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How does artificial intelligence impact employees' engagement in lean organisations?

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ABSTRACT
Driven by the digital transformation currently pursued by organisations, artificial intelligence (AI) applications have become more frequent. Nevertheless, its impact on employees' behaviors and attitudes is still poorly known. As employees' engagement (EE) is a key element for a successful Lean Production (LP) implementation, there is the need to understand such AI's implications on EE in this scenario. This paper aims to investigate the impact of AI on EE in lean organisations. We performed a qualitative-empirical approach in which we first interviewed twelve academic experts to grasp the investigated problem. Then, we conducted a multi-case study in manufacturing organisations undergoing a LP implementation to refine such understanding based on the observation of real-world evidence. Identifying commonalities between these stages allowed the formulation of propositions for future theory testing and validation. Findings indicate that AI may positively impact EE dimensions (physical, cognitive, and emotional) in human-centred work environments, such as lean organisations, although not at the same extent. Results also suggest that employees' psychological conditions (safety, meaningfulness, and availability) are positively affected by the relationship between AI and EE. The demystification of AI's effect on EE helps practitioners anticipate potential issues that can impair the LP implementation in the Fourth Industrial Revolution era.

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SUSTAINABLE DEVELOPMENT GOALS
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1. Introduction

Lean Production (LP) can be defined as a systemic approach to continuously improve the flow of value according to customers' requirements through constant waste elimination based on active employees' engagement (EE) (Womack and Jones 1996; Womack, Jones, and Roos 1990). Derived from the Toyota Production System, LP gained notoriety for its significant impact on firms' performance, not only in the automotive industry but in many other sectors (Negrão, Godinho Filho, and Marodin 2017; Shah and Ward 2003), being a topic of both academic and practical relevance in the past four decades (Furstenau et al. 2021; Stone 2012). Commonly regarded as a socio-technical system (Hadid, Mansouri, and Gallear 2016; Soliman and Saurin 2017), LP implementation relies on both the technical (tangible elements such as practices, processes, and procedures) and social (non-tangible elements such as behaviors, values, and culture within the organisation) components. In this context, developing truly engaging work environments at organisational, tactical, and operational levels is a requirement to assure LP's long-term success (Hasle et al. 2012; Hernandez-Matias et al. 2020). However, this is not a simple task, as it depends on a series of factors. For instance, it demands an organisational culture (Bortolotti, Boscari, and Danese 2015) and proper leadership behaviors to encourage it (Van Dun, Hicks, and Wilderom 2017), team members willing to share and communicate (Tortorella et al. 2021a), and meaningful work activities and job satisfaction (Sawhney et al. 2020).

Fostered by the digital frenzy caused by the Fourth Industrial Revolution, also denoted as Industry 4.0 (I4.0) (Kagermann et al. 2013), new digital technologies, such as Internet-of-Things (IoT), blockchain, and artificial intelligence (AI), have been incorporated into organisations to enhance the interconnectivity among prod-

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ucts, processes, services, and people (Koh, Orzes, and Jia 2019; Olsen and Tomlin 2020; Xu, Xu, and Li 2018). The increased level of automation has also been supporting the link between the cyber and physical environments, yielding real-time acquisition, sharing, and processing of data (Fettermann et al. 2018; Santos et al. 2020). Among the expected benefits, the easier identification of problems, more assertive decision-making, more flexible processes, and emergence of new business models (Dalenogare et al. 2018; Schroeder et al. 2019; Veile et al. 2019) usually stand out. Due to such benefits, there have been some initiatives to combine I4.0 digital technologies with LP practices that aim to achieve even superior performance results (Rossini et al. 2022; Yilmaz et al. 2022).

Within the portfolio of I4.0 technologies, AI has been considered a prominent one with various and diversified applications, such as web search engines, recommendation systems, and generative tools (Mithas et al. 2022; Zhang and Lu 2021). Such versatility has raised the attention of operations management researchers and practitioners, who aim to unveil the full potential of AI (Choi et al. 2022; Grover, Kar, and Dwivedi 2022; Leoni et al. 2022). Traditionally, AI research involves reasoning, knowledge representation, planning, learning, natural language processing, perception, and support for robotics (Russell and Norvig 2021). For that, a wide range of problem-solving techniques have been adapted and integrated, generating expectations of greater productivity and quality (Fosso Wamba et al. 2022). Nevertheless, there has been a growing discussion about AI's implications on humans' behaviors in organisational environments (e.g. Aly 2020; Nishant, Kennedy, and Corbett 2020; Vrontis et al. 2022), which generally suggests that little is known about how this technology can affect work environments. In fact, some researchers (e.g. Ivanov 2023; Leng et al. 2022; Xu et al. 2021) suggest that the evolution of I4.0 to a more human-centric approach (represented here by the EE level) might give rise to Industry 5.0, which is still at its infancy. Although some studies (e.g. Tortorella et al. 2022; Virmani and Salve 2021) verified the effect of I4.0 technologies on employees' well-being, no study specifically addressed the effect of the relationship between AI and EE on employees' psychological conditions in lean organisations. Hence, when specifically considering the relationship between AI and EE, literature evidence is still scarce and it represents a major practical challenge for most companies undergoing a LP implementation (Koemtzi et al. 2023; Marodin et al. 2023). Such a gap in both theory and practice raises the following research questions (RQs):

RQ_1. How does AI impact EE in lean organisations?

RQ_2. How does the relationship between AI and EE affect employees' psychological conditions in lean organisations?

To answer these RQs and fill the aforementioned gap, this paper presents an inductive research based on a qualitative-empirical approach. First, we interviewed twelve academic experts to initially grasp the impact of AI on EE in lean organisations. Then, we performed a multi-case study in manufacturing organisations undergoing a LP implementation to refine such understanding based on the observation of real-world evidence. The identification of commonalities between these stages allowed the formulation of propositions for future theory testing and validation. This study was framed according to the concepts of Kahn's model of EE (Kahn 1990), which is widely deemed as one of the foundational theories for EE. Kahn's model suggests three main dimensions of EE (physical, cognitive and emotional), which contribute to three employees' psychological conditions, i.e. safety, meaningfulness, and availability (May, Gilson, and Harter 2004).

