Are lean and digital engaging better problem solvers? An empirical study on Italian manufacturing firms

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Abstract

Purpose – We studied the relationship between job engagement and systematic problem solving (SPS) among shop-floor employees and how lean production (LP) and Internet of Things (IoT) systems moderate this relationship.

Design/methodology/approach – We collected data from a sample of 440 shop floor workers in 101 manufacturing work units across 33 plants. Because our data is nested, we employed a series of multilevel regression models to test the hypotheses. The application of IoT systems within work units was evaluated by our research team through direct observations from on-site visits.

Findings – Our findings indicate a positive association between job engagement and SPS. Additionally, we found that the adoption of lean bundles positively moderates this relationship, while, surprisingly, the adoption of IoT systems negatively moderates this relationship. Interestingly, we found that, when the adoption of IoT systems is complemented by a lean management system, workers tend to experience a higher effect on the SPS of their engagement.

Research limitations/implications – One limitation of this research is the reliance on the self-reported data collected from both workers (job engagement, SPS and control variables) and supervisors (lean bundles). Furthermore, our study was conducted in a specific country, Italy, which might have limitations on the generalizability of the results since cross-cultural differences in job engagement and SPS have been documented.

Practical implications – Our findings highlight that employees' strong engagement in SPS behaviors is shaped by the managerial and technological systems implemented on the shop floor. Specifically, we point out that implementing IoT systems without the appropriate managerial practices can pose challenges to fostering employee engagement and SPS.

Originality/value – This paper provides new insights on how lean and new technologies contribute to the development of learning-to-learn capabilities at the individual level by empirically analyzing the moderating effects of IoT systems and LP on the relationship between job engagement and SPS.

Keywords Lean, Industry 4.0, Internet of things, Systematic problem solving, People

Paper type Research paper

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1. Introduction

Manufacturing firms implement lean production (LP) to gain a competitive advantage, drawing on the adoption of lean bundles such as total quality management (TQM) and just-in-time (JIT) to reduce costs and enhance operational performances. However, sustaining LP over time often proves challenging without the development of a learning-to-learn capability that enables firms to evolve from mere efficient production systems to learning organizations by continuously improving practices and methods (Holweg, 2007). A learning-to-learn capability is a dynamic capability enacted by the systematic problem solving (SPS) behaviors of employees (Saabye *et al.*, 2022, 2023). SPS is defined as the process through which workers tackle problems by analyzing underlying causes, critically evaluating possible solutions and implementing the most effective ones (Carpini *et al.*, 2017; Furlan *et al.*, 2019; Mohaghegh and Furlan, 2020). This scientific problem-solving approach facilitates the creation of new knowledge, skill development and employee-driven innovation (Ciriello *et al.*, 2016; Letmathé *et al.*, 2012; Opland *et al.*, 2022), that are crucial for the development of the firm's learning-to-learn capability (Bessant and Caffyn, 1997; Saabye *et al.*, 2022, 2023).

Previous studies acknowledge that SPS can be supported by the adoption of lean practices such as group coaching sessions, leaders' support and the institutionalization of learning and problem-solving routines such as A3 thinking and 5-whys analysis (Mohaghegh and Furlan, 2020; Saabye *et al.*, 2022, 2023). However, changing habits and action patterns can be challenging (Bessant, 1998; Morrison, 2015) and, even in firms that extensively implement lean practices, workers can disregard SPS by adopting workarounds to find quick fixes to their problems (Morrison, 2015). As Mohaghegh and Furlan (2020) argue, we need to further our understanding on how lean practices adopted at the organizational level can effectively support individual SPS behaviors.

We fill this gap by investigating the moderating effect of lean bundles on the relationship between one of the most studied behavioral antecedents, i.e. job engagement and SPS. It is commonly accepted that job engagement acts as a positive antecedent of SPS (Parker *et al.*, 2006). When a worker is engaged in her job, she invests cognitive, physical and emotional efforts beyond their assigned tasks to initiate change-oriented behaviors such as SPS.

We argue that lean bundles positively moderate the relationship between SPS and job engagement. Lean bundles act as artifacts that channel the actions of the employees towards SPS. By interpreting lean bundles as systems of artifacts, Aoki (2020) shows that practices such as standardized procedures, visual representations, Kanban cards and andon signals can help employees to solve the learning-performance paradox. Similarly, we maintain that lean bundles help engaged employees to support their effort in systematically solving problems.

Lean bundles are not the only artifacts that act as moderator on the relationship between job engagement and SPS. We propose that also process technologies are important artifacts that can shape the SPS actions of employees. We focus on a particular type of process technologies, i.e. the Internet of Things (IoT) (Laudien and Daxböck, 2016). We define IoT as a system integrating four key technological groups — sensors, connectivity components, algorithms and interfaces (Bassi *et al.*, 2013; Iansiti and Lakhani, 2014; Li *et al.*, 2015; Qu *et al.*, 2016; Wang *et al.*, 2021). IoT systems represent a base technology that differentiates Industry 4.0 technologies from previous waves and are the foundational layer to most sophisticated front-end technologies (Ancarani *et al.*, 2020; Ardito *et al.*, 2018; Ashton, 2009; Frank *et al.*, 2019). These systems equip industrial processes with a broad array of production parameters, timely and enriched insights that support task performance and decision-making processes (Cagliano *et al.*, 2019; Dewett and Jones, 2001; Taylor *et al.*, 2020; Waschull *et al.*, 2020; Wang *et al.*, 2020; Bortolini *et al.*, 2017; Leyer *et al.*, 2019; Lee and Lee, 2015). IoT features generate a set of artifacts (D'Adderio, 2021) such as reports, visual recommendations and graphical data analysis that support employees in executing actions, offering general recommendations, or guiding their attention on limited human activities (D'Adderio, 2008; Anthony, 2021). We suggest that IoT systems act as positive moderators in the relationship between job engagement and SPS by providing artifacts that assist workers in directing their efforts towards SPS (Dworschak and Zaiser, 2014).

Our hypotheses were empirically investigated using data collected from a sample of 440 shop floor workers in 101 manufacturing work units across 33 plants. The scales for measuring SPS, job engagement and the lean bundles were based on questionnaires filled in by the shop floor workers. In contrast, the technologies related to the IoT systems were evaluated at the work unit level by our research team based on on-site visits, allowing us to overcome the limitations associated with perceptual scales and continuous variables commonly used in previous studies (Boyer and Pagell, 2000). Given the nested nature of our data (workers within work units clustered within plants) and the presence of the variables measured at both the individual and work unit levels, we employed a series of multilevel regression models to test the hypotheses. Our findings indicate a positive association between job engagement and SPS. In addition, we found that the implementation of LP positively moderates it. Contrary to our hypothesized arguments, we found that IoT negatively moderates this relationship. To further investigate this countervailing result, we explored whether the negative moderating effect of the IoT may become positive with the presence of LP. Interestingly, we found that, when IoT technologies are complemented by a lean management system, workers tend to use these artifacts more effectively, thus reinforcing the job engagement-SPS relationship.

These findings make two significant contributions to the operations management literature. First, this research provides valuable insights to address the mixed results observed in previous research regarding the effects of the interaction between LP and Industry 4.0 technologies (Cifone *et al.*, 2021; Marodin *et al.*, 2018, 2022; Tortorella *et al.*, 2019, 2021). We show that the implementation of lean bundles mitigates the potential negative effects of IoT systems. Second, this research adds to the learning-based lean research (Powell and Coughlan, 2020; Tortorella *et al.*, 2020; Saabye *et al.*, 2022, 2023). We maintain that lean bundles are a constitute part of the organizational learning routines since they represent enabling artifacts that support engaged employees to perform SPS behaviors.

2. Theoretical background and hypotheses development

Lean enterprises are learning organizations that build their sustainable competitive advantage on the development of a learning-to-learn capability (Powell and Coughlan, 2020; Saabye *et al.*, 2022). Compared to an efficiency-led perspective of lean enterprises that views lean as a socio-technical system focused on implementing both hard and soft lean bundles guided by lean principles, a learning-led perspective seeks to comprehend how LP "constantly find, frame, face and solve problems" (Saabye *et al.*, 2023, p. 134) in order to adapt both hard and soft lean bundles to new strategic objectives and the external environment. While this stream of literature clarifies how a learning-to-learn capability influences changes in lean bundles, it remains unclear how existing lean bundles contribute to the development of a learning-to-learn capability.

