Organizational learning paths based upon Industry 4.0 adoption: an empirical study with Brazilian manufacturers

Abstract

This article aims at examining the mediating role played by Organizational Learning (OL) capabilities at different contextualization levels on the association between Industry 4.0 (I4.0) technologies and operational performance. For that, we gathered information from 135 firms that have initiated their digital transformation towards the fourth industrial revolution era. Data was analyzed by means of multivariate data techniques. Our results show that learning capabilities at an organization level positively mediate the impact of I4.0 for achieving higher operational performance levels. However, OL at a team and individual level may not present a significant effect on such mediation. As I4.0 is claimed to facilitate a faster and more efficient identification and solution of manufacturing problems, our research provides empirical evidence to indicate that companies that systematically foster learning and knowledge sharing at an organization level can obtain greater benefits from I4.0 technologies adoption.

Keywords: Organizational learning, Industry 4.0, Operational performance, Survey.

1. Introduction

Industry 4.0 (I4.0) has been referred to as the new industrial paradigm that will possibly lead companies to superior performance results through an extensive adoption level of novel information and communication technologies (Lasi et al., 2014). The endorsement of I4.0 technologies entails the establishment of a highly interconnected and integrated organization, allowing modular and changeable production systems required to produce highly customized products in a large scale (Weyer et al., 2015). The envisioned benefits from I4.0 adoption have motivated an increasing body of evidence on the topic, provided either through academic research (e.g. Fatorachian & Kazemi, 2018), practitioners' reports (e.g. Kagermann et al., 2013) or governmental initiatives (e.g. Mexican Ministry of Economy, 2016).

Overall, I4.0 technologies are claimed to contribute to several organizational aspects, such as development of products and services (Dalenogare et al., 2018; Frank et al., 2019a), manufacturing management (Fettermann et al., 2018), and business models' innovation (Burmeister et al., 2016; Nascimento et al., 2018). These contributions fundamentally shift the way people work and manage their activities (Stock et al., 2018; Sahi et al., 2019). However, despite the technology-driven approach implied by I4.0, people-related aspects (e.g. employees' involvement and active participation into problem-solving activities) will remain to play a key role for operational performance improvement (Tortorella et al., 2018). In this sense, I4.0 technologies do not only influence the technical factors of an organization, but they can also impact the sociocultural ones.

Sociocultural factors refer to emotional or intangible elements usually underestimated, but deemed as relevant for enhancing operational performance (Tortorella & Fogliatto, 2014). These factors integrate the way organizations, teams and individuals learn, contributing to behavioral shifts that underpin performance results (Van Buren et al., 2011). Hence, such factors can be associated with Senge's (1990) concept of Learning Organization, which denotes an organization that continuously learns and transforms itself. Furthermore, a Learning Organization is supposed to effectively sustain innovation towards the achievement of an improved performance level (Heraty, 2004). Organizational Learning (OL) can be seen as an improvement process based upon a clearer understanding and deeper knowledge directly linked with organizational culture and environment (Song et al., 2009; Tortorella et al., 2015a). Thus, we argue that to efficiently support operational performance improvement in the Fourth Industrial Revolution era, it is relevant to better comprehend the relationship between I4.0 technologies and the capabilities that promote OL.

Based on these arguments, we raise the following research questions:

(i) What is the impact of I4.0 technologies adoption on OL development?; and

(ii) How do OL capabilities at different context levels influence the association between I4.0 technologies and operational performance improvement?

To answer these questions, we have surveyed 135 leaders from manufacturing firms that are in the process of adopting I4.0 technologies. For that, we combined into a questionnaire the learning organization dimensions grouped into three context levels (i.e. individual, team and organization), as proposed by Marsick & Watkins (2003) and Marsick (2013), and the I4.0 base technologies suggested by Frank et al. (2019b). The gathered data was analyzed by means of multivariate data techniques so that an empirical examination of the aforementioned relationships is performed. It is noteworthy that this study expands upon Tortorella et al. (2018) and Frank et al. (2019b). The former study examined the mediating effect of employees' involvement on the relationship between I4.0 and operational performance improvement. Employees' Involvement represented the level of engagement and participation of manufacturing employees on continuous improvement activities. Although it approaches the mediating effect of a correlated sociocultural factor (i.e. employees' involvement), Tortorella et al. (2018) did not specifically address the OL capabilities at different levels, which is an original contribution of our study. The latter research from Frank et al. (2019b) has carried out a survey-based study to verify the validity of a proposed theoretical framework, which comprised the four base technologies used in our study. Nevertheless, we added on it by empirically evidencing that these four base technologies not only can be considered a single construct of I4.0, but also present an indirect effect on operation performance through the development of OL capabilities. As far as our knowledge goes, there is no similar study in the literature that verifies the effect of such OL capabilities on I4.0 and performance improvement.

Hence, the contribution of the present study is three-fold. As the adoption of I4.0 technologies is a relatively recent advent (Tortorella & Fettermann, 2018), knowledge of its implications on organizations is still very incipient, especially when considering sociocultural factors such as OL capabilities. A few studies (e.g. Erol et al., 2016; Shamim et al., 2016) suggested the association between I4.0 and OL, but no empirical validation of such relationship has been provided. Thus, a first contribution of this study is to provide evidence that empirically verifies I4.0 impacts on OL development. Second, as the development of OL foreruns I4.0 adoption (Schuh et al., 2015), understanding how OL capabilities mediate the association between I4.0 technologies and operational performance features another theoretical implication. Although there is a common belief that both approaches (OL and I4.0) may converge to similar objectives, such as performance improvement, their intrinsic characteristics and requirements may lead to results that were not yet confirmed (Tvenge et al., 2016). In other words, there is still much speculation on the impact of I4.0 technologies and their potential synergy with existing sociocultural factors such as OL capabilities. Thus, this research outcome allows to more assertively address the holistic integration of I4.0 into existing sociocultural factors so that company's performance is significantly enhanced. Finally, in practical terms, findings from this research are envisioned to help managers setting clearer expectations with regards to the incorporation of I4.0 technologies. These technologies usually demand significant levels of capital expenditures (Liao et al., 2017), hence, generating overestimated expectations in terms of performance improvement, which can disappoint management and impair further efforts.