The contribution of this work is two-fold. First, we provide initial evidence on how emerging I4.0 technologies, such as AI, can impact EE in lean organisations, whose studies are still scarce. This favors a better understanding of the actual role of disruptive digital technologies on employees' behaviors and psychological conditions in organisational settings that excel in promoting a human-centred organisational culture, such as lean organisations. Second, the demystification of AI's effect on EE helps practitioners anticipate potential issues that can impair LP implementation in the Fourth Industrial Revolution era. As digital transformation evolves, organisations undergoing a LP implementation must learn how to cope with the integration of AI into their processes and benefit from it without undermining the principles and behaviors that commonly drive a lean organisation. As EE is a key element in a successful lean organisation, understanding the implications of AI, a trendy digital technology with a huge potential, on EE becomes not only a practical issue but also may imply new insights to theory on EE in light of the digital transformation era.

The remainder of this paper is structured as follows. Section 2 brings the background on the main concepts studied in this work. Section 3 describes the research method, whose results are presented and discussed in sections 4 and 5, respectively. Section 6 concludes the manuscript and indicates future research opportunities.

2. Background

2.1. Industry 4.0 and artificial intelligence

I4.0 is claimed to enable modular production systems that contribute to mass customisation of products (Kagermann et al. 2013; Liao et al. 2017; Xu, Xu, and Li 2018). I4.0 also supports more decentralised and simpler organisational structures over large and complex systems, reinforcing smaller, more easily, and less complex integrated modules (Fettermann et al. 2018; Olsen and Tomlin 2020; Züehlke 2010). Nevertheless, evidence of I4.0's impact on human aspects is still contradictory. On one hand, the few studies that approached the anthropocentric factors of I4.0 argue that it must not be adopted at the expense of the human aspect (David et al. 2016; Kagermann et al. 2013). The emerging I4.0 technologies will likely bring mobility to employees, enabling self-organisation and shifting the traditional sense of hierarchy. The access to larger amounts of data reinforces employees' trust, shaping perceptions of general openness in the organisation, hence, influencing EE (Dalenogare et al. 2018; Koh, Orzes, and Jia 2019). On the other hand, I4.0 demands high-skilled labour, which might affect the existing recruiting, training, and human resources development strategies in most companies (Costa and Portioli-Staudacher 2021). Additionally, misinterpretations of I4.0's benefits or inadequate application of digital technologies may result in negative effects on employees' behaviors and managerial routines (Buer, Strandhagen, and Chan 2018). Thus, the advent of I4.0 raises many opportunities for organisations but, at the same time, new challenges arising from digital transformation (Choi et al. 2022; Hecklau et al. 2016).

Among I4.0 technologies, the potential applications of AI have generated much discussion among academics and practitioners. AI allows machines to learn from experience, adjust to new inputs and perform human-like activities (Benbya, Davenport, and Pachidi 2020). Most AI applications utilise deep learning and natural language processing to perform such activities, and rapidly and logically process large amounts of data and identify patterns in the data (Von Krogh 2018; Zhang and Lu 2021). Although coined in 1956, the term AI has become more popular with the recent increased data volumes, advanced algorithms, and improvements in computing power and storage (Cao et al. 2021). Nevertheless, most organisations have not yet initiated AI implementations (Mikalef et al. 2021). One of the reasons for such a slow start might be associated with concerns about data privacy, human value reduction, ingrained biases, lack of transparency, and potential replacement of human relationships with human-machine relationships (Chiu, Zhu, and Corbett 2021; Levy 2018). The breadth of AI's scope represents another challenge, varying from technological and managerial aspects to social, ethical, economic, political, and legal ones (Dwivedi et al. 2021). Further, AI is not completely free of bias, as it relies on datasets and programmers that cannot fully avoid bias when developing or training the algorithms (Leyer and Schneider 2021; Martin 2019).

Because AI's transformative effects might affect emplo yees' intention to remain in their organisations (Brougham and Haar 2018), an adaptation to an AI-driven digital future is needed (Wesche and Sonderegger 2019). Employees' appraisals in the pre-adoptive stage might affect the behavioral responses to AI, which tends to be an issue due to the infancy of its adoption (Chiu, Zhu, and Corbett 2021). While beliefs in positive impacts brought by AI (e.g. quality and productivity increase) entail positive affective attitudes (Borges et al. 2021; Gursoy et al. 2019), perceptions of threats (e.g. lack of knowledge about AI, job loss caused by replacement by AI) cause negative cognitive and affective attitudes (Abdullah and Fakieh 2020; Brougham and Haar 2018).

2.2. Employees' engagement and Kahn's model

EE has become a topic of interest in the last few decades. Organisations have sought greater EE to enhance motivation, enthusiasm and buy-in to their overall goals, objectives and strategy (Shuck 2011). The general understanding is that an effective EE leads to superior work performance, positively affecting companies' bottom line (Gruman and Saks 2011; Kaur and Randhawa 2020). EE has been generally considered a multi-faceted construct that could be simply conceptualized as 'passion for work' (Truss et al. 2006). Nevertheless, there remains a paucity of critical academic literature about it, which leads to a good deal of conceptual confusion (Susanto, Syailendra, and Suryawan 2023). For instance, currently, there is no consistency in its definition, and its operationalisation and measurement have been made in several different manners (Kular et al. 2008; Sun and Bunchapattanasakda 2018). The fact that distinct definitions exist impairs the determination of the state-of-knowledge of EE, since each work analyses EE from a different perspective (Kwon and Kim 2020). This issue also undermines EE management (Ferguson 2007; Shuck and Wollard 2010), highlighting comparability problems caused by such a lack of consensus.

