlight the physiological response to prolonged stress exposure. Breathing rate typically increases as part of the body’s acute stress response, and a lower SDNN reflects reduced variability in heart rate, which is commonly associated with heightened stress. However, the lack of significant differences in LF and self-reported stress suggests that the physiological markers of stress may not fully align with drivers’ perceptions, possibly due to an underestimation of stress levels or a delayed psychological response to ongoing stressors.

Concerning driving behavior and attention, the second half of the shift was associated with more instances of hard acceleration, hard braking, and sharp turning, thus supporting H3c. These findings could be attributed to the increased fatigue and stress. As fatigue deepens, it may impair judgment and reaction time, leading drivers to make more abrupt and less calculated driving decisions. The heightened stress could also contribute to more aggressive driving behaviors as a manifestation of reduced patience or increased frustration.

However, no significant results were found for attention, indicating that H3d is not supported. Despite increased fatigue and stress, the lack of significant changes in attention levels during the second half of shifts suggests that drivers might be compensating to maintain necessary attention for driving. This could indicate that drivers prioritize vigilance even as they become more fatigued or stressed, potentially exerting more effort to stay focused. It's also possible that the methods used to assess attention in this study weren't sensitive enough to detect subtle changes in attention that occur over time. This finding underscores the need for using more sensitive measures to understand how attention is maintained or fluctuates in response to increasing fatigue and stress during shifts.

6.5.1.4 Delivery Timing

Results revealed that late deliveries were associated with lower breathing rates, indicating greater physiological fatigue. However, no significant association was found with HF, SDNN, or self-reported fatigue, indicating partial support for H4a. Late deliveries were also associated with greater stress, as shown by an increase in the LF/HF ratio. However, no significant association was found for LF, SDNN, or self-reported stress, indicating partial support for H4b.

The association between late deliveries and physiological changes among drivers highlights the complex dynamics of stress and fatigue in the context of delivery timelines. Specifically, the finding that late deliveries were associated with lower breathing rates reflects greater physiological fatigue. Lower breathing rates can indicate a shift towards a more fatigued state, as the body conserves energy and reduces metabolic demands in response to prolonged stress and exertion. This physiological response might be particularly pronounced when drivers rush to meet delivery deadlines, thus intensifying their fatigue.

However, the lack of significant changes in HF, SDNN, or self-reported fatigue suggests a nuanced picture. While lower breathing rates indicate increased physiological fatigue, the absence of corresponding changes in HF and SDNN could imply that these aspects of the autonomic response to fatigue might not be as sensitive or that there is individual variability in how fatigue manifests physiologically among drivers. Additionally, the absence of significant differences in self-reported fatigue could be due to drivers not fully recognizing or acknowledging their fatigue levels, potentially due to a focus on task completion or normalization of fatigue symptoms over time.

Regarding stress, the increase in the LF/HF ratio associated with late deliveries suggests a higher stress response, reflecting the body's acute stress reaction. However, the lack of significant changes in LF, SDNN, and self-reported stress again highlights the complexity of measuring and interpreting stress responses. It's possible that the physiological indicators of stress such as LF and SDNN are not as reactive to the specific stressors associated with late deliveries, or that the drivers' subjective perceptions of stress do not align with the physiological indicators, perhaps due to desensitization to the stress of delivery pressures over time.

Concerning driving behavior and attention, delivery timing had no significant effect on hard acceleration, hard braking, or attention. In fact, being late was significantly associated with fewer sharp turns, contrary to what was hypothesized. Overall, both H4c and H4d are not supported.

The results concerning the impact of delivery timing on driving behavior and attention reveal some intriguing dynamics. Notably, the absence of significant effects on hard acceleration, hard braking, and overall attention suggests that the timing of deliveries might not drastically alter these particular aspects of driving performance under the conditions studied. This could indicate that drivers maintain a consistent driving style in terms of acceleration and braking, regardless of whether they are on time or late, possibly due to training or regulatory standards that encourage uniform driving behaviors.

Interestingly, the finding that being late was significantly associated with fewer sharp turns, contrary to the hypothesis, suggests a possible adaptation or strategic change in driving behavior under time pressure. Drivers who are late might choose more straightforward routes or might be more cautious in maneuvering to minimize additional delays or risks that could arise from more aggressive driving tactics like sharp turning. This could reflect compensatory behavior where drivers, aware of their lateness, are possibly avoiding maneuvers that could further delay them or increase their risk on the road.

The lack of significant findings in terms of changes in attention also underscores the possibility that drivers are able to sustain a necessary level of focus, regardless of delivery timing pressures. This resilience in maintaining attention could be due to the high demands of driving that require constant vigilance. Thus, drivers might prioritize maintaining attention over modifying other driving behaviors, even when late.

6.5.2 Effect of Fatigue and Stress on Risky Driving Behaviour and Attention

6.5.2.1 Fatigue

Generally, results indicated that fatigue was associated with more instances of risky driving, which is consistent with findings in the literature (Cardoso et al., 2019; Loew et al., 2024; Öz et al., 2010; Useche et al., 2017). Increased HF was associated with more instances of hard braking, but no association was found with hard acceleration or sharp turning. Increased self-reported fatigue was associated with more instances of hard braking or sharp turning but not hard acceleration. Higher SDNN was associated with more instances of hard acceleration but was not associated with hard braking or sharp turning. Concerning attention, increased HF was associated with greater instances of distracted driving. No significant relationship was found between SDNN and self-reported fatigue. Overall, we see partial support for H5a and H5b.

The relationship between fatigue and risky driving behaviors, as evidenced by our study, reveals nuanced interactions between physiological states and driver actions. For instance, the correlation between increased HF and a higher incidence of hard braking illustrates how heightened fatigue can disrupt normal driving patterns. This result suggests that drivers' ability to maintain steady control deteriorates as drivers become more fatigued, leading to abrupt reactions like hard braking. This finding is consistent with observations of heightened physiological stress in conditions such as downtown driving or during longer shifts, which similarly increase the likelihood of sudden, reactive maneuvers.

However, the lack of association between HF and other risky behaviors (hard acceleration and sharp turning) indicates that the influence of physiological fatigue may manifest differently across various driving actions. Hard braking might be particularly sensitive to the immediate impacts of mental fatigue, such as slowed reaction times. In contrast, other behaviors like acceleration and turning might be influenced by additional factors including stress or external pressures not directly measured by HF.

The connection between higher SDNN and more instances of hard acceleration is particularly compelling. This might suggest that drivers experiencing greater fatigue, as indicated by higher SDNN, could be compensating for their reduced responsiveness by engaging more frequently in aggressive driving behaviors like rapid acceleration, possibly as a misguided attempt to counteract their decreasing alertness.

Furthermore, the link between self-reported fatigue and an increase in both hard braking and sharp turning but not hard acceleration provides further evidence that drivers fatigue correlates with specific types of risky behaviors. This subjective awareness might reflect a degraded ability to manage and modulate driving actions effectively under fatigue.

Regarding attention, the connection between increased HF and more frequent instances of distracted driving underscores the impact of fatigue on drivers’ vigilance. The absence of a significant relationship between increased SDNN and attention, or between self-reported fatigue and attention, may indicate that while these measures are effective at indicating general fatigue, they may not precisely capture the direct cognitive impairments that lead to reduced attentional focus.

6.5.2.2 Stress

Results indicated that stress was associated with more instances of risky driving, which is consistent with results from the literature (Ge et al., 2014; Useche et al., 2017). A higher respiration rate was associated with more instances of hard acceleration, but no association was found with hard braking or sharp turning. Higher LF and LF/HF ratio was associated with more instances of hard braking, but no association was found with hard acceleration or hard turning. Counterintuitively, greater self-reported stress was associated with fewer instances of hard braking and sharp turning. Concerning attention, both an increase in breathing rate and the LF/HF ratio were associated with greater instances of distracted driving. No associations were found for LF and SDNN. However, a higher self-reported stress was associated with fewer instances of distracted driving, contrary to our hypothesis. Overall, we see partial support for H6a and H6b.

These findings shed light on the specific ways that physiological and psychological stress manifest in driving dynamics. Notably, we found that a higher respiration rate, indicative of elevated stress levels, was associated with more instances of hard acceleration. This may suggest that as drivers experience higher stress, their physiological arousal translates into more aggressive driving behaviors, specifically in the form of increased acceleration.

Interestingly, while high respiration rates linked to increased hard acceleration, they did not correlate with hard braking or sharp turning, suggesting that, once again, the influence of stress on driving behavior might be specific to the type of maneuver and perhaps the immediate driving context or driver intentions at that moment. Conversely, higher LF and a higher LF/HF ratio were related to more instances of hard braking but not to hard acceleration or hard turning.

Counterintuitively, the results showed that greater self-reported stress was associated with fewer instances of hard braking and sharp turning. This could suggest a dissociation between perceived stress and actual driving responses, where drivers who report feeling more stressed might consciously or subconsciously attempt to drive more cautiously, avoiding aggressive maneuvers like hard braking and sharp turning to prevent exacerbating an already stressful situation.

Regarding attention, the findings indicated that both an increase in breathing rate and the LF/HF ratio were associated with more instances of distracted driving, suggesting that higher physiological stress impacts drivers' ability to maintain focus. These measures of stress affecting attention align with the understanding that stress can overload cognitive capacities, diverting mental resources away from driving tasks and leading to increased distraction.