2. Background and hypotheses formulation

2.1. Organizational Learning

The development of OL capabilities impacts knowledge, beliefs and behaviors within an organization, allowing business growth and innovation as new learning is systematically incorporated into organizational routines (Ortenbiad, 2002; Desai, 2010; Watkins and Kim, 2018). Hence, a misguided conceptualization refers OL to the sum of each individual learning in an organization (Tortorella et al., 2015b). In fact, Marsick and Watkins (2003), and more recently Marsick (2013), proposed and validated the Dimensions of Learning Organization Questionnaire (DLOQ), which aims at assessing OL capabilities according to different context levels, such as individual, team and organization. Hence, this instrument provides a wider understanding of the current maturity of a company with regards to OL capabilities.

Furthermore, researchers state that OL is likely to occur through two main approaches. The first approach comprises learning that is directly acquired based upon trial and error situations, which allow to accrue experience and consolidate new knowledge (Marsick & Watkins, 2015; Kogan et al., 2017). The second approach consists of work procedures and routines developed from stored knowledge in organization's memory (Wang and Noe, 2010; Tortorella & Fogliatto, 2014) applied into subsequent situations similar to those that initially provided the experience (Desai, 2011).

Despite the fact that many studies (e.g. Škerlavaj et al., 2007; Martínez-Costa & Jiménez-Jiménez, 2009; Hung et al., 2010; Akgün et al., 2014) indicate that learning and knowledge sharing across an organization is essential for improving its performance, Ellwart et al. (2012) and Rupčić (2018) emphasized that the true achievement of an effective OL significantly challenges individuals, teams and organizations as a whole. Moreover, Garvin et al. (2008) advised that several organizations tend to assume that OL will naturally occur and be incorporated into their routines and procedures effortlessly, without substantial shifts in management and operational processes. Therefore, although most of the evidence in the literature indicates that OL is key for sustainable performance improvements, the barriers that impair OL's widespread development still deserve further comprehension.

2.2. Industry 4.0

The term I4.0 coined the beginning of the Fourth Industrial Revolution, which refers to an increasingly automatized manufacturing industry through the integration of technologies such as Cyber-Physical Systems (CPS), Internet of Things (IoT) and Cloud Computing (Kagermann et al., 2013; Lasi et al. 2014). This integration allows the interconnection between the virtual space and the physical world, entailing more flexible manufacturing processes and the real-time analysis of large amounts of information (Xu et al., 2018; Alqahtani et al., 2019). Although most technologies had been developed before the formal acknowledgement of I4.0 (Wan et al., 2015; Rüßmann et al., 2015), it was only after the cheapening of some key components that I4.0 became more financially feasible (Porter & Heppelmann, 2014).

The technologies encompassed in I4.0 allow to monitor and control equipment, products and services in a way that large quantities of data are collected, inputted into integrated systems and analyzed through virtual models, hence enhancing decision-making processes (Wang et al., 2015; Frank et al., 2019b). Furthermore, I4.0 technologies underpin digital integration from three main perspectives: vertical, horizontal and end-to-end engineering (Weyer et al., 2015; Fatorachian & Kazemi, 2018). Such digital integration enables the interconnectivity and information exchange within the whole value chain (Liao et al., 2017), which may favor an enhanced collaboration and a systematic learning at all levels.

Many authors have proposed different frameworks for I4.0 implementation. Lu (2017), for instance, presented a conceptual framework of I4.0's interoperability comprised of four levels: operational (organizational), systematical (applicable), technical and semantic. Mittal et al. (2019), based on an extensive literature review, consolidated a set of five defining characteristics, 11 technologies and three enabling factors relevant for I4.0 implementation. Similarly, Xu et al. (2018) listed four main enablers of I4.0: (*i*) IoT and related technologies, (*ii*) cloud computing, (*iii*) cyber-physical systems, and (*iv*) industrial integration, enterprise architecture and enterprise application integration. Overall, these frameworks emerged from extensive literature review as guidelines for I4.0 implementation, although most of them still lack empirical validation and neglect potential influence of context. In opposition, Frank et al. (2019b) carried out a survey-based study in Brazilian manufacturers and empirically validated a theoretical framework consisted of four main I4.0 technologies, named as 'base technologies' due to their versatility and widespread utilization. They include: Internet of Things (IoT), Cloud Computing, Big Data and Data Analytics (e.g. machine learning and data mining). These base technologies are claimed to leverage I4.0 concepts, facilitating interconnectivity and providing intelligence to manufacturing systems. Therefore, due to similarities on the studied context (Brazilian industrial sector) and the empirical validation of the proposed framework, Frank et al.'s (2019b) base technologies were adopted in this research as measures for I4.0 implementation.

Nevertheless, the relationship between I4.0 technologies and the underlying sociocultural factors that promote such collaboration and learning throughout an organization is not yet clearly understood in the literature (Dalenogare et al., 2018; Xu et al., 2018), and hence further empirical evidence still lacks to determine how I4.0 can specifically impact these factors. To investigate such gap, the following hypotheses have been formulated:

H1a: The adoption of Industry 4.0 based technologies positively impacts the development of Organizational Learning capabilities at an individual level.

H1b: The adoption of Industry 4.0 based technologies positively impacts the development of Organizational Learning capabilities at a team level.

H1c: The adoption of Industry 4.0 based technologies positively impacts the development of Organizational Learning capabilities at an organization level.

