**Modeling the impact of Industry 4.0 base technologies on the development of organizational learning capabilities**

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**Abstract**

In this paper, we examine the impact of adopting Industry 4.0 (I4.0) base technologies on the development of seven learning dimensions used as proxies for organization learning capabilities. We conducted a grounded theory approach in which 129 practitioners from different manufacturing companies were surveyed, and their responses analyzed through multivariate techniques. Findings allowed us to raise a theoretical framework for explaining learning development in organizations undergoing I4.0 adoption. We identified three clusters of adopters: (*i*) beginners, (*ii*) in-transition, and (*iii*) advanced. We found an ascending learning trend in clusters (*i*) and (*iii*) and a stationary learning pattern in (*ii*). Our study advances the understanding of how learning capabilities are affected as organizations advance I4.0 adoption. Our findings also gauge expectations regarding the effects of I4.0 base technologies' adoption on learning capabilities, helping academics and practitioners anticipate potential issues and develop countermeasures accordingly.

**Keywords:** Industry 4.0, Organizational learning, Learning profiles, I4.0 base technologies, Empirical study.

**Conflict of interest:** The authors have no competing interests to declare that are relevant to the content of this article.

**1. Introduction**

The advent of Industry 4.0 (I4.0) has been implying significant changes in the way companies operate. Technological advances observed in the past decade allowed a higher level of interconnectivity among people, processes, and products, leading to disruptive innovations in many business models (Liao et al., 2017; Müller, 2019; Weking et al., 2020; Frederico, 2021; Khan et al., 2022a). According to Meindl et al. (2021), the integration of those technological advances enables the development of smart systems (e.g., smart manufacturing, smart supply chains, smart products and services, and smart working). More specifically, Frank et al. (2019a) indicated that technologies such as big data, cloud computing, machine learning/artificial intelligence (AI), and the Internet-of-Things (IoT) provide the main foundation for digital front-end applications, hence, being named 'base technologies'. Different combinations of these technologies with processes, products, and services have created new ways of working and managing organizations (Khan et al., 2022b). To cope with the rapid changes entailed by I4.0 (Khan et al., 2021a; 2021b), organizations must adapt not only their processes and routines but the way individuals and teams interact.

Organizational learning represents the continuous process through which organizations learn and transform themselves (Senge, 1990), promoting innovation toward achieving a superior performance level (Heraty, 2004; Gil and Carrillo, 2016). Such process relies on a comprehensive understanding of continuous learning initiatives closely related to organizational culture (Santa and Nurcan, 2016; Tortorella et al., 2021a). In other words, organizational learning plays a relevant role in acquiring, disseminating, and using knowledge to adapt to a changing external environment (Hoe and McShane, 2010). Based on cognitive and behavioral changes, organizational learning allows the development of the prevailing values, norms, and social structures, so that the organization can achieve the expected outcomes (Park and Kim, 2018).

According to Tortorella et al. (2020a), the impact of I4.0 adoption on companies' performance is significantly amplified if they concurrently encourage the development of specific learning capabilities. I4.0 has boosted the learning factory concept, i.e., a realistic manufacturing environment for education, training, and research (Baena et al., 2017; Schallock et al., 2018). Nevertheless, through a systematic literature review, Belinski et al. (2020) highlighted that learning capabilities are still underexplored in the context of I4.0. Based on these arguments, we raise the following research question:

*RQ. How are learning capabilities affected by I4.0 adoption in manufacturing firms?*