To address this gap, we drew on the microfoundations of dynamic capabilities (DC) theory (Felin and Foss, 2011) that suggests that individuals enact the pattern of actions underpinning DCs through the simultaneous integration of cognition, habit and emotion (Salvato and Vassolo, 2018). This implies that the extent to which employees combine their cognitive, physical and emotional engagement (i.e. job engagement) will influence the employees' capacity to contribute to sense, seize and reconfigure internal and external resources by identifying and solving problems. As Saabye *et al.* (2022) proposed that a lean learning-to-learn capability involves organization-level systematic problem-solving abilities premised on the SPS behavior of employees, we argue that the relationship of job engagement and SPS is at the core of the learning-to-learn capability.

Furthermore, as DCs are social accomplishments underscoring the need for the collective involvement of employees, these capabilities are enacted by individuals to leverage the potential of the artifacts they employ in their roles to structure their actions (Latour, 2005). In this sense, lean bundles can be referred to as systems of artifacts, such as standardized procedures, visual representations, Kanban cards and andon signals, that serve as cues or constraints for executing human actions. In other words, we posit that existing lean bundles produce artifacts that shape the patterns of actions performed by employees and coordinate them into a single routine (D'Adderio, 2008; D'Adderio and Pollock, 2020). This implies that lean bundles may be able to influence actions depending on whether and how human actors use them.

Similarly, IoT systems may be viewed as a system of artifacts (D'Adderio, 2021). With the recent digital advancements embedded in technologies such as the IoT systems, these artifacts increasingly incorporate knowledge that raises questions regarding how they contribute to shaping employees' actions. Specifically, IoT systems can provide employees with general information on how to execute actions, offer general recommendations, or even automate processes with limited human intervention (D'Adderio, 2008; Anthony, 2021).

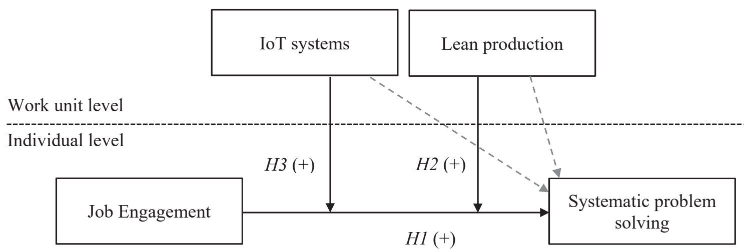
As a result, the same artifacts may enact different responses across employees, making it unclear how IoT systems are implicated in employees' actions.

Our theoretical arguments set the foundations to examine the relationship between job engagement and SPS through the moderating roles of LP and IoT systems. Figure 1 presents a graphical representation of the relationships among the main variables of interest.

2.1 The relationship between job engagement and SPS

This section explores the relationship between job engagement and SPS behaviors at the individual level. The rationale is grounded in the understanding that actively engaging each employee in SPS behaviors is fundamental to the microfoundational development of the learning-to-learn capability at the organizational level (Saabye *et al.*, 2022).

SPS indicates the degree to which an employee proactively seeks out the root causes of problems in order to prevent their recurrence (Furlan *et al.*, 2019). Employees who exhibit SPS behaviors typically engage in a systematic analysis of problems, carefully consider various solutions and implement the most suitable one, thus avoiding the need for temporary workarounds. While temporary solutions may enable employees to swiftly resume interrupted work, they are less likely to contribute to develop new skills and competencies that enhance work performance (Letmathé *et al.*, 2012; Morrison, 2015). Therefore, SPS behaviors nurture employees' knowledge base, providing them with a strong foundation for continuously participating in learning initiatives.



Source(s): Author's own creation

Figure 1.
Theoretical model

SPS strongly aligns with the "employee-driven innovation" paradigm, which describes employees' active participation in both creating and promoting innovative ideas (Ciriello *et al.*, 2016). These employees not only initiate ideas but also play essential roles in their development and implementation (Opland *et al.*, 2022). Overall, the workers performing SPS frequently become catalysts for positive transformations within organizations (Hines *et al.*, 2004; Mohaghegh and Furlan, 2020), thus explaining their pivotal role in the development of the learning-to-learn capability.

Job engagement is defined as "the simultaneous employment and expression of a person's 'preferred self' in task behaviors that promote connections to work and to others, personal presence (physical, cognitive, and emotional) and active, full performances" (Kahn, 1990, p. 700). Engaged employees invest their personal resources to carry out tasks at best, constantly putting efforts, attention and feelings into what they do (Rich *et al.*, 2010). Christian *et al.* (2011) argued that job engagement encompasses multiple dimensions of the self; it refers to individuals who employ their physical energy, are fully concentrated and express an emotional connection with the work performance. It is therefore a motivational concept that explains the extent to which individuals immerse themselves in their jobs in a holistic way.

Based on prior studies, there is a well-established consensus that job engagement is positively related to proactive behaviors, including SPS (Blader and Tyler, 2009; Christian *et al.*, 2011; Halbesleben, 2010; Rich *et al.*, 2010; Saks, 2019). Specifically, as engaged employees are more cognitively absorbed, enthusiastic and committed, they tend to be more effective in performing their work, actively seeking ways to improve their task performances and taking on additional responsibilities beyond their formal job roles (Christian *et al.*, 2011; Schaufeli and Bakker, 2004). Furthermore, they experience higher levels of autonomy and control, are more likely to perceive their work as meaningful and have a stronger sense of self-efficacy (Lorente *et al.*, 2014; Taipale *et al.*, 2011). Overall, these factors motivate employees to invest their personal energies to face problems when they arise, feel a sense of competence in understanding the causes and demonstrate a goal-orientated approach to effectively implementing the most suitable solution, thus triggering a learning process through SPS.

According to previous literature, job engagement is strictly linked to the concept of psychological ownership (PO), which explains the psychological state in which an individual feels her job as an integral extension of her identity (Pierce *et al.*, 2001; Brown *et al.*, 2014a, b). The link between job engagement and PO unfolds in three different ways (Wang *et al.*, 2019). First, highly engaged employees exert their physical, cognitive and emotional energies into their roles, thus personalizing their jobs (Belk, 1988, 1991, 2000). Second, job engagement empowers employees to have greater control over their jobs, increasing their perceptions of their mastery over their job resources and outcomes, which underscores the essence of ownership (Rudmin and Berry, 1987; Pierce *et al.*, 2003). Last, engaged employees have a more comprehensive knowledge of their jobs, thereby anchoring their jobs to their self-conception (Pierce *et al.*, 2003).

The PO-job engagement perspective provides a further rationale to demonstrate how job engagement fosters SPS, as employees view their jobs as being intrinsically linked to their identity, providing a sense of continuity between their present role and that of their anticipated future (Pierce *et al.*, 2003). This perspective extends beyond immediate tasks or accomplishments, encompassing a more strategic, long-term vision. Such a forward-looking orientation motivates engaged employees to involve in learning processes by viewing problems as opportunities for long-term improvement. Furthermore, the feeling of ownership transforms an employee's job from a mere aggregation of tasks into an intricate mosaic of accumulated experiences, skills and insights (Belk, 1991). They provide employees with a solid foundation for engaging into continuous learning processes because they can encapsulate past successes and lessons, while enhancing their confidence to address any problems that may arise (Belk, 1991, 2000). Therefore, these employees stand out not just for their proactivity but also for their unique proficiency in systematically addressing and resolving issues.

Overall, drawing on the above evidence, we argue that job engagement serves as a crucial underlying mechanism to foster SPS. Specifically, we hypothesize:

H1. Job engagement is positively associated with SPS.

2.2 The moderating role of lean production

In this section, we will explore how LP moderates the impact that employees' job engagement has on their SPS behaviors. LP is operationalized at the organizational level, representing the socio-technical system developed by firms on the shop floor to train and equip employees with the tools and methods for performing their tasks. In our study, LP combined three key bundles: JIT, TQM and human resource management (HRM). JIT implements a range of technical practices aimed at reducing setup times, redesigning layouts and minimizing inventory to facilitate the transition toward production processes based on a pull approach (Mackelprang and Nair, 2010; Shah and Ward, 2003). TQM entails a set of technical practices that incorporate intelligent automation, statistical controls and fool-proof techniques throughout the production processes to minimize waste and improve product quality (Jayaram *et al.*, 2010; Kaynak, 2003). Finally, HRM encompasses soft practices that promote collaboration and mutual support by using small group sessions, providing training and skill enhancement and encouraging employees to voice their work-related suggestions by using artifacts, such as suggestion boxes, 5-whys techniques and kaizen events. Therefore, LP encompasses both technical bundles, which standardize tasks, enhance operational stability, establish a flow-oriented production system and improve quality by eliminating waste and soft bundles aimed at equipping employees with the skills and knowledge needed to implement methods and techniques, while ensuring a safe, collaborative and empowered workforce.