However, higher self-reported stress correlating with fewer instances of distracted driving contradicts this trend and our initial hypotheses. This might reflect a compensatory mechanism where drivers who are aware of their high stress levels consciously strive to focus more intently on the driving task, possibly as a coping strategy to regain control over their driving environment and mitigate their stress.

6.5.3 Practical Implications

The multi-method approach used in this study leverages a robust and integrative methodology that combines physiological measures, self-reports, and observational data to offer an understanding of the dynamics of driver stress, fatigue, and behavior in real-world settings. This methodology provides insight into the interplay between a driver's physiological state and their driving performance, enhancing the ability to identify critical factors that influence safety.

Physiological measures such as respiration rate and heart rate metrics provide objective data regarding a driver’s autonomic nervous system activity. These measures are useful for understanding how the body physiologically responds to stress and fatigue over the course of driving shifts. For instance, variations in HRV and respiration rates can indicate changes in stress levels that might not be consciously perceived by the driver. Self-reported data, gathered through tools like the Stanford Sleepiness Scale and visual analog scales for stress, offer insights into the drivers’ subjective experiences and perceptions of their fatigue and stress levels. This subjective data is vital as it provides context to the physiological measurements, giving a more rounded view of how drivers are experiencing their work environment and its demands. Observational data, collected through video monitoring and behavior tracking, adds another layer of understanding by directly recording driving behaviors such as hard braking, sharp turning, and acceleration patterns. This data helps correlate the physiological and self-reported data with actual on-road behavior, providing a clear picture of how stress and fatigue manifest in risky driving actions.

Integrating these diverse methods creates a powerful toolset for analyzing driver behavior. It not only enhances the ecological validity of the research by studying drivers in their natural operational settings but also ensures that the findings are relevant and applicable to real-world driving scenarios. This approach allows for a reliable assessment of drivers, capturing both the overt and subtle influences on driving behavior, which are critical for developing effective interventions to improve driver safety and well-being. By applying this comprehensive methodology to a real-life case study, we have been able to directly observe and validate its effectiveness in a naturalistic setting.

The practical application of this methodology has demonstrated its value, revealing insights directly applicable to enhancing driver training and management. Training programs, for instance, could be significantly improved by incorporating modules on stress management and fatigue awareness, specifically tailored to address the distinct stress and fatigue triggers identified through our research. For example, by understanding the differing impacts of downtown versus suburban driving conditions, or the varying effects across different segments of a shift, training can be customized to equip drivers with the necessary skills to effectively manage these specific challenges. Management strategies could also be adapted to include more structured shift schedules or more frequent breaks, particularly during the latter half of shifts, where increased fatigue and stress are observed. Such adjustments could help mitigate the physiological symptoms and risky behaviors identified in the study, improving overall driver well-being and safety.

In terms of policy development, the correlation between late deliveries and increased stress and risky behaviors underscores the need for reevaluating delivery schedules and deadlines. Policies allowing more flexible delivery times could alleviate stress and reduce associated risky driving behaviors, thus enhancing road safety. Furthermore, insights from this study could inform regulatory frameworks concerning maximum shift lengths and the scheduling of high-demand driving periods. Regulations might be adapted to consider not only the duration but also the timing and context of shifts to optimize driver performance and safety.

Technological interventions could significantly enhance driver safety by implementing real-time monitoring systems in vehicles that provide feedback on signs of stress and fatigue, enabling drivers to take proactive steps to manage their condition, such as taking a break or engaging in stress-reduction techniques. For instance, Amazon has effectively implemented real-time monitoring systems to improve driver safety (Staff, 2022). Amazon uses in-vehicle cameras and sensors to monitor driver behavior, detecting signs of fatigue, distraction, and unsafe driving practices such as hard braking and rapid acceleration. Telematics devices track vehicle speed, location, and engine performance, allowing for real-time alerts to warn drivers about unsafe practices. AI and machine learning analyze this data to predict potential safety issues, providing targeted safety training based on specific behaviors.

Overall, this study's approach and its findings offer significant contributions to the fields of occupational health and transportation safety. By applying these findings, stakeholders across various sectors can develop more effective strategies to enhance driver safety, optimize working conditions, and, ultimately, reduce the risk of accidents and injuries on the road.

6.5.4 Limitations and Future Directions

This field study, while comprehensive, has several limitations that must be acknowledged. First, the sample size was relatively small, which may limit the generalizability of the findings. The specific environmental and operational conditions of the drivers studied—such as the particular geographic area and the nature of their delivery tasks—might not fully represent the diversity of driving contexts in other regions or different types of driving jobs. However, the longitudinal evaluation, spanning full workdays over a week, ensured a substantial amount of data was collected, providing a comprehensive view of the drivers' experiences. Additionally, the collection of rich physiological data added depth to the study, offering valuable insights into the real-world impacts on driver well-being and behavior.

Another significant limitation is the correlational nature of the field study. While the multi-method approach allowed for an in-depth analysis of the relationships between stress, fatigue, and driving behavior, the design does not permit strong causal inferences. It is unclear whether the physiological and psychological states observed are causing the changes in driving behavior, or if perhaps the driving conditions are inducing the changes in stress and fatigue levels, or if both are influenced by another factor not measured in the study. However, field studies are most often observational in nature due to the inability to manipulate variables in a real-world environment, which inherently limits causal inference but enhances ecological validity. This observational approach captures the complexity and authenticity of real-world interactions, providing a realistic context that experimental studies might miss.

The field study also focused predominantly on male drivers, which may not capture the potentially different experiences and responses of female drivers to similar driving conditions. The influence of gender on stress and fatigue responses, as well as on driving behavior, is an important area that was not explored in this study. Nonetheless, the findings provide a foundational understanding that can be built upon in future research, highlighting areas where gender differences might be further investigated.

Lastly, we did not measure the attentional impact of the technology utilized by delivery personnel. These individuals often use mobile apps to receive their next destinations, employ GPS for navigation, and multitask constantly, which introduces significant attentional risks. This limitation could have affected our measures of attention and risky driving behavior, as the cognitive load from using these technologies may have contributed to distractions and increased the likelihood of engaging in risky driving practices.

Given these limitations, several directions for future research are suggested. Future research should evaluate how the demands of using technology affect attention, driving behavior, fatigue, and stress. The need to frequently check devices and manage multiple tasks can significantly divert attention from driving, potentially exacerbating fatigue and stress levels.

Also, expanding the study to include a larger and more diverse sample of drivers would enhance the robustness and generalizability of the findings. Future studies could aim to include a broader demographic profile, including a balanced representation of both male and female drivers and drivers from different geographic regions and driving professions (Singh & Kathuria, 2021).

Additionally, exploring the impact of interventions based on the findings of this study would also be a valuable direction for future research. Implementing and evaluating the effectiveness of tailored training programs, flexible scheduling, or in-vehicle monitoring systems could provide practical insights into how best to reduce stress and fatigue among drivers. These studies could help refine the interventions and determine their real-world applicability and impact on driver safety and well-being.

Lastly, investigating the long-term effects of chronic stress and fatigue on drivers' health and job performance would be crucial for understanding the broader implications of these factors. Lengthier longitudinal studies that track drivers over extended periods would be invaluable in this regard, offering deeper insights into how chronic exposure to stress and fatigue affects drivers and what strategies might be most effective in mitigating these effects.

6.6 Conclusion

This study employed a multi-method approach to explore the relationships between situational variables and their impacts on delivery drivers' fatigue, stress, and driving behaviors. The integration of physiological measurements, self-reports, and behavioral observations within this methodology facilitated a comprehensive analysis of how drivers' physiological and psychological states are influenced by varying driving conditions. By correlating these states with specific driving behaviors, the study illustrates the effectiveness of a diverse methodological framework in capturing complex interactions in real-world settings. Employing a combination of physiological data (HRV and respiration), self-reported measures of stress and fatigue, and direct observations of driving behavior (attention and risky driving), this methodology provided a basis for understanding the nuanced effects of different driving environments on driver behavior. This approach allows for a more comprehensive analysis that can inform targeted interventions to improve driver safety and well-being. Our findings underscore the potential of this multi-method approach to identify key risk factors and inform the development of tailored interventions such as optimized shift schedules and targeted stress management programs. The practical application of this methodology in naturalistic driving studies demonstrates its significant value and potential as a standard framework for research aimed at enhancing occupational health and driver safety.

Author contributions: CRediT

Mario Passalacqua: conceptualization, methodology, validation, investigation, writing - original draft, visualization, project administration. **Robert Pellerin:** conceptualization, methodology, resources, writing - review & editing, supervision, funding acquisition. **Sylvain Sénécal:** conceptualization, methodology, resources, supervision, funding acquisition. **Pierre-Majorique Léger:** conceptualization, methodology, resources, writing - review & editing, supervision, funding acquisition.

