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ORIGINAL PAPER

It takes two to tango: technological and non-technological factors of Industry 4.0 implementation in manufacturing firms

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Abstract
It is commonly held that new technologies improve the productivity of organizations. However, technology acceptance does not happen instantaneously—it depends on complementary, non-technological changes in organizational behaviour. The lack of the latter may present a barrier to technology implementation and could even result in adverse effects on productivity. This is often the case in emerging economies that are deeply embedded in mature technological frameworks and with limited readiness for the adoption of new technologies. Using data from organizations in the manufacturing sector of an emerging European economy, we empirically tested the effects of technological and non-technological factors of the organizational implementation of Industry 4.0 principles on productivity. The results of the investigation, based on structural equation modelling, reveal the positive effects of technology-related Industry 4.0 factors—such as the Internet of Things, cyber-physical systems, and cloud computing—on productivity. The findings also reveal that these effects are enhanced by the mediating effect of non-technological changes to business models, organizational structures and cultures, strategies, and shifts in focus regarding customers, products, and services. This study adds to the existing body of knowledge in this area by revealing the relevance of the individual channels through which transitions towards Industry 4.0 can be enhanced, using traditional manufacturing environments often neglected in studies within this research field.

Keywords Industry 4.0 · Technological factors · Non-technological factors · Productivity · Manufacturing

JEL Classification O33 Technological change: choices and consequences · Diffusion processes

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1 Introduction

New technologies can have a beneficial impact on organizational productivity across the entire spectrum of people and process-oriented operations (Bartel et al. 2007; Bartelsman et al. 2016; Grover et al. 1998). Building on this, several recent studies (Brixner et al. 2020; Fettermann et al. 2018; Bai et al. 2020; de la Fuente-Mella et al. 2020) have argued that Industry 4.0 technologies, such as the Internet of Things (IoT), cyber-physical systems, or cloud computing, enhance organizational productivity. However, empirical evidence on whether advanced capabilities of sophisticated technologies at the core of Industry 4.0 can improve organizational performance and productivity is still scarce and far from unanimous (Xu et al. 2018; Frank et al. 2019; Kaczam et al. 2021), with only a few studies reporting positive productivity effects (Schroeder et al. 2019; Calabrese et al. 2021; Fettermann et al. 2018).

The explanations offered for the lack of empirical evidence are typically centred around the "minimum threshold" argument, indicating that Industry 4.0 is in its early stage of development and that the minimum threshold level of its implementation must be achieved in order for productivity gains to materialise (Schneider 2018). These explanations draw their justification from historical evidence concerning productivity lags following previous technological breakthroughs, such as electrification (Brynjolfsson and McAfee 2014) or the emergence of information technologies, lasers, and microprocessors (David 1990). However, these explanations are external in their nature and do not shed light on the intra-organizational channels through which new technologies translate into productivity gains.

As argued through technology acceptance models (Zhao et al. 2015; King and He 2006), economic agents' ability to benefit from new technologies depends on perceived usefulness and ease of use which, in turn, are determined by absorptive capacity embodied in business models, organizational culture, structure, and orientation (Cohen and Levinthal 1990; Vlačić et al. 2019; Marullo et al. 2021; Bouncken et al. 2021; Caputo et al. 2021). Hence, a part of the reason behind the scarcity and ambiguity of empirical findings may lie in our limited understanding of the internal channels through which Industry 4.0 influences organizational productivity (de la Fuente-Mella et al. 2020). The lack of internal absorptive capacity may increase perceived complexity and reduce the perceived ease of use of Industry 4.0 technological factors—especially in terms of represented solutions—thus delaying an organization's readiness for their implementation or, in extreme cases, offsetting the desired productivity gains (Frank et al. 2019).

Whether or not the novel principles of Industry 4.0, both technological and non-technological, have the ability and the necessary degree of sophistication to influence organizational productivity has not been sufficiently studied. Furthermore, how productivity gains occur in Industry 4.0 organizational environments is, as of yet, undetermined. Are they predicated purely on novel technology implementation, which Industry 4.0 heavily promotes, or are properly aligned organizational factors needed to reap the benefits of technological advances?

Thus, building on the foundations outlined above, we argue that Industry 4.0's technological factors spill over into organizational productivity gains through non-technological aspects of the organizational transition towards Industry 4.0 (Kim et al. 2019). We build on theoretical propositions of absorptive capacity and technology acceptance models, along with propositions arguing that Industry 4.0 changes soften (non-technological) factors of organizational behaviour, in terms of business models, organizational cultures, structures, and strategies (Schneider 2018). Conceptually, our study is also close to the literature that views organizational value creation as a function of valuable (e.g., intangible) assets and the ability to manage these assets systematically (Kianto et al. 2014). Our study advances the existing body of knowledge in this area, as studies to date have not empirically examined the productivity of organizations undergoing the Industry 4.0 transformation by distinguishing between the technological and non-technological factors of Industry 4.0. It is crucial that we recognise the channels through which Industry 4.0 practices influence productivity (Rüßmann et al. 2015; de la Fuente-Mella et al. 2020) so that organizations can make informed decisions when it comes to the organizational changes that lead to gains from the implementation of Industry 4.0 practices.

Particular challenges and advancements of our study can be seen in the modelling of organizational productivity and the implementation of Industry 4.0. Common productivity measurement methods, based on the analysis of operational processes, may not provide an accurate picture of productivity changes in the case of infant phenomena, such as Industry 4.0 (Schneider 2018), as they may not reflect immediate effects. Managers' and specialists' perceptions of productivity could offer useful first-hand insights into actual levels of productivity (Van de Walle and Bouckaert 2007), as Industry 4.0's circumstances are currently unclear (Madsen 2019). We thus presume that managers' and specialists' assessments of the state of productivity in organizations is vital, as they can provide direct insights and can observe changes in productivity as they occur. The particular focus here is indeed on managers at various levels, who have more of a well-rounded insight into the workings of organizations and/or operational processes (Hambrick and Mason 1984). However, we must remain mindful of the fact that specialists examining these processes can offer more detailed insights into observed changes in productivity (Schneider 2018). As we have learned from previous revolutions, these changes are not evident in micro-data during the initial stages of the transformation because a certain amount of time is needed for them to manifest (David 1990).

