Technology in Society 74 (2023) 102301

Contents lists available at ScienceDirect

Technology in Society

journal homepage: www.elsevier.com/locate/techsoc

Intelligent automation implementation and corporate sustainability performance: The enabling role of corporate social responsibility strategy

Morteza Ghobakhloo [a,b,*], Shahla Asadi [c], Mohammad Iranmanesh [d], Behzad Foroughi [e], Muhammad Faraz Mubarak [a,g], Elaheh Yadegaridehkordi [f]

[a] School of Economics and Business, Kaunas University of Technology, Kaunas, Lithuania
[b] Division of Industrial Engineering and Management, Uppsala University, P.O. Box 534, Uppsala 75121, Sweden
[c] Faculty of Computing and Engineering, University of Gloucestershire, GL50 2 RH, UK
[d] School of Business and Law, Edith Cowan University, Joondalup, WA 6027, Australia
[e] Department of International Business Administration, I-Shou University, Kaohsiung City, Taiwan
[f] School of Business, Polytechnic Institute Australia, NSW, 2000, Australia
[g] Faculty of Computer Science, Dalhousie University, Halifax, NS, Canada

ARTICLE INFO

Keywords:
Intelligent automation
Artificial intelligence
Robotic process automation
Sustainability
Corporate social sustainability
Implementation

ABSTRACT

Although Intelligent Automation (IA) represents the future of business automation, the organizational implementation and sustainability performance of this emerging technological innovation is vastly understudied. Understanding the implications of IA for sustainability is critical since leveraging these technologies shapes operations and policies that can promote sustainable digitalization and automation practices. We study how firms' technological, organizational, environmental, and human resource contexts impact IA implementation. The study further explains how IA may associate with the firm's triple bottom line while accounting for the moderating role of corporate social responsibility strategy. The study surveyed 207 multinational firms in 2022 and used partial least square-structural equation modeling to test the hypothesized relationships. Results showed that IA implementation is mainly determined by the characteristics of the firm's internal environment, such as absorptive capacity, employee socio-behavioral concerns, and social capital competency. IA may offer valuable opportunities for boosting the firm's economic and environmental sustainability performance. Nonetheless, IA is a double-edged sword for social sustainability, harming social values in implementing firms with informal corporate social sustainability strategies. Conversely, firms with formal corporate social sustainability strategy have a significantly higher opportunity to transform the value of IA into social sustainability performance. Findings are expected to assist managers and decision-makers with streamlining an impartial and sustainable transition of organizations toward automation.

1. Introduction

Intelligent Automation (IA), also known as cognitive automation, has become a trending buzzword in the age of digital industrial transformation [1]. IA is a transformative solution that relies on the integration of Business Process Monitoring (BPM), Artificial Intelligence (A.I), and Robotic Process Automation (RPA). The technological components of IA have been around for the past decade [2]. However, recent advancements in underlying automation technologies such as machine learning systems, deep learning, or natural language processing have empowered IA to streamline the end-to-end process unprecedentedly [3]. IA is revolutionary because of its unique features [4]. IA can simulate human intelligence, interact with humans in real-time (e.g., via speech or vision recognition), learn autonomously and adapt to new business circumstances, make autonomous decisions, and predict possible outcomes [2,5,6].

Industrial reports show that IA represents the future of process automation, and the majority of leading businesses around the globe are moving toward adopting IA solutions [7]. Despite the hype surrounding this emerging technological innovation, the academic literature fails to explain the factors that might affect how firms implement and use IA [8]. Indeed, IA literature is embryonic, limited to a handful of recent

* Corresponding author. Division of Industrial Engineering and Management, Uppsala University, Uppsala, Sweden.
E-mail addresses: morteza.ghobakhloo@angstrom.uu.se, morteza.ghobakhloo@ktu.lt (M. Ghobakhloo), asadi.shahla2003@gmail.com (S. Asadi), m.iranmanesh@ecu.edu.au (M. Iranmanesh), foroughi@isu.edu.tw (B. Foroughi), muhammad.mubarak@ktu.edu (M.F. Mubarak), yellahe@gmail.com (E. Yadegaridehkordi).

https://doi.org/10.1016/j.techsoc.2023.102301
Received 10 March 2023; Received in revised form 7 June 2023; Accepted 14 June 2023
Available online 19 June 2023

studies offering theoretical insights into the strategic management of this technology [2]. For example, as one of the earlier academic contributions, Ref. [6] theoretically explained how the Covid-19 pandemic pushed businesses toward IA implementation. Ref. [4] also conducted a literature review to explain the intellectual state of IA technologies in the service sector. Ref. [2] reviewed IA implementation cases among industry leaders and provided several action principles to guide businesses across their IA implementation journey. More recent contributions to the IA literature involve assessing the impact of 5G on IA evolution [9], defining the specification of efficient IA system preparation [10], and assessing IA implications for pharmacovigilance [11]. Despite these invaluable early contributions to the IA discipline, the organizational implementation of IA is vastly unexplored. To our knowledge, there is little to no empirical research on the determinants of IA implementation among organizations. The Information System (IS) literature proposes that adopting a technological innovation involves multiple stages, from initial adoption to implementation and post-implementation (confirmation) stages (e.g., Ref. [12]). The review of the literature reveals that the IA implementation stage is even more understudied. The business value of IA is scientifically underexplored, and little has been done to understand the sustainability performance implications of this technology.

This knowledge gap can be a significant risk factor for businesses interested in IA, forcing them to move unthinkingly toward the adoption journey. This gap can be detrimental to policy bodies and industrial decision-makers responsible for facilitating the effective and sustainable adoption of novel technologies such as IA across various industries and sectors and preventing the corporate digital divide. Furthermore, investigating the impact of IA on the sustainability performance of businesses is critical in the age of Industry 5.0 for several reasons. First, the ongoing digital industrial revolution (commonly recognized as Industry 4.0) has not been entirely aligned with inclusive sustainability [13]. The emerging Industry 5.0 widely acknowledges the importance of technology governance for aligning digitalization with socio-environmental values. Under such circumstances, IA implementation might raise serious ethical questions about the societal implications. Therefore, understanding IA's impact on sustainability might help businesses address these ethical considerations, empowering them to assess the effects of automation on employment, workforce reskilling, and societal well-being. By doing so, companies can make informed decisions, balancing technological advancements with social responsibility. Unfortunately, such knowledge of the ethical implications of IA implementation is lacking. Second, regulatory bodies and social actors progressively attempt to promote sustainable practices by regulating emerging technologies, as recently seen via the European Commission's efforts to regulate ChatGPT usage in Europe under the Industry 5.0 agenda. Without a profound understanding of the impact of IA on sustainability measures, businesses may face challenges in complying with evolving regulations and fail to productively engage in shaping policies and regulations related to IA. Third, the lack of knowledge concerning the determinants of IA implementation and the underlying sustainability impacts can lead to unintended consequences and risks for the IA stakeholders. For example, such a lack of knowledge can mislead businesses to undermine the effects of IA on employees, preventing them from developing strategies (e.g., reskilling and upskilling programs) that ensure a smooth transition. Furthermore, such lack of knowledge can deviate businesses from considering influential drivers of IA implementation, possibly pushing them toward unsuccessful implementation and causing them to miss the opportunity to strategically align IA with the potential benefits for sustainability.

The present study addresses this critical knowledge gap by empirically studying factors that might determine IA implementation among organizations. The study further measures the IA impacts on corporate sustainability performance, striving to understand how IA application affects the way a company achieves key metrics reflecting sustainability across the three pillars of economic, environmental, and social dimensions [14,15]. This includes, among others, assessing the effect of IA on corporate profitability, resource efficiency, carbon footprint reduction, employee well-being, and customer satisfaction.

Since IA implementation is vastly unknown and the study is among the first to explore this topic, we draw on the Technology, Organization, and Environment (TOE) framework to include a wide range of factors that might describe how organizations implement IA solutions. Although intelligent automation is the future of work, we acknowledge that IA is a disruptive technology that radically changes the workplace environment. Experts believe that IA may intensify the issues of digital skill gaps, employee resistance, job displacement, and job security [7,16]. Concerning the role of human factors, the Human-Organization-Technology (HOT)-fit theory has shown the importance of demonstrating a fit between the human, technology, and organizational circumstances while recognizing the possibility of adopting innovative technology [17]. Therefore, we integrate the TOE framework with the HOT-fit theory to have the theoretical basis for investigating human resource-related factors that might determine IA implementation. Further, we draw on the Resource-Based View (RBV) of the firm [18,19] to have the theoretical support for assessing the post-implementation sustainability performance effects of IA.