2.3. Industry 4.0 and Organizational Learning

Weyer et al. (2015) stated that the technology-driven and highly automated movement implied by I4.0 will not entail a lower level of human interaction or worker-less production facilities. However, Dworschak and Zaiser (2014) and Benešová and Tupa (2017) highlighted that I4.0 technologies are likely to demand specific skills and knowledge so that individuals, teams and organizations can meet the requirements for a successful embracement of the Fourth Industrial Revolution era. Furthermore, the inherent complexity level of I4.0 technologies may also motivate the enhancement of certain learning capabilities within the organization (Schuh et al., 2015), suggesting a synergistic relationship with OL development (Faller & Feldmüller, 2015). In fact, certain research streams indicated that the development level of OL is directly linked to an organization's process design and workplace management (Berg & Chyung, 2008; Irani et al., 2009), which corroborates the assumption of a positive association between I4.0 and OL. Additionally, as I4.0 allows a quicker and clearer understanding of the *status quo* of products, processes and services, either within the company or throughout the value chain (Terziyan et al., 2018), organizations that foster OL development may be expected to have their learning and information sharing catalyzed by these technologies, hence, improving their decision-making processes (Fang et al., 2016; Dalenogare et al., 2018).

On the other hand, there is still some level of skepticism on I4.0 and its relationship with sociocultural factors, such as OL development. A few authors (e.g. Erol et al., 2016; Shamim et al., 2016; Hecklau et al., 2016) advised that misinterpretations or inadequate integration of I4.0 technologies could negatively impact organizational routines and individuals' behaviors, frustrating further digital automation initiatives. Such arguments derive from similar effects observed in the era of Computer-Integrated Manufacturing (Tamás et al., 2016). Furthermore, Pirvu et al. (2015) stated that companies that decide to join the Fourth Industrial Revolution must revisit, adapt and update their communication and information sharing processes, so that they become aligned with implications from I4.0 technologies. Nevertheless, the scarcity of organizational instruments and approaches that integrate such technologies into current OL processes may result in adverse effects on operational performance (Mittal et al., 2018). Hence, the misalignment with existing OL capabilities can jeopardize a successful I4.0 adoption, generating aversion to its technologies and discrediting its envisioned benefits. Thus, to examine the role of OL capabilities at different contextual levels, as indicated by Marsick (2013), with regards to the association between I4.0 and firms' operational performance improvement, the following hypotheses have been formulated:

H2a: The development of Organizational Learning capabilities at an individual level positively mediates the effect of the adoption of Industry 4.0 based technologies on Operational Performance.

H2b: The development of Organizational Learning capabilities at a team level positively mediates the effect of the adoption of Industry 4.0 based technologies on Operational Performance.

H2c: The development of Organizational Learning capabilities at an organization level positively mediates the effect of the adoption of Industry 4.0 based technologies on Operational Performance.

Based on the propositions derived from the formulation of the hypotheses and literature review, the conceptual framework presented in Figure 1 is suggested to investigate the direct effect of I4.0 base technologies on OL capabilities (hypotheses *H1a*, *H1b* and *H1c*) and the mediating effect of such capabilities on the relationship between I4.0 base technologies and operational performance (hypotheses *H2a*, *H2b* and *H2c*). I4.0 base technologies are the independent variables that are suggested to improve organizational performance. OL capabilities are also expected to improve operational performance and positively mediate the impact of I4.0 base technologies. Company size is used as control variable. The subsequent sections report the empirical results of the testing of this theoretical model with its associated hypotheses.

Figure 1 – Investigated theoretical model

3. Method

3.1. Sample selection, instrument development and data collection

Due to the purpose of the present research, specific criteria were determined to select respondents for our study. In this sense, we followed a non-random approach for respondents' selection, which is a common practice in survey-based studies (e.g. Shah & Ward, 2007; Tortorella et al., 2018). First, to ensure the legitimacy of their information, respondents should have been familiar with I4.0 technologies and play a key role (e.g. middle and top managers) in their firms so that their opinions could be fairly representative. Second, to avoid the influence of different socio-economic contexts on responses, as verified by Erthal and

Marques (2018), we aimed for respondents who had worked in companies located in the same country. Therefore, based upon researchers' network and ease of access, respondents should have worked in companies operating in Brazil, which is one of the world's top ten largest economies (FocusEconomics, 2018) and its manufacturing industry corresponds to 25% of its GDP (DEPECON, 2017). It is noteworthy that we did not target for any kind of sector, which allowed the development of a cross-industry analysis that enriched the study findings.

The proposed instrument integrated four main parts (see Appendix). The first one aimed at gathering information on respondents and their firms, so that the fulfillment of the selection criteria could be verified. It is worth mentioning that we asked all respondents to provide a brief example of digital technology application within his/her company. The quality of the answers to this question enabled researchers to perform an additional sorting among respondents, leading to the final valid sample.

Second, respondents' perceptions on their respective firms' operational performance were assessed. Because information on financial performance is usually protected by companies and most of the times only senior management have access to it, this set of operational performance indicators was considered as a proxy for financial performance. A similar approach was also observed in previous studies that aimed at assessing the impact of specific management practices on company's performance (e.g. Fang et al., 2016; Tortorella et al., 2017; Prajogo et al., 2018). Furthermore, variations in operational performance are usually easier to be observed, increasing the validity of respondents, especially in the case of middle managers. Thus, respondents were asked to indicate in a Likert scale from 1 (worsened significantly) to 5 (improved significantly) the observed variation during the last three years of the following performance indicators: Safety (work accidents), Delivery service level, Quality (scrap and rework), Productivity and Inventory level.