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Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Chat GPT4o in order to optimize the readability of sentences throughout the text. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

CHAPTER 7 GENERAL DISCUSSION AND CONCLUSION

This thesis investigated the impact of Industry 4.0 technology on the psychological dimensions of human-technology interaction within supply chain operations, specifically focusing on the psychosocial, cognitive, and behavioral aspects. The aim was to inform the design and implementation of supportive, efficient, and human-centered technological systems. To achieve this goal, several sub-objectives were identified through a review of the literature. The first sub-objective was to identify and characterize the psychosocial, cognitive, and behavioral outcomes in Industry 4.0 research, analyze their antecedents and consequences, and develop a roadmap for future human-centered research. The second sub-objective was to experimentally assess how different levels of AI decision support, defined as the AI's level of decision control, affect the psychosocial, cognitive, and behavioral aspects of human-AI collaboration. The third sub-objective was to experimentally assess and guide the development of worker training programs that enhance collaboration with AI, focusing on improving psychosocial, cognitive, and behavioral outcomes. The fourth sub-objective was to longitudinally and naturalistically assess how risk factors impact workers' psychosocial, cognitive, and behavioral outcomes in the context of last-mile delivery driving.

The following sections will illustrate how each of the articles allowed us to reach the sub-objectives of this thesis. It will also discuss the managerial and practical insights, as well as future research directions.

7.1 SO1: Provide an in-depth examination of psychosocial, cognitive, and behavioural factors in I4.0 contexts, identifying their outcomes, antecedents, consequences, and the methodologies used to address them, to uncover gaps in the current literature

The systematic literature review (Chapter 2) directly addressed Sub-Objective 1 by reviewing the literature on the psychosocial, cognitive, and behavioral impacts of AI in manufacturing. It identified significant gaps, highlighting the methodological and theoretical disconnect between empirical and non-empirical studies. The review emphasised the necessity of a multi-dimensional view of worker perception, attitudes, and behaviour, focusing on critical variables such as perceived autonomy, stress, and motivation. These findings aligned with the initial literature review, underscoring the transformative impact of Industry 4.0 technologies on worker roles and the importance of comprehensively considering human factors.

The systematic review made substantial contributions by identifying key gaps in the existing literature, particularly the lack of empirical studies on psychosocial factors in human-AI interactions. It stressed the need for multi-dimensional and multi-method approaches to study these human factors comprehensively. It provided a roadmap for future research, emphasising the importance of experimental methodologies and multi-method approaches to address the psychosocial impacts of AI. It also highlighted the necessity of integrating human-centric theoretical frameworks into AI research, aligning with the principles of Industry 5.0.

The review pinpointed key psychosocial variables such as trust, perceived autonomy, stress, and motivation, which are crucial for understanding human-AI interactions. It noted that while non-empirical articles have extensively explored these variables, empirical studies have lagged. The review called for more empirical research examining these variables in the context of AI integration, using robust experimental designs to establish causal relationships. Future research should prioritise experimental studies that manipulate technological variables to assess their impact on psychosocial outcomes. Multi-method approaches incorporating perceptual, psychophysiological, and observational measures are essential to capture the full spectrum of worker experiences. Interdisciplinary research combining insights from ergonomics, organisational psychology, and related fields will provide a comprehensive understanding of human-AI interactions. Practical implications include designing AI systems that enhance worker autonomy and motivation, developing effective change management strategies, and employing data-driven methods to refine training and retention practices. Cross-functional collaboration is vital to ensure a balanced and integrated approach to AI deployment, leveraging the strengths of various disciplines to create more effective and supportive AI systems.

7.2 SO2: Experimentally Assess how Different Levels of AI Decision Support Affect the Psychosocial, Cognitive, and Behavioral Aspects of Human-AI Collaboration

Article 1 addressed Sub-Objective 2 by experimentally investigating the impact of different levels of AI decision support on psychosocial, cognitive, and behavioral outcomes. Building on the gaps identified in the literature review, this study directly addressed the need for empirical research on how AI affects worker motivation, autonomy, and engagement. By employing a multi-method approach, it examined how partial and full automation influence these variables, providing concrete evidence on the benefits of maintaining human involvement in decision-making processes. This study supports a core principle of I5.0, i.e., balancing technological efficiency with human-centric values.

This article makes several contributions to the understanding of AI's impact on worker well-being and performance. Firstly, it provides empirical evidence that partial automation—balancing AI assistance with human control—supports better psychosocial outcomes, such as perceived autonomy, competence, and job meaningfulness, compared to full automation. This finding is significant as it suggests that maintaining a level of human involvement in decision-making processes is crucial for motivation, engagement, well-being, and performance.

The study also highlights the potential downsides of excessive automation, particularly in terms of reduced job meaningfulness and self-determined motivation. These insights are essential for designing AI systems that do not undermine human expertise and engagement. The findings validate the application of SDT in evaluating the psychosocial impacts of AI automation, demonstrating its utility in guiding the development of human-centric AI systems.

However, the study's limitations must be acknowledged. The experimental setting, while a controlled replication of a manufacturing environment, may not fully capture the complexities of real-world environments. The short duration of the study might not account for long-term effects, and the use of engineering students with manufacturing experience rather than actual factory workers may limit the generalisability of the findings.

Overall, this article paves the way for future research directions. Future research should explore different contexts and industries to generalise these findings further. Potential next steps involve longitudinal studies to observe the long-term impacts of AI decision support on worker outcomes and the development of training programs that enhance workers' ability to collaborate with AI effectively. Additionally, incorporating a broader range of participants, including those from diverse industrial backgrounds, will provide a more comprehensive understanding of the impacts of AI automation.

Appendix D presents a conference article which introduces a methodology for such a longitudinal field study, which could serve as the logical next step for this article and thesis. More specifically, we propose a longitudinal study that tracks workers' experiences over six months, gathering data before and after AI system deployment. This study will employ a mixed-methods approach, combining surveys to measure variables like trust, motivation, and stress; interviews to gain in-depth qualitative insights; physiological measures such as heart rate variability to assess stress responses; and behavioural observations to monitor changes in work practices and interactions with AI. By integrating these methods, we aim to provide an understanding of how workers adapt to AI over time, offering practical insights for organisations to enhance employee well-being and optimise AI integration.

7.3 SO3: Experimentally Assess and Guide the Development of Worker Training Programs that Enhance Collaboration with AI

Article 2 addressed Sub-Objective 3 by investigating how different levels of AI automation during training impact skill acquisition, motivation, and engagement. This study addresses the need for designing effective training programs that enable workers to collaborate effectively with AI systems. It aligns with the systematic review's call for training that fosters problem-solving, analytical, and decision-making skills, which are crucial for effective human-AI collaboration. The experimental findings reveal that partially automated decision support leads to better performance and motivational outcomes, emphasizing the importance of human decisional control in training environments.

Specifically, partial automation fosters a stronger sense of autonomy and identified regulation among participants. Identified regulation, driven by the perceived meaningfulness of the task, was significantly higher in the partial automation condition. This type of motivation is essential as it reflects a deeper internalisation of the task's value, leading to enhanced engagement and dedication. Participants who experienced partial automation reported feeling more in control of their decisions and actions. This finding is critical for organisations as it suggests that maintaining a balance where AI supports but does not entirely take over decision-making can lead to better training outcomes and more effective skill acquisition. Additionally, the enhanced motivation and engagement from partial automation are likely to translate into better long-term performance and greater organisational commitment, reducing turnover and improving overall productivity.

Similar to Article 1, the study's limitations include the use of a simulated manufacturing environment, engineering students, and short-term evaluation of our variables. Within Article 2, this may mean the observed effect is actually underestimated, as students likely put in extra effort to succeed and impress, possibly reducing the negative impact of fully automated AI training. Despite this, we still found a strong negative effect on error-detection performance. Observing such a pronounced effect in the short term also suggests the potential for an even greater impact over time, as training benefits typically diminish. Future research should involve longitudinal studies, which could be useful to observe the long-term implications of training with various levels of AI assistance. Additionally, field studies in real-world industrial settings can validate the findings and develop scalable training programs for various domains. Additionally, applying self-determination theory to the training of workers using highly automated AI systems should be further explored to support workers' motivational needs effectively. Lastly, experimentally evaluating the use of other Industry 4.0 technologies for worker training, such as augmented/virtual reality and digital twins, using the multi-method, multi-dimensional, and human-centered approach utilised in this study, will also provide valuable insights for optimising worker training programs in highly automated environments (e.g., Loic Couture et al., 2024; Loïc Couture et al., 2024).

7.4 SO4: Longitudinally and Naturalistically Assess how Risk Factors Impact Workers' Psychosocial, Cognitive, and Behavioral Outcomes

Article 3 addressed Sub-Objective 4 by examining the real-world implications of everyday risk factors on the psychosocial, cognitive, and behavioral aspects of delivery driver well-being. Through a comprehensive, multi-method naturalistic study, it investigated how various situational factors—such as delivery areas, shift length, and timeliness—influence fatigue, stress, attention, and risky driving behaviors. This study highlights the necessity of understanding these relationships to develop effective interventions that enhance driver safety and well-being. It complements the findings from the first two articles by extending the human-centric approach to a different domain, emphasizing the broad applicability of the identified principles.

The article contributes to understanding the real-world impacts of situational factors on delivery drivers' stress, fatigue, and driving behaviour. It provides insights into how various operational demands influence these factors, highlighting the importance of considering the work environment in safety and well-being assessments. The study reinforces the necessity of a multi-method approach, integrating physiological, perceptual, and observational data to capture the complexity of drivers' experiences. The findings offer practical implications for developing targeted interventions to enhance driver safety, emphasising the importance of considering human factors in last-mile delivery operations.