Finally, we draw on CSR and Environmental, Social, and Governance policy background (e.g., Refs. [20,21]) and postulate that the 'IA implementation-sustainability performance' association might be a function of the firm's Corporate Social Responsibility (CSR) strategy. Formal CSR strategy in the present study refers to a documented and structured strategic approach adopted by a company to integrate ethical, social, and environmental considerations into its business operations. It outlines specific goals, initiatives, and actions that align with the company's commitment to responsible business practices, stakeholder engagement, and sustainability, driving positive social and environmental impact [22]. In this study, we measure if the associations between IA implementation and corporate sustainability performance would be meaningfully different when accounting for the role of CSR strategy. Accordingly, the present study strives to answer the following research questions:

RQ1. What are the technological, organizational, environmental, and human-based determinants of IA implementation among organizations?

RQ2. How would IA implementation affect organizations' economic, environmental, and social sustainability performance?

RQ3. How would the CSR strategy moderate the sustainability performance effects of IA implementation?

The present study targets multinational manufacturing companies to assess the IA implementation, underlying determinants, and sustainability implications. IA implementation is believed to be highly consequential to the sustainability performance of multinational manufacturers due to their scale and impact on global resource utilization, complex operations, regulatory compliance challenges, supply chain sustainability considerations, technological potential, and stakeholder visibility considerations. We expect this research to make notable contributions to the theory and practice while answering the above research questions. The study reviews the IA background and explains how it is understood against relevant concepts such as classic automation and hyper-automation. The study contributes to the literature by (i) identifying the determinants of successful AI implementation, (ii) extending the TOE framework by incorporating human determinants, (iii) exploring the impacts of IA implementation on the economic, environmental, and social performance of firms, and (iv) exploring how formal CSR strategy of firms may boost the sustainability benefits of IA adoption and implementation. We draw on the Partial Least Squares-Structural Equation Modeling (PLS-SEM) results to provide IA stakeholders with theoretical and managerial insights that might facilitate firms' movement toward sustainable IA integration and utilization. The findings of the study provide policymakers with a valuable basis on which to guide their efforts to boost the penetration rate of IA among businesses. Furthermore, the study provides insight into the driving forces behind IA implementation and its impact on sustainability performance for managers of manufacturing companies.

2. Intelligent automation background

IA, also labeled cognitive automation, refers to using smart automation technologies such as A.I, BPM, and RPA to automate, streamline, and scale business decision processes [7]. IA is the evolutionary step from the classic process automation toward the futuristic vision of hyper-automation [23]. IA revolutionizes traditional process automation in two ways. First, IA is not limited to the automation of discrete routine tasks in the process chain, focusing on the automation of the entirety of the workflow lifecycle [24,25]. Second, IA has the cognitive capabilities to infer real-world business circumstances and autonomously make data-driven and informed decisions concerning a specific process [3]. IA cannot be interchangeably used with hyper-automation, as it is considered a stepping stone and a constituent of hyper-automation [23]. While both concepts entail using A.I-driven automation platforms and advanced technologies to streamline business processes, hyper-automation is much broader in scope, involving adopting various technologies such as the digital twin to achieve complete automation in the organization as extensively as possible [26].

IA uniquely improves firm competitiveness and delivers value [2]. First and foremost, IA helps businesses identify disruptions and changes throughout the business environment (e.g., market fluctuations or Covid-related employee behavior changes) and proactively prepare necessary strategic responses [6]. IA can augment the workforce, improve human resource productivity, and reduce labor costs [1,25]. Through process consistency, IA increases the quality and accuracy of business processes [27]. The resulting enhancements in response time, customer services, and product quality improve customer satisfaction [4,11]. IA also enhances adherence to regulatory requirements and policies via automation-empowered consistency in security, reporting, and compliance [28].

The technological constituents of IA and their institutionalization process are relatively well-studied within the literature (see Table 1). BPM involves technologies, tools, and techniques that allow businesses to assess, model, and optimize their processes and strategies [29]. BPM can be categorized as document-centric, integration-centric, and human-centric variant. As an example, human-centric BPM mainly addresses business processes that are critically dependent on human involvement [30]. The literature identifies various factors that may impact the firm's decision to implement BPM [31]. Examples include corporate size, business sector, organizational culture, management commitment, external stakeholders, and strategic alignment [29,32,33]. Previous studies, such as the work of [34]; have shown that BPM implementation and the resulting managerial and technical BPM capabilities can improve business performance. Alternatively, RPA, commonly called software robotics, aims to automate back-office tasks like accounting or record maintenance. RPA involves using chatbots and software robots as well as combining application programming and user interfaces to automate repetitive and routine tasks [28]. Budgetary constraints, Information Technology (IT) capability, infrastructure, management support, road-mapping ability, supply chain collaboration, and government regulations are among the critical determinants of RPA implementation in organizations [35]. The review of the literature reveals that RPA implementation may offer various benefits, such as improved talent acquisition, data quality, employee productivity, and reduced human errors [36,37]. A.I is the most studied and cutting-edge technological constituent of IA. In the intelligent automation context, A.I plays the role of a decision engine, which involves using complex algorithms, deep learning, and machine learning to synthesize unstructured or structured data and create the knowledge base and business intelligence for formulating data-driven predictions [3]. A.I has numerous business implications, and as a result, a wide variety of factors determine its adoption among businesses [38]. The compatibility and complexity of A.I tools, managerial competencies, internal knowledge competencies, regulatory forces, and competitive pressure are among the widely acknowledged determinants of A.I implementation in organizations (e.g., Refs. [39,40]). Depending on the business application type, A.I can offer diverse advantages, from prediction accuracy and decision process efficiency to improved risk detection, human resource cost reduction, or sales growth [41].

IA is a transformative digital solution that integrates A.I, BPM, and RPA to gain the necessary cognitive, decision, and analytical capabilities to streamline and simplify repetitive yet more complex tasks [23,28]. IA is arguably more integrative and complex compared to its technological components. The IA adoption process is consistently expected to be more disruptive and challenging. IA is a new concept, and industrial reports reveal that leading corporations in nearly every business context are introducing ambitious and aggressive plans for future IA investment and implementation [7]. The IA literature is equally embryonic, and scholars have recently shown interest in investigating the business implications of this concept [1], particularly as a response to the Covid-19 disruption [6]. The following table presents a overview of previous studies that have contributed to advancing IA knowledge within the existing literature. These studies have contributed to understanding various aspects of IA implementation, its impacts, and associated challenges.

Overall, the review of recent IA literature implies that various factors

Table 1
Comparative overview of previous studies advancing IA knowledge.

Study	Focus Area	Methodology	Key Findings
[4]	IA impact on organizational knowledge and service work	Systematic review/conceptual analysis	Provides a new conceptualization of IA. Offers a business value-based model of IA for knowledge and service work
[6]	IA implementation under Covid-19 consideration	Conceptual analysis	IA can boost business value but may increase worker automation anxiety. IA's technical capabilities and human skills should be merged to maximize value
[8]	The agility of IA implementation projects	Expert consultation and total interpretive structural modeling	Several factors might lead to the agility of IA projects, such as stakeholder alignment or leadership
[2]	The strategic management of IA in organizations	Six years of in-depth analysis of IA implementation projects	Offers 39 action principles to guide and empower top managers in managing the IA implementation journey
[1]	Investigating the engineering applications of IA for business growth	A systematic review of IA literature	Highlights the application of IA in various sections such as aviation or supply chain. Highlights the underlying challenges of IA implementation
[16]	IA implementation impact on working conditions of tourism workers	Multi-theoretical synthesis and conceptual analysis	There are several social risks involved with the use of IA in tourism, such as job displacement or income inequality
[9]	Assessing the effect of 5G in IA evolution	Systematic review/conceptual analysis	5G technology promotes various technical aspects of IA, such as industrial and robotic control. It also addresses some technical challenges of IA usage
[64]	IA implication for boosting service quality and the customer experience in tourism	Semi-structured interviews with tourism service managers in Cyprus	Formal CSR strategies enhance the social value of IA implementation, while informal CSR strategies have a detrimental effect on the social value of IA implementation

in a business's technological, organizational, and environmental contexts might affect the IA implementation process. Furthermore, studies consistently acknowledge that human workforce characteristics also play a critical role in how organizations approach and utilize IA. The literature also points to the possible value gains of IA while warring against the possibility of adverse effects on societal values. Considering these facts, the present study draws on The TOE and HOT-fit frameworks and RBV to have the theoretical support to assess and understand how a wide variety of determinants might affect IA implementation and sustainability performance in the corporate context. The following section thoroughly discusses our decision to integrate TOE and HOT-fit frameworks for such a purpose.