The implementation of Industry 4.0 is approached through several dimensions adopted from recent models aimed at assessing the readiness of organizations for Industry 4.0. In recent years, these models have become a popular way of evaluating organizational progress towards Industry 4.0 implementation, both within academia and in the business community. We combine insights from comprehensive models presented by the Acatech (Schuh et al. 2017) and the University of Warwick (Agca et al. 2017), along with more recent studies (Wagire et al. 2021; Lin et al. 2020). The choices of Industry 4.0 dimensions are based on the theoretical predictions of previous studies and their potential to induce changes in organizational performance, and we shaped theoretical contribution according to Corley and Gioia (2011). These models are not directly focused on organizational productivity, but rather on the alignment of organizational processes and behaviour with Industry 4.0's principles. Nevertheless, they provide a useful tool for modelling Industry 4.0 readiness and/or implementation.

This analysis is centred around the context of the manufacturing sector of Slovenia: one of the more advanced emerging European economies. It draws upon results from a survey of 323 respondents conducted in the 2019–2020 period using a structural equations framework. No manufacturing firms were excluded from the study based on their size or activity, as we acknowledge that we do not sufficiently understand all of the ways in which Industry 4.0 manifests itself globally across the entire manufacturing industry (Schneider 2018; Madsen 2019). The manufacturing industries were found to be inferior to service sector industries in terms of their degrees of proactiveness, innovativeness, and risk-taking (Rigtering et al. 2014). Many find it more challenging to adapt to the new realm in which a changing technological paradigm operates. At the same time, proactive strategies are a necessary prerequisite for the achievement of performance objectives (Rehman et al. 2021). The choice of the manufacturing sector and the emerging economy setting is not a coincidence. This further adds to the value of our study. Industry 4.0 can operationally be viewed as a paradigm that seeks to integrate and connect manufacturing systems with digital technologies. Its effects are commonly assessed within the context of the manufacturing sectors of advanced economies. However, emerging economies present a particularly relevant—yet neglected—area of investigation for examining the effects of Industry 4.0.

The manufacturing sectors of these economies are deeply embedded in traditional technological frameworks, and they reside in lower, more labor-intensive, routinized segments of global value chains (Stojčić et al. 2020). As such, they lie far behind the technological frontier and face considerable risks in terms of becoming obsolete in an Industry 4.0-driven environment. However, firms in settings such as these often lack the knowledge and skills (non-technological factors) relevant for the adoption of new technologies, which reduces their ability to benefit from Industry 4.0's technological attributes. Whether or not firms in these settings can translate Industry 4.0 factors into higher productivity rates (and through which non-technological channels) is a question that is vital to their survival. Our empirical findings, derived from structural equation modelling (SEM), can be used by organizations as a guide for determining where to focus attention first when implementing Industry 4.0 in order to maximize the benefits obtained.

2 Conceptual framework and hypotheses development

2.1 Productivity measurement

Productivity is a key measure of organizational performance that ultimately determines organizational survival (Melitz 2003). It is commonly defined as *the ratio between inputs, such as employees, processes, technologies, communications, innovations, and the environment, and outputs of a given organizational activity*

(Bartelsman and Doms 2000). Various approaches in determining productivity at different levels can be taken when examining organizations (Syverson 2011). For manufacturing, the most useful approaches differentiate between two partial productivity measures. The most important of these is production productivity, followed by the productivity of employees. These approaches incorporate the most beneficial factors with regards to the output of the manufacturing firm (Bresnahan et al. 2002; Bartel et al. 2007; Bartelsman et al. 2016). Productivity increases when the same amount of goods is produced with less resources or, in turn, a larger amount of goods with the same resources (Bartelsman and Dhrymes 1998). Usual approaches to the measurement of organizational productivity are based on processes' microdata and data from outcomes such as revenue and market success (Syverson 2011; Bartelsman and Doms 2000). However, such an approach places too much weight on the quantitative side of productivity, understating its qualitative dimension.

The alternative approach takes into consideration organizational managers' and specialists' perceptions of productivity (Van de Walle and Bouckaert 2007; Haapakangas et al. 2018). This is particularly suitable for infant processes, such as Industry 4.0, in which microdata on particular phenomena are unavailable or are scattered across databases. While this does not offer concrete, data-driven conclusions, this method has the ability to determine levels of productivity in the areas of organizations in which it is hard to measure events with processed data, and where exact criteria are absent.

2.2 The impact of technological and non-technological factors of Industry 4.0 on productivity

From a manufacturing and organizational perspective, Industry 4.0 can be defined as a *digitalization-based paradigm that refers to the integration of advanced technologies into manufacturing systems*. It comes along with changes in business practices, leading to flatter organizational structures, general customer orientation, openness to change, and better connections between processes and employees in organizations, which—together with technologies—form the philosophies of Industry 4.0 (Schneider 2018). Organizations induce these changes motivated by the prospects of gains in terms of productivity and competitiveness (Lin et al. 2020; Fettermann et al. 2018). However, the concept is far from understood and there is no universally accepted definition of its meaning (Castelo-Branco et al. 2019).

Assuming an operational perspective, Industry 4.0 concerns three clusters of technologies, which we consider to be the key technological factors of Industry 4.0. These are known as the IoT, cyber-physical systems (CPSs), and smart factories (Kipper et al. 2020). IoT refers to the integration of processes with ICT, cloud computing, smart objects, and machines (Atzori et al. 2010), which ultimately drives the creation of cyber-physical systems (Wang and Wang 2018). CPSs involve the use of advanced technologies to control production processes and systems through two-way communication between machines and big data (Rossit et al. 2019). Finally, smart factories are smaller, less centralized, digitalized, and autonomous production units (Zheng et al. 2018; Lin et al. 2020) integrated with artificial intelligence, which means that smart factories are able to self-organize and self-optimize, resulting in more efficient and productive processes (Orellana and Torres 2019).

The transition of organizations towards Industry 4.0 is commonly assessed through different conceptual models (Agca et al. 2017; Schuh et al. 2017; Wagire et al. 2021) that measure the level of adoption of different dimensions of Industry 4.0, selected on the basis of expectations about the dimensions' potential impact on one or more organizational areas (Lin et al. 2020; Schuh et al. 2017). To this end, these models can be considered to reveal the achieved level of integration and the adoption of Industry 4.0-related technological and non-technological factors in an organization's process of Industry 4.0 adoption. Although individual models exhibit some degree of variation, in the absence of other data categories and methodologies, they are considered a reliable measure of the level of implementation of Industry 4.0 in organizations.

In our study, we draw upon three such models derived by the Acatech (Schuh et al. 2017) and the University of Warwick (Agca et al. 2017), which have been used in previous studies, and one more recently developed by (Wagire et al. 2021). In this way, we acknowledge that Industry 4.0 affects more than one technological and non-technological aspect of organizational activities and we assess the level of Industry 4.0 implementation from different standpoints recognized as important in previous literature. Alongside technological dimensions, we focus on *changes in products and services* driven with the use of digital tools (Zhang et al. 2020); *Industry 4.0 concepts and technologies* that have the potential to transform manufacturing and communication processes within the organizations; and the *supply-chain* integration of real-time communication and inventory control (Hahn 2020; Müller et al. 2017), 3D printing, and big data analytics (Makris et al. 2019).