The case study found that different delivery areas significantly impacted drivers' stress and fatigue levels, with urban (downtown) environments being more challenging due to higher traffic density and navigation complexity. Longer shifts were associated with increased physiological fatigue and stress, highlighting the cumulative burden of extended driving periods. The second half of shifts showed greater fatigue and stress, reflecting the impact of prolonged driving on driver well-being. Late deliveries were associated with increased stress and physiological fatigue, underscoring the pressure of meeting delivery deadlines. Additionally, we found that driver stress and fatigue were significantly associated with risky driving behaviour and inattention at the wheel. This finding underscores the critical need for interventions that mitigate stress and fatigue to improve driver performance and safety, suggesting that addressing these factors could reduce the occurrence of risky driving behaviours and enhance overall road safety.

However, the case study has limitations. The small sample size and the correlational nature of the study limits the ability to draw strong causal inferences. Future research should expand the sample size and include more diverse driving contexts and driver demographics. Longitudinal studies can be useful to understand the long-term effects of stress and fatigue on driver behaviour and well-being. Investigating the impact of interventions, such as flexible scheduling and real-time monitoring systems, would provide valuable insights into improving driver safety and well-being.

7.5 Managerial and Practical Insight

The transformative potential of I4.0 technologies, particularly AI, necessitates a comprehensive approach that balances technological advancements with human-centric considerations. The results of this thesis raise important managerial and practical implications that offer valuable insights for practitioners and decision-makers striving to optimize both productivity and employee well-being.

Firstly, the integration of AI technologies has significantly altered worker roles and responsibilities, often shifting from routine maintenance tasks to more strategic and cognitively demanding activities. This presents an opportunity to enhance job satisfaction and deepen the sense of meaningfulness in work. To capitalize on this, managers should prioritize skill development and training, equipping workers to handle these complex roles effectively. By doing so, organizations can foster a work environment that not only enhances performance but also supports worker autonomy, competence, and motivation.

However, AI's dual-edged nature also imposes high cognitive demands and stress on workers. To mitigate these challenges, decision-makers must ensure a balanced workload and robust support systems. Designing AI systems that enhance worker autonomy, reduce monotony, and provide clear pathways for career advancement can alleviate stress and improve overall well-being. A human-centric approach in AI development is crucial, focusing on creating systems that complement and empower rather than replace human work, particularly in decision-making processes. This approach can significantly enhance workers' perceptions of autonomy, motivation, and overall job satisfaction, ultimately leading to improved performance and well-being.

Employee well-being and retention are critical factors influenced by the introduction of AI. Organizations that address both the positive and negative impacts of AI can enhance motivation, engagement, and long-term retention. Incorporating psychosocial factors into managerial decision-making processes is essential. Managers and leaders must understand AI's potential impacts on employee trust, autonomy, and motivation, using this knowledge to develop effective change management strategies.

A holistic approach to AI integration is essential for its successful deployment. Practitioners must consider the psychosocial, cognitive, and behavioral impacts of AI on workers, moving beyond a purely technical and efficiency focus. A human-centered approach in designing AI systems ensures they are safe, trustworthy, and aligned with human needs. This may not only improves worker acceptance and satisfaction but also enhances the overall efficacy of AI systems. A data-driven approach in human resource management, using insights on technology acceptance and employee experiences with AI, is indispensable for refining training and retention strategies that align with the changing workplace dynamics introduced by AI.

Strategic planning for AI deployment involves a thorough assessment of the work environment and the specific needs of the workforce. Continuous monitoring and adaptation of AI systems based on employee feedback is crucial for maintaining high levels of productivity and innovation. Regular organizational assessments of worker perceptions and attitudes towards AI are recommended to fine-tune AI strategies effectively. Monitoring key indicators such as employee satisfaction, motivation, engagement, productivity, and stress levels will provide insights into the long-term impact of AI integration, allowing for informed adjustments.

Moreover, recognizing the medium- to long-term effects of AI on workers is vital. Organizations should foster an environment of open communication where employees feel comfortable expressing their concerns and suggestions related to AI use. This inclusive approach ensures that AI technologies evolve in ways that benefit both the organization and its workforce. Cross-functional collaboration can also be beneficial in AI implementation, involving teams from various departments, including IT, HR, and operations, to ensure a balanced and holistic approach. This collaboration should harmonize technical feasibility with worker well-being and operational efficiency, reflecting a commitment to the effective and empathetic deployment of AI in the workplace.

Lastly, the conceptual model introduced in this thesis offers a practical framework for integrating AI in a way that aligns with both technological advancements and human needs. Rather than merely focusing on technical efficiency, the model emphasizes a holistic approach, incorporating a range of factors to guide AI implementation. It provides actionable insights into how organizations can balance AI capabilities with employee autonomy and well-being. This model serves as a guide for practitioners to anticipate and address potential challenges in AI adoption, ensuring that AI systems are not only effective but also supportive of a positive and productive work environment. By applying this model, organizations can foster a more resilient and adaptable workforce, better equipped to thrive alongside AI technologies.

7.6 Future Research

Future research should continue to explore these interdisciplinary intersections, leveraging diverse methodologies and perspectives to uncover deeper insights into how technology and new work demands can enhance human work. Longitudinal studies will be particularly invaluable in understanding the long-term impacts of these changes on worker well-being and performance. By tracking changes over time, researchers can identify patterns and relationships that short-term studies may miss. These studies can reveal how workers adapt to new work environments over extended periods, providing critical data on the sustainability of these changes in the workplace.

Furthermore, there is still a need to explore the impact of varying levels of AI decision automation on employee and organizational outcomes. The current thesis has identified a potential critical boundary beyond which the benefits of automation begin to diminish. Future studies could aim to pinpoint this boundary more precisely across different industries and job roles. By examining the conditions under which partial automation enhances or detracts from worker satisfaction, motivation, and engagement, researchers can provide practical guidelines for optimizing AI deployment in diverse contexts.

Another critical area for future research is the application of psychological theory, such as self-determination theory, in the training of workers who interact with highly automated AI systems. Understanding how to effectively support workers' motivational needs within these environments is crucial for fostering long-term learning, engagement and job satisfaction. This line of inquiry should include both experimental studies and longitudinal validation with actual factory workers to ensure the applicability and effectiveness of the proposed strategies.

Within a similar vein, future research should leverage the conceptual model introduced in this thesis to guide the exploration of AI's impact on worker and organizational outcomes. Researchers can use this model as a framework to design studies that test its applicability across different industries and contexts, helping to validate its effectiveness. By applying the model in longitudinal studies, future research can refine the model's components and identify areas for further development.

Moreover, expanding research to include diverse industrial contexts and demographics is essential. The variability in work environments and worker experiences means that findings from one domain or demographic group may not be universally applicable. By encompassing a broad range of settings and populations, research can develop strategies for integrating new technologies and work processes that are flexible and adaptable to various contexts. This inclusivity ensures that technological and organizational changes can be implemented in ways that are equitable and beneficial across different industries and workforce segments.

Exploring the interplay between AI automation, organizational culture, and leadership practices is another promising research avenue. Investigating how different leadership styles and organizational policies influence the effectiveness of AI in supporting or undermining psychosocial outcomes could yield valuable insights. For instance, future research could examine the role of training, support, and communication strategies in facilitating a positive human-AI interaction experience, ultimately contributing to more effective and humane AI integration.

Lastly, there is a need to investigate the potential of other I4.0 technologies, such as augmented/virtual reality and digital twins. Using a multi-method, multi-dimensional, and human-centered approach, similar to the one employed in this research, could offer new insights into how these technologies impact worker autonomy, motivation, learning, and performance. This exploration could lead to more effective technology integration and training programs that are better aligned with the evolving demands of the modern workplace.

7.7 Conclusion

This thesis has provided significant insights into the integration of advanced technologies within supply chain operations, particularly regarding their impact on human factors. By achieving our sub-objectives, we have contributed to the broader goal of understanding how Industry 4.0 technologies affect psychological dimensions of human-technology interaction, which is essential for designing supportive, efficient, and human-centered systems. The findings have important implications for the future of work, policy-making, technological design, and organizational management, all of which are crucial to advancing the vision of a human-centric Industry 5.0.

A key conclusion of this thesis is the need to balance technological advancements with human well-being, aligning with the principles of Industry 5.0. Balanced automation and thoughtful AI system design can significantly enhance workers' sense of autonomy, competence, and job meaningfulness, leading to higher motivation, engagement, and performance. Organizations that maintain human decisional control and involvement in processes are likely to see reduced turnover, absenteeism, and increased productivity. Furthermore, the integration of AI should be seen as an opportunity to augment human capabilities rather than replace them. By supporting human skills, organizations can create collaborative environments where both AI and human workers thrive, leading to a more adaptable and resilient workforce. This approach ensures that technology serves as a tool for empowerment, enabling workers to perform complex and creative tasks that require human insight.