The third part targeted at examining the adoption level of four main technologies that enable I4.0 concepts; i.e. IoT, Cloud Computing, Big Data and Data Analytics (e.g. machine learning and data mining) (Frank et al., 2019b). Because the concept of I4.0 is relatively recent (it was formally coined in 2011 on the Hannover Fair in Germany), its understanding may still be incipient and underdeveloped. However, Wan et al. (2015) and Rüßmann et al. (2015) emphasize that I4.0 is comprised by enabling technologies whose developed has occurred before 2011, such as Cloud Computing and Big Data. Therefore, manufacturers may have initiated the adoption of such digital technologies previously to their categorization as part of I4.0. As the questionnaire did not explicitly mentioned that these digital technologies were part of I4.0 and only focused on their adoption level, blurred perceptions of respondents may be minimized. A similar approach was also observed in previous studies on I4.0 (e.g. Tortorella and Fettermann, 2018; Frank et al., 2019b). Thus, a 5-point scale, in which 1 referred to 'not used' and 5 denoted 'fully adopted', was applied to assess the adoption of these technologies.

Finally, the last part incorporated the DLOQ (Marsick & Watkins, 2003) into the survey. DLOQ is comprised of 43 statements that vary according three contextual levels (individual, team and organization) that evaluate OL development using a scale that varies from 1 (almost never) to 5 (almost always).

Regarding data collection, the questionnaire was first e-mailed to 351 respondents that fulfilled the selection requirements. These 351 companies were already known by the researchers due to previous contacts and relationships, such as development of collaborative activities, on-site visits and participation in industry conferences/seminars, allowing their pre-selection. A message with the enclosed questionnaire was sent by the beginning of July 2018, and two follow-up emails were forwarded in the subsequent weeks. The resulting valid sample was comprised of 135 responses, corresponding to 38.46% return rate, which is larger than the 15% average rate (Hair et al., 2014). Hence, 57.0% of respondents worked in manufacturing companies with more than 500 employees, and 32.6% of them were from the metal-mechanics sector. Concerning respondents' roles, 85.9% held a middle manager position, while only 14.1% were directors or senior managers. Furthermore, all respondents claimed to be quite familiar with the encompassed I4.0 technologies due to current implementation initiatives in their respective companies.

3.2. Common method bias

First, to check for non-response bias between early (those who responded the first email message; n_1 = 74) and late respondents (those who responded after the follow-ups; n_2 = 61), we verified differences in means and variance (Armstrong & Overton, 1977). T-test and Levene's test showed no significant differences in terms of means and variance (p-value < 0.05 in both tests) between the two groups. Such outcome allowed us to disregard any potential issue related to non-response bias.

Second, as our dataset was comprised by information obtained through psychometric scales applied to single respondents (representative of each firm), common method variance might entail systematic errors (Huber & Power, 1985). A few countermeasures recommended by Podsakoff and Organ (1986) and Podsakoff et al. (2003) were undertaken to avoid that. With regards to questionnaire design, dependent variables were located first and far from independent ones. In terms of respondent bias, an explicit statement was inserted in the email message, informing about the anonymity nature of our study, and that there were no right answers for the questionnaire. Additionally, Harman's single-factor test (Malhotra et al., 2006) was conducted using all the study variables. Since test results showed that a first factor accounted for 22.45% of the total variance, we argued that no single factor explained most of the variance in our model.

3.3. Construct validity and reliability

For operational performance (dependent variable), we performed an Exploratory Factor Analysis (EFA) via Principal Component Analysis (PCA) using varimax rotation to extract orthogonal components (see Table 1). All performance indicators loaded into a single factor with an eigenvalue of 3.376 and representing approximately 67.52% of variation. Moreover, Cronbach's alpha was 0.876, which showed a high consistency (James, 2002). Thus, we named this construct as 'Operational Performance', following indications from Tortorella et al. (2018).

Table 1 - PCA to validate operational performance bundle component matrix (Adapted from Tortorella et al., 2018)

Analogously, for I4.0 we carried out another PCA with varimax rotation considering the responses for the four base technologies (Frank et al., 2019b). This analysis resulted in one single factor with an eigenvalue, percent of variance explained and Cronbach's alpha of 2.826, 70.65% and 0.860, respectively (see Table 2). Therefore, these results confirmed the empirical validity of this I4.0 construct, which was labelled as 'BASE_TECH'.

Table 2 - PCA to validate I4.0 base technologies bundle component matrix (Adapted from Frank et al., 2019b)

Finally, regarding the validity of constructs related to OL, a Confirmatory Factor Analysis (CFA) using STATA 14.2 was performed to confirm convergent validity and unidimensionality of the three multi-item dimensions suggested by Marsick and Watkins (2003). Thus, we estimated a single CFA model for each context level (individual, team and organization), representing the corresponding construct. Each item's factor loading should be equal to or larger than 0.50 (Tabachnick & Fidell, 2007). We then verified the models' goodness-of-fit comparing the following indexes and their suggested thresholds (Hu & Bentler, 1999; Hair et al. 2014): chi-square test ($\chi 2$/df), Comparative Fit Index (CFI > 0.90), Standardized Root Mean Squared Residual (SRMR < 0.08), Cronbach's alpha (> 0.70). The constructs for all three context levels satisfactorily met the cut-off values, which confirmed their validity and reliability (see Table 3).

We also verified convergent validity based on the Fornell and Larcker's (1981) criteria, which states that the average variance extracted (AVE) and composite reliability (CR) of all constructs should be greater than 0.5 and 0.7, respectively (Hair et al., 2014); all three constructs met these criteria. To assess discriminant validity, we checked whether the AVE of each construct was larger than the squared correlation coefficients involving the constructs (see Table 4). Since, all AVE values accomplished such criterion, discriminant validity was confirmed for the constructs. Thus, the representing values for each validated construct were calculated based upon their corresponding factor loadings.