Technological breakthroughs have, for a long time, been associated with productivity improvements (Bartel et al. 2007; Grover et al. 1998; Bartelsman and Doms 2000) and Industry 4.0 is not an exception (Fragapane et al. 2020). The mechanisms through which production technologies improve productivity stem from the reduction of senseless tasks, errors, and prolonged labour-intensive processes, which could be made more autonomous. In the case of information technologies, the benefits arise as a result of improved communication processes, reductions in the time it takes to make a decision, and the availability of the data that aids decision-making in terms of organizational improvement. The use of production technologies (de la Fuente-Mella et al. 2020), such as Industry 4.0 related IoT, autonomous process control, cyber-physical connections, and smart manufacturing (Lin et al. 2020; Rossit et al. 2019; Atzori et al. 2010; Korte et al. 2021), may improve production productivity, while the automation of repetitive tasks (Smithies 2017), better information access through cloud computing (Wang and Wang 2018), better knowledge sharing and innovation (Gressgård et al. 2014), and greater contributions of employees overall towards organizational success can improve employee productivity.

H1 *Industry 4.0 technological factors improve organizational productivity.*

Alongside the technological dimensions of Industry 4.0 implementation, we also focus on non-technological factors, including *strategic and organizational features* aligned with Industry 4.0 principles; *business model* transformations aimed at improving the agility towards accommodating customer needs; *law and policy* procedures compliant with data protection regulations (Larrucea et al. 2020); changes in *organizational culture and openness* towards new trends; and changes in organizational structure that enable more agile internal processes, reduced notions of hierarchy, decentralized decision-making with regard to processes, and centralized strategic orientation decisions. Relevant literature suggests that diverse organizational practices and the behavioural characteristics of firms improves their perfromance (Meijaard et al. 2005; Pucheta-Martínez and Gallego-Álvarez 2020). Especially in times of organizational change (Ingham 1992), dynamic and systemic aproaches to reshaping the firm's workings seem to benefit organizational performance at large.

H2 *Industry 4.0 non-technological factors improve organizational productivity.*

2.3 The mediating role of non-technological Industry 4.0 factors

In light of the above, we argue that productivity-enhancing effects do not depend solely on technology adoption, but require adjustments in the non-technological dimension too. Organizations may come into contact with technologies for which they lack knowledge, skills, or other capabilities. As noted by Cohen and Levinthal (1990), the ability of firms to recognize the value of new technologies, assimilate them, and apply them in organizational activities determines their innovativeness and market success (Zhao et al. 2015; Kaartemo and Nyström, 2021). This absorptive capacity resides in prior knowledge or memories of organizations and becomes accumulated through organizational life. Such knowledge helps firms to adapt their behaviour to changes along existing technological trajectories (i.e., in case of incremental innovations), but may fall short to optimum in the case of radical technological changes which require shifts in the organization's overall behaviours and developments or those which necessitate the acquisition of new sets of knowledge and skills unrelated to previous ones (Ritala and Hurmelinna-Laukkanen 2013; Lim and Anderson 2016).

It follows from there that organizational absorptive capacity determines the company's ability to make use of novel technology, such as Industry 4.0. Indeed, Industry 4.0 literature has acknowledged that a lack of human, financial, and managerial resources required for the adaptation of organizational business models often stands between firms and their prospective gains from Industry 4.0 technologies (Messeni Petruzzelli et al. 2021).

Contributions within technology acceptance literature argue that the decision of organizations to interact with specific technology and their ability to benefit from the use of these systems is dependent on perceived usefulness and ease of use (Lim and Anderson 2016). We argue that this perception will be diminished in situations where organizations come in contact with novel technologies unrelated to their accumulated technological knowledge. It follows from there that a greater distance from the technological frontier is likely to make an organization's ability to benefit from novel technologies more challenging, delaying or offsetting prospective productivity gains (Frank et al. 2019). It is in such cases that non-technological factors come into play, mediating the relationship between novel technologies and organizational productivity.

All of the points discussed so far bear particular weight in the context of emerging economies. The economic structure and the level of technological development of these countries often present insurmountable barriers for their organizations when it comes to the adoption of novel technologies. Firms from these economies operate in the lower tiers of global value chains, where standardised and routinised activities vulnerable to Industry 4.0 technologies prevail (Stojčić et al. 2020). Their innovation systems are structurally weak and scarce in terms of the knowledge needed for the adoption and use of new technologies (Dabić et al. 2021). Being far from the technological frontier, organizations from these economies may, thus, find emerging technologies complex and difficult to use. They may therefore miss out on their productivity benefits. It follows from the above that the mere acquisition of Industry 4.0 technologies in emerging economies does not warrant organizational productivity gains if these technologies are not accompanied by non-technological improvements in absorptive capacity.

The contribution of non-technological factors related to people, culture, ethics, and various organizational activities to organizational productivity is well documented, both outside of and within the Industry 4.0 context. However, their mediating role has not received equal attention in comparison to that given to the technological aspects of Industry 4.0. This is particularly true with regard to individual, non-technological channels. For organizations to be able to shift their efforts and resources to the right productivity boosting activities, it is important to determine the non-technological channels through which Industry 4.0 technologies impact upon organizational productivity the most. In summary, if the organizational non-technological dimensions do not enable the proper use of a technology that serves to facilitate more efficient processes, then technologies by themselves are ineffective (Bresnahan et al. 2002; David 1990).

H3 *Non-technological Industry 4.0 factors mediate the relationship between technological Industry 4.0 factors and organizational productivity.*

The model outlining the hypothesized relationships in our study is presented in Fig. 1.