Additionally, this thesis underscores the importance of designing technological systems and training programs that are not only technically efficient but also psychologically supportive, particularly in the context of highly automated AI systems. As industries continue to evolve, workers must develop advanced skills in critical thinking, problem-solving, and decision-making to effectively collaborate with AI systems. Training programs should emphasize continuous feedback, decision-making authority, and meaningful engagement to enhance skill acquisition and motivation. Additionally, these programs should focus on non-routine skills such as creativity and emotional intelligence, which AI cannot easily replicate, ensuring that workers complement AI capabilities rather than compete with them. As AI continues to automate routine tasks, fostering problem-solving and analytical skills will be crucial for maintaining worker autonomy and engagement.

Lastly, the thesis underscores the crucial importance of cross-domain and interdisciplinary research in fully understanding the complex impacts of new technologies on workers. To navigate the multifaceted challenges of modern work environments, it is essential to integrate insights from fields such as ergonomics, organizational psychology, cognitive science, and industrial engineering. This interdisciplinary approach ensures that technological systems are designed and implemented with a comprehensive understanding of human behavior, cognitive processes, and organizational dynamics. A critical element of this approach is the use of multi-method research strategies, which combine perceptual, physiological, and observational measures to provide a nuanced analysis of worker experiences. By melding these disciplines, we can create work environments that not only enhance productivity but also promote human well-being, driving forward the vision of a human-centric Industry 5.0. This collaborative and scientifically grounded exploration ensures that the future of work is both technologically advanced and deeply humane, where advancements in technology are harmonized with human values and needs.

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Zirar, A., Ali, S. I., & Islam, N. (2023). Worker and workplace Artificial Intelligence (AI) coexistence: Emerging themes and research agenda. *Technovation*, *124*, 102747.

APPENDIX A: SYSTEMATIC REVIEW METHODOLOGY

This section presents the methodology used for the review. We used the PRISMA checklist to ensure transparency and comprehensiveness in the reporting of this systematic review (Shamseer et al., 2015). This review was registered with the International Prospective Register of Systematic Reviews (PROSPERO: CRD42022308729). To ensure transparency, accountability, reproducibility, and ethical conduct, the PRISMA protocol was published, before the start of the review, in the conference proceedings of HCI International (Passalacqua et al., 2022). It can be accessed through the following link: https://doi.org/10.1007/978-3-031-21707-4_34.

A.1 Eligibility Criteria

We employed the SPIDER Tool for Qualitative Evidence Synthesis, offering directives to construct a systematic search strategy tailored to handle non-quantitative research questions (Cooke et al., 2012). Table A.1 shows how the tool was used for our research question.

Table A.1: SPIDER Framework

SPIDER Facet	Description
(S) Sample	Research that involved employees or users working with AI-based technology in a manufacturing or logistics setting were included.
(PI) Phenomenon of interest	We incorporated studies focusing on human interaction with AI-based systems, emphasising our interest in the dynamics of the human-AI relationship.
(D) Study design	All types of research designs were included.

Table A1 (continued and end)

(E) Evaluation	Research that highlighted the effects of AI-based technology on workers or users, from a psychosocial and human factors perspective. Notably, our focus was on a substantive exploration of human factors and/or psychosocial variables, such as motivation, engagement, stress, cognitive workload, fatigue, well-being, empowerment, trust, acceptance, understandability, explainability, vigilance, job satisfaction, and usability.
(R) Research type	We considered all peer-reviewed studies written in English, French, Italian, and German.

A.2 Information Sources

Web of science, Engineering village (Inspec and Compendex), IEEE Xplore, ACM digital library, and PsycInfo databases were used to gather data. They were searched up to July 1st, 2024. Furthermore, we carried out both a backward and forward citation for the articles chosen for data extraction. When articles were unavailable, we reached out to the authors.

A.3 Search Strategy

Our search strategy was designed following recommendations of the Cochrane Handbook for Systematic Reviews of Interventions (Lefebvre et al., 2022). The search query used to search the databases is shown in Table A.2. The search query was divided into three categories, connected by the Boolean operator “AND”. The first category contained terms related to the domain or context (for instance, Industry 4.0/5.0); the second encompassed terms linked to human and psychosocial aspects (such as ergonomics and motivation); and the third category incorporated terms associated with AI (like intelligent agent and neural network).

Table A.2: Search Query (reprinted with permission of Springer Nature from (Passalacqua et al., 2022))

Category	Search terms
Domain/context	“industr* 4.0” OR “industry 5.0” OR “smart manufacturing” OR “operator 4.0” OR “connected manufacturing”
	AND
Human factors and psychosocial factors	“human?cent?red” OR “user?cent?red“ OR “human factor*” OR ergonom* OR sociotechnical OR socio-technical OR anthropocentric OR psychosocial OR psychophysiolog* OR motivation OR engagement OR stress OR “cognitive load” OR “cognitive workload” OR fatigue OR “well being” OR well-being OR empowerment OR trust OR distrust OR acceptance OR acceptability OR personality OR comprehensib* OR understandab* OR explainab* OR vigilance OR “job satisfaction” OR “work satisfaction” OR Usability OR “User Experience” OR UX
	AND
AI-related	“artificial intelligence” OR AI OR ML OR “deep learning” OR “data mining” OR “machine learning” OR RL OR “reinforcement learning” OR “supervised learning” OR “unsupervised learning” OR “autonomo?s agent*” OR “intelligent agent*” OR “neural network” OR “machine intelligence”

Before proceeding with the application of the search query to the databases, we adopted an iterative approach to identify additional search terms that may have been omitted, ensuring the comprehensiveness our search. Our search terms were expanded in two stages. In the first stage, we used two of the three categories (domain AND human factors) to expand our search and identify additional relevant search terms. In the second step, we used a different combination (domain AND AI). Essentially, using only two of three categories per step broadened our search and allowed us to find search terms that we otherwise would not have found. For each step, we limited the search to a maximum of 50 papers per database across the five databases, totalling a maximum of 250 papers per step. This limit ensured manageability and focus while allowing us to efficiently add to the search terms, enhancing the accuracy and relevance of our search without being overwhelmed by an excessive number of articles. The iterative refinement of search terms is a common and recommended practice in systematic reviews by both the Cochrane Handbook and PRISMA, allowing for improved accuracy and relevance (Cooper et al., 2018; Lefebvre et al., 2022; Shamseer et al., 2015).

A.4 Selection and Data Collection Process

We utilised the Zotero (2023) bibliography manager for citation managing. Data was extracted and recorded using Covidence (2023), a web-based platform designed for systematic review management. The final data was exported to Excel. Zotero automatically identified duplicates, which were subsequently manually removed by one reviewer (MP). Two separate reviewers (MP and LD; MP/FM) undertook the title/abstract screening, full-text screening, and data extraction processes without knowledge of each other's choices. Results from each reviewer were compared, and the inter-rater reliability was examined. Discrepancies between the two reviewers were collaboratively assessed with the aim of reaching a joint consensus. If a resolution was not reached, a third reviewer intervened to finalise the decision. Table A.3 shows the data that was extracted from each chosen article.

Table A.3: Data extracted from each article

Article section	Extracted data	Explanation
-	Summary	Two- to three-sentence recap of the article
Introduction	Research question	Research question(s) and objective(s) addressed
	Theoretical framework	Theoretical model(s) referenced (e.g., technology acceptance model, self-determination theory)

Table A3 (continued and end)

Methodology	Article type	Type of article (empirical, review, conceptual, or system/framework design with user test)
	Research design	For empirical articles, the research design used (experimental, observational, case study)
	Participants	If the article is empirical, number of participants and their characteristics (e.g., students, operators)
	Data gathering method	Methodology used to gather data (e.g., questionnaire, interviews, psychophysiological instruments)
	Antecedent/ manipulated variable	The independent variable manipulated by the researchers (e.g., interface design, task complexity, personality traits). Alternatively, the antecedents of the outcome variables (e.g., balanced task complexity (antecedent) lead to lower cognitive load).
	Outcome variables	Outcome or dependent variables highlighted by the paper's authors via experimentation, review of the literature, discussion, or other techniques.
Results	Result synopsis	A synopsis of the results
Discussion	Noteworthy points	Noteworthy observations, encompassing areas of unexplored research, future studies, and elements pertinent to the research question or objectives of the review

A.5 Risk of Bias Assessment

Every article selected for extraction was independently assessed by two reviewers (MP and LD/FM) for any bias in the study's methodology, execution, and analysis using the JBI Critical Appraisal Tool (Aromataris & Munn, 2020). Given that multiple JBI checklists exist, each tailored for a distinct type of study (https://jbi.global/critical-appraisal-tools), our selection was adjusted based on the nature of the study (e.g., near-experimental, qualitative). Discrepancies between the two reviewers were collaboratively assessed with the aim of reaching a joint consensus. If a resolution was not reached, a third reviewer intervened to finalise the decision.

A.6 Data Synthesis Method

We found a predominant number of conceptual and qualitative empirical articles compared to quantitative experimental studies, because of the emerging nature of the field (human-centred AI within a manufacturing context). As a result, our data collection leans more towards qualitative insights but with some quantitative metrics as well. Consequently, we have chosen a narrative synthesis approach for data assimilation. This approach has been shown to be effective to integrate diverse forms of data types (e.g., qualitative and quantitative) across different articles. Additionally, this method will aid in describing the primary attributes of the studies while highlighting commonalities and variances among them (Peters et al., 2020; Popay et al., 2006).