One of the first researchers to identify the concept of EE was William Kahn, who defined EE as 'the harnessing of organization members' selves to their work roles; in engagement, people employ and express themselves physically, cognitively, and emotionally during role performances' (Kahn 1990, 694) (see Figure 1). The

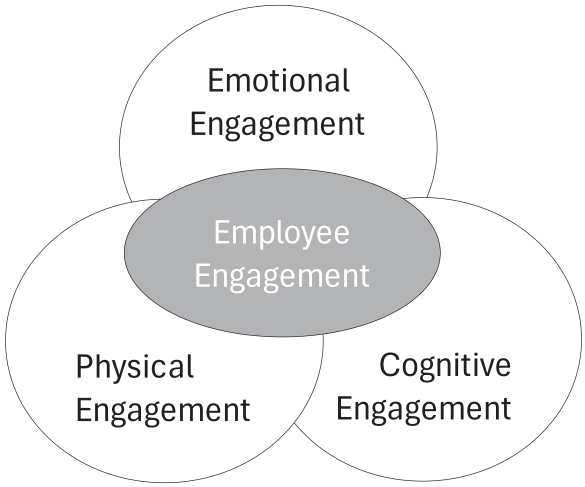

Figure 1. Kahn's three dimensions of EE.

physical dimension concerns the efforts, both physical and mental, exerted by employees to accomplish their activities. This dimension has been positively linked with increased feelings of confidence (Marin 2021). The cognitive dimension of EE refers to employees' beliefs about the organisation, leadership, and work environment. Employees must know their employer's vision and strategies, and the expected performance level to actively collaborate, reinforcing more creative and confident decisions (Anthony-McMann et al. 2017). Finally, the emotional dimension represents how employees feel about the organisation, leadership, and work environment, and whether they have positive or negative attitudes towards them. A positive attitude requires the creation of a sense of belonging at work, encouraging employees to trust and buy-in to the values and mission of the company (Saks 2022; Saks and Gruman 2014).

Kahn (1990) related these three dimensions of engagement (physical, cognitive and emotional) with three psychological conditions: (*i*) safety, which verifies whether the employees feel safe bringing his/her full self to work without risk of negative consequences; (*ii*) meaningfulness, which checks whether the employee finds his/her work meaningful enough (to the organisation and to society) to engage his/her full self; and (*iii*) availability, which refers to having the right energy and resources to harness his/her full self. Overall, a positive association between dimensions and psychological conditions was suggested, being empirically confirmed by May, Gilson, and Harter (2004). Later, Bailey et al. (2015) explored and categorised the most widely used definitions and conceptualisations of EE drawing on and extending typologies suggested by Simpson (2009) and Shuck (2011), as follows: personal role engagement, work task or job engagement, multidimensional engagement, engagement as a composite behavioral construct, engagement as practice, and self-engagement with performance.

2.3. Employees' engagement in lean organisations

EE plays a key role in lean organisations. Lucey, Bateman, and Hines (2004) suggest that EE is absolutely vital for the success of lean transformations, representing the lifeblood of any continuous improvement programme (p.8). Furthermore, Fok-Yew (2016) identifies EE as a mediator of lean practices on business excellence. Being a human-centred approach, LP fosters the development of new behaviors and, hence, organisational culture through the implementation of continuous improvement practices (Cusumano et al. 2021; Yamamoto, Milstead, and LIoyd 2019). Lean organisations promote employees' creativity over investment, driving the necessary levels of EE to succeed (Tortorella et al. 2021b).

Kyndt and Baert (2013) and Bortolotti, Boscari, and Danese (2015) emphasised the importance of EE to maintain growth and continuous improvement in organisations. Traditional EE sought to establish a sense of belonging towards the organisation through a high commitment level. Moreover, employees must be empowered to make changes in their work environment by providing and implementing suggestions for performance improvement. Therefore, EE entails superior performance results, while enhancing job satisfaction and work-life quality (Mann 2009; Sawhney et al. 2020). However, the performance and competitiveness of a lean organisation also rely on how its employees are managed and engaged in daily activities (Hecklau et al. 2016; Marin-Garcia and Bonavia 2015; Welikala and Sohal 2008).

Thus, leadership has a key role in fostering and securing sufficient levels of EE (Weerasooriyan and Alwis 2017). Through the adoption of lean leadership principles (Netland, Powell, and Hines 2019), lean managers are able to actively engage employees in problem-solving activities (Angelis et al. 2011; Treville and Antonakis 2006), which makes the desired changes become more sustainable in the long term (Bortolotti, Boscari, and Danese 2015). In addition to leadership, other aspects may also contribute to enhanced EE in lean organisations, such as setting interpersonal trust and communication, organisational openness and reputation, adequate social and technical skills, career opportunities, brand alignment, recognition, and work–life balance (Beraldin, Danese, and Romano 2019; Hecklau et al. 2016; O. Connor and Cormican 2022).

Therefore, although there is much expectation about the potential benefits of AI in the work environment, there is also a considerable parcel of caution due to its