Table 3 – DLOQ, CFA and factor loadings (Adapted from Marsick & Watkins, 2003)

Table 4 – Correlation, Cronbach's alpha and composite reliability of analyzed variables

3.4. Data analysis

Next, we carried out a set of Ordinary Least Square (OLS) hierarchical linear regression models to test the theoretical model illustrated in Figure 1. Hence, we examined three models. The first one individually regressed each of the three OL contructs on the I4.0 base technologies (independent variable) denoted as [BASE_TECH]. In Model 2, we solely regressed the Operational Performance (dependent variable) on [BASE_TECH]. Finally, in Model 3, Operational Performance was regressed on both independent and mediating (OL constructs) variables.

To verify multicollinearity on the estimated coefficients, we calculated the variance inflation factors (VIF) for all variables, which were all below five. Hence, multicollinearity between variables was disregarded (Belsley et al., 2005). It is noteworthy that assumptions related to normality, linearity and homoscedasticity were verified between independent, mediating and dependent variable (Operational Performance) (Hair et al., 2014). Residuals were analyzed to confirm normality of the error term distribution. Further, linearity was checked with plots of partial regression for each model. Complementarily, homoscedasticity was assessed by plotting standardized residuals against predicted value and examining visually. Overall, all tests confirmed the requirements for an OLS regression analysis.

4. Results and discussion

Results in Table 5 display the unstandardized coefficients, since scales were standardized before the analysis, for the three regression analysis models. In Model 1, the individual regression analysis showed that all OL constructs were significantly and positively associated with the adoption of I4.0 based technologies (p-value < 0.01 in all coefficients), with an adjusted R^2 that varied from 0.667 to 0.717. Such results suggest that when manufacturing companies adopt I4.0 based technologies, their OL capabilities are also likely to be improved at all context levels, supporting hypotheses *H1a*, *H1b* and *H1c*.

These findings are consistent with indications from Schuh et al. (2015), which state that I4.0 provides technological driven opportunities to support work-based learning in manufacturing environments. In fact, our results show that I4.0 based technologies can significantly contribute to the development of OL capabilities at all levels (i.e. individual, team and organization). In other words, companies that adopt I4.0 technologies, such as IoT or Cloud Computing, are more likely to systemically reinforce their learning and knowledge sharing across the organization. These outcomes are also aligned with the recommendations envisioned by Brettel et al. (2014), who argue that I4.0 incorporation will fundamentally impact the way in which organizations work. Moreover, base technologies are claimed to enable the development of front-end-technologies (e.g. smart manufacturing and smart products), which encompass the transformation of manufacturing management and operation (Frank et al., 2019b). As I4.0 technologies are supposed to facilitate and catalyze data gathering and communication, individuals, teams and organization as a whole can benefit from such support, exchanging information and making decisions in a more efficient fashion. Therefore, when considering a work-based perspective, it is reasonable to expect that OL capabilities are enhanced by the introduction of such technologies, which is confirmed by our results.

Table 5 – Unstandardized $\hat{\beta}$ coefficients for hierarchical regression analysis

Results for Model 2 indicated that the adoption of I4.0 base technologies are indeed positively associated with Operational Performance ($\hat{\beta}$ = 0.610; p-value < 0.01), explaining 38.4% of its variation (F-value = 42.77; p-value < 0.01). However, when OL capabilities are included in the regression analysis (Model 3), results displayed a significant increase in the ability to predict Operational Performance variation (change in adjusted R^2 = 0.058; p-value < 0.01). Such fact denotes that, although the adoption I4.0 base technologies do have a positive direct effect (Model 2), the inclusion of their indirect effects through the development of OL capabilities (mediating effect) significantly improves the level of Operational Performance (Model 3). This mediating effect is especially observed when considering the development of OL capabilities at an organization level ($\hat{\beta}$ = 0.415; p-value < 0.01). Therefore, these findings support hypothesis *H2c*, but do not underpin hypotheses *H2a* and *H2b*. This suggests that, at organizational level, the development of OL capabilities mediates the effect of the adoption of Industry 4.0 based technologies on Operational Performance, which is not the case at individual and team levels.

These outcomes are somewhat surprising in face of the existing indications from the literature. According to Erol et al. (2016), the introduction of I4.0 technologies into manufacturing companies allows to establish a working environment that contributes to individual development and learning. According to Marsick (2013), learning at an individual level can be represented by the way learning is designed, so that individuals learn as they work and increase their skills by frequently questioning and experimenting. In this sense, although the need of individuals to acquire new skills and knowledge is extensively deemed for I4.0 adoption (Hecklau et al., 2016; Tortorella et al., 2018), our results suggest that learning at an individual level does not play a significant mediating role in the impact of I4.0 based technologies on operational performance. Similarly, learning at a team level can be perceived by the level of collaboration and among teams so that they learn to work together

(Watkins & Kim, 2018). Surprisingly, OL capabilities associated with this contextual level do not seem to mediate the association between I4.0 based technologies and operational performance improvement.

Overall, one explanation for these unexpected results could be the current emphasis that companies have been putting on I4.0, especially the ones located in socioeconomic contexts such as that of Brazil. Frank et al. (2019b) suggested the adoption and, hence, comprehension of I4.0 based technologies is still incipient in Brazilian companies, since the application of certain technologies (e.g. Big Data) is less pervasive than others (e.g. IoT). Additionally, as I4.0 adoption requires a significant capital expenditure level that most Brazilian companies may struggle to afford (Tortorella & Fettermann, 2018), the incorporation of I4.0 based technologies may be prioritized and narrowed down to critical processes that usually embrace higher levels of the organization by involving multiple products, departments, sites, customers, or suppliers (i.e. mega processes). This fact might justify why OL capabilities at an individual and team levels, which are supposed to be influenced by micro and macro processes (i.e. intra and interdepartments), did not display any mediation on the association between I4.0 and operational performance improvement.