These technical and soft bundles operate at the organizational level, impacting not only production and managerial processes (i.e. the organizational level), but also exerting an impact on individual employees (i.e. the individual level). Previous studies have presented contrasting results on the relationship between LP and employees (for a literature review, see Hasle *et al.*, 2012; Magnani *et al.*, 2019). Some have suggested a negative impact, pointing to increased job demands, work pressures and job insecurity as potential consequences (de Treville and Antonakis, 2006; Thompson, 2011). Others have argued for a positive effect, proposing that LP can lead to increased engagement, autonomy, job enrichment and job satisfaction (Bouville and Alis, 2014; Cullinane *et al.*, 2017; Leyer *et al.*, 2021).

Drawing on de Treville and Antonakis (2006), we contend that these controversial effects of LP on employees depend on individuals' interpretative systems. The mutually reinforcing JIT, TQM and HRM bundles represent organizational configurations incorporating various artifacts (Knol *et al.*, 2022) whose intended role is to provide equal support and guidance to all employees on both technical and soft dimensions. However, despite this intention, employee interpretations lead to distinct perceptions of these artifacts. Thus, the perceptions of employees explain whether they effectively use and incorporate LP into their daily jobs, thus affecting their engagement and behaviors.

We argue that LP, if properly implemented, tends to be perceived positively by employees, thus creating an organizational context encompassing artifacts that strengthen the effect of employees' engagement on SPS. Aoki (2020) showed that visual representations such as Kanban cards and poka-yoke techniques act as triggering artifacts, directing attention toward problems. Additionally, he demonstrated that artifacts such as shop floor layouts marked with painted lines and labels used for material organization act as supporting artifacts, enabling employees to initiate transformative activities. Furthermore, studies have highlighted that artifacts arising from the TQM bundle, such as statistical processes and quality control, promote the constant measurement of results, significantly promoting statistical thinking and problem identification and solving attitudes among employees (Juran, 1988; Schmidt and Finnigan, 1992; Spechler, 1991). Finally, HRM bundles are identified as connecting artifacts, ensuring that both workers and managers interpret artifacts as cues that promote problem-solving (Aoki, 2020). They facilitate problem analysis through post-it notes and graphs, guide conversations effectively and provide training for employees to maintain a consistent problem-solving focus (Bechky, 2003; Ewenstein and Whyte, 2009; Knight and Paroutis, 2017). In line with this stream of research, we contend that LP develops artifacts that foster employees to harness their cognitive, emotional and physical efforts more effectively in pursuit of SPS behaviors. Therefore, we hypothesize:

H2. LP positively moderates the relationship between job engagement and SPS.

2.3 The moderating role of IoT systems

We define IoT systems as the integration of four key technological groups: sensors, connectivity components, algorithms and interfaces (Bassi *et al.*, 2013; Iansiti and Lakhani, 2014; Li *et al.*, 2015; Qu *et al.*, 2016; Wang *et al.*, 2021). Sensors dynamically and automatically gather raw data from the surrounding environment (Bassi *et al.*, 2013), generating continuous data streams. Connectivity components establish the data transport architecture, facilitating the sharing of data among network nodes (Li *et al.*, 2015). This data is then aggregated, processed and transformed into valuable information using algorithms (Porter and Heppelmann, 2015). Through the use of interfaces, such valuable information becomes available to operators (Bibby and Dehe, 2018; Li *et al.*, 2015; Qu *et al.*, 2016).

The integration of IoT systems in the workplace represents a paradigm shift from previous technological advancements, placing greater importance on the collection and the provision of accurate information on both the machines and human operators, thus fundamentally reshaping the dynamics of human-technology interaction (Ancarani *et al.*, 2020; Oztemel and Gursev, 2020; Zhong *et al.*, 2017). This increased availability of accurate information brings several benefits. First, it enables a higher level of customization, as machines can dynamically align with the specific operator's preferences, skills and goals by adapting the workflow, machine settings, or task assignments based on data collected on past performance, preferences and expertise (Benitez *et al.*, 2022). Second, it enhances the human operators' understanding of machine performance, enabling better control, monitoring and proactive issue detection (Cagliano *et al.*, 2019; Taylor *et al.*, 2020; Waschull *et al.*, 2020). Furthermore, as IoT systems provide real-time instructions, suggestions and feedback, employees gain a better comprehension on their actions, productivity, efficiency and areas for improvement, facilitating immediate corrections and their adaptation of work practices (Bienhaus and Haddud, 2018; Strandhagen *et al.*, 2017; Asokan *et al.*, 2022). Finally, IoT systems act as a catalyst for directing, assessing, or regulating employees' performance (Kellogg *et al.*, 2020), ensuring control and their adherence to organizational policies and procedures. Therefore, IoT systems represent artifacts that incorporate the knowledge used to frame employees' patterns of actions (Latour, 2005; D'Adderio, 2008, 2011).

IoT systems equip employees with real-time information about their own performance and the machines they operate (Bortolini *et al.*, 2017; Cagliano *et al.*, 2019; Leyer *et al.*, 2019; Taylor *et al.*, 2020; Waschull *et al.*, 2020). Although these artifacts are capable of autonomously collecting data from embedded sensors, human operators can input data into the IoT system in various ways, such as through manual data entry or interaction with intelligent devices and intuitive interfaces. The human contribution in providing data to the system enriches the information gathered by the IoT systems with human context and interpretation. Workers can contribute with specific details, contextual observations and subjective evaluations that enhance the understanding of the collected data. This human contribution is particularly valuable in situations where raw data may not provide a complete representation of the situation or may require human interpretation to extract meaningful insights. As a result, workers have access to a multitude of information that equips them with the necessary means to address problems more effectively, make better decisions and facilitate and support their problem-solving efforts (Lu and Cecil, 2016; Galeazzo and Furlan, 2019), thereby contributing to SPS.

Furthermore, IoT systems provide individuals with a greater sense of autonomy and control over their work processes (Parker and Grote, 2022). It allows employees to manage their tasks with increased flexibility (Gregg, 2011), adapting their work processes and methods to align with their specific needs and preferences. Decentralized decision-making is further facilitated by IoT systems, which enable the gathering of a wide range of data encompassing information from processes, objects, events, real-time performance metrics and contextual factors. This data is then transformed into actionable information that becomes readily available to the employees involved in decision-making processes. With access to this information, employees have the authority and autonomy to make informed decisions regarding their tasks rather than relying solely on top-down directives (Grote and Baitsch, 1991; Zuboff, 1988). As a result, employees develop a greater sense of responsibility for their jobs and the outcomes they achieve. They also perceive themselves as valued and trusted, fostering elevated levels of engagement and motivation to proactively identify and resolve problems.

Therefore, it is hypothesized that the stronger the implementation of the advanced IoT systems, the more effective the relationship between job engagement and SPS. Building upon these premises, we propose the following hypothesis:

H3. IoT systems positively moderate the effect of job engagement on SPS.

3. Methodology

3.1 Sampling and data collection

All our data was collected by employing a survey approach. As our objective was to investigate workers within their operational context, the data was collected at three levels of the organization: employees, work units and firms. Drawing on similar studies that adopted a multi-level approach (Furlan *et al.*, 2019; Tang *et al.*, 2021), a mixed-method sampling strategy was employed, combining cluster sampling and purposive sampling techniques (Teddlie and Yu, 2007; Wright and Marsden, 2010) to collect the data. To construct the survey questionnaire, preliminary interviews were conducted with key informants from 14 manufacturing firms, which helped determine the relevant arguments regarding the relationship between the operational context and the workers' individual characteristics, attitudes and behaviors.

The data collection took place from February to September of 2021 following a stepwise procedure. First, an initial dataset consisting of medium-to large-sized Italian manufacturing firms located in Northern Italy, a region that encompasses over 52% of the Italian manufacturing firms (ISTAT, 2020), was selected from the Italian Company Information and Business Intelligence (AIDA) (it encompasses data on over 200,000 Italian firms and was provided by Bureau Van Dijk). Second, the research team leveraged their professional networks and identified 326 email addresses of key informants from the selected firms. It then sent an email to these key informants by providing a comprehensive overview of the research's purpose and a detailed description of the data collection methodology. As a token of appreciation for their participation, the team offered them a benchmarking report. From the initial contact, a total of 43 firms responded to the emails and expressed their willingness to engage in a virtual meeting for further discussion regarding the research. Following these virtual meetings, ten firms decided to withdraw from the data collection process. Their decision was primarily driven by time constraints. Additionally, some internal stakeholders, such as HR departments, may have expressed reservations or concerns that led to the firms' decision to discontinue their involvement. Third, the research team conducted in-person visits to each of the participating firms. These visits served to select the work units that would be included in the research. The selection process was carried out collaboratively between the research teams and plant managers by choosing from the assembly lines, workshops, or cells to accurately represent the different operational contexts within the plants.