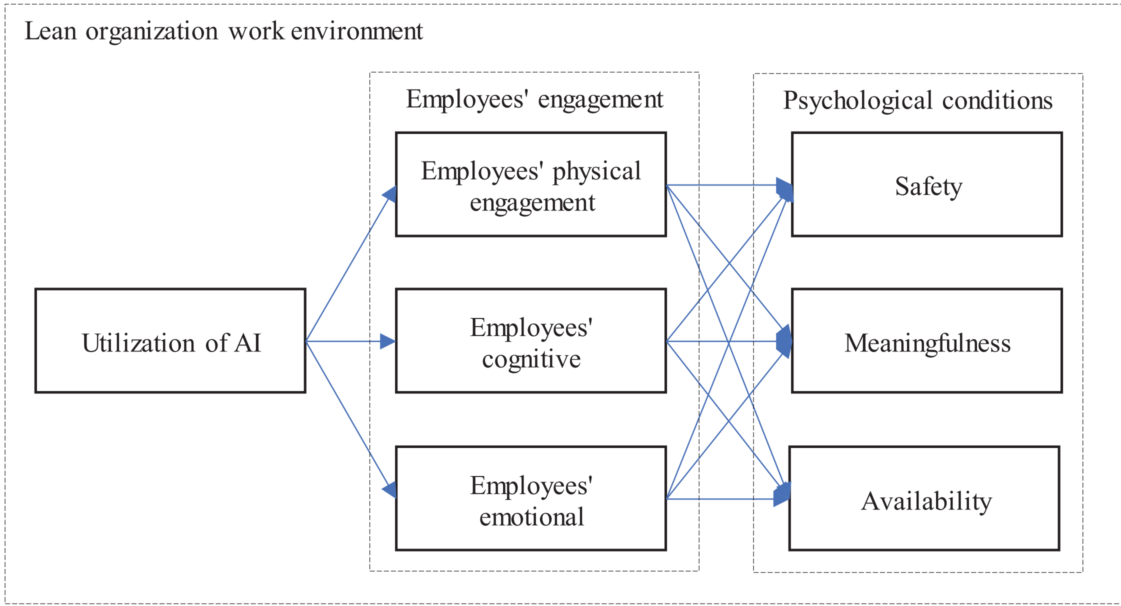

Figure 2. Theoretical model investigated.

unknown implications on the labour force. The paradoxical impact of AI on work environments motivated our study, with a particular focus on EE, which is a key element for a successful lean organisation.

3. Method

As the literature about the impact of AI on EE in lean organisations is scarce, we performed an inductive research based on a qualitative-empirical approach, which is reasonable with the exploratory and descriptive nature of this study (Barratt, Choi, and Li 2011; Voss, Tsikriktsis, and Frohlich 2002). Based on the aforementioned RQs and framing our study according to Kahn's model of EE, we investigated the theoretical model displayed in Figure 2.

The research method comprised three main stages (see Figure 3). In the first stage, interviews with experts were conducted to allow an initial understanding of the relationship between AI and EE in the context of lean organisations. This stage was composed by (*i*) a selection of experts, (*ii*) interviews, and (*iii*) content analysis. A multi-case study approach was adopted in the second stage of this research, helping verify whether the indications from experts were also observed in practice. Multiple case studies support external validity and minimise observer bias, enabling the determination of more sound and testable indications (Barratt, Choi, and Li 2011; Yin 2012). This stage was divided into (*i*) selection of case studies, (*ii*) data collection, and (*iii*) content analysis. Outcomes from both stages should not be considered as proof of statistical validation (Wikfeldt 2016), but as

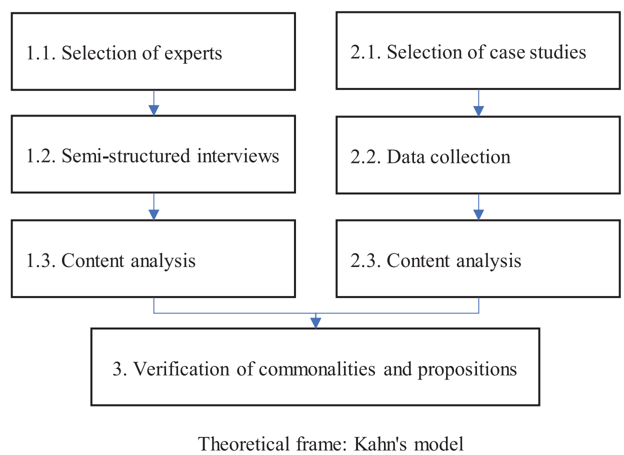

Figure 3. Research method.

evidence to build theoretical premises that allow assertions about the topic of investigation (Yin 2013). Lastly, a final stage aimed at identifying and verifying commonalities between both previous stages, so that propositions could be formulated.

3.1. Stage 1 – interviews with experts

3.1.1. Selection of experts

A few criteria were defined to select interviewees to assure the legitimacy of their opinions. Due to the investigated problem, interviewees should be experienced in two main topics: AI and LP. Further, because the understanding of these topics has advanced through a close relationship between practice and theory (Hines et al. 2023), interviewees should present experience as both

Table 1. Profiles of interviewees.

Expert	Experience in LP	Experience in I4.0	Nationality	Field
E_1	22 years	7 years	Australia	Business Management
E_2	15 years	5 years	New Zealand	Business Management
E_3	17 years	8 years	UK	Business Management
E_4	23 years	8 years	Germany	Industrial Engineering
E_5	17 years	6 years	Italy	Industrial Engineering
E_6	5 years	5 years	Spain	Computer and Information Science
E_7	11 years	7 years	Portugal	Computer and Information Science
E_8	10 years	6 years	Mexico	Business Management
E_9	16 years	7 years	India	Industrial Engineering
E_{10}	8 years	5 years	Uruguay	Industrial Engineering
E_{11}	6 years	5 years	Brazil	Computer and Information Science
E_{12}	18 years	7 years	Brazil	Industrial Engineering

academics and practitioners. Because research on LP and AI has been mainly led by academics from Engineering, Business Management, and Computer and Information Science (Pagliosa, Tortorella, and Ferreira 2021), we focused on selecting experts from these fields. Finally, as the integration between LP and I4.0 may be context-sensitive, we involved experts from different nationalities so that the commonalities identified in their perceptions would allow a better generalisation of our indications.

Fifteen academics who met the selection criteria were identified, but only twelve were available to participate in the interviews after receiving a consent form and a plain language statement where it was informed that participation was voluntary and anonymous. Their profile is shown in Table 1. The sample of experts was relatively well-balanced in terms of experience, field, and socioeconomic context (emerging and developed economies), which is aligned with the recommendations from Shetty (2020) to ensure the quality and legitimacy of experts' opinions. Further, as suggested by previous qualitative studies (e.g. Boddy 2016; Braun and Clarke 2016; Fugard and Potts 2015; Guest, Bunce, and Johnson 2006), a sample size of twelve supposedly meets the threshold for achieving data saturation among a fairly homogeneous population. Hence, the number of selected experts was considered satisfactory to describe the phenomenon of interest, avoiding repetitive data, and attaining theoretical saturation (Vasileiou et al. 2018).

