Effect of Industry 4.0 on the relationship between socio-technical practices and workers' performance

Abstract

Purpose - This paper examines the moderating effect of Industry 4.0 (I4.0) technologies on the relationship between socio-technical (ST) practices and workers' health, quality, and productivity performance.

Design/methodology/approach - 192 practitioners from different manufacturing firms adopting I4.0 technologies were surveyed, analyzed the collected data using multivariate techniques, and discussed the results in light of ST theory.

Findings - Findings indicate that I4.0 moderates the relationship between ST practices and performance, to an extent and direction that varied according to the focus of the technologies and practices adopted.

Originality/value - The I4.0 movement has triggered changes in the work organization at unprecedented rates, impacting firms' social and technical aspects. This study bridges a gap in the literature concerning the integration of I4.0 technologies into manufacturing firms adopting ST practices, enabling the verification of the moderating effects on workers' performance. Although previous studies have investigated that relationship, the moderating effect of I4.0 on performance is still underexplored, characterizing an important contribution of this research.

Keywords: Industry 4.0, Socio-technical systems, Productivity, Quality, Workers' health.

1. Introduction

The Fourth Industrial Revolution or Industry 4.0 (I4.0) era has triggered changes in the work organization at unprecedented rates (Bonekamp and Sure, 2015; Ghobakhloo, 2018). As I4.0 comprises disruptive technologies (e.g., Internet-of-Things – IoT, big data, and machine learning) that enhance interconnectivity among people, processes, products, and services (Lasi et al., 2014), the way employees interact and are engaged in their working environment shifted (Tortorella et al., 2021a). Thus, despite its technology-oriented approach, successful implementation of I4.0 not only requires the proper technical elements (e.g., technologies) but also involves sociocultural components that support behavioral and cultural changes (Cimini et al., 2020; Marcon et al., 2021). These characteristics indicate that I4.0 adoption should be viewed as part of a socio-technical (ST) system (Sony and Naik, 2020).

Most studies on ST systems have, to a large extent, investigated the regular production work. As I4.0 favors decentralized and real-time data-based decision-making processes, flexible and modular production systems to cope with a customized mass production, and the integration between physical and cyber systems (Xu et al., 2018; Santos and Martinho; 2019; Olsen and Tomlin, 2020), it raises a new work paradigm that goes beyond the traditional context reported in the ST systems' literature. The ST theory assumes that the design and performance of new systems can be enhanced if social and technical aspects are brought together and interdependently approached as part of the work system (Cooper and Foster, 1971; Clegg, 2000). ST systems are formed by highly interdependent sub-systems, and therefore changes may reverberate across the system in unanticipated ways.

In general, most organizations present some level of implementation of management practices that establish the basis of their ST systems (Tortorella et al., 2017). With the advent of I4.0, new technologies are integrated into those practices, leading to new performance results and challenges (Jamkhaneh et al., 2021). I4.0 implies disruptive changes in organizations, not only from a purely technical but also from an ST perspective. The impacts of those changes are still largely unknown (Kadir et al., 2019; 2020; Reiman et al., 2021), especially when considering multiple performance dimensions simultaneously (e.g., workers' health, quality, and productivity). In addition, there is no consensus whether ST practices as currently adopted present a positive interaction with new technologies from I4.0. The scarcity of empirical evidence related to such relationship raises the following research question:

RQ. What is the moderating role of I4.0 technologies on the impact of ST practices on workers' health, quality, and productivity performance indicators?

To answer this question, 192 practitioners from different manufacturing companies undergoing the adoption of I4.0 technologies were surveyed, analyzing the collected data through multivariate techniques. This research is grounded on ST theory, which encompasses the work design and quality of working life, explicitly embracing the concept that all aspects of a system are interconnected and must be concurrently approached, i.e., no aspect should prevail over the other (Molleman and Broekhuis, 2001; Kang et al., 2016). This study bridges a gap observed in the literature concerning the integration of I4.0 technologies into manufacturers adopting ST practices, enabling the verification of the interaction effects on workers' health, quality, and productivity. Although some studies (e.g., Kopp et al., 2019; Sony and Naik, 2020; Marcon et al., 2021) have investigated the relationship between I4.0 and ST systems/practices, their concomitant effect on performance is still underexplored, especially from an empirical point of view, motivating this investigation.