Finally, questionnaires were administered to both the shop floor employees and their supervisors in each of the selected work units. A total of 483 shop floor employees participated in the survey, answering questions about their individual characteristics, attitudes and behaviors. In addition, 108 supervisors provided their assessments about the extent of the implementation of lean bundles focusing on the work units under their responsibility. The survey administration took place during regular working hours, with the participants gathered in one designated room in their respective plants under the supervision of at least one member of the research team. It was communicated to the respondents that only the researchers would have access to the response data, ensuring their confidentiality and creating a safe environment for providing honest statements. This approach aimed to mitigate any potential self-serving biases and promote the reliability and accuracy of the participants' responses (Ketokivi, 2019).

Because of missing values, some data was dropped, reducing the final sample size to 440 workers from 101 separate work units across 33 manufacturing plants. On average, three work units with 4.3 employees were selected per plant. Most of the participants were male, accounting for 68.7% of the sample. Regarding age distribution, 24% fell within the 18–30 years range, 40% were between 31 and 45 years old, 35% were in the 46–60 years range and 1% were over 60 years old. In terms of educational background, 2% of the workers held an elementary school degree, 47% reported a junior high school degree and 51% possessed a high school degree. In terms of work units, although many work units did not utilize any IoT systems, the majority (55 work units) implemented a range of IoT systems involving 53.9% of the employees.

To examine the risk of the common method variance (CMV), we implemented various strategies in survey design and administration. Specifically, we separated questions related to independent variables from those related to the dependent variable to minimize information recall bias; we used validated scales to enhance respondents' understanding of scale items; we ensured anonymity to address social desirability bias; we selected participants with at least six months of experience in the same work position in order to mitigate inability to provide accurate answers; we emphasized voluntary participation; we administered questionnaires during working hours, accompanied by instructions explaining the significance of the research and encouraging participants to freely express their thoughts; and, finally, we checked for response order effects by creating three versions of the questionnaire with different question and item orders. A post-hoc analysis using multigroup confirmatory factor analysis (CFA) indicated no significant differences in constructs among the different versions of the questionnaire ($p = 0.201$), suggesting that the response order effect was not a concern.

As a post-hoc analysis to assess CMV, we used the CFA marker test (Richardson *et al.*, 2009). The test recommended selecting an individual-level marker variable that is theoretically unrelated to the variables under investigation. The categorical variable representing different levels of technological proficiency (0 for no technological skills, 1 for basic skills and 2 for advanced skills) was selected as the marker. This variable showed weak correlations (from 0.05 to 0.06) with the variables of interest (job engagement and SPS), indicating its theoretical unrelatedness to these constructs. The partial correlation technique returned that the original correlations between the variables of interest did not change after correcting for the same-source effect, thus minimizing the risk of CMV in this study.

3.2 Measurement items

The present survey employed previously established scales from organizational behavior and job design literature demonstrating content validity. These measures were originally written in English, then translated into Italian and subsequently translated back into English, following the rigorous procedure outlined by Brislin (1986). Unless otherwise stated, all the measures were rated on a seven-point Likert scale, ranging from "strongly disagree" to "strongly agree." A comprehensive overview of the variables and their descriptions can be found in Table S1 of the supplementary material.

The dependent variable, SPS, was assessed using the nine-item scale developed by Maydeu-Olivares and D'Zurilla (1996) based on the Heppner and Petersen's (1982) problem-solving inventory (PSI). The scale assesses various problem-solving aspects. To assist the respondents in providing accurate responses, the questionnaire included a note specifying the types of problems to consider (e.g. machine breakdowns, material shortages, time wasted searching for tools/parts). Initially, a CFA was conducted with all items loading on a single factor. However, this model did not exhibit satisfactory factor loadings or fit indices. As a result, two items, that is, sps07 and sps08, were dropped due to their factor loadings (less than 0.5). Subsequently, another CFA was conducted using the reduced scale, which demonstrated improved fit indices: a chi-square to degrees of freedom ratio (χ^2/df) of 3.32 ($p = 0.00$), a comparative fit index (CFI) of 0.98, a Tucker–Lewis Index (TLI) of 0.96 and root mean square error of approximation (RMSEA) of 0.07.

The independent variable of job engagement, based on a scale developed by Rich *et al.* (2010), measured the extent to which employees engage emotionally, cognitively and physically in their job performance. To determine the factor structure, several CFAs were conducted. Among the different models tested, the one with three first-order factors—physical engagement (6 item), emotional engagement (5 items) and cognitive engagement (6 items)—loading on a second-order factor demonstrated the best fit. This model exhibited good fit indices: χ^2/df = 3.45 ($p = 0.00$), CFI = 0.96, TLI = 0.95 and RMSEA = 0.08. Alternative models, such as the first-order model with all the items loading directly on one factor or second-order models with three or two first-order variables, did not exhibit good fit indices.

The implementation of IoT systems was assessed using dichotomous variables that measured the extent to which the system of technologies that constitute IoT have been adopted in the sampled work units. This assessment was based on the direct observations conducted by the research team. The study employed a two-step process to classify IoT systems in work units. First, a structured literature review identified a list of 26 IoT technologies. Second, the data collection involved interviews and observations with plant managers and supervisors to determine the presence of these technologies. Dummy variables were created for each technology. A clustering analysis was performed to categorize the work units based on their patterns of IoT systems' adoption consistent with prior studies (Frank *et al.*, 2019; Tortorella and Fettermann, 2018). Specifically, we used a hierarchical algorithm (Ward's method) in combination with the Calinski–Harabasz index and the dendrogram's treelike structure (Brusco *et al.*, 2017) to identify the optimal number of clusters, which was determined to be three. The k-median clustering method was then used, which is superior to the commonly used k-means clustering when dealing with binary data and an unknown number of clusters (Brusco *et al.*, 2017). To ensure the reliability (Ketchen and Shook, 1996), we ran the k-median algorithm 5,000 times with randomly chosen starting seeds, addressing the problem of selecting a suboptimal solution (Hair *et al.*, 2010). Furthermore, a split-half replication analysis was conducted to test further validity.

The clustering analysis resulted in three distinct clusters. To represent these clusters, we created three dichotomous variables. The first cluster, labeled "No IoT systems," encompasses 45 work unit and it is characterized by a lack of technological advancements such as sensors, connectivity to other information technology (IT) systems, digital interfaces and any form of artificial intelligence (AI) integration. Job tasks within these units exemplify manual processes, such as sewing buckles onto belts or manually assembling hospital beds or coffee machines. The second cluster, labeled "Basic IoT systems," comprises 20 work units with limited adoption of IoT technologies. All the observed work units were equipped with industrial sensors, Internet gateways and basic interfaces like monitors, keyboards and barcode readers. Within these units, employees mainly interface with a computer linked to an Enterprise Resource Planning (ERP) system primarily used for carrying out uncomplicated tasks such as initiating production programs for machine tools or updating inventory data. The predominant mode of information dissemination in these units is through text-based formats. The third cluster, labeled "Advanced IoT systems," consists of 36 work units that utilize advanced sensor systems, such as radio frequency identification (RFID), near-field communication (NFC) and quick response (QR) codes, along with augmented reality tools. These cutting-edge technologies empower autonomous product identification at the workstation, streamline the accurate placement of assembly items and offer predictive capabilities for the cutting process. In the following analyses, "No IoT systems" was used as the baseline.

The LP variable measured how extensively the work units implemented a combination of both technical and organizational lean bundles. Following previous studies (Bevilacqua *et al.*, 2017), we operationalized the technical lean practices in terms of JIT and TQM, whereas the organizational lean practices were operationalized by using a HRM bundle. JIT consisted of seven items, TQM included five items and HRM had eight items. All the measures were drawn from Furlan *et al.* (2011). A CFA was performed on each lean bundle separately to assess its construct validity. Following Hair *et al.* (2010), as the items with loadings lower than 0.5 should be not considered acceptable, items jit01, jit07, tqm01, hrm01, hrm03 and hrm04 were removed from their respective models. The new models had satisfactory fit indices, with the χ^2/df ratio = 3.71 (p = 0.00), CFI = 0.96, TLI = 0.95 and RMSEA = 0.08. The additional internal reliability and construct validity measures were calculated as reported in Table S1 of the supplementary material. All the measures properly met all the minimum cutoff values, thus confirming that all the variables were reliable and valid constructs. Once the technical and organizational lean bundles were validated, the average measures of each bundle were created. This process involved calculating the mean score for the variables within each bundle and subsequently averaging them to form the LP variable.