To answer this question, we surveyed 129 practitioners from different manufacturing companies in various stages of I4.0 technologies adoption. As digital applications may vary across organizations, we focused on the adoption level of I4.0 base technologies (Frank et al., 2019a), whose concepts are commonly understood. Improvement levels of seven learning dimensions (originally proposed by Marsick and Watkins, 2003, and later discussed by Marsick, 2013) were used as proxies of learning capabilities. We adopted a grounded theory approach based on the empirical data (Makri and Neely, 2021) to propose learning dimensions' patterns for different I4.0 base technologies adoption levels. Grounded theory provides a means to construct methods to better understand a specific phenomenon for which no initial hypothesis or pre-conceived view is established (Sato, 2019). Results from the collected data allowed us to raise a theoretical framework for better explaining the development of learning in organizations undergoing I4.0 implementation. That is a central aspect of operations as it contributes to overall organizational effectiveness, although it is still not fully understood (Samson and Kalchschmidt, 2019). We also analyzed the adoption levels of the four base technologies in (*i*) the complete sample of firms and (*ii*) in the clusters of firms obtained using scores of a factor in which the four base technologies loaded significantly as the clustering variable.

Our study builds on findings from Tortorella et al. (2020a), as two theoretical contributions stand out. First, based on our sample of companies, we proposed mathematical models to describe relationships between I4.0 base technologies' adoption levels and the development level of seven learning dimensions. Second, we clustered companies according to their aggregate adoption level of I4.0 base technologies and investigated the learning behavior of each cluster of companies, as well as their technologies' adoption patterns. In addition to its theoretical contributions, our research allows managers and practitioners a deeper understanding of how learning capabilities may be affected as companies advance I4.0 adoption, enabling the identification of potential issues and the development of countermeasures to address them proactively. As the improvement of learning capabilities requires changes in behaviors and attitudes that are usually time-demanding, our findings allow organizations to anticipate such changes, setting the proper expectations regarding the effects of I4.0 base technologies' adoption on learning capabilities.

The remaining of this article is organized as follows. Section 2 presents the literature background on the main topics encompassed in this study: I4.0 and organizational learning. Section 3 describes the research method, whose results are presented and discussed in sections 4 and 5, respectively. Section 6 concludes the article, indicating limitations and future research opportunities.

**2. Background**

**2.1. Industry 4.0**

Formally acknowledged at the Hannover Fair in 2011 as part of the technology-oriented manufacturing strategy of the German government, the term I4.0 refers to high interconnectivity among people, objects, and systems via real-time data sharing (Xu et al., 2018; Shin et al., 2019). The application of novel technologies, such as IoT, cyber-physical systems (CPS), and big data, into manufacturing systems enhances their modularity and flexibility, providing competitive advantages in the massive production of highly customized products (Liao et al., 2017; Fatorachian and Kazemi, 2018). I4.0 environments are also decentralized and based on simpler structures (Pozzi et al., 2021; Khan et al., 2021c).

Although I4.0 generates several opportunities for organizations, new challenges also arise from continuous automation, digitization, and interconnectivity (Raj et al., 2020; Costa and Portioli-Staudacher, 2021). According to Sony and Naik (2020), I4.0 is a socio-technical approach that depends on both tangible (e.g., digital technologies) and non-tangible (e.g., principles and behaviors) factors. As organizations tend to focus on the technical side of I4.0, the challenge usually lies in finding a proper balance between technology and the company's underlying principles and behaviors (Cimini et al., 2020; Yu et al., 2022). For that, Hermann et al. (2016) proposed four I4.0 design principles: (*i*) interconnection, (*ii*) information transparency, (*iii*) decentralized decisions, and (*iv*) technical assistance. More recently, Cañas et al. (2021) complemented those principles by adding the human factor, intelligence/awareness, interoperability, organization, conceptual frameworks, and production planning. Additionally, other issues constrain the widespread of I4.0 (Khan et al., 2021d), such as increasing managerial complexity (Mohamed, 2018), high capital expenditure capacity (Olsen and Tomlin, 2020), and skilled workforce (Bhuiyan et al., 2020).

The literature on the benefits of I4.0 adoption reports positive impact on areas such as product development (Dalenogare et al., 2018), process control (Ghadge et al., 2020), servitization of manufacturers (Frank et al., 2019b), and supply chain management (Schroeder et al., 2019; Irfan et al., 2019). Industry sectors adopting I4.0 are also diversified (Khan et al., 2021b), including automotive (Lin et al., 2018), chemical (Sikorski et al., 2017), food (Kayikci et al., 2020), and semiconductor manufacturing (Chang et al., 2021). The growing pervasiveness of I4.0 in production systems increases the relevance of better understanding its implications in companies' learning capabilities.