3.1.2. Semi-structured interviews

The data collection approach was based on theoretical sampling, which aims at gathering data from places, individuals, and events that maximise opportunities to grasp concepts and identify their relationship, unveiling potential variations (Corbin and Strauss 2008). This approach is responsive to the data, allowing the discovery of important concepts as it advances. The semi-structured interviews occurred online during May and June 2023 following the protocol displayed in Appendix A. The first part of the questions asked about the professional background of experts. Then, we asked their opinions about AI's impact on EE in lean organisations considering the physical, cognitive, and emotional dimensions suggested by Kahn (1990). Lastly, we sought information about the effect of the relationship between AI and EE on three psychological conditions (safety, meaningfulness, and availability) in lean organisations. All interviews were audio-recorded and used the same protocol, lasting from 25 to 45 min. We did not incorporate information from earlier interviews into subsequent ones (Guest et al. 2017). Two authors attended each interview to confidently enhance the ability to handle the information (Dubé and Paré 2003).

3.1.3. Content analysis

We coded and cross-analysed interviews, checking facts to interpret the data during July 2023. We transcribed the information, summarising it after the authors had discussed it and reached consensus (Miles and Huberman 1994). Excerpts from the transcripts were utilised to code the findings, producing a narrative that also included ideas and insights obtained from interviews. Information was categorised and analysed according to two main axis: (*i*) AI's impact on EE in lean organisations considering the physical, cognitive, and emotional dimensions; and (*ii*) effect of the relationship between AI and EE on three psychological conditions (safety, meaningfulness, and availability) in lean organisations. Justifications and arguments for each opinion were also assessed in terms of the abundance of evidence, examples, and rationale provided by interviewees. We disregarded idiosyncratic responses to focus on dominant patterns in the information and reduce its subjectivity. Two authors individually assessed the transcripts to assure reliability and minimise biased findings. Additionally, we cross-compared experts' responses based on their nationality (emerging and developed economies) and field so that bias could be mitigated. We only regarded arguments multiply mentioned by interviewees and avoided using those clearly associated with certain contextual characteristic of the expert.

3.2. Stage 2 – case studies

3.2.1. Selection of case studies

Some selection criteria were predefined to guarantee case studies had sufficient relevance to offer evidence that helped answer the RQ. Due to this study's objective, we only involved companies that have been implementing both LP and I4.0 for at least two years. More specifically, AI should be actively used as a supporting tool in the work environment, helping employees to accomplish their daily operational tasks at a team level. Because not many organisations concomitantly present all these initiatives, no differentiation between manufacturing or service industries was done, enabling the proposition of more generalisable indications about the relationship between AI and EE in lean organisations. Similarly, we did not restrict companies located in a specific socio-economic context, which is aligned with the selection of experts in the previous stage. This would allow some heterogeneity to our cases, helping develop broader propositions and preventing limitations associated with an over-homogeneous sample. We adopted a convenience sampling approach (Obilor 2023) since it offered us easier access to case studies, geographical proximity, availability at a given time, and willingness to participate in the research. In each case, three employees whose work environment had AI integrated and who have been working for the company for at least five years were invited to participate in the study.

3.2.2. Data collection

To allow the in-case and cross-case analysis, we collected data from multiple sources of evidence, such as semi-structured interviews, secondary data, and non-participant observation. Interviews with practitioners happened during July 2023 following the protocol displayed in Appendix B. The first part asked about the interviewees' role in the company's experience with LP and I4.0. The second part sought information about the use of AI in the interviewees' work environment. The last part involved questions about the impact of the relationship between AI and EE on the three psychological conditions displayed in Figure 1. This protocol was used for all interviewees, whose answers were audio-recorded lasting between 20 and 30 min. To obtain candid responses, we adopted similar procedures of confidentiality and anonymity utilised during the interview with experts in the previous stage. Regarding secondary data gathering, we collected information from the interviewees' workplace (e.g. operational performance indicators, process characteristics, skill level of the employees, etc.). With regards to the non-participant observation, each case study was visited by the researchers, who aimed to verify the level of LP implementation, seek examples that could support the data collected in the interviews and confirm trends identified in the secondary data. In essence, the meaning of observations was checked to prevent drawbacks (Corbin and Strauss 2008). Non-participant observation also helps enhance researchers' familiarity with the investigated issue, allowing a deeper contextualisation of the phenomenon.

3.2.3. Content analysis

Data from the interviews with practitioners was processed, transcribed, and analysed following similar procedures utilised with experts, as described in section 3.1.3. We summarised and consolidated the information, allowing the categorisation, tagging, and thematic analysis of the qualitative data (Mayring 2004), resulting in the verification of communication patterns that occurred in a replicable and systematic way (Bell, Bryman, and Harley 2018). This enabled the understanding of latent interpretations' intricacies and meanings (White and Marsh 2006). During coding of the findings, we used words and sentences as labels to facilitate organisation (Hsieh and Shannon 2005). Codes were categorised according to (*i*) the impact of AI on EE's dimensions, and (*ii*) the effect of the relationship between AI and EE on psychological conditions. This information was then compared with the outcomes from the secondary data and non-participant observation to verify consistency and convergence. Hence, we revisited excerpts from narratives, insights, and arguments from interviews to allow data documentation both in-case and across-cases (Narasimhan 2014). Only the items whose information from the three sources of evidence converged were acknowledged as results, assuring greater reliability of our findings.

3.3. Verification of commonalities and propositions

Finally, we compared the results from the first two stages to verify commonalities between them and develop a chain of evidence (Carter et al. 2014) that underpinned the formulation of propositions for theory testing in future studies. Such a triangulation of results about the same phenomenon helps increase research's credibility (Hussein 2015). Information was grouped according to the three dimensions of Kahn (1990) and psychological conditions. Information observed in only one of the stages was categorised as 'partially evidenced', whereas similar information obtained on both stages was denoted as 'fully evidenced'. Hence, based on the evidenced information, we formulated propositions that stressed the impact of AI on EE from the perspective of each dimension and implications on psychological conditions.