To account for potential omitted covariates and minimize confounding effects, we included in our analysis several control variables at both the individual and plant levels. At the individual level, we controlled for gender (using a dummy variable where 1 represents male and 0 represents female), age (using a dummy variable where 1 represents age below 45 and 0 represents age 45 and above), tenure within the organization (measured in years), education (using a dummy variable where 1 represents respondents with an elementary or junior high school degree and 0 represents others) and proactive personality (measured using four items from Bateman and Crant, 1993). Proactive personality has been shown to significantly influence job design and psychological well-being (Parker *et al.*, 2006).

Furthermore, we also controlled for job characteristics. Specifically, we controlled for job complexity (using four items from Morgeson and Humphrey, 2006), task variety (using four items from Morgeson and Humphrey, 2006) and job autonomy (measured as a second-order factor model that incorporates three first-order factors, namely work-scheduling autonomy, decision-making autonomy and work-method autonomy – from Morgeson and Humphrey, 2006). Prior research has established a strong association between job characteristics, engagement and SPS (Carpini *et al.*, 2017). In general, these control variables can be seen as indirect indicators of employees' capabilities. For instance, tenure and education can gauge an employee's level of experience and skill sets that, in turn, contribute to their overall abilities and expertise in their role. Meanwhile, job characteristics encompass the specific technical competencies and knowledge relevant to a particular job.

3.3 Measurement validation

Table S1 in the supplementary material provides an overview of the factor loadings, reliability estimates [Cronbach's alpha and composite reliability (CR)] and validity indicators [average variance extracted (AVE)] for the variables of interest. Both the reliability estimates and the AVE for all the constructs were found to be above the recommended thresholds, with the exception of SPS and proactive personality, that displayed AVE values of 0.48 and 0.43, respectively. Although these values are slightly below the conventional 0.5 limit, these constructs exhibit significant dissimilarity from the other constructs because their CR values exceed the threshold of 0.6 (SPS has a CR equal to 0.87 and proactive personality has a CR of 0.75), as recommended by Fornell and Larcker (1981). The convergent validity of the constructs was further supported by the significant factor loadings, which indicate that the items significantly loaded on their respective constructs ($p < 0.001$). The factor loadings ranged from 0.55 to 0.97, suggesting adequate convergent validity. The discriminant validity was demonstrated by comparing the square root of AVE for each construct with the correlation coefficients between constructs (Fornell and Larcker, 1981). It was found that the AVE square root was higher than the correlations, indicating discriminant validity. Overall, the variables of interest exhibited satisfactory levels of reliability and construct validity.

4. Results

Table 1 shows the means, standard deviations and correlations among the study variables. To test our hypotheses, we utilized multi-level mixed-effects linear regressions ("xtmixed" command in Stata 17). Given the nested nature of our data (workers within work units clustered within plants) and the presence of the variables measured at both the individual and work unit levels, multi-level regression analysis was deemed appropriate.

Furthermore, the intraclass correlation coefficient (ICC) was calculated at both the plant level and work unit level. The ICC at the plant level was determined to be 0.17, indicating that 17% of the variance in the dependent variable can be attributed to the differences between plants. Similarly, the ICC at the work unit level was found to be 0.40, suggesting that 40% of the variance in the dependent variable can be attributed to the differences between the work units. These ICC values are above the 0.05 value recommended by Geldhof *et al.* (2014). These results further underscore the importance of utilizing a multi-level regression analysis (e.g. Furlan *et al.*, 2019).

Table 2 presents the findings of our theoretical model. Model 0 contains only the control variables of the study. Model 1 adds the main variables of interest. Model 2 further includes the interaction variable derived from the product of job engagement and LP, in addition to the variables in Model 1. Model 3 incorporates the interaction variables resulting from the product of job engagement and IoT systems, in addition to the variables in Model 1.

The results in Model 1 provide support for H1 ($\beta = 0.213, p < 0.01$), suggesting that there is a positive and significant effect of job engagement on SPS. The results in Model 2 provide support for H2 ($\beta = 0.152, p < 0.05$), indicating a significant and positive moderating effect of LP on the relationship between job engagement and SPS ($\beta = 0.152, p < 0.05$). Figure 2 shows the effect of the moderation of LP on the slope of job engagement and SPS. The graph illustrates that the positive relationship between job engagement and SPS is stronger in firms

Table 1. Mean, standard deviation (s.d.) and correlation analyses of the variables of interest

	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Individual-level variables																
1. SPS	4.89	0.84	(0.69)													
2. Job engagement	5.92	0.73	0.27*	(0.77)												
3. Job autonomy	4.37	1.31	0.17*	0.25*	(0.89)											
4. Job complexity	4.27	1.36	−0.00	0.07	−0.00	(0.76)										
5. Task variety	5.00	1.44	0.13*	0.28*	0.42*	0.18*	(0.91)									
6. Proactive personality	5.13	1.04	0.24*	0.27*	0.18*	0.03	0.07	(0.66)								
7. Gender	0.69	0.46	0.08	−0.16*	0.16*	0.11*	0.03	0.08	1							
8. Age	1.11	0.77	0.06	0.09	0.01	0.03	0.04	−0.09	−0.05	1						
9. Tenure	7.81	7.95	0.04	0.03	0.04	0.03	0.08	−0.07	0.04	0.46*	1					
10. Education	0.51	0.50	−0.09	−0.06	−0.02	0.07	−0.04	0.03	0.02	0.33*	−0.20*	1				
Work unit-level variables																
11. IoT systems	0.86	0.88	0.12*	0.00	−0.11*	0.08	−0.07	0.01	0.04	0.18*	−0.14*	0.08	1			
12. JIT	4.43	0.91	0.23*	0.08	−0.08	−0.02	−0.08	0.06	0.05	0.09	−0.01	−0.00	−0.01	(0.79)		
13. TQM	4.87	1.02	0.20*	0.10*	−0.04	0.03	0.01	−0.01	0.14*	0.07	0.05	−0.04	0.22*	0.59*	(0.86)	
14. HRM	4.67	0.94	0.24*	0.09	−0.04	0.02	0.04	0.01	0.07	0.07	0.05	−0.07	0.22*	0.55*	0.74*	(0.81)

Note(s): S.D. refers to standard deviation. Square root of AVE on diagonal. *$p < 0.01$