**2.2. Organizational learning**

Organizational learning emerges from daily routines and activities in which individuals, working teams, organizations, and communities openly communicate, take risks, and acquire new knowledge (Kontoghiorghes et al., 2005; Hsu, 2007). As a result, changes in knowledge, beliefs, and behaviors are observed, increasing the organization's capability to innovate and grow (Salmador and Florín, 2013; Watkins and Kim, 2018). Nevertheless, there is still a misconceived perception that organizational learning would be the accrued individual learning in an organization (Tortorella et al., 2015a).

Many organizations tend to mistakenly assume that the development of organizational learning will occur naturally, and innovative methods and practices will be integrated into work routines effortlessly (Garvin et al., 2008; Ellwart et al., 2012; Rupčić, 2018). Such misguided understanding impairs a more extensive development of organizational learning. Previous studies (e.g., Song et al., 2009; Wang and Noe, 2010; Desai, 2011; Tortorella and Fogliatto, 2014; Marsick and Watkins, 2015; Kogan et al., 2017) claimed that organizational learning occurs through two distinct but complementary approaches. The first one encompasses learning obtained from trial-and-error episodes, allowing the accumulation of experience and the development of new knowledge. The second approach comprises work-related activities and processes that rely on the stored knowledge in the organization's memory and are applied to situations similar to those that generated them.

Marsick and Watkins (2003) and Marsick (2013) developed the dimensions of learning organization questionnaire (DLOQ) to assess organizational learning capabilities. The DLOQ is comprised of 43 statements combined into seven interrelated dimensions (see Table 1), providing a broad understanding of the current maturity of an organization with regards to the development of its learning capabilities.

Table 1 – Learning dimensions according to DLOQ (adapted from Kim and Marsick, 2013)

**3. Method**

**3.1. Questionnaire development**

We developed a questionnaire organized into three parts. We first collected demographic information on participants (i.e., roles and experience) and their organizations (i.e., size and industry sector). Next, we asked respondents about the adoption level of I4.0 base technologies, namely IoT, cloud computing, big data, and data analytics (e.g., machine learning and data mining) (Frank et al., 2019a). For that, we used a 5-point scale ranging from 1 (not adopted) to 5 (fully adopted). As suggested by Tortorella et al. (2020a), the questionnaire did not explicitly mention that those technologies were part of I4.0 to avoid misconceptions. Finally, we integrated 43 items from the DLOQ into the questionnaire (Marsick and Watkins, 2003; Marsick, 2013). In those items, respondents were asked to state the frequency of occurrence of desirable learning conditions using a 5-point scale varying from 1 (almost never) to 5 (almost always).

The questionnaire opened with statements describing its objectives and presenting the researchers and institutions responsible for the study. We also stated that anonymity and confidentiality of the provided responses would be assured and that there were no right or wrong answers. Since the second and third parts of the questionnaire collected data using psychometric scales responded by single representatives from each organization, common method variance could be an issue (Huber and Power, 1985). To mitigate that, we followed the indications from Podsakoff and Organ (1986) and Podsakoff et al. (2003) and positioned independent variables (i.e., I4.0 base technologies) far from dependent variables (i.e., DLOQ items). Complementarily, we ran Harman's single-factor test (Malhotra et al., 2006) using all the study variables. Results yielded a first factor that accounted for 24.78% of the total variance. As no single factor explained most of the variance in the model, issues related to common method bias were disregarded.