To conduct our narrative synthesis, we followed recommendations from the Cochrane-Campbell Handbook for Qualitative Evidence Synthesis (McKenzie & Brennan, 2019). Essentially, the synthesis began with developing a preliminary synthesis. This involved systematically extracting data from the selected articles, focusing on key elements such as research questions, theoretical frameworks, methodologies, and findings, as shown in Table A3. The extracted information was then categorized to identify patterns and themes across the studies. We conducted a descriptive analysis to summarize the characteristics of the included studies, such as the types of human factors examined, the methodologies used, and the main findings. Next, we explored relationships within and between studies, identifying recurring themes and concepts related to human factors in I4.0 contexts and how they have been addressed in the literature. A comparative analysis was also conducted to highlight differences and similarities in how various studies approached the same or similar human factors, helping us understand the diversity of methodologies and theoretical frameworks used.

APPENDIX B: BIBLIOMETRIC ANALYSIS (SYSTEMATIC REVIEW)

This section presents the bibliometric analysis of the literature.

Looking at the 67 human-focused articles selected for this review, the number of publications per year has been steadily increasing since 2017. Note that 2024 represents half of a year (January 1st to July 1st). Figure B.1 shows the number of articles published per year.

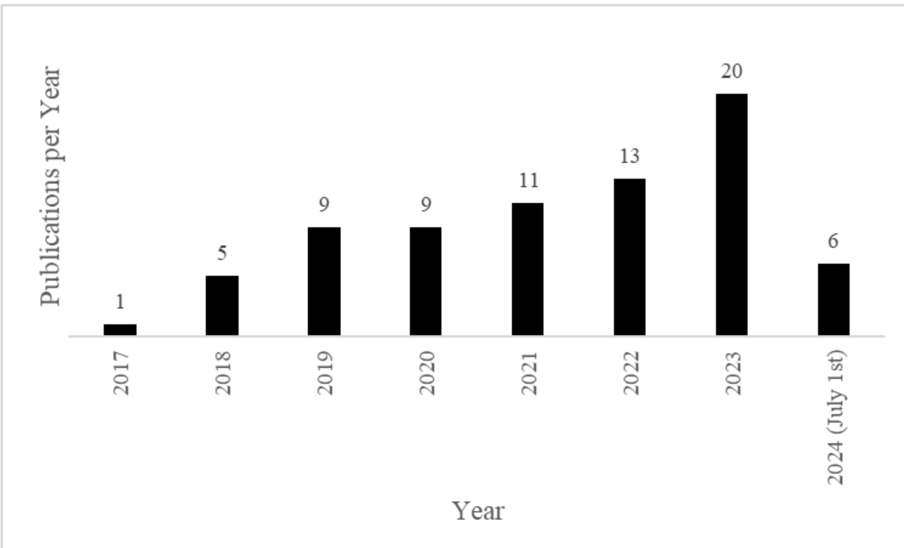


Figure B.1: Number of publications per year

When looking at the number of publications by country of the first author's affiliation, Italy has the most, with a total of 13 articles, representing 19% of all selected articles. Germany is close behind (10), followed by the USA (5), UK (four), Spain (three), Canada (three), and India (three).

Pertaining to the publication outlet, the International Journal of Production Research has published four of the 67 included articles. Ergonomics, the International Journal of Environmental Research and Public Health, the Journal of Manufacturing Systems, and the International Conference on Advances in Production Management Systems have each published three articles. A total of 53 articles (79%) have been published in journals, while 14 articles (21%) have been published in conference proceedings.

As for the distribution of article types within our sample, conceptual and review were the most common type, with 21 and 20 articles respectively. Figure B.2 presents the full results.

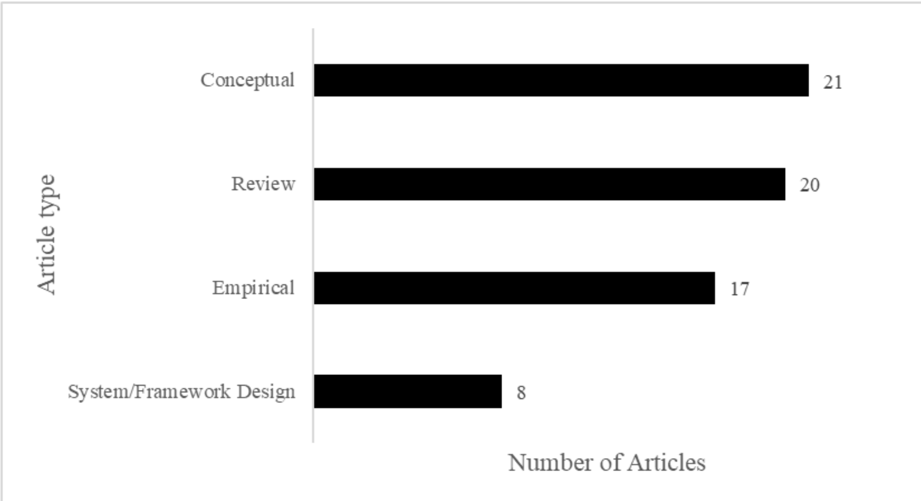


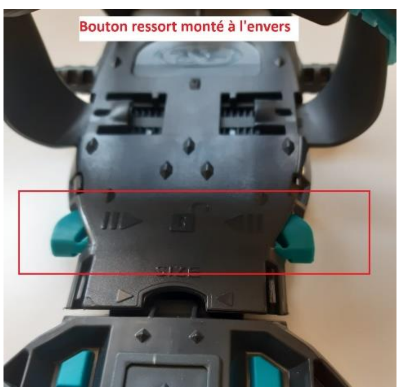
Figure B.2: Distribution of article type

APPENDIX C: LIST OF ALL POSSIBILE ERRORS

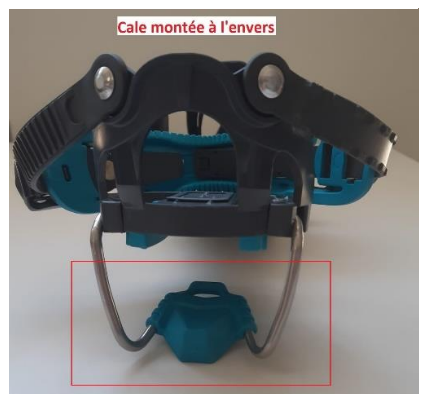
Error 1: Inverted angle of straps

Error 2: Fastener on wrong side

Error 3: Knob is upside-down



Error 4: Metal piece is reversed



Error 5: Strap is not attached

Error 6: Missing a screw

APPENDIX D: ASSESSING THE PSYCHOSOCIAL, COGNITIVE, AND BEHAVIOURAL IMPACT OF AI INTEGRATION: A METHODOLOGY FOR A LONGITUDINAL FIELD STUDY[2]

D.1 Introduction

The integration of Artificial Intelligence (AI) into the manufacturing domain represents a significant milestone in the evolution of industrial practices, marking a transition towards increasingly intelligent, efficient, and interconnected operational systems (Moeuf et al., 2018). This evolution, emblematic of the shift towards Industry 4.0 and beyond, heralds a new era of manufacturing where AI-driven technologies promise to revolutionise traditional processes, from production lines to quality control mechanisms (Danjou et al., 2017). While the operational benefits of such integration, including enhanced productivity, reduced error rates, and predictive maintenance, are widely recognised, the broader implications of AI on the workforce—especially in terms of psychosocial well-being, cognitive demands, and behavioural adaptations—warrant a deeper, more nuanced investigation (Ghislieri et al., 2018; Grosse et al., 2023; Y. Lu et al., 2022).

As manufacturing plants increasingly adopt AI technologies, employees are confronted with a rapidly changing work environment. These changes extend beyond the automation of tasks to encompass complex interactions with intelligent systems capable of learning and decision-making (Rosin et al., 2022). This new paradigm raises important questions about how workers perceive and adapt to AI, the cognitive impact of interacting with sophisticated technologies, and the potential for shifts in workplace dynamics and roles. Given the profound potential of AI to influence not just operational efficiency but also the very nature of work (Gagné et al., 2022; Molino et al., 2021), there is a critical need for methodologies capable of assessing these multifaceted impacts in a holistic, longitudinal manner.

The primary aim of this paper is to present the methodology of an upcoming longitudinal field study designed to capture both the immediate and enduring impacts of AI integration on the operators of a snowshoe manufacturing plant. The presented study aims to provide a holistic

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[2] The content of this appendix was presented at the Administrative Sciences Association of Canada 2024 conference (best student paper award)

understanding of how the introduction of AI-based decision support systems influences the daily experiences and work dynamics of manufacturing employees involved in quality control tasks.

Specifically, we aim to assess the psychosocial, cognitive, and behavioural impacts of AI integration on workers. The psychosocial dimension examines the interaction between an individual's psychological experiences and the social environment, examining how these two domains mutually influence and shape one another (Neumann et al., 2021; Vijayakumar & Sgarbossa, 2020). This dimension includes concepts like worker motivation, agency, and stress. The cognitive dimension involves changes in mental processes such as attention, memory, and decision-making, examining whether AI tools enhance or overload workers' cognitive capacities (Longo et al., 2019). The behavioural dimension focuses on observable changes in actions and routines, including how workers adapt to and interact with AI technologies and any shifts in work practices (Meyer et al., 2010). Together, these dimensions provide a comprehensive view of the multifaceted effects of AI integration on the workforce.