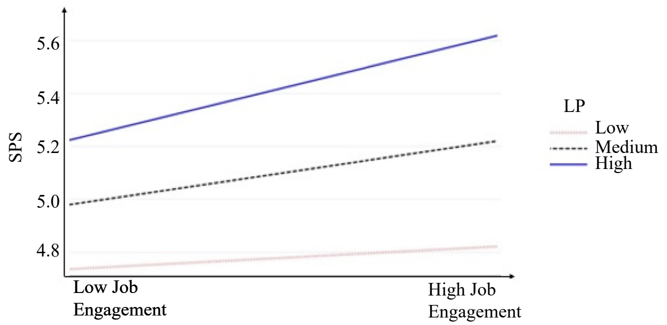
Source(s): Author's own creation

Variables	Model 0	Model 1	SPS Model 2	Model 3	Model 4
Job engagement		0.213***	−0.513	0.297***	0.133
		(0.0532)	*(0.317)*	*(0.0743)*	*(0.438)*
Basic IoT systems		−0.0901	−0.0761	−0.0785	−0.895
		(0.149)	*(0.151)*	*(0.151)*	*(0.918)*
Advanced IoT systems		0.277**	0.275**	0.272**	−0.983
		(0.127)	*(0.129)*	*(0.129)*	*(0.693)*
LP		0.197***	0.220***	0.218***	0.103
		(0.0668)	*(0.0674)*	*(0.0675)*	*(0.0921)*
Job engagement*Basic IoT systems				−0.276**	−1.499
				(0.126)	*(0.921)*
Job engagement*Advanced IoT systems				−0.146	−1.667**
				(0.125)	*(0.723)*
Job engagement*LP			0.152**		0.0347
			(0.0671)		*(0.0964)*
Basic IoT systems*LP					0.183
					(0.200)
Advanced IoT systems*LP					0.266*
					(0.144)
Job engagement* Basic IoT systems*LP					0.263
					(0.198)
Job engagement* Advanced IoT systems*LP					0.305**
					(0.150)
Job autonomy	0.0523*	0.0430	0.0524*	0.0469	0.0554*
	(0.0295)	*(0.0299)*	*(0.0298)*	*(0.0297)*	*(0.0293)*
Job complexity	0.00104	−0.0150	−0.0160	−0.00816	−0.00970
	(0.0265)	*(0.0268)*	*(0.0267)*	*(0.0267)*	*(0.0264)*
Task variety	0.0288	0.00786	0.0113	0.0132	0.0185
	(0.0273)	*(0.0276)*	*(0.0275)*	*(0.0275)*	*(0.0272)*
Gender	0.0368	0.109	0.0718	0.0903	0.0663
	(0.0892)	*(0.0931)*	*(0.0926)*	*(0.0925)*	*(0.0912)*
Age	0.0131	−0.00308	0.00614	−0.000715	0.00652
	(0.0535)	*(0.0540)*	*(0.0539)*	*(0.0538)*	*(0.0531)*
Tenure	0.00564	0.00495	0.00535	0.00570	0.00580
	(0.00497)	*(0.00501)*	*(0.00500)*	*(0.00501)*	*(0.00493)*
Proactive personality	0.147***	0.121***	0.126***	0.128***	0.127***
	(0.0330)	*(0.0340)*	*(0.0336)*	*(0.0336)*	*(0.0331)*
Education	−0.116	−0.0871	−0.0734	−0.0785	−0.0689
	(0.0723)	*(0.0726)*	*(0.0725)*	*(0.0725)*	*(0.0716)*
Constant	3.726***	1.777***	2.856***	2.834***	3.296***
	(0.252)	*(0.441)*	*(0.403)*	*(0.404)*	*(0.494)*
Observations	429	406	406	406	406
Number of groups	101	96	96	96	96

Note(s): Standard deviation in brackets. **p*-value<0.1; ***p*-value<0.05; ****p*-value<0.01
Source(s): Author's own creation

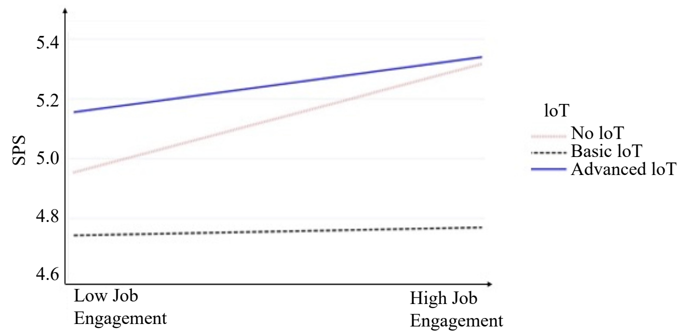
Table 2.
Results

with high LP implementation compared to those with lower LP implementation. Finally, the results in Model 3 do not provide support for H3. Contrary to our expectations, we find that basic IoT systems negatively moderate the relationship between job engagement and SPS ($\beta = -0.276$, $p < 0.05$), whereas the moderating effect of advanced IoT systems is not statistically significant ($\beta = -0.146$, $p > 0.10$). Figure 3 provides the impact of the moderation of IoT systems on the job engagement-SPS relationship. The graph indicates that the positive relationship between job engagement and SPS is weaker in workshops equipped with basic IoT systems compared to those without technologies.



Note(s): Medium LP = mean level of LP; High LP = 1 SD above the mean; Low LP = 1 SD below the mean
Source(s): Author's own creation

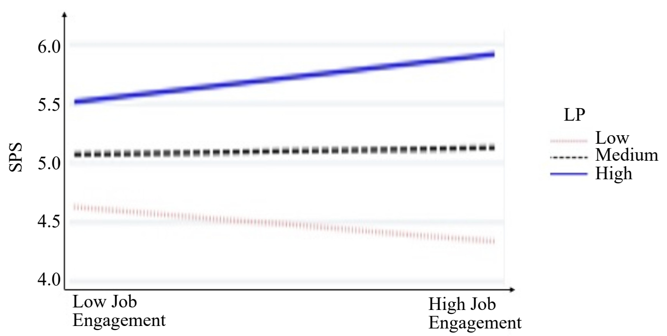
Figure 2. The moderating effect of LP on the job engagement-SPS relationship



Source(s): Author's own creation

Figure 3. The moderating effect of IoT systems on the job engagement-SPS relationship

To further examine the contrasting moderating effects of LP and IoT systems, a three-way interaction between job engagement, lean bundles and IoT systems was calculated. Model 4 presents the results of this three-way interaction, indicating a positive and significant effect in the case of the advanced use of IoT systems in the work units ($\beta = 0.305$, $p < 0.05$). Figure 4 presents the effect of LP on the job engagement-SPS relationship when the work unit is



Source(s): Author's own creation

Figure 4. The moderating effect of LP on the job engagement-SPS relationship with advanced IoT systems

equipped with advanced IoT systems. This finding highlights that the relationship between job engagement and SPS becomes positive and significant when a worker is integrated into IoT-transformed work units shaped by lean management systems.

5. Discussion

Our study investigated how LP and IoT systems could be integrated to engage workers in SPS behaviors. With the growing implementation of lean management systems in manufacturing plants and the emergence of digital transformation driven by technologies like the IoT, a fundamental dilemma arises: can a human-centered management system like LP and a digital environment effectively strengthen employees' engagement in SPS behaviors? Our findings indicate that, all else being equal, LP reinforces the positive relationship between job engagement and SPS, while IoT systems diminish such a relationship. To shed light on these contrasting forces, we examined whether a lean management system integrated into IoT-driven working environments could reverse the negative impact of the IoT system on the relationship between job engagement and SPS. Surprisingly, our analysis demonstrates that a strong presence of lean management systems provides employees with the opportunity to fully harness the benefits of IoT systems in facilitating engaged employees to perform SPS behaviors.

5.1 The role of LP

Our findings confirmed the positive influence of LP on the relationship between job engagement and SPS, aligning with previous research in the lean literature that supports the positive impact of LP on employees (Seppälä and Klemola, 2004; Losonci *et al.*, 2011; Perez Toralla *et al.*, 2012; Cullinane *et al.*, 2013; Longoni *et al.*, 2013; Galeazzo *et al.*, 2021). In particular, we contribute to this stream of literature demonstrating that LP provides the tools and instruments (i.e. artifacts) that enhance employees' engagement in better understanding and tackling problems on the production process. For instance, JIT practices enable employees to visually evaluate whether their actions contribute to or disrupt the flow of production. In addition, TQM practices, such as standardization andon and fool-proof techniques, direct employees' attention toward the potential negative consequences of their actions, which can lead to problems. Finally, HRM practices develop immaterial artifacts, such as small group sessions and kaizen events, that support a culture that does not place blame when errors occur, but rather highlights them as opportunities for improvements (Anand *et al.*, 2009; Farris *et al.*, 2009). Overall, our research highlights how LP develops artifacts that provide clear objectives, monitoring and regulation and enhancing their understanding of consequences.

Our findings also contribute to the stream of lean literature arguing that lean enterprises should develop learning-to-learn capabilities to gain a sustainable competitive advantage from LP (Hines *et al.*, 2004; Powell and Coughlan, 2020; Saabye *et al.*, 2022). However, past studies have mostly focused on identifying the distinctive components of a learning-to-learn capability, such as the key role of employees' SPS behaviors (Saabye *et al.*, 2022, 2023), the processes that drive this capability, that is, action learning (Powell and Coughlan, 2020; Saabye *et al.*, 2022) and its objectives, that is, continuously adjusting LP (Bessant, 1998). Our findings offer preliminary insights into the interplay among these components.