**3.2. Data collection**

We defined some criteria to select participants whose background and experience would legitimate their perceptions. Such non-random approach for selecting respondents is common in empirical studies that gathered data through surveys (e.g., Fettermann et al., 2018; Guimarães et al., 2021). First, respondents should be familiar with I4.0 and play a key role in their organizations (e.g., middle and top managers). Second, we targeted respondents who worked for organizations in the same country because I4.0 adoption may vary across different socio-economic contexts (Tortorella et al., 2019b). Given the researchers' networks and ease of access, we focused on organizations operating in Brazil, which is one of the world's top ten largest economies (FocusEconomics, 2018), with a large portion of its manufacturing sector already exposed to I4.0 (National Confederation of Industry Brazil, 2016). No specific industry sector was targeted, allowing a cross-industry study.

We initially identified 351 potential respondents that met the selection criteria. A first email was sent with the questionnaire, and a follow-up email was sent after 15 days. In total, 135 responses were collected (38.46%), which is a relatively good response rate (Hair et al., 2014). However, six of them were partially complete and, hence, were excluded from the dataset, leading to a final sample of 129 respondents. Most respondents were from large-sized companies (73; 56.6%), and 32.5% (42) worked in the metal-mechanics sector. Regarding the participants' profiles, the majority played a middle manager role (110; 85.2%), and all of them claimed to be familiar with I4.0. Additionally, all respondents had a minimum experience of 5 years in their roles.

To verify nonresponse bias between early (those who responded the first email message; *n*1 = 69) and late respondents (those who responded after the follow-up; *n*2 = 60), difference in medians was assessed via the Kruskal-Wallis test, which is non-parametric (Siegel, 1988). Results indicated no significant difference between the two groups (*p*-value < 0.05), which allowed us to disregard nonresponse bias issues.

**3.3. Constructs' validity and reliability**

For I4.0 base technologies (independent variable), we performed an Exploratory Factor Analysis (EFA) via Principal Component Analysis (PCA) using varimax rotation to extract orthogonal components (see Table 2). All four I4.0 base technologies loaded into a single factor with an eigenvalue of 2.826, accounting for 70.65% of the total variation. Cronbach's alpha was 0.860, indicating a high consistency in responses (James, 2002). The construct associated with the single factor was named 'Base Technologies', following the denomination proposed by Frank et al. (2019a).

Table 2 **–** EFA to validate I4.0 base technologies construct

To validate the learning dimensions constructs, we performed a Confirmatory Factor Analysis (CFA) using STATA 14.2. We verified the convergent validity and unidimensionality of the seven multi-item dimensions suggested by Marsick and Watkins (2003) and Marsick (2013). Individual CFA models were estimated for each dimension, representing a corresponding learning dimension construct. Items with factor loadings smaller than 0.45 were excluded (Tabachnick and Fidell, 2007), and their respective models were refitted, with results displayed in Table 3. Models' goodness of fit were verified through the following indexes and recommended cut-off values (Hu and Bentler, 1999; Hair et al. 2014): chi-square test (χ2/df), Comparative Fit Index (CFI > 0.95), Standardized Root Mean Squared Residual (SRMR < 0.08), Cronbach's alpha (> 0.70). All reassessed constructs satisfactorily met the threshold values, confirming their validity and reliability. 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). To evaluate discriminant validity, the AVE of each construct should be larger than the squared correlation coefficients involving the constructs (see Table 4). Since all AVE values satisfied such criterion, discriminant validity was confirmed for the constructs.

Table 3 – CFA for learning dimensions

Table 4 – Pairwise correlations

**3.4. Data analysis**

In this step, we verified how each learning dimension (dependent variable) varied with the adoption of I4.0 base technologies (independent variable). To identify the patterns of this relationship, we ﬁrst observed data and then examined whether the outcomes were supported by extant theories (Eisenhardt 1989; Oktay, 2012). For that, we applied the locally weighted regression (LOESS), which is a nonparametric approach for ﬁtting the best curve that does not require *a priori* specification, unveiling the relationship between two variables (Cleveland and Devlin, 1988). This LOESS feature is specifically relevant for the development of a grounded theory research method (Netland and Ferdows, 2016). Standardized scores from the Base Technologies factor (Table 2) and the seven factors associated with learning dimensions (Table 3) were used as independent and dependent variables, respectively.