The findings also suggest that the indirect effect of I4.0 based technologies through OL development at an organization level has a prevailing effect on operational performance. Learning at an organization level is represented by the way a company creates systems to capture and share learning, empowers individuals into a collective vision and direction, connects organization and its environment, and provide strategic leadership for learning (Marsick & Watkins, 2003). Complementarily, I4.0 based technologies closely support the main design principles of I4.0, such as interoperability, transparency (Qin et al., 2016) and decentralization (Hermann et al., 2016), which are claimed to favor information sharing and collaboration within organizations. Therefore, if I4.0 based technologies are properly adopted in a company that extensively reinforces OL capabilities and whose objectives tend to converge to these technologies' principles, operational performance results are likely to present larger improvement leaps. Our results empirically confirmed this mediation effect, as illustrated in Figure 2.

Figure 2 – Operational performance improvement and I4.0 base technologies mediated by learning at an organization level

5. Conclusions

This study aimed to examine the impact of I4.0 technologies on OL capabilities development and the influence of these OL capabilities on the relationship between I4.0 and operational performance. Therefore, this research is among the very first studies that have focused on investigating the interaction between I4.0 technologies and the process of creating, retaining, and transferring knowledge within organizations. As far as our knowledge goes, no studies have empirically evidenced such relationship, which characterizes an original contribution of our work. For this reason, this study fills a research gap as previously highlighted in Section 1 and extends our knowledge by:

- *Investigating whether the adoption of Industry 4.0 base technologies positively impacts the development of OL capabilities at an individual, team and organizational level;*
- *Exploring whether the development of OL capabilities at an individual, team and organizational levels positively mediates the effect of the adoption of Industry 4.0 base technologies on operational performance.*

These contributions and their implications are valuable for both academics and practitioners involved with I4.0 integration into manufacturing companies. In theoretical terms, this research has shown how I4.0 impacts on OL development, which is a key sociocultural factor for companies' long-term success. Additionally, our study indicates that OL capabilities developed at an organization level are more prone to significantly influence the improvements entailed by I4.0 adoption on operational performance. In turn, the effects of learning at individual and team levels on I4.0's impact still need to be better comprehended, since the results did not present a significant mediation for these OL capabilities. The absence of mediation of individual and team learning on the relationship between I4.0 and operational performance may also denote the still limited approach for I4.0 implementation. In other words, the incipience of I4.0 implementation impairs a truly holistic analysis of its implementation that might lead to some counterintuitive outcomes, such as the effect of learning at individual and team levels. Overall, our study does indicate a positive mediation of OL development on the relationship between I4.0 and operational performance. However, the extent of such mediation is much less pervasive than common belief.

From a practitioners' perspective, the understanding of the investigated relationships also provides a relevant contribution. First, the identification of the mediating role played by OL capabilities on the relationship between I4.0 and operational performance emphasizes that solely applying novel technologies will not lead to superior performance results. Our results demonstrate that companies need to concurrently develop their sociocultural factors in order to fully benefit from I4.0 technologies. Companies usually neglect the importance of reinforcing such OL capabilities to support the integration of technical changes, such as the ones implied by I4.0 technologies. Nevertheless, our findings also indicate that I4.0 is still being implemented in a shallow way. We argue that due to capital expenditure limitations, most efforts to incorporate digital technologies into manufacturers have occurred at an organizational level, which might justify why learning at this level does mediate I4.0's impact. This fact also emphasizes the existence of further opportunities for I4.0 implementation at a team and individual level, possibly benefitting from learning at these levels. In this sense, our study provides managers evidence on the role played by OL capabilities throughout the I4.0 adoption, which will allow them to anticipate eventual issues and proactively address countermeasures that will increase their likelihood of success. These insights are particularly relevant when considering the level of capital expenditures and operational efforts required by I4.0 integration. Therefore, the practical contribution of this research is not only significant for manufacturing companies that aim at effectively deploying I4.0 technologies but also to those that intend to embrace them as part of their organizational culture.

This research also presents certain economic and societal implications that are relevant to highlight. This study was conducted within the Brazilian manufacturing context, which plays a key role in country's GDP and is responsible for 16.5% of all formal jobs (DEPECON, 2017). Among the existing challenges in this particular socioeconomic context, it is worth noting that the high levels of capital expenditures and high-skilled labour demanded for incorporating I4.0 technologies. Thus, a better understanding of the benefits and challenges of the relationship between I4.0 and the sociocultural factors, such as OL capabilities, would allow Brazilian manufacturers to achieve similar performance results as those operating in developed economies (e.g. UK, Germany and USA). An improved operational performance would enable manufacturers to supply to different markets and increase their competitiveness, while acting as a pathway for raising economic growth and social development; which is fundamental to Brazil. We argue that helping to identify means to turn Brazilian manufacturers more competitive significantly impacts the country's economy and society.

Our study presents a number of limitations with compounding factors that are imperative to consider in order for future similar future studies to consider. More specifically, with respect to the study's dataset, all respondents were from Brazilian manufacturers. As I4.0 has been more extensively adopted in manufacturers located in developed economies such as Germany, UK and USA, the intrinsic socio-economic context of our respondents (developing economy) may restrict our findings to manufacturers under similar contextual conditions. In this sense, further studies could expand sample size in order to complement our research in two ways. First, collecting data of companies from other developing economies with a strong manufacturing background, such as Mexico and China, would validate our indications and provide a more robust understanding of I4.0 implications on OL in this kind of socio-economic context. Second, similar studies undertaken with manufacturers from developed economies would enable to compare the extent of the identified relationships and verify the effect of socio-economic context on them, which is an issue that has not been unveiled yet. Finally, it is worth mentioning that, since I4.0 is a quite a recent concept, its comprehension is still being lapidated, which features a limitation of this study. As more companies advance towards the fourth industrial revolution, it is expected that the understanding on I4.0 increases, leading to different outcomes that could motivate further research.