5.2 The role of IoT systems

Contrary to our initial hypothesis, our findings indicate a significant negative moderating effect of the IoT systems on the relationship between job engagement and SPS. This unexpected outcome contributes to the stream of literature on operations management that highlights the downsides of digital technologies such as the IoT on individuals (Letmathe and Rößler, 2022; Roscoe *et al.*, 2019; Wuttke *et al.*, 2022), eventually demonstrating a detrimental impact of these technologies on the development of learning-to-learn capabilities. These studies shed light on the negative effects of digital technologies by demonstrating that employees who use these technologies in their jobs face challenges in retaining knowledge and transforming it into learning. Building on these studies, our findings provide further insights by highlighting that the adoption of digital technologies can impact both the motivational and behavioral aspects of human work, namely job engagement and SPS, that are crucial for shaping human learning processes (Marquardt and Yeo, 2012). Lower motivation and SPS may result from individuals' excessive reliance on automated systems' decisions without critically evaluating the available information, leading to the presence of automation bias (Mosier and Skitka, 1996; Parasuraman and Riley, 1997). Consequently, this excessive dependence on automated systems can gradually erode the workers' knowledge and skills required for task execution, potentially diminishing their confidence in critical evaluation skills and independent decision-making capabilities (Lindebaum *et al.*, 2020). Moreover, with the increasing use of algorithms in IoT systems, there is a concern that algorithms may learn and make decisions independently of human comprehension, making it challenging for workers to understand and interpret all the information provided by the IoT system (Burrell, 2016). Despite the abundance of information, workers may become less capable of processing information and incorporating it into their expertise in problem-solving (Kellogg *et al.*, 2020). This automation bias and ambiguity in interpreting information can contribute to workers becoming less actively engaged in their jobs and relying less on their expertise to address problems, which helps explain why IoT systems may not enable employees to foster their engagement in SPS.

5.3 The interplay of LP and IoT systems

In recent years, researchers have focused on investigating whether and how the joint implementation of LP and digital technologies can be effectively integrated into real production systems (Bittencourt *et al.*, 2020; Buer *et al.*, 2018; Powell *et al.*, 2018; Rossini *et al.*, 2019). Some authors argue that lean practices serve as an antecedent for the implementation of digital technologies. For example, Rossini *et al.* (2019) provided evidence suggesting that companies already implementing LP are more inclined to adopt digital technologies associated with Industry 4.0. Conversely, companies with limited implementation of LP may encounter challenges in prioritizing the adoption of these technologies. This can be attributed to the fact that, while digital technologies have the potential to automate processes, automation alone is insufficient to effectively convert an inefficient process into an efficient one. Consequently, the implementation of LP becomes necessary to mitigate the risk of automating inefficiencies within the production system (Bittencourt *et al.*, 2020).

Other authors emphasized the synergistic effects between LP and digital technologies. LP creates favorable conditions for the introduction of digital technologies, while the latter can support LP by enabling process standardization, transparency, improved communication and data analysis. Notably, Kolberg and Zühlke (2015) argued that the integration of IoT systems and LP enhances visibility and control over production processes, leading to improved efficiency, waste reduction and increased flexibility. They provided examples of how smart devices equip operators with real-time information on production cycle time and autonomously detect failures, facilitating efficient planning, organization and minimizing time waste during repair interventions. Similarly, Hoellthaler *et al.* (2018) explored the integration and synergies between these two approaches to address the challenges posed by volatile markets. While LP encountered limitations in dealing with growing manufacturing process complexities, digitalization offers an opportunity to overcome these limitations by enhancing the capacity to handle complexity and increase flexibility. Through transparent data collection across different product variants, digital technologies enable efficient management of diverse product portfolios, meeting market demands for flexibility without amplifying complexity, thus facilitating greater adaptability.

However, most of these studies have primarily focused on the overall synergistic effects of LP and digital technologies with respect to operational and financial performance (e.g. Kolberg and Zühlke, 2015; Sanders *et al.*, 2016; Tortorella and Fettermann, 2018), overlooking the behavioral consequences at the individual level. Considering that employees remain a vital component on the shop floor (Bittencourt *et al.*, 2020), it is essential to pay attention to individuals within the relationship between LP and digital technologies. With our study, we contribute to filling this research gap by finding that the presence of a lean system, implemented through JIT, TQM and HRM bundles, enables employees to fully leverage the benefits of the IoT system in facilitating engaged employees to perform SPS behaviors.

In deepening our discussion, we must re-evaluate the complex nature of PO (Pierce *et al.*, 2001, 2003). While we initially used this concept to highlight the relationship between job engagement and SPS, the existing literature on PO offers crucial insights into the evolving dynamics of employee perceptions. Specifically, it assists in elucidating the differing reactions observed when the IoT systems are introduced in isolation versus in combination with LP bundles. Dirks *et al.* (1996) suggested that PO can be related to either positive or negative attitudes towards change, contingent on the nature of the change. They classified the changes into three categories: self-initiated versus imposed, evolutionary versus revolutionary and additive versus subtractive. Our initial finding of a negative moderation of IoT systems on the relationship between job engagement and SPS highlights that the mere introduction of the IoT system may be perceived by employees as an imposed, revolutionary and subtractive alteration, thereby triggering resistance. Since technological changes such as the IoT systems are typically mandated by top management, employees may resist these top-down changes, viewing them as threats to their control, disruptions to their roles, or reductions to their key job elements. This phenomenon can activate the "dark side" of PO (Dirks *et al.*, 1996), leading employees to perceive the change as an intrusion into their domain.

However, the introduction of lean practices has the potential to alter this dynamic. Since lean systems ensure that changes occur collaboratively, emphasizing gradual transition rather than abrupt disruptions and valuing employees' participation and feedback, the lean approach could serve as a cue for employees to feel more involved, valued and empowered amid transitions. Thus, LP can convert the initially negative effect of IoT systems into a positive effect, thus strengthening the relationship between job engagement and SPS.

Another possible explanation for these findings lies in the interplay of the artifacts that may play different roles based on effectively promoting SPS behaviors (Anand *et al.*, 2009; Furlan *et al.*, 2019; Letmathe *et al.*, 2012). While the implementation of IoT systems provides companies with access to valuable information, it is the presence of lean artifacts that enables operators to effectively utilize this information and adopt a problem-focused approach, thus unlocking its full potential. As highlighted by operations managers from the surveyed plants, the employees in such environments access a richer and higher-quality dataset compared to their counterparts in traditional units. This advantage empowers them and their continuous improvement teams to draw upon a vast pool of information during problem-solving discussions. Moreover, employees who are supported by HRM practices such as training and incentive programs are likely to be less influenced by the "automation bias." In addition, the implementation of technical artifacts related to JIT and TQM, through standard operating procedures, tools that enhance operational stability and the establishment of a flow-oriented production system, creates a system of artifacts that facilitates and optimizes the effective utilization of the information provided by IoT systems during problem-solving processes. This abundance of information enhances the individual engagement and problem-solving approaches. As one operations manager noted, "Operators feel a higher sense of responsibility in their roles and are more proactive in voicing concerns, insights, and suggesting improvements." On the other hand, in the absence of a proper system of lean artifacts, valuable insights may be lost and the focus could be solely on the mere execution of tasks. In such cases, operators may perceive the information simply as operative instructions, leading to mechanical actions without fully comprehending the available information and its potential for process improvement beyond task execution.

Overall, our study extends the works of Aoki (2020) and Knol *et al.* (2022) by demonstrating the significant role of lean artifacts in shaping employees' behaviors and attitudes when IoT systems are implemented.

5.4 Managerial contributions

Our findings provide significant managerial contributions. The employees who adopt SPS behaviors play a crucial role in expediting the achievement of enhanced productivity, efficiency and learning-to-learn capabilities within manufacturing firms. Our research informs managers that their employees' engagement in SPS behaviors strongly depends on the technological and managerial systems implemented in the work units in which they operate. Furthermore, our findings indicate that implementing digital technologies without the appropriate managerial practices can pose challenges in fostering employee engagement and SPS. This implies that managers can draw inspiration from lean management to shape employees' behaviors toward SPS when digital transformation is taking place. Finally, our findings recommend that managers adopt a human-centered approach when implementing IoT systems. Specifically, incorporating LP can ease the transition to an advanced technological environment within plants, making it less disruptive for employees. This is because LP is rooted on the principles of valuing, respecting and actively involving employees in improvement processes, thereby transforming them from passive observers into engaged participants in the process. This transformation encourages greater adaptability and a more open attitude toward technological advancements.

6. Conclusion, limitations and future research directions

The rapid pace of change witnessed in the last decade requires academics and managers to explicitly consider the applicability of existing management theories in the evolving organizational environment. The context thus emerges as a noteworthy factor to investigate previously established relationships. For this reason, we have questioned whether the strength of the positive relationship between job engagement and SPS is amplified or diminished in the presence of LP and IoT systems. Our findings show that it is easier to engage the employees performing SPS behaviors in operational contexts endowed with both IoT systems and LP than in contexts where only IoT systems are implemented.

The main findings of this research should be interpreted within its limitations. Despite the fact that our study used measures based on widely accepted scales and adhered to the established guidelines in questionnaire design, one key limitation of this research is the reliance on self-reported data collected from both workers (job engagement, SPS and control variables) and supervisors (lean bundles). The reliance on subjective perceptions can introduce biased responses and social desirability bias. In particular, recent literature has highlighted that the perceived level of lean implementation can be different among top management and middle managers (e.g. supervisors) (Januszek *et al.*, 2023). To strengthen the validity of the findings, future research should consider gathering data from multiple respondents or employing other triangulation methods that combine self-reported measures with independent ratings, similar to the approach taken in measuring the IoT system.