3. Theoretical development

Fig. 1 represents the theoretical framework of the study. This framework proposes that IA is an integrative technology that is the byproduct of integrating three cognitive technologies: A.I, BPM, and RPA. The mainstream technology adoption literature widely acknowledges that the adoption of technological innovation is a multifaceted phenomenon, taking place across two discrete phases [42]; Ghobakhloo et al., 2011). In the initial adoption phase, organizations decide whether and how they will commit to acquiring and implementing new technology [39]. In the post-adoption (implementation) phase, organizations integrate and use technology extensively to support their business operations [43,44]. As shown in Fig. 1, the present study concerns the post-IA adoption phase, addressing both IA implementation and IA performance assessment stages. Our decision to assess the business performance effects of IA implementation follows the RBV of the firm [12,18] IS success model, explaining that organizations can enjoy the net benefits of new digital technology once it has been implemented and strategically integrated within business operations. Indeed, the research model in Fig. 1 draws on RBV and proposes that IA can be considered as spanning information resources that, when leveraged strategically, can lead to improved firm performance. This postulation also aligns with [12] IS success model arguing that firms can benefit from improved corporate performance when they integrate new digital technology into their business operations and use it expensively.

Our theoretical framework assumes that a collection of environmental, human-based, organizational, and technological factors determines IA implementation in the corporate context. This assumption builds on the integration of the TOE framework and HOT-fit framework. TOE framework, initially developed by Ref. [45]; has been extensively used by scholars to investigate the technological innovation diffusion processes within organizations [17,46]. This framework assumes that technological, organizational, and environmental circumstances directly determine the technology adoption process in an organization. Under this framework, technological circumstances refer to the technical attributes of the technological innovation solution (either off-the-shelf or bespoke products) that organizations intend to implement [47]. Organizational circumstances denote the firm-specific internal characteristics, such as resource-based attributes, that affect a firm's implementation behavior [48]. Finally, the external environmental circumstances of the firm, such as competitive rivalry in a specific industrial context, constitute the environmental context of the TOE framework [49]. Prior studies have extensively applied the TOE framework to study the organizational implementation of various technologies such as A.I [39]; Chen and Chen, 2021; [50], process and robotic automation [51], business process monitoring [31], big data analytics [52], blockchain [53], cloud enterprise resource planning [54], and 3D printing [55]. Scholars such as [56] believe that the TOE framework can be regarded as a solid theoretical basis due to several advantages, such as a high freedom degree in choosing a variety of determinants or compatibility with other mainstream theories such as the Technology Acceptance Model (TAM) [57]. Despite these advantages, scholars argue that TOE falls short in accounting for the role of human resource circumstances in the general process of technology adoption in organizations [46,58].

To address this shortcoming, scholars such as [49,59] have integrated the TOE framework with the HOT-fit framework to account for human attributes regarding the organizational implementation of new technology. Initially developed by Ref. [60]; the HOT-fit framework proposes that a firm's human, organizational, and technological contexts may define the technology implementation behavior [61]. TOE and HOT-fit frameworks share a similar ground concerning the organizational and technological determinants of technology implementation [46]. They are also complementary since their integration would offer a comprehensive set of environmental and human attributes that may impact technological innovation diffusion at the organizational analysis level [58]. Overall, both TOE and HOT-fit frameworks have provided reliable theoretical bases for reliably predicting the determinants of technology implementation in the corporate context. Table 2 briefly

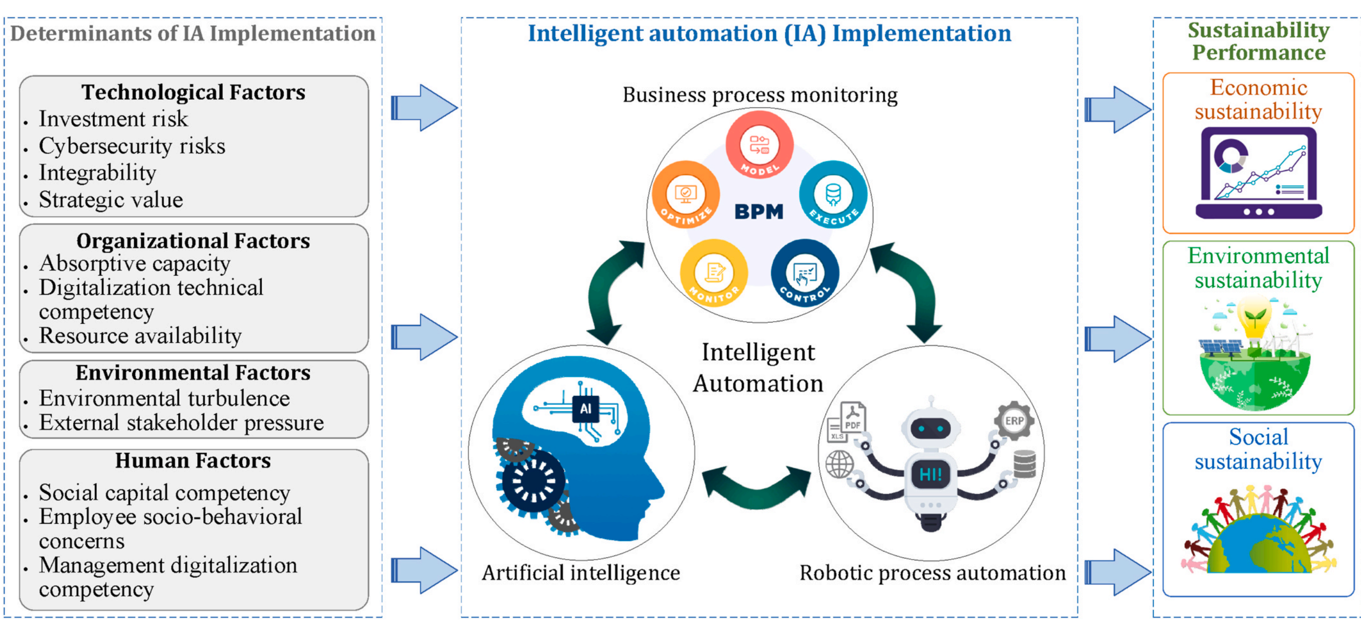

Fig. 1. The theoretical framework of IA implementation.

Table 2
A summary of selected TOE/HOT-fit literature on new technology implementation.

Study	Theory	Technology	Adoption phase	Determinants (Independent variables)
[59]	TOE/HOT-fit	Cloud computing	Adoption decision	Management innovativeness, HR IT technical competency, data security, complexity, compatibility, costs, relative advantage, management support, resources, benefits, government policy, and industry pressure.
[65]	TOE/HOT-fit/DOI	Hospital information system	Adoption decision	Relative advantage, compatibility, complexity, security issues, business size, management support, infrastructure, financial resource, external pressure, competition, vendor support, IT knowledge, competencies, IT expertise, and management innovativeness
[66]	TOE	Industry 4.0 technologies (e.g., AI, robotics, automation)	Initial adoption & Implementation	Perceived value, costs, compatibility, information requirement, IT knowledge, digitalization road-mapping competency, environmental imposition, and competitive pressure.
[53]	TOE	Blockchain	Implementation decision (adoption vs non-adoption)	Management support, business size, and IT innovation readiness.
[67]	TOE	IIoT	Adoption intention	Relative advantage, expertise, infrastructure, compatibility, security, cost, firm readiness, management support, vendor support, and competitive pressure.
[68]	TOE	Social commerce	Adoption intention	Perceived usefulness, security concerns, management support, organizational readiness, business partner pressure, and consumer pressure.
[52]	TOE/RBV	Big data analytics	Implementation (strategic use)	Compatibility, complexity, observability, trialability, risk, relative advantage, organizational readiness, management support, regulations, government support, and competitive pressure.
[39]	TOE/TAM	AI	Adoption intention	Perceived ease of use, leadership support, perceived usefulness
[51]	TOE	IA/Robotics	Adoption intention	Relative advantage, complexity, cost justification, market position, employee resistance, customer readiness, legal circumstances, customer experience, and competition.
[50]	TOE	AI-empowered robotics	Adoption intention & Potential use	Perceived benefits, compatibility, IT infrastructure, external pressure, vendor support, and government support.
[69]	TOE	AI	Implementation (usage level)	Relative advantage, complexity, firm size, technology competency, industry settings, and regulatory forces.