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Appendix – Applied questionnaire

1- Please, fulfil the information about you and your company below:

a) Company size: ( ) Less than 500 employees

( ) More than 500 employees

b) Company sector: ______________________________

c) Your role within your company: ( ) Supervisor or Coordinator

( ) Manager or Director

d) In a few words, describe an example of a digital technology application within your company:

____

____

2- Regarding your company's operational performance, please indicate the improvement level of the following indicators over the last three years:

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

Performance indicator	1	2	3	4	5
Safety (work accidents)					
Delivery service level					
Quality (scrap and rework)					
Productivity					
Inventory level					

3- Regarding the implementation of the following digital technologies in your company, please indicate the adoption level:

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

Performance indicator	1	2	3	4	5
Internet of Things					
Cloud Computing					
Big Data					
Data Analytics (e.g. machine learning and data mining)					

4- Regarding the Organizational Learning process in your company, please indicate the occurrence frequency of the situations below:

Scale: from 1 (almost never) to 5 (almost always)

Items	1	2	3	4	5
In my organization, people have open discussions about errors and ways to learn from them					
In my organization, people identify needed skills for future activities					
In my organization, people help each other to learn					
In my organization, people receive financial help to support learning					
In my organization, people have available time to support learning					
In my organization, people see problems as learning opportunities					
In my organization, people are rewarded by learning					
In my organization, people give open feedback to each other					
In my organization, people listen to others opinion before talking					
In my organization, people are encouraged to ask why					
In my organization, when people say their opinion they also ask others what they think					
In my organization, people treat each other with respect					
In my organization, people use time to build trust among them					
In my organization, teams are free to adapt their targets according to the need					
In my organization, teams treat their members as equals					
In my organization, teams focus both, the task and how well the team is performing					
In my organization, teams review their opinion according to data or discussions					
In my organization, teams are rewarded by their results as teams					
In my organization, teams trust that the organization will act according to their suggestion					
My organization uses 2-way communication in a regular way					
My organization allows people to have easy and fast access to needed information at any time					
My organization keeps a data base with employees' skills					
My organization creates systems to measure expected and actual performance					
My organization keeps available knowledge to all employees					
My organization tracks time and money invested on training					
My organization recognizes people by their initiative					
My organization gives people choice on their tasks					
My organization invites people to contribute to the business vision					
My organization empowers people regarding resources to complete their tasks					
My organization supports employees that risk in a safe way					
My organization aligns vision across different teams and work levels					
My organization helps employees balance work and family time					
My organization encourages people to think in a global way					
My organization encourages people to bring the customer perspective to business					
My organization considers the decisions impact over employees' morale					
My organization works with local community to meet common needs					
My organization encourages people to develop problem solving inside the company					
In my organization, leaders generally support learning and training opportunities					

In my organization, leaders share information with employees about market trends, etc					
In my organization, leaders empower others to help achieve company's vision					
In my organization, leaders are mentors and develop their teams					
In my organization, leaders continuously look for learning opportunities					
In my organization, leaders make sure that attitudes are consistent with company's values					

Figure(s)

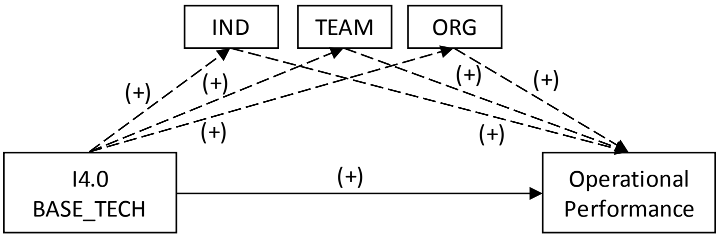

Figure 1 – Investigated theoretical model

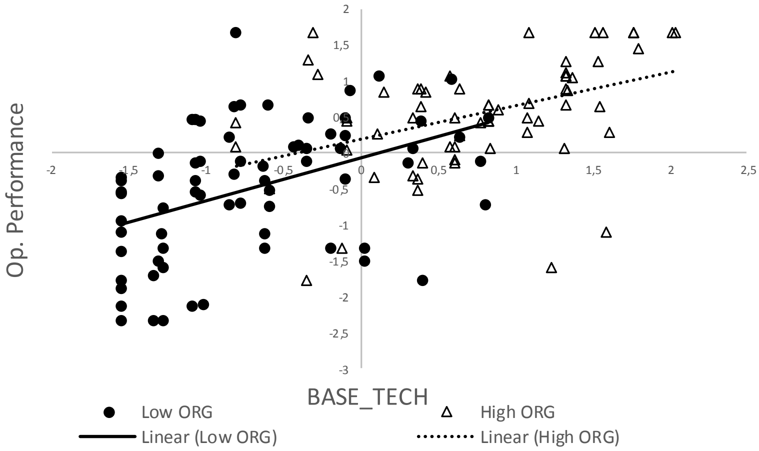

Figure 2 – Operational performance improvement and I4.0 base technologies mediated by learning at an organization level

Table(s)

Table 1 - PCA to validate operational performance bundle component matrix (Adapted from Tortorella et al., 2018)

Operational performance indicators	Mean	Std. Dev.	Communalities	Factor loadings
Safety (work accidents)	3.674	1.331	0.620	0.787
Delivery service level	3.518	1.098	0.611	0.782
Quality (scrap and rework)	3.267	1.080	0.775	0.880
Productivity	3.178	1.280	0.730	0.855
Inventory level	3.022	1.301	0.640	0.800
Eigenvalues			3.376	
Extraction sum of squared loadings (total)			3.376	
Percent of variance explained			67.518	
Cronbach α (sample *n* = 135)			0.876	
Bartlett's test of sphericity			351.50 (df 10. *p*-value<0.001)	
Kaiser-Meyer-Olkin measure of sampling adequacy			0.834	

Extraction Method: Principal component analysis.