3 Methods

3.1 Sample and procedure

We obtained the data for this study between November 2019 and January 2020, using random sampling among manufacturing organizations. We selected

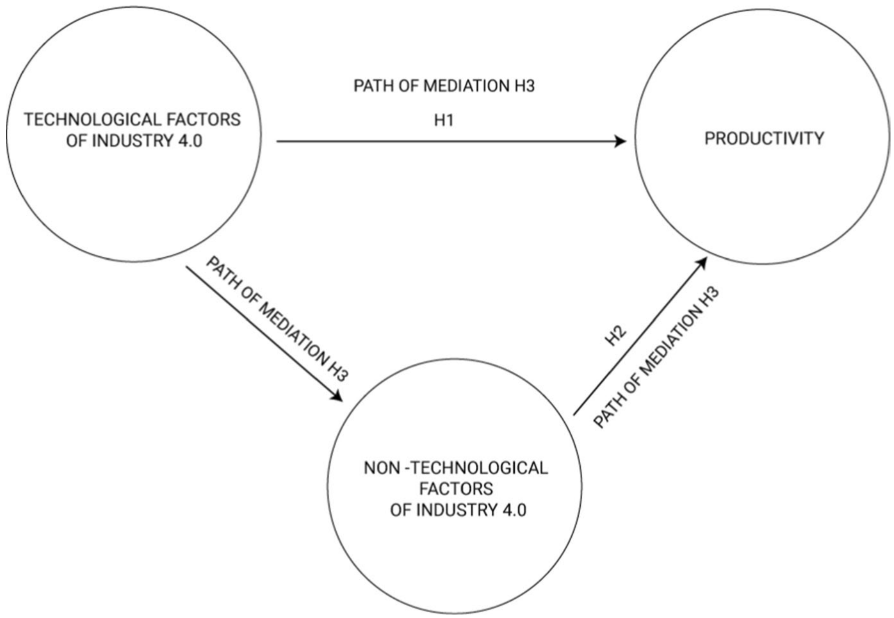

Fig. 1 The hypothesized model

organizations that were classified according to NACE Statistical Classification of Economic Activities in the European Community. These organizations were in the C category, i.e., the manufacturing sector. Information on which organizations fit the selected category was obtained online from a Slovenian business information repository (i.e., AJPES). No organizations were excluded from the sample by any criteria other than NACE C, due to the observation that the phenomenon of Industry 4.0 is not comprehensively documented in scholarly literature with regards to its effect on organizations across the entire manufacturing sector (Schneider 2018). Organizations' contact information was retrieved from their websites. We sent 2800 emails with a link to the survey to members of these organizations, with a focus on managers. We sent a maximum of two emails per organization. We received 323 completed responses, achieving a response rate of 7.96%, which can be considered a large enough sample size to conduct a multivariate SEM analysis and draw reliable conclusions from the results (Mai et al. 2021).

Data was gathered before the official declaration of the COVID-19 pandemic in Slovenia (12th March 2020), implying that our observations were not influenced by COVID-related circumstances. In any sense, the expected lags in organizational transformation due to the pandemic and the economic shutdown had not yet occurred. It can be argued that this further expedited the digital transformation on which Industry 4.0 is built (Amis and Janz 2020; Li et al. 2022).

Sample characteristics show that respondents were, on average, 42.98 years old and had on average 19.56 years' worth of work experience. 70.6% of respondents were male and 29.4% were female. In terms of education, 36.8% of respondents had completed secondary school, 49.2% had bachelor's degrees, and 14% had a master's degree and/or a PhD. Regarding respondents' positions in organizations, 8.4% were specialists, 2.5% worked in lower management, 12.1% worked in middle management, 22% were top managers, and 48.9% were CEOs and owners. The organizational size of the sample of respondents was as follows: 22% micro-organizations (1–9 employees); 39% small organizations (10–49 employees); 26.6% medium-sized organizations (50–250 employees); and 12.4% large organizations (more than 250 employees).

The diverse range of respondents in different managerial or specialist positions and the range of organizational sizes did not show any notable or significant correlations with regards to the principal variables in the study, the highest of which was $R = 0.105$ for both, indicating no meaningful influence on the obtained results. One-way ANOVA was also performed to test the homogeneity of the sample regarding the organizations' size and position against the principal variables. Position did not indicate a difference in variance across the sample ($p > 0.05$). However, organizational size showed the difference across groups ($p < 0.05$). The differences were minimal and, due to the exploratory nature of the study and the unexplored effects of Industry 4.0 on the aggregate manufacturing sector, we chose not to limit the results to just the selected groups of organizational sizes (Dabić et al. 2013; Schneider 2018).

3.2 Instrument

The instrument for this study consisted of three parts. In the first part, we asked participants about the demographic characteristics typically used in business studies (Dabić et al. 2021). The second part measured the level of Industry 4.0 implementation, both technological and non-technological, by utilizing dimensions from two comprehensive enough models developed by Acatech and the University of Warwick (Schuh et al. 2017; Agca et al. 2017), containing 53 questions. The third part consisted of assessing managers' and specialists' perceptions of productivity related to the Industry 4.0 adoption, focusing on employee and production productivity. This part contained 6 questions for employee productivity and 6 questions for production productivity.

3.3 Measures

The level of Industry 4.0 implementation was measured using 53 statements reflecting the following organizational areas of change arising as a result of Industry 4.0 implementation. Firstly, the technological channel of Industry 4.0 implementation was assessed through constructs of manufacturing concepts or technologies and IT concepts and technologies (Agca et al. 2017; Schuh et al. 2017). Secondly, measuring the non-technological or organizational channels of Industry 4.0 implementation incorporated strategic and organizational features, products and services, supply chains, business model transformation, legal and policy aspects, culture and openness, and organizational structure dimensions (Agca et al. 2017; Schuh et al. 2017). The scale selection reflected the multiple levels of implementation and/or influence.

Accounting for the exploratory nature of the research, longer scales were used when appropriate to grasp the vastness of the phenomena (Ho 2006; Tóth-Király et al. 2017). Respondents assessed each statement using an 11-point interval scale, with options ranging from 0 (not implemented) to 10 (fully implemented). Although the adopted statements were initially used in studies to assess an organization's readiness for Industry 4.0, instructions for survey participants were specifically designed to measure various statements regarding the degree of implementation of Industry 4.0 principles.

In continuation, we constructed a factor structure, which can be found in the appendix, that is closely aligned with the theoretical propositions (Agca et al. 2017; Schuh et al. 2017). The following latent variables were constructed, reflecting major organizational aspects influenced by the implementation of Industry 4.0, where the first two refer to Industry 4.0 technological factors and the rest to Industry 4.0 non-technological factors (N = number of items):