Note. IIoT, Industrial Internet of Things; RBV, Resource-Based View.

reviews the selected previous studies that have drawn on TOE, HOT-fit, or a combination of both for investigating the technology implementation determinants. The literature acknowledges that IA will fundamentally alter the work environment as an integrative and disruptive technology [62]. This technology is also knowledge and skill intensive, significantly relying on the characteristics of human resources for effective implementation [4,63]. Therefore, following [58,59]; we believe integrating TOE with the HOT-fit framework allows us to account for the human resource attributes that may play a critical role in shaping firms' IA implementation.

4. Hypotheses development

Fig. 2 presents the proposed research model of IA implementation among organizations. This figure presumes that 12 technological, organizational, environmental, and human factors determine IA implementation. We selected the 12 factors based on a meta-analysis of studies on factors that determine the implementation of IA technological components, including BMP, AI, and RPA. The model also hypothesizes that CSR moderates the relationships between IA implementation and sustainability performance dimensions. Notably, the term investment risk in the present study refers explicitly to the potential risks associated with investing in different available IA products. We consider investment risk a technological factor because it directly relates to the evaluation and selection of technical products offered by vendors. Corporate sustainability performance in the present study denotes how a company achieves key metrics reflecting sustainability across the three pillars of economic, environmental, and social dimensions [14,15]. This includes, among other indicators, profitability, resource efficiency, carbon footprint reduction, employee well-being, and customer satisfaction. The formal CSR strategy in the study refers to a documented and structured strategic approach adopted by a company to integrate ethical, social, and environmental considerations into its business operations. It outlines specific goals, initiatives, and actions that align with the company's commitment to responsible business practices, stakeholder engagement, and sustainability, driving positive social and environmental impact [22]. In this study, for the purpose of moderation analysis, we assessed if the participating companies possess and implement such a formal strategy. Each of the hypothesized relationships is discussed and justified in the following.

4.1. Investment risk

Technology acquisition and adoption can be significantly risky, especially when the new technology is complex and tend to transform business practices [4,70]. As a result, a rash technology investment decision that might appear to be a proper strategic choice might eventually cost the business significantly more than it gains [71]. IA is a complex and integrative technology that involves several investment risks [1]. For example, an improper IA sourcing model that internalizes all implementation processes might result in high costs, especially when the organization lacks the necessary competencies to integrate a new IA solution into the business processes effectively [2]. The literature acknowledges that risks associated with the new technology investment have been a significant barrier to technology implementation [72]. IA is no exception since numerous risks can lead to investment failure [73]. According to Ref. [2]; numerous IA implementation projects have failed to deliver value due to the lack of standardization in IA tools or compliance risks of existing solutions. We propose that organizations would be less strategically capable of successfully integrating IA into business operations when they face certain uncertainties and risks associated with IA solutions. Accordingly, we hypothesize that:

H1. Investment risk significantly affects IA implementation.

4.2. Cybersecurity risk

IA's data-driven, decentralized, and integrative nature significantly increases the risk of cyber-security threats [74]. Indeed, the ongoing digital transformation under the Industry 4.0 framework has resulted in an alarming increase in cyberattacks [75]. Despite recent advancements in cyber protection mechanisms, many businesses are reluctant to consider IA due to the prevalence of cyber threats such as ransomware-based attacks or stealing intellectual property [76]. Within the A.I environment, all manner of information, from product designs, confidential customer data, or trade secrets, can be at risk of cyber-attacks. Cyberattacks can also target the RPA or BPM aspects of IA, hijacking or disrupting production systems or inflicting severe damage to Operations Technologies (OT) or IT infrastructure [37,77]. Recent studies reveal that the cyber risks of modern technological innovations act as a barrier to implementing IA solutions [78,79]. In particular, Ref. [80] explain that manufacturers avoid automation and intelligence technologies that expose them to major cyber risks. Accordingly, we hypothesize that businesses would be less productive in integrating IA solutions if they observe that available automation and intelligence solutions expose them to operational disruption, ransomware-based attacks, or breach of intellectual property:

H2. Cybersecurity risk significantly affects IA implementation.

4.3. Integrability

IA is an integrative technology that relies on vertical and end-to-end integration to deliver its functions [2]. In the IA context, end-to-end integrability implies that IA modules should facilitate the integration of cyber-physical system components and the digital replica of business systems [81]. IA should also facilitate the vertical integration of discrete business components such as back-end systems, processes, operators, and enterprise systems [25,82]. Recent studies show that technology integrability is essential for adopting Industry 4.0 technologies such as AI or process automation [83]. Ref. [84] notably showed that the complexity or lack of integrability had been a critical barrier to adopting AI-driven self-adaptive technologies among Japanese manufacturers. By the same logic, we propose that businesses use IA for managing daily operations more frequently and productively when available solutions are adequately integrable with their existing operations technologies, IT infrastructure, business processes management software, or back-end systems.

H3. Integrability significantly affects IA implementation.

4.4. Strategic value

New technology's value has long been acknowledged as a critical determinant of innovation implementation and usage [52]. Strategic value involves direct and indirect values that the business can gain by implementing the new technology [85]. The strategic value of IA resides in improving competitive advantage via enhancing labor productivity, innovation capacity, production scalability, customer experience, and process efficiency [1,3]. Therefore, the perceived strategic value of IA would expectedly have a substantial impact on organizations' implementation behavior. Indeed, comparative studies published recently reveal that strategic value gains drive businesses toward favorable implementation behavior concerning A.I-empowered process automation [50], A.I-driven production systems [39], and robotic automation (Ghobakhoo and Ching, 2019). Accordingly, and consistent with the use-net benefit loop proposed in Ref. [12] IS success model, we hypothesize that firms integrate and use IA more frequently and extensively when they positively evaluate the strategic value gains of the implemented IA solution.

H4. Strategic value significantly affects IA implementation.

4.5. Absorptive capacity

IA implementation is highly knowledge-intensive and inclusive, requiring an enterprise-wide information-driven IA strategy [86,87]. The functionality of such a strategy involves preventing automation fatigue, eliminating functional silos, and avoiding data uncertainties or algorithmic errors [88]. IA integration extends across the entire value chain of the business, entailing stakeholder engagement as a part of the adoption strategy [5]. Therefore, the firm's ability to involve internal/external stakeholders in the IA implementation process, gather information on the state of the art of IA from internal/external sources, and identify new technology implementation opportunities are expected to be crucial to IA implementation [89]. In other words, the capacity to acquire and exploit IA knowledge will improve firms' capacity, readiness, and technical competencies to progressively integrate IA solutions [90]. Accordingly, absorptive capacity is expected to streamline the implementation and exploitation of IA as it allows firms to redesign or streamline the internal processes better according to the requirements of AI-driven business process monitoring and automation [91]. We also expect absorptive capacity to help with the firm's ability to integrate IA into legacy infrastructure and adapt to the dynamism of this technology.

H5. Absorptive capacity significantly affects IA implementation.

4.6. Digitalization technical competency

IA institutionalization entails the seamless integration of new technological solutions, such as software robotics or automation technologies, into existing information and operations technologies or legacy enterprise systems [16]. Successful IA integration for creating a cohesive digital ecosystem that supports decentralization and real-time capability requires businesses to have a certain degree of digitalization technical competency [24]. Digitalization technical competency for IA implementation is multifaceted. It involves various necessary competencies, from digital technology governance capabilities or integrability and interoperability of existing OT to the adequacy or seamless integrability of IT infrastructure [50,83]. The enabling role of digitalization technical competency for new technology implementation is well-documented within the literature. For example, Ref. [88,92], showed that digitalization technical competency propels manufacturers toward the progressive implementation of Industry 4.0 technologies. This competency has been frequently reported to determine firms' behavior concerning the implementation of robotic process automation [35], A.I-empowered industrial automation [50], and A.I-driven business process automation (Ghobkhloo and Ng, 2019). Thus, we develop the following hypotheses regarding the enabling role of digitalization technical competency.