Furthermore, our study operationalized the digital technologies associated with the IoT system using dichotomous variables. This approach limited our ability to capture the nuanced effects of individual technologies and lean bundles, as well as the impact of multiple combinations of different technological and lean-related features on the relationship between job engagement and SPS. To address this limitation, future research could explore the specific effects of individual bundles and technologies on the relationship. Moreover, future research could employ qualitative comparative analyses to provide a more comprehensive understanding of how specific combinations of lean bundles and digital technologies contribute to the variables of interest. Finally, it is worth noting that our study was conducted in a specific country, Italy, which is a limitation of our research. While this is not uncommon in the literature (e.g. Jansen *et al.*, 2016; Boemelburg *et al.*, 2023), it is important to recognize that cross-cultural differences in job engagement and SPS have been documented (Huang *et al.*, 2005; Zhong *et al.*, 2016). Therefore, future research should replicate our study in different cultural contexts to enhance the generalizability of the findings.

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Supplementary material

Scale	Item description	First-order factor loadings >0.5	Second-order factor loadings >0.5	Alpha >0.7	AVE >0.5	CR >0.6
Individual-level variables						
SPS				0.87	0.48	0.86
	sps01. When considering solutions to a problem, I do not take the time to assess the potential success of each alternative. *(reversed)*	0.55				
	sps02. When confronted with a problem, I usually first survey the situation to determine the relevant information	0.76				
	sps03. When I have a problem, I think of as many possible ways to handle it as I can until I can't come up with any more ideas	0.70				
	sps04. After following a course of action to solve a problem, I compare the actual outcome with the one I had anticipated	0.70				
	sps05. When making a decision, I compare alternatives and weigh the consequences of one against the other	0.78				
	sps06. When confronted with a problem, I stop and think about it before deciding on a next step	0.73				
	sps07. When thinking of ways to handle a problem, I seldom combine ideas from various alternatives to arrive at a workable solution (reversed) (dropped)	–				
	sps08. I try to predict the result of a particular course of action (dropped)	–				
	sps09. When a solution to a problem has failed, I do not examine why it didn't work (reversed)	0.57				
Job engagement				0.94	0.61	0.82
Physical engagement			0.79	0.92	0.67	0.92
	pe01. I work with intensity on my job	0.79				
	pe02. I exert my full effort to my job	0.87				
	pe03. I devote a lot of energy to my job	0.92				
	pe04. I try my hardest to perform well on my job	0.72				
	pe05. I strive as hard as I can to complete my job	0.76				
	pe06. I exert a lot of energy on my job	0.82				
Emotional engagement			0.61	0.92	0.70	0.92
	ee01. I am enthusiastic in my job	0.86				
	ee02. I feel energetic at my job	0.84				
	ee03. I am interested in my job	0.83				
	ee04. I feel positive about my job	0.82				
	ee05. I am excited about my job	0.83				

(*continued*)

Table S1. Variables, item description, factor loadings, Cronbach's alpha, AVE and CR

Scale	Item description	First-order factor loadings >0.5	Second-order factor loadings >0.5	Alpha >0.7	AVE >0.5	CR >0.6
Cognitive engagement			0.91	0.93	0.94	0.74
	ce01. At work, my mind is focused on my job	0.83				
	ce02. At work, I pay a lot of attention to my job	0.89				
	ce03. At work, I focus a great deal of attention on my job	0.92				
	ce04. At work, I am absorbed by my job	0.68				
	ce05. At work, I concentrate on my job	0.90				
	ce06. At work, I devote a lot of attention to my job	0.91				
Job autonomy				0.94	0.80	0.92
Work-scheduling autonomy			0.88	0.89	0.74	0.90
	sa01. The job allows me to make my own decisions about how to schedule my work	0.82				
	sa02. The job allows me to decide on the order in which things are done on the job	0.88				
	sa03. The job allows me to plan how I do my work	0.89				
Decision-making autonomy			0.93	0.92	0.73	0.89
	da01. The job gives me a chance to use my personal initiative or judgment in carrying out the work	0.85				
	da02. The job allows me to make a lot of decisions on my own	0.87				
	da03. The job provides me with significant autonomy in making decisions	0.85				
Work-methods autonomy			0.86	0.91	0.82	0.93
	wa01. The job allows me to make decisions about what methods I use to complete my work	0.91				
	wa02. The job gives me considerable opportunity for independence and freedom in how I do the work	0.86				
	wa03. The job allows me to decide on my own how to go about doing my work	0.94				
Job complexity				0.87	0.58	0.85
	jc01. The job requires that I only do one task or activity at a time (reverse scored)	0.70				
	jc02. The tasks on the job are simple and uncomplicated (reverse scored)	0.78				
	jc03. The job comprises relatively uncomplicated tasks (reverse scored)	0.67				
	jc04. The job involves performing relatively simple tasks (reverse scored)	0.89				
Task variety				0.95	0.83	0.95
	tv01. The job involves a great deal of task variety	0.88				
	tv02. The job involves doing a number of different things	0.86				

Table S1.

(*continued*)

Scale	Item description	First-order factor loadings >0.5	Second-order factor loadings >0.5	Alpha >0.7	AVE >0.5	CR >0.6
	tv03. The job requires the performance of a wide range of tasks	0.97				
	tv04. The job involves performing a variety of tasks	0.93				
Proactive personality				0.75	0.43	0.75
	pp01. No matter what the odds, if I believe in something I will make it happen	0.71				
	pp02. I love being a champion for my ideas, even against others' opposition	0.55				
	pp03. I excel at identifying opportunities	0.61				
	pp04. If I believe in an idea, no obstacle will prevent me from making it happen	0.74				
Work unit-level variables						
Lean production				0.94	0.71	0.88
Just in time			0.75	0.91	0.62	0.89
	jit01. We usually complete our daily schedule as planned (dropped)	–				
	jit02. The layout of our shop floor facilitates low inventories and fast throughput	0.80				
	jit03. Suppliers frequently deliver materials to us	0.82				
	jit04. Our customers receive JIT deliveries from us	0.82				
	jit05. We use a kanban pull system for production control	0.69				
	jit06. We have low setup times of equipment in our plant	0.79				
	jit07. We emphasize small lot sizes, to increase manufacturing flexibility (dropped)	–				
Total quality management			0.93	0.92	0.74	0.92
	tqm01. Our plant emphasizes putting all tools and fixtures in their place	0.85				
	tqm02. We actively develop proprietary equipment (dropped)	–				
	tqm03. A large percent of the processes on the shop floor are currently under statistical quality control	0.85				
	tqm04. In the past, many equipment problems have been solved through small group sessions	0.85				
	tqm05. Processes in our plant are designed to be "foolproof"	0.88				
Human resource management			0.84	0.90	0.65	0.90
	hrm01. We encourage employees to work together to achieve common goals, rather than encourage competition among individuals (dropped)	–				

(*continued*)

Table S1.

Scale	Item description	First-order factor loadings >0.5	Second-order factor loadings >0.5	Alpha >0.7	AVE >0.5	CR >0.6
	hrm02. Management tells us why our suggestions are implemented or not used	0.80				
	hrm03. Our organization structure is relatively flat (dropped)	–				
	hrm04. Our employees receive training to perform multiple tasks (dropped)	–				
	hrm05. Engineers are located near the shop floor, to provide quick assistance when production stops	0.75				
	hrm06. In the past three years, many problems have been solved through small group sessions	0.77				
	hrm07. Our plant employees receive training and development in workplace skills, on a regular basis	0.88				
	hrm08. We strive to continually improve all aspects of products and processes, rather than taking a static approach	0.81				

Note(s): The job autonomy model exhibited good fit indices: χ^2/df = 2.93 (p = 0.00), CFI = 0.99, TLI = 0.98, and RMSEA = 0.07. The job complexity model exhibited good fit indices: χ^2/df = 2.76 (p = 0.00), CFI = 0.99, TLI = 0.99, and RMSEA = 0.06. The task variety model exhibited good fit indices: χ^2/df = 2.55 (p = 0.00), CFI = 0.99, TLI = 0.99, and RMSEA = 0.06. The proactive personality model exhibited good fit indices: χ^2/df = 0.46 (p = 0.00), CFI = 1, TLI = 1, and RMSEA = 0.06

Table S1.

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