4. Results

4.1. Stage 1

This section reports the results from experts' interviews conducted in stage 1. Regarding the impact of AI on EE from a physical perspective, experts suggested that the utilisation of AI tends to reduce both physical and mental efforts exerted by employees to accomplish their activities in lean organisations. Despite the various potential applications of AI, experts E_1, E_5, E_9, and E_{12} highlighted that the use of machine learning algorithms to process information can be particularly useful to perform routine tasks that require less interaction with other employees. This would save employees' time and energy, allowing them to redirect their efforts to activities that demand further communication and involvement with their colleagues and respective work environment. Such implications might be particularly reinforced in lean organisations, as visual management and standardisation (fundamental practices of LP) are likely to be well established promoting easy-to-understand visual overviews so that employees can identify abnormalities and engage into the solutions. According to E_4 and E_{11}, this is likely to support an increase of meaningfulness and availability, as employees perform a more challenging activity and have the proper energy to harness their full self, respectively.

From a cognitive standpoint, experts were less emphatic about the impact of AI on employees' beliefs about the organisation, leadership, and work environment in lean organisations. Although E_2 and E_7 stated that AI-driven applications to predict human behavior might contribute to keep employees connected to their roles and stimulate more creative and confident decisions, which are key for continuous improvement, most experts did not support that. In fact, they did not indicate a clear relationship between AI and cognitive engagement in lean organisations, arguing that most factors that influence cognitive engagement are beyond the scope of existing AI applications, as revealed below. This may be contrary to the indications from Bittencourt, Alves, and Leão (2021), which argue that such a relationship may be found when LP triggers I4.0 technologies. The lack of evidence on the impact of AI on cognitive engagement also undermined the verification of the effect of their relationship on psychological conditions.

> Cognitive engagement relies on assuring that employees know what their company's vision and strategies are, and the expected performance level they must deliver. Lean organizations achieve that through proper guidelines deployment and standard daily management routines. I do not see how AI can contribute to that. (E_4)

> Although natural language processing has significantly evolved, AI is not very prompt to really understand words, unexpected phrases, or irony, falling short in demonstrations of empathy or critical reasoning. These are essential aspects to develop cognitive engagement. Thus, despite the implementation of lean practices in the work environment, AI may not help employees in that particular sense. (E_{11})

For emotional engagement, experts presented contradictory arguments. On one hand, experts E_6 and E_{12} indicated that lean organisations thrive for encouraging employees' ownership for continuous improvement. In this sense, the use of inverse reinforcement learning (one of the AI tools), for instance, can seek information according to employees' preferences and customise solutions to increase their ownership in the continuous improvement process. This would positively affect meaningfulness and availability, since employees would be utilising adequate resources to perform tasks that make sense to them. On the other hand, E_7 and E_{10} suggested that the potential replacement of human activities by AI tools might negatively affect such ownership, distancing them from the actual purpose of the work and reducing employees' feeling of safety. E_3 also argued:

> AI has been disrupting workplaces as we know. Thus, regardless of employees' commitment level, which is typically high in lean organizations, questioning about the need to maintain the same labor intensity is inevitable. This will eventually negatively affect employees' feeling of safety in their work environments. (E_3)

4.2. Stage 2

Two large-sized manufacturing companies, one located in Brazil and one in Australia, met the selection criteria and agreed to join the research. Based on previous collaboration activities, researchers were already familiar with these companies, which enabled a more in-depth understanding of the studied cases. Three employees from each company, whose characteristics are shown in Table 2, were selected for the interviews. All interviewed practitioners were from the operational level, being two operators and one team leader per company.

Company A is a multinational organisation that manufactures auto parts, i.e. cockpits for cars assembled in Brazil. It has been implementing LP for 18 years, showing a wide diversity of lean practices (e.g. 5S, visual management, kanban, standardised work, *andon*, cross-functional teams, etc.) adoption and high awareness of lean principles. In 2021, the company initiated its assembly line digitalisation through the adoption of I4.0 technologies, such as wireless sensors, Internet-of-Things, big data, cloud computing, remote monitoring and control, and AI. These technologies' application was focused on quality inspection operations, which used to be fully manual relying on operators' attention and experience. AI was specifically integrated to guide operators' activities and enhance quality assurance via assistance to decision-making. It is worth mentioning that the number of activities performed by the operators did not reduce due to AI's utilisation. Machine learning has been utilised on quality inspection results to recommend process adjustments in upstream workstations through the assembly line business intelligence panel; i.e. an AI-based

Table 2. Case studies' characteristics.

Company	Industry sector	Location	LP implementation	AI utilisation	Production area	Interviewed practitioner	Role	Experience in the company
A	Automotive	Brazil	18 years	2 years	Assembly line	A1	Operator	12 years
						A2	Operator	8 years
						A3	Team leader	15 years
B	Beverage	Australia	14 years	3 years	Syrup mixing line	B1	Operator	6 years
						B2	Operator	11 years
						B3	Team leader	10 years

recommendation system. Since the integration of AI into quality operations, the levels of scrap and quality rework have been reduced by 23%. When asked about the impact of AI on EE in the assembly line, A_1 responded:

> The use of AI in quality inspections has been helping me to better communicate with my colleagues, since it more assertively recommends the adjustments in the previous workstations. This also avoids unnecessary error-and-trial efforts, as well as endless discussions about where the source of the quality problem might be. (A_1)

A_2 and A3 complemented this by indicating how the relationship between AI and EE has affected his psychological conditions:

> AI integration helps me with activities that require less of my creativity, allowing me to focus on real value-added ones. Hence, I feel that I really contribute to my team performance without having to wear myself out unnecessarily. (A_2)

> I have observed that AI has helped our team members to devise solutions more rapidly and assertively. This raised the performance results, generating greater pride and satisfaction in the work environment. With LP implementation, we already had some established EE practices, such as shift start-up meetings, visual displays, and work standardization. I believe the AI recommendation system for quality adjustments has boosted the effect of such EE practices. (A_3)