H6. Digitalization technical competency significantly affects IA implementation.

4.7. Resource availability

In general, new technology acquisition is resource intensive [43], and the literature identifies resource availability as one of the more critical determinants of technology implementation [93,94]. IA is complex, disruptive, and integrative, requiring businesses to possess various tangible and intangible resources [95]. Companies should afford the upfront (e.g., acquisition) and continuous (e.g., maintenance, upgrading, and ancillary) costs associated with IA implementation [80]. Each of these cost categories can vary significantly. For example, the acquisition may involve licensing or system configuration costs, whereas ancillary costs may include continuous training or IA performance monitoring expenses [96]. Scholars have shown that resource availability critically impacts how organizations implement robotic process automation [35], BDA-powered A.I [43], and A.I-powered industrial automation [50]. Accordingly, we postulate that organizations with the necessary resources to afford IA costs (e.g., hardware, software, training, and business process disruptions) would engage in IA implementation more extensively.

H7. Resource availability significantly affects IA implementation.

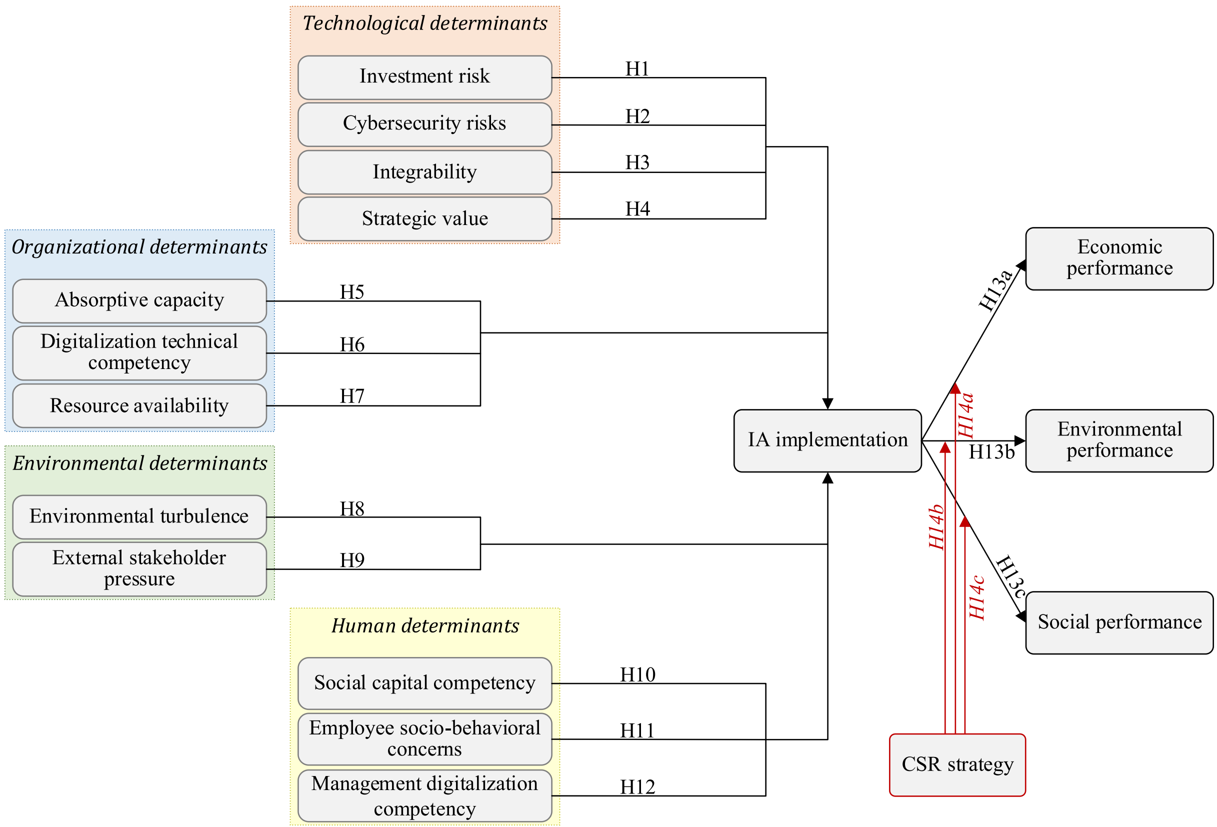

Fig. 2. The research model of study.

4.8. Environmental turbulence

The holy grail of organizational goals is the sustainable competitive advantage, where businesses can gain a stable and favorable position against competitors [97]. Achieving sustainable competitiveness has become more challenging than ever since the external environment of most businesses is nowadays characterized by volatility, turbulence, and unpredictability. The Covid-19 crisis significantly disrupted most industrial sectors, and the Russia-Ukrain conflict has now caught the global economy off guard. Under such circumstances, experts widely acknowledge that businesses draw on digital transformation to respond dynamically to environmental turbulence [98]. Scholars also argue that digitalization can intensify hyper-competition, and the resulting digitalization may overpush mainstream businesses toward digital transformation [97]. Indeed, the environmental turbulence and the resulting competitive pressure have long been acknowledged as critical drivers of technology implementation among businesses [99]. Empirical studies show that environmental turbulence expedites organizational transition toward business process automation [66], AI-driven talent acquisition technology [48], and robotic hotel management technologies [100]. In line with these discussions, we assume that businesses consider IA an effective tool for addressing environmental uncertainties and competitive pressure due to the expected benefits of this technology, such as process adaptability, cost-saving, and decision accuracy.

H8. Environmental turbulence significantly affects IA implementation.

4.9. External stakeholder pressure

Nowadays, external stakeholders, including customers, social actors, and business partners, play a more prominent role in shaping corporate strategic decision-making processes and business strategy [101]. Under the hypercompetitive business environment of Industry 4.0, servitization and product personalization are realized as the pillar of corporate survival [102]. As a result, external stakeholders require manufacturers to diversify their product mix and introduce new service-oriented business models [103]. Alternatively, social actors like the government increase pressure on manufacturing supply chains to reduce their carbon footprint and move toward circular economy [104]. Thus, supply partners are constantly pressured to enhance their product and process efficiency to afford the cost of socio-environmental responsibility [105]. Businesses often implement new technological innovations to address external stakeholders' requirements economically [66,106]. For example, manufacturers may use A.I-driven industrial automation technologies to satisfy customer demand for improved product quality or delivery [50]. Drawing on the potential benefits of IA, we expect organizations to increasingly consider IA as a strategic option for addressing external stakeholder pressure for the product, process, and environmental performance improvement.

H9. External stakeholder pressure significantly affects IA implementation.

4.10. Social capital

This term denotes the tangible or intangible outcomes of human resource interactions. Social capital refers to the human relationships and interactions that improve organizational effectiveness [107]. Social capital contribution to new technology implementation is multifaceted. Social capital promotes collaboration and open communication among internal stakeholders of technological innovation. This condition, in turn, allows employees (e.g., IT experts, end-users, and analysts) to build meaningful relationships and collaborate better on technology implementation tasks [108]. The resulting shared value also assists with building interdepartmental trust and eliminating information silos, streamlining information and knowledge sharing concerning innovation implementation [109]. Shared value also facilitates collective learning, addressing the knowledge intensity of new technology institutionalization [110]. Although the enabling role of social capital for technology adoption is understudied, literature offers valuable early insights into this interaction [111]. For example [93], showed that adopting Industry 4.0 technologies, such as process automation, requires a new social work environment in which inter and intra-organizational teams openly collaborate to gain necessary social and technical skills for interacting with new technological innovation. An empirical study on Industry 4.0 readiness of manufacturing firms reveals that cognitive, social, and structural social capital positively determine a firm's ability to utilize AI and autonomous process monitoring technologies [112]. We build on these arguments and propose that human resources' ability for open inter and intra-organizational collaboration and knowledge sharing would drive businesses to more extensive IA implementation.

H10. Social capital significantly affects IA implementation.