Besides its theoretical contribution, this study has managerial implications as it allows managers and practitioners to better understand the needs and advantages of jointly adopting I4.0 and ST practices across manufacturing sectors. Moreover, identifying their interaction effects might contribute to addressing specific improvement activities that best support the expected performance results on workers' health, quality, and productivity. Following an exploratory research design, a set of hypotheses was formulated and verified to better understand the topic and its boundary conditions.

The rest of this paper is structured as follows. Section 2 presents the background on key concepts covered in the study that allow the development of the investigated hypotheses. Section 3 describes the research method, whose results are displayed in section 4 and discussed in section 5. Section 6 concludes the article and indicates future research opportunities.

2. Background and hypotheses

2.1. Socio-technical systems

An effective work organization can balance work demands and conditions towards achieving the desired productivity, quality, and human health outcomes (Genaidy and Karwowski, 2003; Jaworek et al., 2010). Management practices in an ST system enhance the work environment regarding its physical, cognitive, and organizational demands, offering better working conditions to employees and entailing a better operational performance (Tortorella et al., 2019a). The establishment of a healthy and collaborative organizational climate influences employees' motivation, reinforcing open communication and a better relationship with management (Blaikie et al., 2014). In this sense, the inherent concepts of ST practices should be incorporated into the planning and execution of operational activities so that the required conditions to the expected results are achieved throughout the interaction between workers and the work environment (Saurin and Patriarca, 2020).

Although an ST system involves the concurrent adoption of different management practices (see Table 1), their interrelationship is not as evident as imagined, sometimes leading to unintended implications that only become obvious when the system is operating (Molleman and Broekhuis, 2001; Dixon et al., 2009). That reinforces the need for an in-depth understanding of how ST practices impact employees' performance. The distance between planning and execution roles tends to be reduced in the firm, as the adoption of ST practices generates shifts in organizational responsibilities (Eklund, 2000; Dul and Neumann, 2009; Koukoulaki, 2010; Righi and Saurin, 2015). In general, ST practices foster employees' ownership and systematic learning across different organizational levels (Thun et al., 2011; Marquardt, 2019).

Table 1 - ST practices frequently cited in the literature

Previous studies on ST systems (e.g., Zare et al., 2016; Pavlovic-Veselinovic et al., 2016; Tortorella et al., 2017; Falegnami et al., 2020) have suggested that a narrow view of the work activities might misguide problem-solving activities related to job design. Truly ST systems promote an environment in which all work components (both social and technical) must be regarded to improve operational performance (Kang et al., 2016). Tortorella et al. (2019a) indicated that the implementation of ST practices positively affects workers' health and quality, which corroborates the establishment of a holistic approach for developing ST systems.

2.2. Industry 4.0

Coined in 2011 in the Hannover Fair in Germany, the term I4.0 refers to an approach centered around cyber-physical systems, positing that the real-time connection of physical and digital systems together with novel digital technologies will shift the way work is imagined, done, and managed (Lasi et al., 2014; Olsen and Tomlin, 2020). I4.0 can change the traditional operations' trade-offs among the operational priorities of cost, flexibility, speed, and quality (Pagliosa et al., 2019; Santos et al., 2020). Nevertheless, the increased automation level will not lead to less human interaction or worker-less production systems. Instead, researchers (e.g., Dworschak and

Zaiser, 2014; Hecklau et al., 2016; Srinivasan et al., 2020; Tortorella et al., 2021b) claim that I4.0 implementation will mostly change the necessary skillset from employees.

The most frequently mentioned I4.0 technologies in the literature are shown in Table 2. Although common in the majority of studies, their applications vary in terms of focus and context (Tortorella et al., 2022a). For instance, with respect to the application focus, research can be found integrating I4.0 technologies into activities such as maintenance (Zonta et al., 2020), scheduling (Rossit et al., 2019), product development (Nunes et al., 2017), circular economy (Nascimento et al., 2018), and logistics and supply chain (Hofmann and Rüsch, 2017). Regarding the context, I4.0 applications are reported in a diversity of industry sectors, such as automotive (Bhatia and Kumar, 2020), pharmaceutical (Reinhardt et al., 2020), food (Khan et al., 2020), clothing and footwear (Chen, 2019), among others. Such versatility justifies the current digital transformation frenzy observed in organizations (Tortorella et al., 2020a).