Company B is a large beverage manufacturer with multiple sites in Australia. It has been implementing LP for fourteen years ago, starting from the shopfloor with basic stability practices, such as Total Productive Maintenance, and expanding it to administrative areas. Its automation level has always been relatively high, which is typical in the continuous flow-process industry. As part of its continuous improvement strategy, the company joined the I4.0 era three years ago by adopting new digital technologies to enhance bottleneck operations performance, such as the syrup mixing line. AI has been integrated to support the autonomous maintenance activities of this area, helping operators optimise their inspection and verification activities. With AI, machines alert operators where and when to address any issue of the machines, suggesting the proper corrective measure, and registering and learning from those occurrences to improve its system. Since its utilisation, the overall equipment effectiveness of this area has increased from 67% to 79% and the mean-time-between-failures has increased by 18%, approximately. Operators and team leader commented about the impact of AI on EE, as follows:

> With the support of AI, we have optimized the frequency of inspection and execution of small repairs. This prevents from wasteful activities, saving time and efforts. Further, as AI specifies what needs to be done in the machine, I clearly know what is expected from me, making me more confident in my decisions. (B_1)

> Utilizing AI as a supporting tool to autonomous maintenance allowed a better interaction with employees, as I observed they have been sharing their experiences with AI more actively. This contributes to teambuilding and a more collaborative environment regardless of employees' skill level. (B_3)

In terms of the effect of the relationship between AI and EE on psychological conditions, safety, meaningfulness, and availability seem to have been positively affected, as raised by the responses below:

> Since the integration of AI into autonomous maintenance activities, I feel that my work has been more assertively performed, reducing the level of exhaustion I had at the end of the day. This has also increased my satisfaction and pride with what I do. (B_2)

> … such an enhanced collaboration among employees increases their confidence in the team, establishing a safer environment to work in. (B_3)

5. Discussion and propositions

Table 3 consolidates the findings from stages 1 and 2, enabling the identification of commonalities to create the chain of evidence (either partially or fully evidenced relationships) for propositions formulation in stage 3. We now discuss the results in light of Kahn's EE dimensions (i.e. physical, cognitive, and emotional engagement) and psychological conditions of employees.

Regarding the impact of AI on physical engagement in lean organisations, findings from both stages indicated that AI utilisation avoids the performance of wasteful or unnecessary activities, saving employees' time and effort. Such outcomes align with previous indications

Table 3. Consolidation of outcomes from stages 1 and 2.

		Stage 1	Stage 2	Stage 3
Impact of AI on	Physical engagement	– Save employees' time and energy	– Prevention from wasteful activities – Reduced stress level	++
	Cognitive engagement	– Greater communication and involvement with work colleagues – Stimulate more creative work environments – Failure in showing critical reasoning	– Clearer work activities specification and expectation – Greater communication	+
	Emotional engagement	– Increase ownership in the continuous improvement initiatives – Concerns about maintaining existing labour intensity	– Greater employees' interaction and knowledge sharing – Improved teambuilding	++
Effect of the relationship between AI and EE on	Safety Meaningfulness Availability	– Risk of employees' replacement – Performance of higher value-added activities – Redirection of energy to perform value-added tasks	– Safer work environment – Increased job satisfaction and pride – Enhanced collaboration and confidence	++

Notes: '+' partially evidenced; and '++' fully evidenced.

from studies focused on the ergonomics implications and workload demands of I4.0 (e.g. Tortorella et al. 2022; Virmani and Salve 2021). Although the adoption of new digital technologies may initially generate some apprehension and hesitation among employees, there is a consensus that both physical and mental demands tend to be reduced by those. Our findings corroborate this by specifically indicating that AI utilisation in lean organisations, which already tend to have a more balanced workload (Saurin and Ferreira 2009; Silva, Tortorella, and Amaral 2016), can save employees' energy and efforts in daily operational routines which enhance their physical engagement. Consequently, as physical and mental efforts are reduced, employees can dedicate their energy to more value-added activities that truly challenge their creativity, harnessing their full potential. This converges with indications from Marodin et al. (2023), which suggested that employees become more motivated when performing activities that foster their creativity and to which reasonable resources are available. Thus, based on our evidence, the following proposition is formulated:

> Proposition 1: In lean organizations, the utilization of AI in the work environment is likely to positively impact employees' physical engagement, hence, contributing to greater meaningfulness and availability.

With regards to cognitive engagement, our findings showed less prominent evidence. While experts from stage 1 suggested conflicting indications about the impact of AI on such EE dimension, positive associations emerged from both case studies in stage 2. However, some of the arguments observed in stage 2 converge with experts' indications in stage 1. For instance, there seems to be an agreement that AI utilisation tends to improve communication and knowledge sharing among employees. Spear and Bowen (1999) and Spear (2009) highlighted this characteristic as a key success factor of lean organisations. Our study adds to this by stating that AI can bolster this success factor, while still failing to demonstrate critical thinking (pointed out by experts). Further, having operational tasks specifically determined and guided by AI appears to clarify expectations on employees' roles, reducing their anxiety and increasing self-confidence. According to Losonci, Demeter, and Jenei (2011) and Hasle (2014), the establishment of a trustworthy work environment in lean organisations entails communication openness and creativity. This is prone to contribute to a greater feeling of safety and support from the organisation (i.e. proper resources to perform the expected tasks). Therefore, to further explore this argument, we formulate the following proposition:

> Proposition 2: In lean organizations, the utilization of AI in the work environment is likely to positively impact employees' cognitive engagement, hence, contributing to greater safety and availability.

Finally, concerning emotional engagement, AI was claimed to positively impact employees' ownership and interaction. Lean organisations are typically charac terised by management practices that enhance employees' participation through continuous improvement activities (Cusumano et al. 2021; Yamamoto, Milstead, and LIoyd 2019). The use of AI seems to promote even more collaborative workplaces; it prevents employees from performing basic and repetitive activities redirecting them to devise more complex daily tasks through active engagement with team members. This leads to more positive personal interrelationships and group dynamics, raising employees' emotional engagement. As a result, employees tend to face a safer work environment, where relationships are key, as they perform more challenging tasks. Following Liker and Hoseus (2010) and Liker and Convis (2012), one of the main ways to show respect in lean organisations is to challenge employees' potential through problem-solving, where they must go beyond obvious solutions. We claim that AI integration in lean organisations might contribute to that, which tends to develop closer relationships between teams and redesign workstations for higher value-added activities. In light of these arguments, we pose the following proposition:

> Proposition 3: In lean organizations, the utilization of AI in the work environment is likely to positively impact employees' emotional engagement, hence, contributing to greater safety and meaningfulness.