4.11. Employee socio-behavioral concerns

The organizational implementation of disruptive digital technologies like IA fundamentally changes the workplace structure [62,63]. Anger, psychological distancing induced by fear, and anxiety are among the socio-behavioral concerns that IA may cause among employees [80,113]. These socio-behavioral concerns stem from the IA's disruptive nature [13]. IA can damage the workplace environment as it might replace human labor, undermine human autonomy, displace employees, or undesirably change work processes [114,115]. The scholarly literature explains that organizations would be reluctant to use new technology when socio-behavioral concerns about the implementation cause employees to resist technology change [116]. An empirical study of Chinese businesses showed that employees with higher A.I anxiety and concerns are less likely to change to using A.I [62]. Similar findings exist regarding the negative impact of socio-behavioral concerns on the implementation of Industry 4.0 technologies [79] and hospital sensor-based technology [116]. Consistently, we expect businesses to be less open to extensive IA implementation when their employees generally believe that IA disrupts their workplace regarding job loss, work stress, or undermining dignity and autonomy.

H11. Employee socio-behavioral concerns significantly affects IA implementation.

4.12. Management digitalization competency

Scholarly literature identifies the competencies of the top management team as one of the critical determinants of technology integration and usage among organizations [117]. Technologies such as IA are complex and integrative, requiring businesses to have specific digitalization governance competencies to manage the transformation caused by digitalization and automation of business processes [38,118]. Recent literature focuses on the critical role of management and explains that managerial competencies such as involvement, commitment, risk management, and digitalization roadmapping are critical to the firm digitalization success [88,93]. According to Ref. [119]; management competencies such as digitalization support, awareness, commitment, and operational presence are critical to implementing Industry 4.0 technologies such as autonomous robots. Similarly, an empirical study of smart manufacturing technology implementation revealed that management competencies strategically steer digitalization and determine manufacturers' decisions for extensive integration of robotics and process automation technologies [66]. We build on these findings and hypothesize that management competency in terms of empowerment, resource commitment, cost-benefit assessment ability, and technology management capability defines firms' readiness for more extensive integration and utilization of IA solutions.

H12. Management digitalization competency significantly affects IA implementation.

4.13. IA and corporate sustainability performance

Experts believe that IA can impact corporate sustainability performance in various ways [1]. IA may offer a wide range of opportunities for boosting the economic dimension of corporate sustainability performance, examples of which may include optimizing resource management, improving risk management, enhancing customer experience, reducing operational costs, streamlining data-driven decision-making, enhancing productivity, and increasing agility [11,96]. For example, IA can offer cost-saving opportunities by automating repetitive and mundane tasks, increasing operational efficiency, and reducing labor costs [13]. By streamlining processes and minimizing human errors, companies can save costs and allocate resources more effectively [120]. Alternatively, IA can provide businesses the flexibility to respond quickly to market changes and customer demands, leading to better competitiveness and improved economic performance in turbulent business environments [121].

IA can positively contribute to the environmental pillar of corporate sustainability performance by minimizing waste, enabling environmental monitoring, enhancing energy efficiency, and stimulating sustainable supply chain practices (Tsolakis et al., 2023). For example, IA can empower businesses to streamline operations and reduce errors. By doing so, IA allows companies to prevent material waste, lowering the strain on natural resources and minimizing environmental pollution [122,123]. Nevertheless, IA implementation might associate with potential adverse impacts, like e-waste. Indeed, IA relies on integrating a wide range of electronic hardware and components, which can contribute to electronic waste when they become obsolete, causing environmental concerns at the end-of-life and recycling stage [124].

Finally, IA can impact the social pillar of corporate sustainability in controversial ways, with positive and negative implications. IA may offer various positive social implications such as employee empowerment, job enhancement, workplace safety, well-being, job enrichment, and supply chain transparency (which can combat child labor) [64]. For instance, IA can help automate repetitive and monotonous tasks, decreasing work-related stress and burnout, conditions that can positively affect employee well-being, mental health, and work-life balance [13]. Conversely, the misgovernance of IA implementation may lead to various adverse societal effects, such as job displacement, social inequality, and skills gap [16,125]. For example, IA may replace specific job roles, leading to unemployment and job insecurity. Under such circumstances, the displaced workforce may face challenges transitioning to the new employment realities, negatively impacting their livelihoods and well-being [16,125].

Overall, IA implementation and the underlying benefits are not limited to any specific business context, as its application can span various industrial sectors [16,25,86]. For example, IA can offer implications for fraud prevention within the banking, insurance, or financial service sectors, as it optimizes the accuracy, scale, scope, and speed of fraud detection and offers the necessary solution for the issues flagged [28]. IA also provides numerous benefits to manufacturing companies, from supply and demand prediction, adaptability of production capacity, and errors or risk prevention to reducing manual labor, enhancing employee productivity, and improving product quality [1,27]. These arguments lead us to hypothesize that:

H13a. IA implementation significantly affects economic sustainability performance.

H13b. IA implementation significantly affects environmental sustainability performance.

H13c. IA implementation significantly affects social sustainability performance.

4.14. CSR strategy as moderator

CSR strategy denotes the firm's overall strategic plan for executing and optimizing its accountability responsibilities against itself, stakeholders, and the socio-environmental actors [126]. The literature shows that CSR strategy is indispensable to contemporary business [127] and identifies various mechanisms through which CSR strategy might affect the performance of firms [20,21]. While the direct relationship between the firm's CSR profile and financial performance is debated [128], scholars propose that CSR may indirectly boost corporate financial and socio-environmental performance by expanding innovation capabilities [129]. Accordingly, CSR investment has emerged as a pivotal facilitator for a company's pursuit of its environmental, social, and governance objectives [47].

CSR strategy may be critical in how businesses approach and leverage IA for boosting corporate performance. Indeed, it is widely recognized that a CSR strategy is closely associated with corporate sustainability performance [20]. Through implementing the CSR strategy, organizations become more committed to operating ethically, engaging with stakeholders, and contributing to societal values [130]. CSR boosts the overall sustainability of the corporation by fostering positive relationships with stakeholders, minimizing negative environmental impacts through process efficiency, promoting responsible resource management, and prioritizing social development [21]. CSR initiatives empower companies to enhance their reputation, attract and retain talented employees, manage risks, strengthen community ties, and ultimately contribute to long-term economic success while aligning with sustainability values [131]. As a result, a well-implemented CSR strategy is instrumental in aligning corporate digitalization strategy with corporate sustainability priorities. This role is expected to be even more salient for IA, which can be a double-edged sword for the firm's sustainability performance. While IA can potentially boost the triple bottom line, its misgovernance could be detrimental to a few or all aspects of sustainability. Since the scope of CSR strategy spans philanthropic, technological, economic, and socioenvironmental responsibilities [128,132], we expect firms with formal CSR strategies to be more successful in governing IA implementation. In the same vein, we expect firms with formal CSR strategies to better translate the value of IA implementation governance into sustainability performance. Thus, we hypothesize that:

H14a. CSR strategy moderates the relationship between IA implementation and economic sustainability performance.

H14b. CSR strategy moderates the relationship between IA implementation and environmental sustainability performance.

H14c. CSR strategy moderates the relationship between IA implementation and social sustainability performance.

5. Research methodology

This study followed the widely accepted guides to develop the measurement instrument, approach the respondents, and perform the cross-sectional survey to acquire the needed data for testing the hypothesized relationships. The research methods employed are discussed in the following.

5.1. Measurement instrument development

This study measured all variables, excluding CSR strategy, as latent reflective constructs. We developed the measurement items using previously validated items in the literature. The measurement items used in the questionnaire and their respective sources are listed in Appendix. For example, the items measuring the economic, environmental, and social aspects of corporate sustainability performance were adapted from the work of [14,15]. We drew on the work of [39,50,66] and developed three items to measure IA implementation. Following the standard procedure in the technology adoption literature, we measured the corporate sustainability performance and IA implementation constructs within the preceding three years.

After developing the initial measurement instrument, we established a focus group of three distinguished scholars highly experienced in IA and digital organizational transformation. The measurement instrument was pre-tested and revised according to the experts' comments and suggestions. We piloted the revised measurement instrument among 30 multinational firms and applied minor improvements to the questions based on the participants' feedback. We used a 7-point Likert scale to measure all constructs and their respective measures. Following [133]; we defined formal CSR strategy as having well-defined and formalized strategies for designing and executing CSR initiatives as well as explicitly integrating them into corporate management systems. Therefore, CSR strategy was constructed as a dichotomous variable, with values representing either formal or informal CSR strategy.