Table 2 –I4.0 technologies mentioned in the literature

However, despite the evidenced benefits from I4.0 adoption, researchers also raise attention to the new challenges imposed by its technologies (Kans, 2013). Frank et al. (2019), for example, mentioned that most companies still struggle to grasp the concepts and benefits of some technologies, such as big data. Another challenge refers to the capital expenditure capacity required to provide the proper information technology infrastructure for I4.0 adoption, which sometimes can be a constraint for small and medium enterprises (Masood and Sonntag, 2020) or companies in emerging economies (Tortorella et al., 2021a). As companies start overcoming the inherent challenges of I4.0 adoption, they might achieve superior performance results (Dalenogare et al., 2018; Veile et al., 2019).

2.3. Socio-technical systems and Industry 4.0

Throughout history, each industrial revolution was marked by a set of characteristics that implied disruptive changes in both technical and sociocultural aspects of organizations and society (Morrar et al., 2017). From the advent of the steam machine of the First Industrial Revolution to the cyber-physical systems and interconnectivity of I4.0, disruptive innovations have impacted the way work is organized, employees relate and communicate, and products and services are developed and processed (Coccia and Bellitto, 2018). Despite that, many organizations still lack an integrated approach that addresses the ST changes implied by the Fourth Industrial Revolution. For instance, most I4.0 implementation initiatives are technology-centered, with the social system designed around it (Kadir et al., 2020; Srinivasan et al., 2020). That may compromise the coverage and perspective of I4.0, undermining the benefits of the accompanying ST system (Reiman et al., 2021).

According to Kagermann et al. (2013), the incorporation of I4.0 technologies is likely to transform work content, processes, organizations, and environments in manufacturing companies. In the Fourth Industrial Revolution era, the organization of work might call for employees with higher problem-solving and abstraction skills and able to cope with complexity (Kadir et al., 2019). That will also require more effective communication and higher autonomy among employees, which may affect their cognitive load (Kong, 2019). Nevertheless, researchers (e.g., Knight, 2014; Sony and Naik, 2020; Neumann et al., 2021) claim that such changes may enrich work activities, contributing to a more interesting workplace and mitigating their negative effects. Additionally, technologies such as collaborative robots and 3D printing are supposed to reduce physical stress (Broday, 2020), potentially leading to positive results in workers' health, quality, and productivity indicators. In fact, the moderating role played by I4.0 technologies on the impact of certain managerial approaches has already been evidenced by some studies (e.g., Tortorella et al., 2019b; 2022b).

Therefore, a holistic view of the interaction between I4.0 technologies and ST practices is needed to identify if their concurrent adoption underpins or impairs the performance of human-related operational indicators. From a practical perspective, the implementation and knowledge related to ST practices are more disseminated in organizations than I4.0 technologies, leading to the assumption that I4.0 is being integrated into organizations where ST practices have already been in place. To better understand the relationship between ST practices and I4.0 technologies and their impact on performance, the following hypotheses were formulated:

H_1: The adoption of ST practices is positively associated with workers' health, quality, and productivity indicators.

H_2: The adoption of I4.0 technologies positively moderates the relationship between ST practices and workers' health, quality, and productivity indicators.

Figure 1 – Hypothesized model

3. Method

This study examines the role of I4.0 technologies on the relationship between socio-technical practices and productivity, quality, and workers' health indicators. This exploratory research followed an empirical approach based on evidence collected from non-random participants who met specific selection criteria (Goodwin, 2005). The survey method was applied to gather data due to its high representativeness, low cost, statistical significance, and standardized stimulus to all participants (Montgomery, 2013). There are four main steps to the proposed method: (*i*) sample selection and data collection, (*ii*) questionnaire development, (*iii*) reliability and validity of constructs, and (*iv*) data analysis.

3.1. Sample selection and data collection

Respondents were selected according to the following criteria. First, the study targeted participants who worked in manufacturing companies, as I4.0 was originally conceived in such environment (Lasi et al., 2014). However, since the pervasiveness of I4.0 across industry sectors is varied, manufacturers from different industrial sectors were included. Second, as the extent of I4.0 adoption may be influenced by the socio-economic context in which companies are inserted (Tortorella et al., 2021c), this research sought respondents located in the same region of Brazil. Considering a single geographic location increases sample homogeneity and reduces exogenous variables' effects (e.g., availability of skilled labor and regional culture). Third, to allow a holistic perspective of the investigated phenomenon, respondents from different organizational levels, such as operational (technicians and engineers), tactical (supervisors and coordinators), and strategic (managers and directors) were included. Finally, all respondents should be familiar with I4.0 technologies.