Additionally, we aim to adopt a multimethod approach to measure these dimensions, leveraging perceptual, physiological, and observational measures. Perceptual measures, including surveys and interviews, will explore workers' attitudes, anxieties, and perceptions of AI. Physiological measures, such as heart rate variability and electrodermal activity, will offer objective data on the cognitive and emotional responses to AI technologies, shedding light on the unseen burdens or enhancements. Finally, observational measures, including workplace ethnography and performance measurement, will document behavioural changes and adaptations, revealing how AI integration reshapes work practices and daily routines.

Central to our investigation is the following research question: What are the short- and long-term psychosocial, cognitive, and behavioural impacts of AI decision support system integration on operators within a snowshoe manufacturing plant? Through this investigation, we aspire to contribute to the development of AI technologies and work practices that support employee well-being and productivity, ensuring that the benefits of AI in manufacturing extend beyond operational gains to foster a positive, empowering work environment for employees. In doing so, this research aligns with the goals of Industry 5.0, a new manufacturing paradigm which emphasises the harmonisation of technological advancement with human-centred values, advocating for a future where technology serves to augment human capabilities and enhance the quality of working life (Enang et al., 2023).

The rest of the article is structured as follow: Section 2 will briefly review the literature on human-centred AI empirical work with Industry 4.0/5.0; Section 3 will describe the proposed longitudinal methodology; and Section 4 will discuss the expected implications for both practice and research.

D.2 Literature Review

The integration of artificial intelligence (AI) into manufacturing processes represents a frontier of innovation, aimed at enhancing efficiency and productivity. However, this technological evolution has also illuminated a significant oversight in the existing body of research: a lack of attention to the impact of AI on the psychosocial, cognitive, and behavioural dimensions of the human workforce (Grosse et al., 2023; Kadir et al., 2019; Ngoc et al., 2021; Reiman et al., 2021). This gap has been identified and highlighted by numerous researchers across various studies, underscoring a critical need for a shift in the research agenda towards a more human-centric perspective. As this consensus among scholars grows stronger, it becomes evident that the current trajectory of AI in manufacturing, while technologically forward-looking, may neglect the interplay between AI systems and human workers, potentially overlooking how these technologies affect individuals' well-being, decision-making processes, and interactions within the workplace.

Recognising this deficiency, there is a unified call for research that serves as a constructive blueprint for future investigations, aiming to bridge the divide between technological advancement and human well-being. The consensus among scholars emphasises the adoption of empirical methodologies (e.g., experimental, longitudinal) (Del Giudice et al., 2023; Ismatullaev & Kim, 2022; Y. Lu et al., 2022). These methodologies are crucial for discerning the direct impacts of AI on workers, facilitating the controlled variation of factors such as automation levels and the extent of human oversight. This methodological precision is key to moving beyond observational correlations, providing stronger evidence for potential causal links between AI deployment and worker outcomes. Such insights are instrumental in guiding the development of AI systems that are attuned not only to operational objectives but also to the enhancement of the work environment and employee experience.

Alongside the call for empirical research, there is a significant emphasis on the importance of embedding research within robust theoretical frameworks (Grosse et al., 2023; Langer & Landers, 2021; Shneiderman, 2020). Such frameworks are vital for understanding the intricate dynamics at play, allowing researchers to explore how AI influences not only the psychosocial health of employees but also their cognitive processing and behavioural responses. Theoretical grounding in organisational psychology, human factors, and related disciplines offers a comprehensive lens through which the effects of AI can be examined, providing a structured approach to uncover the deeper, often overlooked consequences of AI integration into manufacturing. In this context, Self-Determination Theory (SDT) and Job Characteristics Theory (JCT) are particularly useful. SDT (Deci et al., 2017; Deci & Ryan, 1980) focuses on motivation within the workplace, emphasising the importance of autonomy, competence, and relatedness in fostering self-determined motivation and engagement. SDT could aid in measuring shifts in the fulfilment of these psychological needs due to AI integration, helping organisations adjust implementations proactively to avoid demotivation and disengagement. JCT (Hackman, 1980; Hackman & Oldham, 1976), on the other hand, examines how specific job characteristics (such as task variety, task identity, task significance, autonomy, and feedback) impact job satisfaction, motivation, and performance. JCT could provide a way to analyse how AI implementation transforms existing job characteristics, informing how work could be redesigned to maintain positive outcomes for employees. Together, SDT and JCT can help researchers and practitioners understand how AI-driven changes in job design can affect worker motivation, satisfaction, and overall well-being, leading to more human-centred AI implementations.

Moreover, many authors advocate for a multi-method approach to properly capture the complexity of the worker-AI interaction (Brunzini et al., 2021; Ciccarelli et al., 2022; Peruzzini et al., 2020; Vijayakumar & Sgarbossa, 2020). By integrating a variety of research tools—including perceptual surveys, psychophysiological measures, and behavioural observations—this strategy aims to provide a holistic view of how AI technologies impact workers. This comprehensive approach seeks to overcome the limitations of single-method research by offering a richer, more nuanced understanding of human-AI interaction. Through such diverse methodologies, researchers can better assess the multifaceted effects of AI, encompassing psychosocial, cognitive, and behavioural aspects.

In summary, the literature reflects a critical pivot towards acknowledging and addressing the human dimensions of AI in manufacturing. This shift is marked by a growing recognition of the research gap and a concerted effort to propose a roadmap for future studies that consider the full implications of AI technologies on workers. By focusing on theoretical depth, methodological rigor, and a multi-faceted research approach, the field is poised to advance towards AI implementations that harmonise technological innovation with the holistic well-being of the human workforce.

Integrating these insights, the planned longitudinal study will aim to apply the roadmap laid out by the literature review, into practical research. This study aims to longitudinally track the evolution of AI's impact on the workforce, focusing on the psychosocial, cognitive, and behavioural dimensions identified as critical yet underexplored. By leveraging the theoretical frameworks, empirical methodologies, and multi-method approaches advocated by scholars, the study will provide empirical evidence on how AI integration unfolds over time within the manufacturing domain. This approach will not only validate the theoretical constructs but also offer actionable insights into designing AI systems and work environments that support the well-being and productivity of the workforce. Thus, the longitudinal study seeks to embody the principles of human-centred AI research, advancing the field towards a future where technological innovation and human welfare are mutually reinforcing objectives.

D.3 Methodology

This research sets out to investigate the psychosocial, cognitive, and behavioural impacts of implementing an AI-based decision support system within quality control tasks at a snowshoe manufacturing plant. Utilising a longitudinal, mixed-methods field study design, the project aims to document the progression of worker experiences during the AI implementation process.

D.3.1 Study Design

Spanning approximately 6 months, the study covers the transition period before and after AI integration, offering a detailed view of the changes within the manufacturing setting. Our choice timeframe is based on previous longitudinal research involving the evolution of psychosocial factors in the workplace. For example, Howard et al. (2021) examined motivation and Herr et al. (2023) examined work meaningfulness and well-being over four-month periods.

The timeline for data collection is carefully organised to cover all stages, from baseline (pre-implementation) to various post-implementation phases (T1 through T6), facilitating an in-depth examination of the initial reactions, ongoing adjustments, and eventual stabilisation following the AI system's deployment. T1 will be measured directly following the AI implementation, while each subsequent measure (T2-T6) will be taken at one-month intervals. Figure D.1 illustrates the proposed experimental design. Prior to the AI system's deployment, participants will undergo a standardised training program designed to equip them with the necessary skills and knowledge to effectively interact with the new technology. Due to the comprehensive nature of the AI system's implementation across the entire plant, it is not feasible to include a control group; instead, we will utilise pre-implementation data as a benchmark, when possible, to assess post-implementation changes.

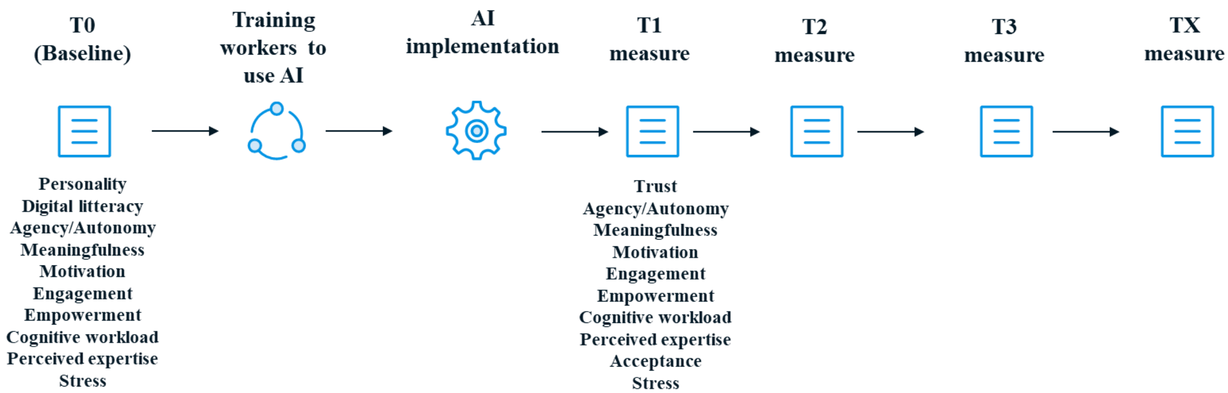

Figure D.3: Proposed experimental design

D.3.2 Participants

Focusing on production line employees engaged in quality control, the study anticipates potential participant attrition common in longitudinal research by targeting a pool of 25-30 participants. This strategy ensures a sufficient sample size and aims to capture a diverse array of perspectives by including workers of different ages, genders, and experience levels. Addressing participant attrition is crucial for maintaining the integrity of our longitudinal study. To mitigate the possible impact, we implement several key strategies focused on participant engagement and comprehensive data collection. Our approach includes establishing regular communication with participants to keep them informed and connected to the study's progress, aiming to foster a sense of involvement and commitment. Additionally, we will meticulously monitor attrition rates and examine the characteristics of participants who discontinue their involvement. This will help us understand the reasons behind dropout and assess how it might affect our study's outcomes. Through these focused efforts, we strive to preserve the validity of our research findings, ensuring they accurately reflect the impacts of AI system integration on the workforce.