5.2. Sampling and data collection

The sampling frame of the present study consisted of multinational manufacturing companies. We chose to survey multinationals since these companies are generally pioneers in adopting new technological innovations and are more likely to be familiar with the concept of IA implementation. Moreover, this sampling frame would improve the generalizability of our results. We collaborated with our international research consortium and industrial partners and identified the list of 745 multinational manufacturing companies along with their contact information. The survey was conducted online in mid-2022. We used the multiple informant technique to improve data reliability and reduce the threat of method bias. The value of multiple informant methodology for organizational studies is highly recognized, primarily where survey instrument measures various contextual factors [134]. After administrating the online survey and performing the follow-up activities, we received 207 useable responses, which indicates a response rate of 27.78%. Table 3 lists the descriptive properties of respondents. For instance, the descriptive results showed that the sample is relatively equitably distributed across various manufacturing sectors. Results show that the top five manufacturing sectors in the sample, respectively, are food and beverage (14.49%), motor vehicle equipment (14.01%), metal production (13.04%), machinery equipment (11.59%), and chemical products (10.14%).

Despite using the multiple informant technique, the data collected via a cross-sectional survey can still be susceptible to Common Method Bias (CMB). We used Harman's single-factor test and the statistical remedies technique to assess the presence of CMB [135,136]. Following Harman's approach, exploratory factor analysis was conducted, in which we set the extraction method to principal axis factoring and the number of factors to be extracted fixed to 1. Since the single extracted factor only accounted for 17.01% of the variance, we concluded that there is no trace of CMB in our data. In order to perform statistical remedies, a marker variable ("attitude toward buying green products") was used. There was no significant correlation between the study constructs and the marker variable, which suggests that CMB should not be considered a concern [136]. Since data collection took almost four months, we compared the early responses (the first 25% of the data) against late responses (the last 25% of the data) [66]. The results of independent t-tests showed no meaningful difference between early and late respondents concerning the main variables of the study.

5.3. Data analysis

The study uses PLS-SEM for statistical analysis and assessment of hypothesized relationships. PLS-SEM was selected due to the complexity of the model and the exploratory nature of the study [137]. Since all constructs of the study are measured reflectively, the application of

PLS-SEM in the present work involves assessing reflective measurement models and evaluating the structural path model [137]. We used SmartPls version 3.3.9 [138] for PLS-SEM analysis.

6. Results

6.1. Assessment of reflective measurement model

Following the mainstream guidelines, the study assesses the internal consistency reliability, convergent validity, and discriminant validity to evaluate the reflective measurement models [137]. The results of the measurement model evaluation presented in Table 4 reveal that Cronbach's alpha and composite reliability values of all constructs are above 0.7, indicating satisfying internal consistency reliability. For a given construct, the Average Variance Extracted (AVE) and the outer loading of its reflective indicators can reflect the degree of convergent validity. As a general rule of thumb, the outer loading (indicator reliability) of at least 0.708 and AVE of 0.5 or higher indicate convergent validity [137]. Table 4 reveals that our results adhere to this rule and satisfy the requirements of convergent validity. It is notable that SoSP4 has an outer loading of less than 0.7. However, we decided to maintain this item since its removal did not meaningfully improve internal consistency [137].

Discriminant validity draws on empirical standards to measure how and to what extent a given construct practically (truly) differs from other constructs [139]. Following heterotrait-monotrait (HTMT) approach, discriminant validity is satisfied when all the HTMT values in the HTMT matrix are less than 0.85 [137]. Table 5 represents the results of the HTMT analysis. This table shows that our results adequately satisfy discriminant validity.

6.2. Assessment of structural model

Table 6 and Fig. 3 represent the results of assessing the relevance and significance of hypothesized relationships. Concerning the role of technological factors, results show that investment risk ($\beta = -0.001$, $p > 0.05$), cybersecurity risks ($\beta = 0.024$, $p > 0.05$), and integrability ($\beta = 0.066$, $p > 0.05$) do not significantly determine IA implementation, meaning the rejection of hypotheses H1, H2, and H3. However, strategic value significantly positively affects IA implementation ($\beta = 0.137$, $p < 0.05$), leading to the acceptance of H4.

For organizational factors, results show that absorptive capacity ($\beta = 0.171$, $p < 0.05$), digitalization technical competency ($\beta = 0.215$, $p < 0.01$), and resource availability ($\beta = 0.213$, $p < 0.01$) significantly and positively affect IA implementation. Therefore, hypotheses H5, H6, and H7 are accepted. On the role of environmental determinants, results explain that environmental turbulence ($\beta = 0.086$, $p > 0.05$) and external stakeholder pressure ($\beta = -0.059$, $p > 0.05$) do not exert any significant effect on IA implementation, leading to the rejection of H8 and H9.

Table 3
Descriptive properties of respondents.

Item	Frequency	Percentage
Manufacturing Sector		
Food and beverage	30	14.49%
Motor vehicle equipment	29	14.01%
Metal production	27	13.04%
Machinery equipment	24	11.59%
Chemical products	21	10.14%
Other sectors	76	36.71%
Business size		
Less than 50 employees	43	20.77%
Employees between 50 and 250	89	43.00%
More than 250 employees	75	36.23%
CSR strategy		
With a formal CSR strategy	119	57.49%
Without a formal CSR strategy	88	42.51%

Concerning the human determinants, results in Table 6 and Fig. 3 explain that social capital ($\beta = 0.171$, $p < 0.05$) and management digitalization competency ($\beta = 0.244$, $p < 0.01$) significantly and positively determine IA implementation. Hence, H10 and H12 are accepted. Employee socio-behavioral concerns significantly negatively affect IA implementation ($\beta = -0.213$, $p < 0.01$), leading to the acceptance of H11. Concerning the sustainability performance of IA, results show that IA implementation significantly and positively affects economic ($\beta = 0.447$, $p < 0.01$) and environmental ($\beta = 0.322$, $p < 0.01$) sustainability performance, indicating the acceptance of H13a and H13b. However, H13c is rejected since IA implementation does not significantly determine social sustainability performance ($\beta = 0.078$, $p > 0.05$). The predictors of the study explained 51.7% of the variance in IA implementation. In turn, IA implementation respectively accounted for 20%, 10.4%, and 0.6% of the variance in economic, environmental, and social performance variables.

To assess the predictive relevance of the structural path model, we evaluated Stone-Geisser's (Q^2) values. The Q^2 of more than zero reflects the predictive relevance of a given reflective endogenous construct [140]. Since the Q^2 values for the reflective endogenous constructs of the study, namely IA implementation, economic sustainability performance, and environmental sustainability performance, are respectively 0.394, 0.145, and 0.064, the PLS path model shows satisfying predictive relevance.

6.3. Moderation analysis

Partial Least Squares Multigroup Analysis (PLS-MGA) analysis [141] was applied to test the hypotheses related to the moderating role of CSR strategy. PLS-MGA is a non-parametric test that allows us to calculate the significant differences in path coefficients among the two groups of interest: firms with formal CSR strategy and firms with informal CSR strategy. Table 7 represents the results of bootstrap-based PLS-MGA analysis with 5000 subsamples. Results show no statistically significant difference between IA implementation → economic sustainability performance path coefficients across the two groups ($\Delta PC = 0.051$, $p > 0.05$), indicating the rejection of H14a. Table 7 also suggests the rejection of H14b since IA implementation → environmental sustainability performance path coefficients across firms with formal and informal CSR strategies are not statistically different ($\Delta PC = 0.136$, $p > 0.05$). Nevertheless, there is a statistically significant difference in the IA implementation → social sustainability performance path coefficients between firms with formal and informal CSR strategies ($\Delta PC = 0.846$, $p < 0.01$), pointing to the acceptance of H14c. Interestingly, PLS-MGA results show that IA implementation significantly boosts the social sustainability performance of firms with formal CSR strategy ($\beta = 0.533$, $p < 0.01$). Conversely, this effect is statistically negative among firms with informal CSR strategy ($\beta = -0.293$, $p < 0.01$).

7. Discussion

The study investigated how 12 factors under the TOE-HOT-fit context can impact IA implementation and how IA fairs against the sustainability performance of implementing firms. The summary of findings are presented in Table 8.

Viewed from the technological context, respondents believe that investment risk does not significantly impact IA implementation. This finding implies that the investment risk of IA solutions does not impact how firms build capabilities and mobilize resources for IA digital transformation. A similar pattern was observed for the role of cybersecurity risks. While respondents generally declared that IA entails certain cybersecurity risks, they believed it does not impact how their organizations build capacities and strategies for IA implementation. Our findings on the negative impact of investment and cybersecurity risks on IA implementation align with the works of [52,59]; and [65] that offer similar results in comparable technological contexts such as cloud

Table 4
Measurement model evaluation.