Questionnaires were sent by e-mail to 523 potential respondents who were already part of the network of some of the authors. From those, 85 complete responses were obtained in the first two weeks after the e-mail was sent, and additional 107 responses were obtained in the following two months. The final sample comprised 192 complete responses (36.7% response rate), which is a high response rate compared to usual survey-based studies (Hair et al., 2014). Non-response bias was checked through Levene's test for equality of variances and a t-test for the equality of means between early- ($n_1 = 85$) and late-respondents ($n_2 = 107$) (Armstrong and Overton, 1977). Since no significant differences in means and variances were found between groups (p-value < 0.05), non-response bias issues were disregarded.

Table 3 displays the sample characteristics. Most respondents worked in large-sized manufacturers (67.7%) from the auto parts sector (44.2%). Furthermore, 30.2% of the participants were technicians or engineers, 49.5% played a supervisor or coordinator role, and 20.3% were managers or directors in their companies. Finally, 77.6% of the surveyed practitioners presented more than 5 years of experience in their roles.

Table 3 – Sample characteristics (*n* = 192)

3.2. Questionnaire development

The applied questionnaire consisted of four parts (see Appendix). In the first part, questions related to the demographic information of respondents (e.g., roles and work experience) and their companies (e.g., industry sector and size) were included. The second part asked respondents about the degree of performance variation in their companies in the past two years related to workers' health, quality, and productivity. Those performance indicators were chosen due to their clear relation to ST practices (Mohaghegh and Mosleh, 2009; Tortorella et al., 2019a). A 5-point scale was adopted to indicate the performance variation, in which 1 referred to 'worsened significantly' and 5 'improved significantly'. In the third part, the adoption level of the eighteen ST practices listed in Table 1 was assessed using a 5-point Likert scale that ranged from 1 (not adopted) to 5 (fully adopted). In the last part, it examined the adoption level of nine I4.0 technologies (listed in Table 2) in the respondents' companies. For that, a scale varying from 1 (not adopted) to 5 (fully adopted) was applied.

Since the questionnaire used psychometric scales and comprised a single-respondent dataset (Montabon et al., 2018), some countermeasures to prevent common method and source bias were performed. With regards to the questionnaire design, the dependent variables (performance indicators) were located far from the independent and moderating variables (Podsakoff and Organ, 1986). Additionally, it was stated upfront in the e-mail sent to respondents that anonymity and confidentiality would be ensured, and there were no right responses (Podsakoff et al., 2003). Lastly, Harman's single-factor test with exploratory factor analysis was ran to check whether a single factor's predominantly explained the total variance of the investigated variables (Malhotra et al., 2006). As a first factor that only included 23.78% of the total variance was found, common method variance was not a problem.

3.3. Reliability and validity of constructs

In this step, three Exploratory Factor Analyses (EFAs) using Principal Component (PC) extraction were conducted to identify constructs based on the dataset (Fabrigar et al., 1999). In the first EFA, it was analyzed the performance indicators (dependent variable) using a Varimax rotation, which led to a first PC (eigenvalue of 1.881 and accounting for 62.71% of the total variance) with all factor loadings greater than 0.45 (see Table 4). Construct reliability was tested through Cronbach's alpha which resulted in 0.740, indicating high reliability (Meyers et al., 2006).

Table 4 – PCA to validate performance construct

To carry out the second EFA, it was used responses on the adoption level of the eighteen ST practices to identify ST constructs. After rotating the axes using Varimax, two components with associated eigenvalues greater than 1.0 and accounting for 64.19% of the total variance were obtained. The analysis was replicated via oblique rotation of axes to test for orthogonality and found similar components. All Cronbach's alpha values were greater than 0.6 (as suggested by

Meyers et al., 2006), which confirmed the high reliability of responses, as shown in Table 5. Each construct was named according to the focus of their corresponding ST practices.

The first construct encompassed ST practices oriented to improving the design of the workplace (e.g., st_6-workstations appropriated to workers, and st_{14}-balancing among quality, scope, time, and cost). In general, these practices corroborate enhancing ergonomics and health conditions of the work task, involving other aspects such as the physical and psychological environment of the workplace (Clegg, 2000; Saurin and Ferreira, 2009; Arezes et al., 2015). Therefore, the construct was labeled 'work design'.