1. *Manufacturing concepts and technologies* "M-TECH" (N = 5; α = 0.909)—referring to the system's integration in organizations, the automation of processes, and the ability of machines and systems to be upgraded.
2. *IT concepts and technologies* "IT-TECH" (N = 6; α = 0.879)—focusing on the use of cloud computing, wireless sensors, artificial intelligence, digital data gathering and analysis, and digital data for decision-making.
3. *Strategic and organizational features* "SO" (N = 6; α = 0.920)—referring to the degree of understanding and strategic focus with regard to investments in Industry 4.0, management support for Industry 4.0, the systematic use of business indicators and personnel development, and open cooperation between the departments.
4. *Products and services* "PS" (N = 5; α = 0.748)—referring to the practices of flexible product design, high digital capabilities of products, inclusion of customer demands, and the use of data for product development and market research.
5. *Supply Chain* "SC" (N = 6; α = 0.884)—the use of smart gadgets for inventory control with real-time tracking throughout the entire supply chain, integrated communication systems which enable instant responses to changes in the market, and management support for improving the supply chain area.
6. *Business model* "BM" (N = 6; α = 0.845)—including the shift from a process-based view to a customer-based view of the organization, the use of CRM systems across all marketing channels, the tracking of products through their entire life cycle, and the use of gathered digital data to support market decisions.
7. *Law and Policy* "LAW" (N = 4; α = 0.770)—the standardization of all legal procedures and compatibility with new legal policies, such as GDPR, the use of risk assessment teams, and the protection of intellectual property.
8. *Culture and Openness* "CO" (N = 8; α = 0.915)—the formulation of a learning culture based on data gathering and analysis, knowledge transfer, employees' involvement in decision-making, and the facilitation of open innovation and cooperation through democratic leadership.
9. *Organizational structure* "OS" (N = 7; α = 0.869)—a flat and not strictly hierarchical organizational structure, wherein a lot of work is done through projects, all communications are technologically supported, and employees are central to

decision-making; where strategic decisions are centralized and operational decisions are decentralized.

Productivity—The areas of organizational operations in which we focused our questions with regard to productivity were gathered from the literature review on Industry 4.0 and productivity. To determine the level of productivity in organizations, we focused measures on the perceptions of productivity changes by managers and specialists (Van de Walle and Bouckaert 2007) influenced by Industry 4.0 technologies in two distinct areas. Firstly, employee productivity was addressed by measuring how the implemented principles of Industry 4.0 had changed the various aspects of the employees' work. Six questions were postulated, focusing on communications, information sharing, research, knowledge distribution, and open innovation (Smithies 2017; Wang and Wang 2018; Gressgård et al. 2014). Secondly, production productivity was addressed by measuring how the technologies implemented impacted upon production and other operational processes. Six questions related to technological improvements in the areas of data processing and gathering, products, process automation, maintenance, and increased production flexibility (de la Fuente-Mella et al. 2020; Lin et al. 2020; Rossit et al. 2019) were postulated. A list of the items used to measure both facets of productivity is provided in the appendix.

Both facets of productivity considered were measured on an 11-point interval scale, ranging from 0 (no changes in productivity) to 10 (significant changes in productivity). For perceptions of productivity, valid measures were used when examining uncertain or highly dynamic and variable systems (Van de Walle and Bouckaert 2007; Grover et al. 1998).

The formulation of relevant constructs—Two of the introduced facets of productivity, i.e., employee productivity (N = 6; $\alpha = 0.940$) and production productivity (N = 6; $\alpha = 0.953$), were highly correlated (R = 0.772**; $p < 0.01$). The same is also true for M-TECH (N = 6; $\alpha = 0.915$) and IT-TECH (N = 5; $\alpha = 0.861$); (R = 0.806**; $p < 0.01$), which represent the technological factors of Industry 4.0 implementation.

We observed that the correlations between two facets of productivity, as well as two facets of technological factors of Industry 4.0, indicated that a distinction based on the constructs' content—between dichotomous definitions of productivity as well as technological factors of Industry 4.0 in two facets—may not be needed. This indicates that the same or similar information is shared within the constructs (Ho 2006). From a further exploratory factor analysis done on productivity (KMO = 0.905; $p < 0.001$) and the technological factors of Industry 4.0 (KMO = 0.918; $p < 0.001$), where the factor number was set to two, a reliable two-factor structure appeared in both cases. Based on this, we formed two latent constructs; namely productivity (N = 2; $\alpha = 0.934$) and the technological factors of Industry 4.0. (N = 2; $\alpha = 0.934$).

Strong and moderate corelations were also observed amongst all seven of the non-technological derived factors, the highest of which was (R = 0.825**) and the lowest (R = 0.507**). Considering theoretical presuppositions (Agca et al. 2017; Schuh et al. 2017) and strong correlations, the latent construct "non-technological factors of Industry 4.0" can be formed in SEM (N = 7; $\alpha = 0.933$). Further details of the non-technological constructs' content can be found in the appendix.

Table 1 Mean values, standard deviations, and correlations between the study variables

Variable	M	SD	1	2	3	4	5	6	7
1. Age	42.98	10.64	1						
2. Gender	1.29	.46	−.089	1					
3. Position	4.19	.130	.248**	−.177*	1				
4. Organizational size	2.29	.95	−.021	−.136*	−.114*	1			
5. Education	5.60	1.47	−.082	−.008	−.006	.293**	1		
6. Technological factors I4.0	5.60	1.49	.108	−.033	.008	.075	.003	1	
7. Non-technological factors I4.0	6.35	1.21	.074	−.017	−.024	.105	.060	.806**	1
7. Productivity	6.40	1.43	.022	−.021	.023	.000	−.062	.665**	.689**

N = 323; * $p < .05$; ** $p < .01$; *** $p < .001$

Table 2 Latent variables and their AVE, CR, and Cronbach's alpha

Construct	CR	AVE	Cronbach's alpha
Technological factors of I4.0	.944	.608	.934
Non-technological factors of I4.0	.927	.648	.933
Productivity	.958	.655	.961

*** $p < 0.001$; sample size is 323; AVE and CR are calculated for the mediator model

These results also confirm the notion that firstly the technology, secondly the productivity, and thirdly non-technological factors of an organization determine the operations of all of its essential subsystems (Syverson 2011; Orlikowski 1992; Bartelsman et al. 2016). This should be considered as a whole measure because there is no sense in analysing individual subsystems separately when applying general cognitions (Wiener 1948, 1966). Organizational, non-technological factors were joined in these constructs and are represented in SEM as measurable variables because they act as mediators in the model (Baron and Kenny 1986).

As shown, the demographic variables commonly used in managerial or organizational studies (Dabić et al. 2013; Ralston et al. 2011), shown in Table 1, do not display any significant correlations with the main variables of our study, which means that we can reliably go further with the investigation and consider the assessment of productivity and the level of Industry 4.0 implementation both in terms of technological and non-technological factors and non-biased factors (Ho 2006; Wolf et al. 2013). There is an observed, significant, moderate, positive correlation between the three principal variables in the study, implying that the technological factors of Industry 4.0 and non-technological factors are linked by productivity and hold respectively similar mean values.

Details describing composite reliability (CR), average variance extracted (AVE), and Cronbach's alpha coefficients for the constructs of interest for the mediator model are outlined in Table 2.