We used LOESS models to relate the development level of the seven learning dimensions and the adoption level of I4.0 base technologies. The models and corresponding scatter plots were obtained using the SPSS software. We applied the Epanechnikov kernel function due to its robustness (Gasser et al., 1985), adopting an alpha value of 0.40, as suggested by Jacoby (2000). Based on the shapes of the curves obtained from the scatter plots (see Appendix), the goodness of fit of two models (linear and nonlinear) was tested. Since all models resulted significant at 1%, we selected the best model for each learning dimension based on their *R*2 values and, in case of a tie, choosing the linear model for parsimony (Frost, 2019).

We verified the existence of clusters in the sample of companies through cluster analysis using the scores from the factorial model in Table 2 as the clustering variable. We first ran a hierarchical algorithm to determine the number of clusters, followed by a *k*-means algorithm to determine cluster assignments to companies. We complemented the analysis by verifying each cluster's characteristics through box plots displaying adoption levels of the four base technologies in the cluster.

**4. Results and discussion**

Table 5 depicts the results of the regression models fitted to each learning dimension as a function of the adoption level of I4.0 base technologies. The nonlinear model displayed the highest *R*2 values for all learning dimensions (ranging between 0.52 and 0.69), except for 'encourage collaboration and team learning' and 'provide strategic leadership for learning', for which the linear model was chosen for parsimony.

Graphical representations of the selected models for the variation in each learning dimension according to the adoption level of I4.0 base technologies are given in Figure 1. Overall, learning in all dimensions seems to improve as I4.0 base technologies are extensively adopted. As nonlinear models were the most appropriate for representing five out of the seven relationships between learning dimensions and I4.0 base technologies' adoption, our discussion focused on those models. The functional form of the nonlinear model was cubic in all cases.

Table 5 – Comparison of models for learning dimensions

Figure 1 – Models representing the relationships between learning dimensions and the adoption level of I4.0 base technologies (*n* = 129)

Typically, cubic functions are characterized by graphs that are symmetric around their inflection points and invariant under a rotation of a half-turn around those points (Grinstein and Lipsey, 2001). In our application context, the cubic function describes organizations that seem to rapidly perceive an enhancement in their learning dimensions as they start to integrate I4.0 base technologies, followed by a plateau, and finally, accelerating the perceived enhancement after that. The three main stages of the relationship between learning dimensions and I4.0 base technologies are clearly depicted in Figure 2.

Figure 2 – Relationship between learning dimensions improvement and I4.0 base technologies' adoption

We also analyzed our sample to verify the existence of clusters of companies within each stage of the model in Figure 2. We used the standardized scores of the *Base Technologies* factor as the clustering variable and a hierarchical algorithm to determine the number of clusters that best characterized the sample. The resulting dendrogram is displayed in Figure 3, clearly indicating 3 clusters. We then used a *k*-means technique (setting $k=3$) to determine cluster assignments to companies and analyzed each cluster's characteristics. The results are presented and discussed next.

Figure 3 – Dendrogram indicating three clusters in the sample of companies

In the first stage of Figure 2, organizations are just starting to integrate I4.0 base technologies into their processes, products, and services, increasing their familiarity with IoT, cloud computing, big data, and machine learning applications. Nevertheless, due to the digital transformation frenzy currently observed in manufacturing (Tortorella et al., 2021b; 2021c), the acceptance of those technologies seems to be high, justifying the steep ascent in organizations' learning capabilities (represented here by the perceived improvement in learning dimensions), despite the still incipient adoption of I4.0 base technologies. A parallel may be drawn with the "honeymoon" effect reported in change management studies (e.g., Linstead and Chan, 1994; Boswell et al., 2005; Zhou et al., 2021), which suggests that early experiences tend to be particularly positive. Such positive perception contributes to high expectations, often leading to a more accepting initial environment in anticipation of positive outcomes. Furthermore, at this initial stage, organizations are still trying to understand the benefits of I4.0 (Himang et al., 2020), underestimating the required socio-technical changes for its full adoption and favoring an overly positive picture. Based on these arguments, this stage was denoted as *beginners*. The *beginners* cluster comprised 37 companies from our sample. The box-plot in Figure 4(a) displays the median and dispersion of technology adoption responses. Although all median values are the same (i.e., 1.0), there is a larger dispersion in adoption levels of more advanced technologies, i.e., the adoption level identified when analyzing the complete sample is not entirely clear in the *beginners* cluster.