The second construct, labeled 'organizational practices', comprised practices that structure the work beyond the workstation itself (e.g., communication and information system, visibility of problem-solving indicators, overload towards the achievement of goals, management of staff turnover), being inherent to the organizational routines (Blaikie et al., 2014; Tortorella et al., 2019a). Both constructs are closely linked to Clegg et al.'s (2017) ST perspectives, as work design practices mainly focus on the technical elements of complex systems, and organization practices tend to approach the social elements.

Table 5 – PCA to validate ST constructs – rotated component matrix

The third EFA was run on the adoption level of the nine I4.0 technologies. Similarly, it was used a Varimax rotation to identify the PCs with eigenvalues greater than 1.0. Two components whose eigenvalues were 2.64 and 2.14, respectively, representing 53.12% of the total variance (see Table 6) were found. Similar components were identified when replicating the analysis through an oblique rotation for orthogonality verification. The constructs' Cronbach alpha values were all above 0.6 (Meyers et al., 2006), indicating high reliability. Based on the analysis of the corresponding factor loadings and the role of I4.0 technologies within organizations, constructs were labeled following Tortorella et al.'s (2020b) suggestions. The first construct involved technologies responsible for gathering data and sharing it among the interested parties (e.g., wireless sensors and cloud computing), hence, being labeled 'sensing-communication'. The second construct grouped technologies that aim at transforming data into information to support decision-making or control systems and equipment. Thus, this construct was labeled 'processing-actuation'.

Table 6 – PCA to validate constructs of I4.0 technologies

3.4. Data analysis

To analyze the data and verify the hypotheses, a set of Ordinary Least Squares (OLS) hierarchical linear regression models was performed. It was weighted the average of the responses for the measures in each construct using the corresponding factor loadings as weights. The resulting scores were standardized to avoid scale effects (Goldsby et al., 2013) and entered into the regression models as variables. It was determined the variance inflation factors (VIF) for each variable to assess multicollinearity. As all VIF values were lower than 5.0 (Belsley et al., 2005), multicollinearity issues were disregarded. Further, the correlation and composite reliability (CR) for all variables were analyzed. All significant correlation coefficients were positive, and all CR values were greater than 0.7 (Hair et al., 2014), as displayed in Table 7.

Table 7 – Pairwise correlation coefficients

Three regression models using performance variation (i.e., the performance construct scores) as the dependent variable were examined. In Model 1, performance was regressed on company size, which was the control variable used in this study. Model 2 included the direct effect of the independent variables, i.e., the two ST constructs (work design and organizational practices) and the two I4.0 constructs (sensing-communication and processing-actuation). Finally, Model 3 added the interaction terms to test the moderating effects of the I4.0 technologies. All models were initially tested using dummy variables for the industry sectors, but they were removed from the final models since they did not yield significant coefficients.

Following recommendations in Hair et al. (2014), normality, linearity, and homoscedasticity tests were conducted to check the requirements for performing OLS regression. The error term distribution for normality was assessed through the Kolmogorov Smirnov test, yielding *p*-values above 0.05 for all models. Linearity was checked utilizing plots of the partial regression for each model. Finally, to examine homoscedasticity, the standardized residuals were plotted against the predicted values allowing a visual check. All procedures confirmed the assumptions for the OLS regression models.

In addition, the determinantion of a reasonable sample size at which results of the analysis would remain unchanged from those obtained with larger samples was a point of concern. Although there is no consensus on the ideal sample size, some scholars (e.g., Concato et al., 1995; Peduzzi et al., 1995; Vittinghoff and McCulloch, 2007) have suggested a rule of thumb when using regression analysis, which assumes that there should be at least 10 observations per variable. In the most critical regression analysis, which considers the interaction terms (Model 3), there were nine independent variables. As the sample size was 192 respondents, the 10 to 1 ratio between sample size and independent variables was met. Thus, it was claimed that the 192 responses were enough to enable the regression analyses performed in this study.