The results summarized in Table 2 are based on the standardized path loadings of all items entered in the mediator model, where each significantly explains the corresponding latent constructs. The reliability of latent constructs can be considered acceptable based on the value of AVE, which was greater than 0.5, the value of CR, which was above 0.7 (Fornell and Larcker 1981), and Cronbach's alpha value, which was above 0.7 (Hair et al. 2006). All factor loadings comprising latent constructs in this survey exceed common cut-off values (Henson and Roberts 2006; Dabić et al. 2021). This enabled us to proceed with the analysis.

3.4 Research design and analyses

Our empirical examinations were based on the following steps:

Step 1 We used SEM techniques and confirmatory factor analysis to observe the direct relationships between: (1) the level of Industry 4.0 implementation through the lens of technological factors and the productivity of organizations; and (2) the level of Industry 4.0 implementation through the lens of non-technological factors and the productivity of organizations.

Step 2 We formed a mediator model in SEM (Baron and Kenny 1986), where non-technological factors of Industry 4.0 were shown to mediate the relationship between the technological factors of Industry 4.0 implementation and the productivity of organizations.

Calculations were done using AMOS 21 software.

Fit statistics—The goodness of fit indices of the research models (Table 3) were firstly calculated for the two-factor measurement model including the technological factors of Industry 4.0 and organizational productivity (Model 1); secondly, for a two-factor measurement model including the non-technological factors of Industry 4.0 and organizational productivity (Model 2); and thirdly, a three-factor measurement model was designed to include three latent constructs—namely, the technological factors of Industry 4.0, non-technological (organizational) factors of

Table 3 Fit statistics for the direct effect models and a mediator model

Fit statistics	Model 1 for direct effect technological factors → productivity	Model 2 for direct effect non-technological factors → productivity	Model 3—Mediator model
SRMR	.054	.032	.054
CFI	.939	.943	.913
IFI	.940	.943	.914
$\chi 2$	650.550*** (N = 323; df = 180)	525.298*** (N = 323; df = 129)	1252,362*** (N = 323; df = 345)
RMSEA	.090	.098	.090

N = 323; * $p < .05$; ** $p < .01$; *** $p < .001$

Industry 4.0 as a mediator, and organizational productivity (Model 3). In light of recent findings regarding the use of SEM modelling on novel questions and challenges related to technological forecasting and social change, is crucial strategy in determining accurate prediction models for organizational outcomes (Mai et al. 2021). Following the decision tree for identifying the optimal fit indicator, we tested a novel model, analysing the structural model and obtaining a large sample. SRMR is a recommended fit indicator, followed by CFI (Mai et al. 2021). The models in our research demonstrated a reliable fit with the data and, according to the fit indices in Table 3, were considered acceptable from the standpoint of SRMR (falling below a cut-off point of 0.08), CFI and IFI (above the cut-off point of 0.900), and $\chi 2$, (Hu and Bentler 1999; Byrne 2010; Tóth-Király et al. 2017; Shi et al. 2019; Xia and Yang 2019; Mai et al. 2021). Furthermore, according to the significant correlations between three principal variables in our model (Table 1), the conditions needed for the existence of a mediation effect (Baron and Kenny 1986) were fulfilled.

Common method bias—To measure dependent and independent variables, one instrument was used, increasing the possibility of common method bias (Podsakoff et al. 2012). Due to the high values of correlation coefficients, we tested for multicollinearity as a first step in determining the existence of common method bias (Podsakoff et al. 2012). Tolerance values ranged from 0.130 to 0.359, and VIF values ranged from 2.829 to 7.703, thereby indicating no multicollinearity on the first level (Ho 2006).

Secondly, we tested for common method variance using the following procedure. We loaded 65 items—53 from the Industry 4.0 implementation level and 12 from productivity—onto a single factor. We used exploratory factor analysis with no rotation (Podsakoff et al. 2012). The newly extracted common latent factor explained 44.05% of the variance, enabling further investigation, as it was below the threshold value of 50% (Lindell and Whitney 2001).

Thirdly, a marker variable test was conducted using years of experience as a primary marker (Ralston et al. 2011). Non-significant correlations were observed between three main constructs of interest, and a marker variable with low coefficient values, the highest of which was $R = 0.096$, further confirmed no issues with common method bias (Lindell and Whitney 2001).

4 Results

4.1 The direct effect of the technological and non-technological factors of Industry 4.0 implementation on the productivity of organizations

Figure 2 and Table 4 indicate direct paths based on standardized regression weights between the technological factors of Industry 4.0 implementation and the productivity of organizations. The strength of the direct effect for Model 1 ($\beta = 0.682^{***}$) is significant and positive. Furthermore, 47% of the variance in productivity is explained by the technological factors of Industry 4.0 implementation. This confirms Hypothesis 1.

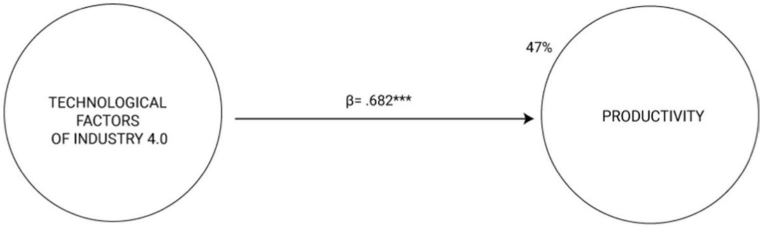

Fig. 2 Model 1—The direct effect of Industry 4.0 technology implementation on productivity

Table 4 Direct relationships between variables concerning Model 1 and Model 2

Hypothesis	Direct relationship	Standardized direct effect	Variance explained	Result
H1	Technological factors of Industry 4.0 implementation → Productivity	.682***	47%	Hypothesis confirmed
H2	Non-technological factors of Industry 4.0 implementation → Productivity	.735***	54%	Hypothesis confirmed

$^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$; sample size is 323

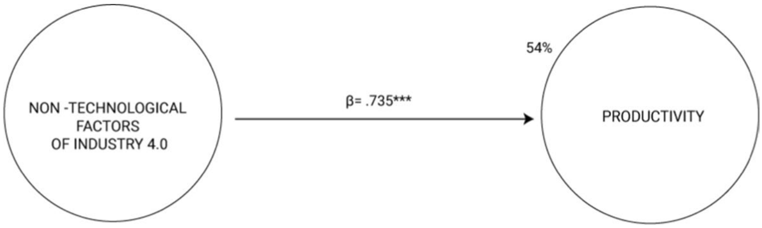

Fig. 3 Model 2—The direct effect of Industry 4.0 non-technological factor implementation on productivity

Figure 3 and Table 4 observe a direct relationship between the non-technological factors of Industry 4.0—which are later used in Model 3 as mediators—and the productivity of organizations. The strength of the direct effect for Model 2 (β = 0.735***) is significant and positive, with 54% of the variance in productivity explained by the implementation of non-technological factors of Industry 4.0. This confirms Hypothesis 2.