D.3.3 Artificial Intelligence System to be Integrated

The technological component of this study is an AI-based decision support system that integrates computer vision and reinforcement learning technologies to improve quality control processes within the snowshoe manufacturing plant. By analysing visual data in real-time, the system aims to identify anomalies and predict potential flaws in the products, thereby aiming to enhance the precision and efficiency of the production line. The system utilises computer vision technology to interpret complex visual inputs, enabling it to identify discrepancies that might be challenging for manual inspection to detect consistently, due to the monotonous nature of the task.

Reinforcement learning, another key component of the system, allows the AI to adapt and refine its decision-making processes over time. This adaptation is facilitated by feedback from the system's performance in the production environment. An important aspect of this feedback mechanism involves the human operators, who can accept or override the AI's quality control suggestions. Such interventions by operators provide direct feedback to the AI, which the reinforcement learning algorithm uses to adjust and improve its future suggestions.

D.3.4 Measures

In the initial phase of data collection at baseline (T0), we will assess a range of demographic (e.g., age, gender, education, experience, employment status) and personality-related variables that could influence subsequent perceptions of and interactions with the AI system. Recognising the potential impact of personality traits on technology acceptance and use, we will administer established inventories such as the Big Five Personality Traits questionnaire (Goldberg, 1993) to gauge the openness, conscientiousness, extraversion, agreeableness, and neuroticism of participants. This will help us understand how these traits may correlate with later attitudes toward and engagement with the AI system.

Additionally, we will measure digital literacy at baseline to account for the participants' varying levels of comfort and proficiency with technology, which could significantly influence their adaptation to and acceptance of the AI system. By identifying these baseline characteristics, we will be better equipped to analyse how individual differences might interact with the psychosocial, cognitive, and behavioural effects observed throughout the study. Such variables are crucial for contextualising the data and could provide insights into the variance in adaptation strategies, learning curves, and overall receptivity to the AI system among the workforce.

To deepen our exploration of how AI integration reshapes the workplace, we will assess, during each phase of the data collection, key facets of the organisational ecosystem—namely, climate, culture, and leadership styles—alongside the foundational demographic and personality metrics initially gathered. This approach will enable us to detect changes over time in these organisational dimensions and explore their potential impact on psychosocial, cognitive, and behavioural factors. We intent to measure climate using the Organizational Climate Measure (Patterson et al., 2005), culture using the Organizational Culture Assessment Instrument (Cameron et al., 2006), and leadership styles using the Multifactor Leadership Questionnaire (Bass & Avolio, 1996).

In the post-implementation phase (T1-T6), we blend quantitative and qualitative data collection methods to comprehensively understand worker experiences as they adapt to the implementation of an AI-based decision support system. Psychosocial factors are evaluated using the Copenhagen Psychosocial Questionnaire and other similar validated tools (e.g., Brien et al., 2012; Hoff & Bashir, 2015; Schaufeli et al., 2003; Spreitzer, 1995), which allow us to assess trust in the AI system, employee agency and autonomy, competence, relatedness, stress, the meaningfulness they attribute to their work, levels of self-determined motivation, engagement, empowerment, perceived expertise, and the acceptance of AI integration into their daily work routines. Alongside these assessments, we will conduct semi-structured interviews to capture the rich, qualitative experiences of employees. These interviews are designed to delve into the workers' personal perceptions of how their work and their interactions with the AI system evolve over time.

Cognitive impacts are measured using the NASA TLX Questionnaire (Hart & Staveland, 1988), which offers a subjective workload assessment, giving us insight into the mental demands placed on workers as a result of the AI integration. Complementing this, we evaluate stress and cognitive workload physiologically through ECG and respiration monitoring (Abdul Samad et al., 2022; Khairai et al., 2020). These measures provide an objective assessment of the physical responses to stress and cognitive demands in the workplace, supplementing the subjective data collected from questionnaires. During each time measure (T0-T6), participants will be equipped with a Hexoskin physiological vest (Carré Technologies, Montreal). This vest captures respiration data (128 Hz ; two sensors), movement data (3-axis accelerometer), and heart rate data (256 Hz; 1-lead electrocardiogram). This vest has been validated for research use (Cherif et al., 2018; Jayasekera et al., 2021; Smith et al., 2019).

Behavioural impacts are quantified by analysing performance metrics, such as productivity figures and error rates, providing concrete evidence of how the AI system influences work practices. Observations will also record any behavioural shifts among workers, including changes in their approach to tasks and their engagement with the AI system.

Care is taken throughout the study to ensure that our data collection methods are minimally intrusive, preserving the authenticity of the workplace environment. This comprehensive approach aims to present a holistic view of the effects of AI system integration, combining the statistical depth of quantitative data with the nuanced understanding provided by qualitative insights.

D.3.5 Data Analysis

Quantitative data will be analysed using a repeated-measures ANCOVA, controlling for personality, digital literacy, demographics, and baseline measurement. Qualitative data from interviews and observations will undergo thematic analysis to identify patterns related to AI integration. We will employ Statistical Product and Service Solutions (SPSS) and R (Team, 2021) to conduct our statistical analyses.

D.3.6 Ethical Considerations

Throughout every phase of this research, we are committed to ensuring the well-being of our participants through ethical principles. Our approach to ethical research is multi-faceted, designed to guarantee that our practices are both responsible and respectful.

Before any data collection begins, we will seek approval from the Institutional Review Board (IRB). Before data collection itself, we will ensure that participants are thoroughly informed, in order for them to provide informed consent. Clear and complete information about the objectives, processes, potential risks, and benefits of the study will be communicated to participants. Additionally, the voluntary nature of their participation will be emphasised. To formalise their understanding and agreement to participate, we will obtain written informed consent from all individuals involved.

Moreover, data privacy and the anonymisation of participant information are greatly important in field research. We will implement stringent protocols to eliminate any identifying details from our data, substituting them with non-identifiable codes. We will also aggregate data for analysis and reporting to enhance anonymity. Finally, our data collection methods have been selected with the particular care to ensure that they are as unobtrusive as possible, thereby minimising any disruption to the participants' regular work routines. This is particularly important for our physiological measures.

D.4 Anticipated Contribution

This longitudinal study aims to delve into the intricate dynamics of human-centred AI integration within the manufacturing domain, spotlighting the multifaceted implications for workers engaged in quality control tasks. By tracking the evolving psychosocial, cognitive, and behavioural interaction between workers and AI over time, we hope to contribute to ethically grounded and human-centric AI deployment practices.

From a practical standpoint, our study aims to truly understand workers' experiences evolve as they adapt to AI-driven technological transformations in their workplace. We delve into the complex changes in workers' attitudes, perception, and behaviour related to AI. By tracking these factors over time, we uncover the drivers behind their evolution—be it specific incidents, AI system functionalities, or shifts in job roles. This will enable organisations to proactively address concerns and foster a realistic and informed understanding of AI's role among employees. Our research goes beyond examining straightforward cause-and-effect dynamics to offer a distinctive view of the ongoing processes that pave the way for effective AI integration. The insights gained aim to assist organisations in navigating the relationship between technological progress and workforce adjustment. By advocating for AI integration strategies that prioritise sustainable worker well-being and productivity, our findings propose a roadmap for achieving a harmonious balance where both human and artificial intelligence work in synergy.

From a theoretical standpoint, the study stands to significantly enrich our understanding of how AI integration impacts worker motivation and job satisfaction, drawing upon Self-Determination Theory and the Job Characteristics Theory. By evaluating changes in autonomy, competence, and relatedness, as well as alterations in job characteristics like task variety and autonomy, the research will offer empirical insights into the compatibility of AI with established work design and motivational theories. Moreover, the inclusion of both quantitative and qualitative data collection methods will provide a nuanced understanding of the AI's impact, potentially revealing unanticipated effects and experiences. This comprehensive approach ensures that the theoretical frameworks of SDT and JCT are robustly tested and possibly expanded to accommodate the unique context of AI in manufacturing.

In sum, this research promises to offer rich insight into the human-oriented integration of AI in manufacturing, advocating for practices that elevate both the efficiency of production processes and the quality of work life for employees. By encouraging constructive dialogue between workers and researchers, this study aims to contribute to a future where AI acts as a driving force for augmenting human potential in the workplace, rather than undermining it.