4. Results

Table 8 shows the unstandardized $\hat{\beta}$ coefficients for the OLS hierarchical regression analyses. All three models presented significant F-values (p-value < 0.01), with R^2 values that ranged from 0.077 to 0.315. Nevertheless, when analyzing the significance of the change in R^2 among the models, Model 3, which encompassed the control, independent, and moderating variables, displayed the greatest predicting capacity. In Model 3, both company size and work design practices displayed significant and positive direct effects on performance ($\hat{\beta}$ = 0.272, p-value < 0.05; $\hat{\beta}$ = 0.489, p-value < 0.01, respectively). Regarding the moderating effects, two interaction terms (i.e., sensing-communication × organizational practices, and processing-actuation × work design practices) presented a negative association with performance ($\hat{\beta}$ = -0.221, p-value < 0.10; $\hat{\beta}$ = -0.396, p-value < 0.01, respectively). In turn, the interaction between processing-actuation technologies and organizational practices was positively associated with performance ($\hat{\beta}$ = 0.296, p-value < 0.05). No significant effect was found for the interaction between sensing-communication technologies and work design practices. These results (with significant relationships illustrated in Figure 2) partially support the hypotheses and are discussed next.

Table 8 – Results for hierarchical regression analyses (unstandardized $\hat{\beta}$ coefficients)

Figure 2 – Empirically verified relationships

5. Discussion

In the sample of manufacturing firms, the interaction between sensing-communication technologies and organizational practices negatively affected workers' health, quality, and productivity indicators. The sensing-communication construct combines technologies (e.g., wireless sensors, IoT, and remote monitoring) to acquire and transmit data, enhancing the interconnectivity among people, equipment, products, and services (Tortorella et al., 2020b). Such data is usually collected at the workplace, where employees perform operational tasks. In turn, organizational practices mainly focus on issues beyond the workstation itself, encompassing administrative processes (Blaikie et al., 2014; Tortorella et al., 2019a), contemplating a broader application scope. Although the data collected from a workstation and shared across the organization should be ideally inputted into organizational practices' routines, results show otherwise: the negative interaction suggests that the hand-off between data collected from the workplace and its actual integration into organization processes appears to be misguided, impairing performance improvement.

A similar phenomenon was observed when information technologies were first incorporated into offices, eventually leading to the reengineering movement of the 1990s. At that point, companies' large expenditures on information technology did not yield better performance results since the new technology was mainly used to mechanize old processes (Hammer, 1990). Results show that something similar is taking place in the manufacturing workplace, i.e., easy access to data is yet not translating into better operational results since work practices need to be restructured to benefit from this new data-rich environment.

A similar conclusion was reached by Tortorella and Fettermann (2018), who pointed out that the availability of large amounts of data should lead to the revision of management practices. Otherwise, the decision-making processes tend to remain the same, conflicting with the current technical structure (i.e., sensing-communication technologies) and undermining the achievement of a better performance. In addition, it may imply ineffective integration of outputs generated from Industry 4.0 technologies with organizational practices for greater visualization, traceability, and real-time communication between processes and products with people (i.e., employees). Adhering to traditional practices is a common issue for ineffective integration, causing sub-optimal employee performance (Chiarini and Kumar, 2021).

While the negative moderating effect of sensing-communication technologies and organizational practices on performance highlights the delay in adapting routines to a rich-data environment, the negative moderating effect of processing-actuation technologies on the relationship between work design practices and performance reveals the delay in using the information derived from such data to design better work processes. As processing-actuation technologies, such as collaborative robots, 3D printing, and augmented reality, tend to contribute to the operational activities (Bonekamp and Sure, 2015; Broday, 2020), their interaction with work design practices (e.g., workstations better suited for workers, following ergonomic directions for workstation design) should be beneficial to workers' health, quality, and productivity. However, results do not support this assumption. Two possible justifications for such an outcome were envisioned.

The first is related to the employees' lack of experience with higher-end I4.0 technologies or their inability to fully embrace them due to the fear of job loss (Cagliano et al., 2019; Hahn, 2020). Early findings from I4.0 research on employees' acceptance of new technology vary between traditional defiance (or functional skepticism) and approaching I4.0 adoption in a more playful manner (Schneider and Sting, 2020). According to Taylor and Baek (2018), if those employees do not possess the proper experience and skills, benefits from technology use are likely to be compromised. Additionally, processing-actuation technologies can be seen as potential substitutes for human labor (Wilkesmann and Wilkesmann, 2018), which might also delay their incorporation into work design practices.

The second is related to the current predominant practice of improving work design through lean interventions in the manufacturing sector. A conflict of objectives between I4.0, which is a cost-intensive operation, and lean, which focuses on cost reduction, has been pointed out by Sanders et al. (2016). Efforts to integrate the two approaches are still developing in the literature, as reviewed by Pereira et al. (2019), and seem far from the manufacturing shopfloor practice, as results indicate. As lean improvement projects make intensive use of value stream mapping (VSM) analysis, the VSM 4.0 proposition by Meudt et al. (2017) may help reduce the observed delay in using the information generated by I4.0 technologies in work design practices, since data can be collected in real-time and faster and more assertive decisions related to work design can be made.