As observed in Table 4, the strength of the direct effect of non-technological factors on productivity is greater than in the case of technological factors. Non-technological factors also explain 7% more of the variance in productivity, which further suggests a possible mediation (Baron and Kenny 1986).

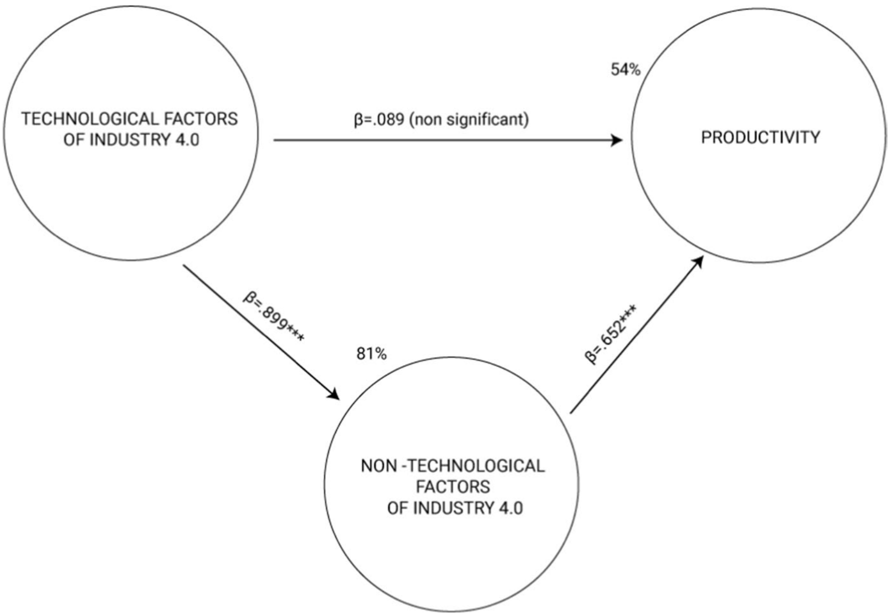

Fig. 4 Model 3—Including non-technological factors of Industry 4.0 implementation as a mediator variable

4.2 Mediation analysis

In Fig. 4 and Table 5, we can see that the technological factors of Industry 4.0 implementation no longer significantly influence ($\beta = 0.089$) organizational productivity when organizational factors are included in the model. Considering the path of mediation, this result suggests that the strength of the effect goes through non-technological factors and is simultaneously greatly reduced when observed directly. In order to confirm the mediation, the indirect effect results should be considered (Baron and Kenny 1986).

The standardized indirect effect presented in Table 5, which is statistically significant ($\beta = 0.587^{**}$), confirms the mediation of Industry 4.0 non-technological factors between technological factors and productivity (Baron and Kenny 1986). Therefore, we can accept Hypothesis 3.

5 Discussion

Drawing from these results, we initially observed that the technological factors of Industry 4.0 and their level of implementation do indeed have a significant positive effect on productivity in manufacturing organizations. The implementation of key technological concepts, based on both manufacturing or information technologies and concepts, seems to have a strong and positive impact, confirming the observations of previous researchers (Melitz 2003; Brixner et al. 2020). It is interesting

Table 5 Direct and indirect relationships showing the impact of the mediation of non-technological factors on variables concerning Model 3

Hypothesis	Direct relationships – path of mediation	Standardized direct effect	Indirect relation	Standardized indirect effect	Mediation
H3	Technological factors of Industry 4.0 implementation → Non-technological factors of Industry 4.0 implementation	β = .899***	Technological factors of Industry 4.0 → Productivity	β = .587**	Full mediation
	Non-technological factors of Industry 4.0 implementation → Productivity	β = .652***			
	Technological factors of Industry 4.0 implementation → Productivity	β = .089 (ns)			

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$; ns = non-significant; sample size is 323

that the implementation or use of non-technological (i.e., organizational) aspects connected to Industry 4.0, such as strategy, organizational structure, culture, supply chain, business model, etc., also have a stronger effect on productivity, and are fully mediating the impact of the technological factors of Industry 4.0 implementation on productivity. This confirms the idea that organizations function in an ecosystem, wherein individual parts, from technological tools to organizational practices, work together to accomplish a goal which, in this case, relates to higher levels of productivity.

Claims that the use of advanced technologies will drive the next industrial revolution need to be considered with caution. Indeed, technological advances have been proven to boost productivity, and industrial revolutions are based on technological advances (Calabrese et al. 2021). However, technologies are tools and cannot be useful by themselves if the organizational framework is not prepared to enable their proper use (David 1990). Industrial revolutions develop over decades and, among other factors, depend on market conditions, not only on productive organizational operations (Blum and McLaughlin 2019). Considering previous revolutions, practically no productivity gains have been seen to arise from the electrification of factories for nearly 30 years. Only when the processes and factories were reimagined, redesigned, and reinvented to suit new technologies could the results, in terms of productivity, be fully evident (Brynjolfsson and McAfee 2014).

There are some issues with regard to the meaning and definition of Industry 4.0 (Madsen 2019). Our results indicate that the term does not only represent an advanced technological revolution in terms of the IoT, cyber-physical systems, or smart manufacturing, rather this is a systemic phenomenon that influences all aspects of organizational workings and, from this, together with a proper organizational framework predicated on non-technological factors, it could be able to influence the desired outcomes in productivity and market relevance for organizations.

5.1 Theoretical implications

To the best of our knowledge, this study is the first to outline a positive, significant, and empirically verified association between the technological factors of Industry 4.0 implementation and productivity in organizations, which is fully mediated by the non-technological (i.e., organizational) factors of Industry 4.0 implementation. Productivity increases can therefore be considered one of the basic motivations for the implementation of Industry 4.0, confirming suspicions that the two concepts are deeply connected (Fragapane et al. 2020). This had previously not been proven in scholarly literature.

Secondly, this study confirms that non-technological factors should not be overlooked when considering the implementation of Industry 4.0 in an attempt to achieve better productivity levels (Schneider 2018). In fact, they are essential in enabling the comprehensive productivity benefits offered by advanced technologies because, if the technologies are not used in the right contexts and circumstances, their effectiveness could be negated (Brynjolfsson and McAfee 2014).

Thirdly, it is worth noting that the technological and non-technological aspects of organizational workings go hand in hand and, for the purposes of theoretical considerations, productivity should be studied as a single, non-partial, and systemic factor when it comes to Industry 4.0 implementation (Bartelsman and Doms 2000).