Table 2 - PCA to validate I4.0 base technologies bundle component matrix (Adapted from Frank et al., 2019b)

I4.0 base technologies	Mean	Std. Dev.	Communalities	Factor loadings
Analytics (e.g. machine learning and data mining)	2.600	1.271	0.807	0.898
Cloud computing	2.593	1.180	0.654	0.808
IoT	2.526	1.215	0.585	0.765
Big Data	2.756	1.330	0.781	0.884
Eigenvalues			2.826	
Extraction sum of squared loadings (total)			2.826	
Percent of variance explained			70.655	
Cronbach α (sample *n* = 135)			0.860	
Bartlett's test of sphericity			347.55 (df 6. *p*-value<0.001)	
Kaiser-Meyer-Olkin measure of sampling adequacy				0.699

Extraction Method: Principal component analysis.

Table 3 – DLOQ, CFA and factor loadings (Adapted from Marsick & Watkins, 2003)

Context level	Items	Factor loadings	AVE	CFI	χ^2/dF	SRMR
Individual [IND] Cronbach's Alpha= 0.833	lo_{1}-In my organization, people have open discussions about errors and ways to learn from them	0.828	0.78	0.93	4.02	0.078
	lo_{2}-In my organization, people identify needed skills for future activities	0.784				
	lo_{3}-In my organization, people help each other to learn	0.832				
	lo_{4}-In my organization, people receive financial help to support learning	0.814				
	lo_{5}-In my organization, people have available time to support learning	0.823				
	lo_{6}-In my organization, people see problems as learning opportunities	0.922				
	lo_{7}-In my organization, people are rewarded by learning	0.767				
	lo_{8}-In my organization, people give open feedback to each other	0.993				
	lo_{9}-In my organization, people listen to others opinion before talking	0.946				
	lo_{10}-In my organization, people are encouraged to ask why	1.016				
	lo_{11}-In my organization, when people say their opinion they also ask others what they think	0.924				
	lo_{12}-In my organization, people treat each other with respect	0.709				
	lo_{13}-In my organization, people use time to build trust among them	0.673				
Team [TEAM] Cronbach's Alpha= 0.842	lo_{14}-In my organization, teams are free to adapt their targets according to the need	0.642	0.72	0.94	3.24	0.061
	lo_{15}-In my organization, teams treat their members as equals	0.956				
	lo_{16}-In my organization, teams focus both, the task and how well the team is performing	0.923				
	lo_{17}-In my organization, teams review their opinion according to data or discussions	0.859				
	lo_{18}-In my organization, teams are rewarded by their results as teams	0.939				
	lo_{19}-In my organization, teams trust that the organization will act according to their suggestion	0.920				
Organization [ORG] Cronbach's Alpha= 0.801	lo_{20}-My organization uses 2-way communication in a regular way	0.936	0.75	0.91	3.06	0.049
	lo_{21}-My organization allows people to have easy and fast access to needed information at any time	0.818				
	lo_{22}-My organization keeps a data base with employees' skills	0.862				
	lo_{23}-My organization creates systems to measure expected and actual performance	0.827				
	lo_{24}-My organization keeps available knowledge to all employees	0.878				
	lo_{25}-My organization tracks time and money invested on training	0.796				
	lo_{26}-My organization recognizes people by their initiative	0.877				
	lo_{27}-My organization gives people choice on their tasks	0.765				
	lo_{28}-My organization invites people to contribute to the business vision	0.777				
	lo_{29}-My organization empowers people regarding resources to complete their tasks	0.735				
	lo_{50}-My organization supports employees that risk in a safe way	0.854				
	lo_{51}-My organization aligns vision across different teams and work levels	0.782				
	lo_{52}-My organization helps employees balance work and family time	0.840				
	lo_{53}-My organization encourages people to think in a global way	0.905				
	lo_{54}-My organization encourages people to bring the customer perspective to business	0.927				
	lo_{55}-My organization considers the decisions impact over employees' morale	0.989				
	lo_{56}-My organization works with local community to meet common needs	0.877				
	lo_{57}-My organization encourages people to develop problem solving inside the company	0.884				
	lo_{58}-In my organization, leaders generally support learning and training opportunities	0.850				
	lo_{59}-In my organization, leaders share information with employees about market trends, etc.	0.881				
	lo_{40}-In my organization, leaders empower others to help achieve company's vision	0.845				
	lo_{41}-In my organization, leaders are mentors and develop their teams	0.866				
	lo_{42}-In my organization, leaders continuously look for learning opportunities	0.914				
	lo_{43}-In my organization, leaders make sure that attitudes are consistent with company's values	0.845				

Table 4 – Correlation, Cronbach's alpha and composite reliability of analyzed variables

Variables	1	2	3	4	5	6
1- Operational Performance	-	-0.171	0.622*	0.573*	0.617*	0.658*
2- Company size		-	-0.144	-0.098	-0.081	-0.123
3- BASE_TECH			-	0.826*	0.819*	0.849*
4- IND				-	0.846*	0.850*
5- TEAM					-	0.847*
6- ORG						-
Cronbach's alpha	0.876		0.860	0.833	0.842	0.801
Composite reliability (CR)	0.874		0.860	0.823	0.828	0.799

Note: * Correlation is significant at the 0.01 level (2-tailed).

Table 5 – Unstandardized $\hat{\beta}$ coefficients for hierarchical regression analysis

Variables	Model 1			Op. Performance	
	IND	TEAM	ORG	Model 2	Model 3
Company size	0.043	0.075	-0.001	-0.167	-0.177
BASE_TECH	0.829***	0.824***	0.849***	0.610***	0.181
IND					-0.110
TEAM					0.203
ORG					0.415***
F-value	141.97***	135.09***	170.96***	42.77***	22.26***
R^2	0.683	0.672	0.721	0.393	0.463
Adjusted R^2	0.678	0.667	0.717	0.384	0.442
Change in Adjusted R^2					0.058***

Note$_1$: * Coefficient significant at 10%; ** Coefficient significant at 5%; *** Coefficient significant at 1%.
Note$_2$: All VIF values < 5