Figure 4 – Box-plots of I4.0 technologies' adoption levels in (a) beginners, (b) in-transition, and (c) advanced clusters

In the second stage of Figure 2, a plateau is observed regarding the perceived impact of I4.0 base technologies on learning dimensions. Despite the increased adoption levels of I4.0 base technologies, learning capabilities (i.e., learning dimensions) improve at lower rates. As the excitement derived from new technologies fades, companies are faced with the hardships of the requirements towards a more extensive I4.0 implementation, gradually developing a better understanding of its impact on learning dimensions. Such phenomenon is also known as the "routine stage" (Blut et al., 2011). In the organizational learning literature, this stage is aligned with the exploration phase, during which the organization is truly discovering and experimenting with the new knowledge (March, 1991; Hahn et al., 2015). As a result, the variation in learning is incremental until individuals, teams, and the organization itself properly adjust their behaviors to cope with the I4.0 adoption. Since such behavioral change is usually time-consuming (Tortorella et al., 2015b), the learning development may stagnate, causing a general frustration and disbelief about the benefits of I4.0 base technologies. The stage is therefore critical and, if not well managed, might lead to a setback in learning. Based on these arguments, this stage was denoted as *in-transition*. The *in-transition* cluster comprised 49 companies from our sample. The box-plot in Figure 4(b) displays the median and dispersion of technology adoption responses. All median values are the same (i.e., 3.0), and the dispersion in adoption levels of technologies is relatively homogenous, except for IoT, for which an increase in dispersion is observed.

Finally, in the third stage, companies extensively adopt I4.0 base technologies and once again perceive rapid improvements in their learning dimensions. This stage is related to the concept of exploitation, which states that when organizations build on what they already know, higher performance improvement rates may be achieved (Kane and Alavi, 2007; Netland and Ferdows, 2016; Tortorella et al., 2021d). The prominence of the exploitation effect may be evident when organizations conduct many activities (Benner and Tushman, 2002). As they master I4.0 base technologies, sociocultural and technical implications are understood and accepted, obtaining the desired learning benefits, such as promoting a more frequent dialogue among individuals and creating systems to capture and share learning. Based on these arguments, this stage was denoted as *advanced*. The *advanced* cluster also comprised 49 companies from our sample. The box-plot in Figure 4(c) displays the median and dispersion of technology adoption responses. All median values are the same (i.e., 4.0). There is very small dispersion in the adoption level of big data, a concentration of companies with adoption levels of analytics and cloud computing below the median, and the opposite for IoT.

In summary, empirical quantitative data results indicate that the relationship between learning dimensions and I4.0 base technologies mainly follows a rotated S-curve pattern. Such pattern is supported by existing theories and is divided into three main stages. These outcomes complement the existing body of knowledge on the relationship between organizational learning development and I4.0 implementation, contributing to indications available in Tortorella et al. (2020a) and Belinski et al. (2020). Further, the identification of three main stages for that relationship along the rotated S-curve pattern raises new insights into the way organizations may learn and benefit from I4.0 implementation, which has not been fully explored in previous studies (e.g., Nardello et al., 2017; Agostini and Filippini, 2019; Saabye et al., 2022). Thus, based on these findings, we formulate the following theory for learning development in organizations undergoing I4.0 implementation:

*As an organization adopts I4.0 base technologies more thoroughly, its learning capabilities improve in a rotated S-curve pattern.*

**5. Conclusions**

This study examined the relationship between the development of learning dimensions and the adoption level of I4.0 base technologies. We proposed a theoretical framework for this relationship based on the grounded theory research method, with practical and theoretical implications discussed below.