Fourthly, with regard to productivity, the proposed model accurately and reliably measures aspects of production and employee productivity as two partial measures of a single comprehensive productivity concept applicable for the Industry 4.0 organizational environment. By extension, the same productivity criteria could be used when assessing productivity with microdata in further studies.

5.2 Practical implications

The most significant practical implications of this study are as follows. First, manufacturing organizations should recognize the need to increase levels of Industry 4.0 implementation in order to boost organizational productivity. Thus, it is important to realize that, if manufacturing organizations want to improve their productivity and remain competitive in the market, they need to implement the principles of Industry 4.0 rather rapidly. Specifically, they should first focus on implementing technological factors from the standpoint of both the manufacturing technologies and information technologies, as provided in the theoretical review (i.e., MTECH and ITTECH), as they directly bring about positive benefits in terms of productivity improvement. These endeavours are the most important according to our results but, at the same time, they remain the hardest to achieve (Frank et al. 2019). However, it is noteworthy that these endeavours have positive implications for general organizational success (Brixner et al. 2020; Fettermann et al. 2018). This is also indicated by our results.

Secondly, going beyond the technological implementation, non-technological factors may be more important considerations, as non-technological factors supersede the impact of the technological factors of Industry 4.0 implementation on organizational productivity. Non-technological factors are mediators and enablers of productivity increases that stem from technological advances. To improve productivity, managers should recognize that organizations must create strategies, invest in Industry 4.0 technologies, and transform their business models to be more customer-orientated, rather than orientated towards internal processes. Furthermore, they should shift their organizational structures to be more open and flatter, focusing on the potential of their employees and creating an innovation culture that will ultimately lead to appropriate and successful products and services offered in the market. As the non-technological factors of Industry 4.0 facilitate successful technological adoption, it could be argued that they are even more crucial to consider when implementing the principles of Industry 4.0 and should be the first on the list to adjust, in compliance with both the ideas of Industry 4.0 as well as technological factors. Focusing on these key elements should bring about better productivity and, by extension, greater market success.

5.3 Limitations

Our study examined a specific context. Therefore, some limitations may apply. Productivity measures were based on the perceptions of managers and specialists, rather than microdata gathered from the processes. Although these measures have proven reliable (Van de Walle and Bouckaert 2007), they may deviate from actual productivity results. Next, we used a self-assessment method to measure both the actual level of Industry 4.0 implementation and perceived productivity, which may distort the real state of the art (Lau et al. 2016). With regard to the sample origins, Slovenian manufacturing organizations often act as suppliers for larger European or global supply chains and, therefore, are not focal companies in comparison to global manufacturers (Dabić et al. 2013). Slovenia also had some major problems when adapting to the free market in the 1990s, following its separation from Yugoslavia, wherein the country's technological infrastructure was outdated, and organizational behaviour was not an area of concern. Free market principles were also hindered by socialistic principles that were at the core of economic development. In organizations, the focus was—and still is—on improving the company's own processes and not on customers' demands and needs (Dabić et al. 2013) Without critical assessment, this may limit the generalizability of the study findings. The main focus of the study was manufacturing organizations, according to NACE C classification, excluding service organizations, which may have different experiences with Industry 4.0 implementation and productivity of their processes at large. Many different organizational sizes are included, as well as managers or specialists at different positions, which could have implications on the consistency of the results. However, correlation analysis and sample homogeneity tests have revealed that these are not an important factor concerning the principal variables in the study or the context of the study.

5.4 Future research directions

Several future research directions are possible. Firstly, to confirm the pattern of the results beyond a single considered country, research should be carried out in more countries, especially in developed Western economies. Secondly, the approach for determining the level of Industry 4.0 implementation presented in this study should be further tested in different countries in order to determine whether or not this approach offers the same criteria for the level of Industry 4.0 implementation, as in the case of Slovenia. In addition to this, research beyond manufacturing organizations would be beneficial in this context. Despite including a comprehensive list of items in the model, encompassing the events across a vast spectrum of organizational workings, other criteria could still emerge from data analyses. Thirdly, more focus should be placed on defining the phenomena of Industry 4.0 so that researchers and practitioners can understand whether this is truly leading toward the next industrial revolution, as indications show that we are not quite there with regard to our capabilities. Fourthly, future research on this topic could incorporate research on the readiness of SMEs, implementing 4IR technology and research on the technology maturity levels of large industries.

Finally, a year-long conundrum about what determines productivity (Syverson 2011) has revealed the importance of longitudinal microdata as one of its main indicators (Bartelsman and Doms 2000). Thus, in order to accurately determine the productivity of organizations undergoing Industry 4.0 transformation, more studies should examine microdata inside individual organizations around the globe, from before and after the implementation, in an attempt to spot differences and accurately determine the effects. Furthermore, studies should be conducted to detect the lag in productivity gains in terms of Industry 4.0. It has been well-noted that a significant lag in productivity occurred during the electrical revolution because the factories were not designed to harvest the benefit of electrification (Brynjolfsson and McAfee 2014; David 1990). Therefore, it should be determined how much redesign and reimagination of processes is occurring in manufacturing organizations directly as a result of Industry 4.0 implementation.

6 Conclusion

This study demonstrates the effect that the implementation of Industry 4.0 principles has on productivity in manufacturing organizations. The effect is overwhelmingly positive, as all of the criteria considered by our implementation model, from the perspective of both technology and non-technological (i.e., organizational) factors of Industry 4.0 implementation, have had a positive effect on the productivity of organizations. The factors that most strongly influence productivity in organizations are connected to production technologies and information and communication technologies that enable better communication, information sharing, and process control. Therefore, implementing Industry 4.0 technologies should be the first measure undertaken when strategizing the transformation. Other non-technological factors connected to Industry 4.0 transformation also have even stronger implications for productivity. These may be easier to implement than technologies, but the comprehensive nature of the Industry 4.0 environment requires a systemic approach to organizational transformation, meaning that all of the considered factors should be implemented in order to secure long-term, sustainable organizational success.

Appendix

Supplement 1 shows items, their mean values, and standard deviations for the developed factors of Industry 4.0's degree of implementation. Nine factors were developed. The first two factors refer to Industry 4.0 technological factors (MTECH and ITTECH) and the other seven reflect non-technological areas of Industry 4.0. implementation—i.e. products and services, strategic and organizational features, supply chain, legal and policy aspects of business models, culture and openness, and organizational structure. The selected items are based upon theoretical presuppositions, mainly from original models developed by Acatech (Schuh et al. 2017) and the University of Warwick (Agca et al. 2017), which have been confirmed by several recent studies in terms of their content (Wagire et al. 2021; Lin et al. 2020).

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