Finally, the concurrent adoption of processing-actuation technologies and organizational practices was found to be positively associated with performance, as hypothesized. Processing-actuation technologies turn data into actual information to support decision-making or control software, mechanisms, or systems (Tortorella et al., 2020b). Interestingly, the individual direct effects of those technologies and organizational practices were not significant. However, when combining them, there seems to be a significant and positive leap in performance variation, as illustrated in Figure 3. In other words, the effect of organizational practices on workers' health, quality, and productivity is boosted by a more extensive adoption of processing-actuation technologies. For instance, processing-actuation technologies such as machine learning may support problem-solving activities and enhance clarity in target definition, leading to more productive and effective workplaces. That converges with Marcon et al.'s (2021) findings, which indicated that practices that promote the improvement of social aspects in manufacturing systems are positively related to higher adoption levels of I4.0. Such result also complements indications from Tortorella et al. (2020a), which argued that, due to the low maturity of most manufacturers regarding I4.0 implementation, I4.0 technologies are more likely to be perceived as advantageous solely at an organizational level, i.e., the integration of new technologies from I4.0 tend to be more frequently evidenced in business processes than in workplace design.

Figure 3 – Moderating effects of I4.0 technologies on the relationship between socio-technical practices and performance. (a) Interaction between sensing-communication technologies and organizational practices on

performance. (b) Interaction between processing-actuation technologies and organizational practices on performance. (c) Interaction between processing-actuation technologies and work design practices on performance.

6. Conclusions

This research examined the role of I4.0 technologies on the effects of ST practices on workers' health, quality, and productivity. Findings indicate that the integration of I4.0 does moderate the relationship between ST practices and performance. However, the extent and orientation of such moderation may vary according to the focus of the technologies and practices considered. Therefore, this study raises meaningful insights for theory and practice in the field.

6.1. Theoretical implications

From a theoretical perspective, this research sheds light on the interaction between ST practices and I4.0 technologies, especially when considering their impact on operational performance indicators closely linked to human factors, such as workers' health, quality, and productivity. As postulated by the ST theory, social and technical elements are required to ensure successful organizational change. Findings corroborate that by indicating that the interaction between I4.0 technologies (i.e., technical elements) and ST practices, which are used as proxies for social elements, is relevant for performance improvements. However, the outcomes of such interaction are not always as expected.

This paper's findings highlight existing approaches for I4.0 implementation and their emphasis. Although research evidence has already pointed out the relevance of sociocultural aspects for a successful I4.0 implementation, this study suggests that the emphasis of I4.0 implementation is still predominantly technical. Such theoretical gap may lead to myopic approaches yielding counterintuitive results, e.g., the negative moderating effects observed in the analyzed dataset. In other words, this work indicates that the adoption of ST practices and I4.0 technologies should be conducted hand-in-hand to generate positive implications for workers' health, quality, and productivity. Regardless of some previous opposing indications from some researchers, the fact that we found some negative effects of the interaction between I4.0 technologies and ST practices highlights the necessity of a more human-centered approach when digitalizing organizations, as suggested by Kandler et al. (2021). Such unexpected effects converge to the concept of ST risk analysis (Gabriel et al., 2021) and readiness (Sitepu et al., 2020), emphasizing that the integration of I4.0 technologies may raise additional ST challenges.

The identification of these relationships complements the findings from Tortorella et al. (2020a), which indicated that the effects of I4.0 were still predominantly observed in organizational processes and not at an individual level. The quantification of these relationships also adds to the indications from Sony and Naik (2020), which proposed a theoretical framework based on an extensive literature review. Moreover, although our study corroborates the findings from Marcon et al. (2021), we expand the discussion by investigating the effects of the interaction between ST practices and I4.0 technologies on workers' performance, which has not been considered. As we are not aware of any previous studies that have empirically examined a similar theoretical model, we argue that this research presents an original contribution to the body of knowledge on I4.0 and ST systems.