**5.1. Theoretical implications**

From a theoretical perspective, we found that learning in organizations undergoing I4.0 adoption follows a rotated S-curve pattern that can be divided into three distinct stages: beginners, in-transition, and advanced. These stages may be compared to some phases observed in the change management literature. A key characteristic of the pattern identified in our study is that learning capabilities seem to rapidly evolve at the beginning of the I4.0 adoption. Such behavior might be explained by the digital frenzy caused by the I4.0 advent in the past few years, particularly increasing the acceptance rate of changes motivated by the adoption of I4.0 base technologies. The initial stage is followed mostly by stagnation in learning development. That occurs when companies realize the magnitude of changes that take place as I4.0 adoption advances. Once those changes are understood, an exploitation phenomenon is observed, leading back to rapid developments in learning capabilities. The rotated S-curve pattern is an original contribution of our study since we are not aware of any similar research on the topic.

Additionally, we identified the rotated S-curve pattern as representative of the development of five learning dimensions in companies, namely: (*i*) create continuous learning opportunities, (*ii*) promote dialogue, (*iii*) create systems to capture and share learning, (*iv*) empower individuals into a collective vision direction, and (*v*) connect organization and its environment. While dimensions (*i*) and (*ii*) are closely related to learning at the individual level, dimensions (*iii*), (*iv*), and (*v*) refer to learning at the organizational level (Marsick and Watkins, 2003). However, it is worth mentioning that the development of learning at team level, represented by the dimension 'encourage collaboration and team learning' through the adoption of I4.0 base technologies, could not be described through the same pattern. It suggests that I4.0 base technologies may trigger different learning mechanisms at team level, which should offer a more straightforward approach for its development as it was represented by a linear model.

**5.2. Practical contributions**

From a practical perspective, our study provides a deeper understanding of how learning capabilities might be developed as organizations advance in their I4.0 implementation. Our findings supported the identification of learning dimensions impacted by the adoption of I4.0, gauging expectations and allowing the development of countermeasures to proactively address problems. The development of learning capabilities requires significant changes in behaviors and attitudes that usually take time to occur. Hence, the anticipation of learning drawbacks might lead to a quicker organization transformation towards the desired results, being a competitive advantage in a manufacturing environment that has been rapidly evolving in the Fourth Industrial Revolution era. For instance, increasing the awareness of companies regarding the three main stages of the development of learning dimensions through the adoption of I4.0 base technologies may help them in developing policies and strategies that can mitigate the duration of the plateau stage (i.e., in-transition stage), moving faster to the exploitation stage (i.e., advanced stage) in which higher performance improvement rates can be achieved. Furthermore, companies that can clearly recognize in which of the three stages they currently are may have a better understanding of the necessary countermeasures for potential upcoming drawbacks. Our study offers arguments to accelerate the development of organizations' learning abilities through I4.0 implementation.

**5.3. Limitations and future research**

This study presents some limitations. The first one is related to the characteristics of the sample. Although I4.0 and organizational learning can also be observed in the services industry (e.g., healthcare, logistics, banking, and finance), our dataset only encompassed practitioners from manufacturing companies. Hence, our findings may be limited to this specific environment, and further generalization would demand a more diversified dataset. Second, the relationships of two learning dimensions with I4.0 base technologies' adoption did not support the assumption of a rotated S-shape model observed for the remaining dimensions. Therefore, future studies could focus on those dimensions to better understand the intricacies that led to the different results. Third, despite the acknowledged technological portfolio of I4.0, new digital applications originated from different combinations of technologies are constantly emerging. Such applications might affect learning differently from what has been reported here. In this sense, as I4.0 digital applications continue to evolve, their implications on learning may also change accordingly, requiring further investigation. Finally, our study was limited to learning within organizations. However, learning across the supply chain might also be significantly impacted by I4.0 adoption, whose comprehension opens further opportunities for researchers.

**Data availability statement:** Due to the nature of this research, participants of this study did not agree for their data to be shared publicly, so supporting data is not available.

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