It is worth mentioning that most arguments presented above focus on the positive aspects of AI implementation on employee engagement (EE). However, for a comprehensive social analysis of a new initiative's implementation, it is necessary to consider the downsides, including potential group and individual losses (Weisz and Vassolo 2023). There are two potential mechanisms through which AI could negatively affect EE. One mechanism relates to the capability gap. The implementation of AI might require certain employees to learn new skills to perform their activities. Since an individual's belief in their ability to succeed affects their feelings and behaviors (Bandura 1997), an employee who perceives a high capability gap in their potential to deal with AI may experience lower self-efficacy, negatively impacting their emotional safety. The other potential mechanism relates to job downsizing due to the productivity gains introduced by AI. Previous studies have highlighted the effects of potential layoffs on employees' emotional engagement, as they create job insecurity (Dlouhy and Casper 2021). Although AI could be considered an important assistant, this positive effect could be outweighed by a threat to labour stability. Nevertheless, the empirical evidence collected here did not suggest that.

6. Conclusions

This work examined the impact of AI on EE in lean organisations and the effect of their relationship on employees' psychological conditions. The inductive research conducted via empirical-qualitative methods allowed to raise interesting contributions to both theory and practice, pointed out as follows.

6.1. Theoretical implications

From a theoretical standpoint, our work adds to Kahn's model of EE (Kahn 1990). We expand the discussion on EE dimensions and psychological conditions by contextualising such relationships in a contemporary work environment where I4.0 technologies prevail. In other words, the human impacts derived from AI integration into workplaces have been raising several concerns. Such implications may be aggravated in human-centred work environments, which is the case of lean organisations. As literature evidence on this contradictory relationship is still incipient, we provide initial arguments to demystify the impact of AI on EE, as well as the effect of their relationship on employees' psychological conditions. Framing the study according to Kahn's model helped categorise and better discriminate AI's impact, hence, contributing to a deeper understanding of the investigated phenomenon. Moreover, comparing outcomes of academic experts and real-world cases allowed us to enhance the reliability of our findings, which generated arguments to formulate research propositions for future validation.

6.2. Practical contributions

In practical terms, identifying a positive impact of AI on EE in lean organisations helps dispel the dichotomy between a human-centred work environment (observed in lean organisations) and a technology-driven approach (preconised by I4.0). As many organisations still struggle to properly integrate AI into workplaces, its implications are not fully known. This generates doubts and uncertainties among employees, raising resistance to technology adoption. Our study clarifies that, providing managers arguments to continue their companies' digital transformation through AI without jeopardising existing EE practices encouraged by LP. In fact, we showed that not only EE but also employees' psychological conditions might be favored if AI is properly integrated into the workplace. This results in greater employees' commitment and job satisfaction, which is helpful for achieving superior operational performance results.

6.3. Limitations and future works

Being an inductive research based on an empirical-qualitative approach, some limitations in this study must be highlighted. First, although we performed the usual procedures to ensure consistency and reliability of our content analyses, our findings may not be fully generalised. Also, our findings were limited to the AI applications found in the case studies. We see this as a limitation since AI applications and types may significantly vary, entailing different impacts on EE. Future studies should utilise our outcomes as inputs to further validation through large-sample statistical proofs and AI applications. Second, we are aware that, to adequately assess the implications of AI and EE on employees' psychological conditions, additional instruments should be utilised. Moreover, other aspects besides safety, meaningfulness, and availability could be included to provide a more holistic understanding. Thus, further research should be conducted to offer more breadth and depth to our findings. Lastly, although we focused on AI utilisation, it may not be applied alone but combined with other digital technologies (e.g. IoT, wireless sensors, cloud computing) that together contribute to processes, products, or services. Hence, we acknowledge that the observed impact was not solely derived from AI's integration, but a set of I4.0 technologies. Discriminating such impact per I4.0 technology, however, might be a topic for a continued discussion in future studies.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

The data that support the findings of this study are available from the corresponding author, GT, upon reasonable request.

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Appendices

Appendix A – Experts' interview protocol

(1) Please, tell us about your professional background with particular emphasis on your LP and I4.0 experience.
(2) Please, tell us how you think AI can impact EE in lean organisations considering the following dimensions:
   (a) Physical dimension (concerns the efforts, both physical and mental, exerted by employees to accomplish their activities)
   (b) Cognitive dimension (refers to employees' beliefs about the organisation, leadership, and work environment)
   (c) Emotional dimension (represents how employees feel about organisation, leadership, and work environment)

Please, justify your answers and give examples.

1. Considering the work environment in lean organisations, how do you think the relationship between AI and EE might affect the following psychological conditions?
   (a) Safety (whether the employee feel safe bringing his/her full self to work)
   (b) Meaningfulness (whether the employee find his/her work meaningful enough)
   (c) Availability (having the right energy and resources to harness his/her full self)

Please, justify your answers and give examples.

Appendix B – practitioners' interview protocol

1. Please, tell us about your role in the company and your experience with LP and I4.0.
2. Please, tell us how AI has been utilised in your work environment, and how it has impacted your:
   (a) Physical engagement (concerns your efforts, both physical and mental, exerted to accomplish your activities)
   (b) Cognitive engagement (refers to your beliefs about the organisation, leadership, and work environment)
   (c) Emotional engagement (represents how you feel about organisation, leadership, and work environment)

Please, justify your answers and give examples.

3. How do you think the relationship between AI and EE has been affecting the following psychological conditions in your work environment:
   (a) Safety (whether you feel safe bringing your full self to work)
   (b) Meaningfulness (whether you find your work meaningful enough)
   (c) Availability (having the right energy and resources to harness your full self)

Please, justify your answers and give examples.