6.2. Contributions to practice

In terms of practical implications, this study provides arguments to managers and practitioners for a better understanding of the benefits and drawbacks of the concurrent adoption of I4.0 technologies and ST practices in manufacturers. Verifying the effects of such interaction favors the development of countermeasures to support the achievement of the desired performance results, especially regarding workers' health, quality, and productivity. As behavioral changes (usually time-consuming and long-term-oriented) are also necessary for the success of an ST system, identifying potential issues might help anticipate improvement actions that can yield competitive advantages in the long run. Therefore, our results reinforce the need for developing a human-centered approach when integrating I4.0 technologies into manufacturers. In other words, companies must carefully consider ergonomics and human aspects in their digitalization initiatives, especially depending on the level of technology integration (e.g., organization, team, or individual).

Results also indicated that special efforts to incorporate I4.0 technologies into work design practices are needed to fully realize their process improvement potential. The most common implications of I4.0 technologies adoption are observed at an organizational level (Tortorella et al., 2020a), where business processes are deployed and managed. This work evidenced that I4.0 technologies may also affect work design practices boosting their effect on workers' performance, hence elucidating manufacturers about additional benefits of the digital transformation. To develop such positive interaction, managers from manufacturing firms must understand that I4.0 technologies, such as 3D printing and collaborative robots (i.e., processing and actuation technologies), should be properly introduced into work environments. Otherwise, companies may observe unexpected negative effects of such technological integration. Overall, this indication dispels the preconceived idea that a technology-driven paradigm such as I4.0 fully conflicts with sociocultural or human factors (represented here as ST practices) in the manufacturing environment, being a key practical implication of our work. It also highlights that companies should tailor their digitalization initiatives around the existing ST practices so that managerial efforts on both fronts can converge towards better workers' performance results.

6.3. Limitations and future research

Some limitations of this research and future research avenues are noteworthy. The first limitation involves the utilization of single respondents in the dataset. Although this is common practice in survey-based studies and all the necessary countermeasures to curb potential bias issues were adopted, it might lead to a narrow perspective of the company's context. Thus, developing multiple case studies could lead to more in-depth analysis, providing complementary insights to this research. Second, this investigation was carried out with manufacturers located in a single socio-economic context, i.e., a developing economy. The generalization of findings will require future research encompassing respondents from other socio-economic contexts (e.g., developed economies) and service industries, such as healthcare, education, and government. Finally, as practitioners become more familiar with I4.0 technologies and principles, the perception of I4.0's implications might evolve. Therefore, longitudinal studies would help prevent a narrow view of an evolutionary ST system.

Data Availability Statement – The data that support the findings of this study are available on request from the corresponding author, GT. The data are not publicly available due to containing information that could compromise the privacy of research participants.

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Appendix – Applied questionnaire

1- Please, provide the information below with respect to you and your company:

(a) Your role at the company: ( ) Engineer/Technician

( ) Supervisor/Coordinator

( ) Manager/Director

(b) Youe experience: ( ) Less than 5 years

( ) More than 5 years

(c) Your company's industry sector:

(d) The number of employees in your company: ( ) Less than 500 employees

( ) More than 500 employees

2- Please, indicate below the degree of performance variation in your companies in the past two years in each of the following indicators:

Scale from 1 (worsened significantly) to 5 (improved significantly)

Indicators	1	2	3	4	5
Workers' health (accidents and injuries)					
Quality (scrap and rework)					
Productivity					

3- Please, indicate below the adoption level of the following practices in your company:

Scale from 1 (not adopted) to 5 (fully adopted)

Practices	1	2	3	4	5
Communication and information system					
Problem solving indicators exposure					
Overload towards the achievement of goals					
Management of staff turnover					
Ergonomics criteria for workstation design					
Workstations appropriated to workers					
Workers' recognition and reward					
Teamwork and coaching					
Clarity in targets definition					
Clarity in defining the role of workers					
Risk alerts utilization					
Search for good organizational climate					
Search for the health and safety of workers					
Balancing among quality, scope, time and cost					
Anticipating and reducing the risk of incidents					

Appreciation for workers training					
Ergonomics recommendations as regulations					
Regulation of technical, organizational and human aspects					

4- Please, indicate below the adoption level of the following technologies in your company:

Scale from 1 (not adopted) to 5 (fully adopted)

Technologies	1	2	3	4	5
Wireless sensors					
3D printing					
Collaborative robots					
Ineternet-of-Things					
Big data					
Cloud computing					
Machine learning					
Augmented reality					
Remote monitoring					