Item	Outer loadings	Cronbach's Alpha	CR	AVE
Absorptive capacity		0.762	0.848	0.583
ABS1	0.771			
ABS2	0.759			
ABS3	0.805			
ABS4	0.716			
Cybersecurity risks		0.831	0.894	0.739
CYB1	0.812			
CYB2	0.841			
CYB3	0.921			
Digitalization technical competency		0.814	0.877	0.641
DTC1	0.842			
DTC2	0.777			
DTC3	0.813			
DTC4	0.767			
Environmental turbulence		0.746	0.838	0.565
ENV1	0.718			
ENV2	0.708			
ENV3	0.847			
ENV4	0.724			
Employee socio-behavioral concerns		0.807	0.873	0.632
ESC1	0.749			
ESC2	0.797			
ESC3	0.844			
ESC4	0.787			
Economic sustainability performance		0.825	0.895	0.741
EcSP1	0.852			
EcSP2	0.848			
EcSP3	0.881			
Environmental sustainability performance		0.773	0.868	0.687
EvSP1	0.787			
EvSP2	0.847			
EvSP3	0.851			
IA implementation		0.885	0.929	0.813
IAI1	0.906			
IAI2	0.888			
IAI3	0.911			
Integrability		0.814	0.887	0.723
INT1	0.799			
INT2	0.844			
INT3	0.905			
Investment risk		0.865	0.903	0.699
INV1	0.786			
INV2	0.877			
INV3	0.843			
INV4	0.837			
Management digitalization competency		0.826	0.884	0.656
MDC1	0.809			
MDC2	0.799			
MDC3	0.768			
MDC4	0.861			
Resource availability		0.854	0.901	0.695
RES1	0.785			
RES2	0.845			
RES3	0.822			
RES4	0.879			
Social capital		0.706	0.836	0.63
SOC1	0.777			
SOC2	0.817			
SOC3	0.786			
External stakeholder pressure		0.721	0.842	0.642
STA1	0.772			
STA2	0.728			
STA3	0.895			
Strategic value		0.885	0.916	0.686
STR1	0.819			
STR2	0.840			
STR3	0.845			
STR4	0.892			
STR5	0.737			
Social sustainability performance		0.856	0.874	0.639
SoSP1	0.902			
SoSP2	0.724			
SoSP3	0.883			
SoSP4	0.662			

Note. CR: Composite Reliability; AVE: Average Variance Extracted.

computing or big data. Nonetheless, the insignificant impact of investment and cybersecurity risks on IA implementation, which resulted in the rejection of H1 and H2, challenges [67,68]; who identified these factors as key determinants of social commerce and IIoT implementation.

Contrary to Refs. [50,66]; we observed no statistically significant relationships between integrability and IA implementation. This controversial finding may be justified by the fact that businesses devise their IA transformation strategies and capabilities regardless of the technical capabilities of available IA solutions. Results further revealed that strategic value significantly and positively determines IA implementation, which supports comparable technology implementation studies in the context of cloud computing [59], IIoT [67], and A.I [69]. Overall, our respondents believed that IA offers value gain regarding employee productivity, innovativeness, process efficiency, customer experience, and market responsiveness. Thus, firms would build the necessary digitalization capabilities and strategic plans to expedite the process of IA implementation when they believe that the IA solutions available would provide them with valuable strategic gains.

Under the organizational context, we assessed the role of absorptive capacity, digitalization technical competency, and resource availability. Our results signified the acceptance of all hypotheses about the organizational context, highlighting the critical role of organizational determinants in shaping IA implementation and usage behavior. Concerning the role of absorptive capacity, results revealed that when organizations have the capacity to involve stakeholders in digital transformation, sense opportunities that new technologies offer for market responsiveness, and gather information on emerging technologies from the business environment, they become more capable of planning and strategizing IA integration. Similarly, higher absorptive capacity in this context leads to shorter IA implementation decision cycles. These findings align well with [89]; who showed that absorptive capacity positively affects firms' willingness to explore and exploit new technological innovations, particularly to automate business operations. These findings also complement the study by Ref. [142]; which showed that absorptive capacity improves firms' ability to implement green technological innovations. We also observed that higher digitalization technical competencies (in terms of adequacy of IT infrastructure, integrability of existing IT/OT, and digitalization governance capabilities) improve the firm's ability to integrate IA progressively into business processes and operations. These results are consistent with comparable studies demonstrating that digitalization technical competencies significantly affect the implementation of IIoT [67], hospital information systems [65], and AI-empowered robotics [50]. Similarly, findings show that resource availability positively affects IA implementation, which is in line with recent contributions highlighting the importance of this factor within cloud computing [59], A.I [39], and digital design technologies [143] adoption contexts. This finding implies that IA is resource-intensive, requiring firms to have the necessary financial resources to afford the direct and indirect implementation costs, such as hardware, software, training, or initial process disruption. This observation further supports Ghobakhloo et al.'s (2022) recent argument that Industry 4.0 technologies, including A.I, are still costly to

Table 5
Heterotrait-monotrait (HTMT).

	ABS	CYB	DTC	EcSP	ESC	EvSP	ENV	IAI	INT	INV	MDC	RES	SOC	SoSP	STA	STR
ABS																
CYB	0.233															
DTC	0.383	0.306														
EcSP	0.270	0.138	0.269													
ESC	0.101	0.126	0.112	0.064												
ENV	0.193	0.127	0.292	0.456	0.047											
EvSP	0.332	0.562	0.372	0.198	0.241	0.115										
IAI	0.504	0.182	0.512	0.523	0.239	0.386	0.302									
INT	0.287	0.321	0.381	0.189	0.137	0.120	0.536	0.294								
INV	0.124	0.346	0.067	0.155	0.199	0.094	0.308	0.055	0.223							
MDC	0.082	0.147	0.074	0.165	0.218	0.160	0.095	0.309	0.092	0.115						
RES	0.391	0.241	0.400	0.092	0.103	0.160	0.348	0.491	0.147	0.044	0.056					
SOC	0.486	0.096	0.301	0.164	0.131	0.214	0.148	0.509	0.243	0.108	0.085	0.312				
SoSP	0.075	0.079	0.116	0.168	0.073	0.213	0.117	0.068	0.068	0.112	0.132	0.100	0.115			
STA	0.332	0.212	0.234	0.074	0.123	0.043	0.495	0.190	0.389	0.112	0.107	0.347	0.170	0.101		
STR	0.381	0.392	0.447	0.209	0.214	0.095	0.373	0.436	0.213	0.249	0.078	0.439	0.375	0.043	0.186	

Table 6
Path coefficient and hypotheses testing.

Relationship	Hypotheses	Path coefficient	t-value	p value
Investment risk → IA implementation	H1	−0.001	0.015	0.988
Cybersecurity risks → IA implementation	H2	0.024	0.365	0.715
Integrability → IA implementation	H3	0.066	1.042	0.298
Strategic value → IA implementation	H4	0.137	2.331	0.020
Absorptive capacity → IA implementation	H5	0.171	2.267	0.024
Digitalization technical competency → IA implementation	H6	0.215	3.064	0.002
Resource availability → IA implementation	H7	0.213	2.796	0.005
Environmental turbulence → IA implementation	H8	0.086	1.229	0.220
External stakeholder pressure → IA implementation	H9	−0.059	0.923	0.356
Social capital competency → IA implementation	H10	0.171	2.568	0.011
Employee socio-behavioral concerns → IA implementation	H11	−0.213	3.530	0.000
Management digitalization competency → IA implementation	H12	0.244	4.562	0.000
IA implementation → Economic sustainability performance	H13a	0.447	7.308	0.000
IA implementation → Environmental sustainability performance	H13b	0.322	4.386	0.000
IA implementation → Social sustainability performance	H13c	0.078	0.633	0.527

implement, and lack of financial resource availability slows down the firm-level technology adoption process.

For environmental context, and contrary to H8 and H9, we observed that environmental competitiveness and external stakeholder pressure are not meaningfully associated with IA implementation, which challenges the comparative studies in the context of A.I-robotics [50,51] and social commerce [68]. These findings imply that in the IA context and viewed from the perspective of our respondents, firms tend to develop their automation and process digitalization strategic plans and competencies based on technological and organizational factors such as available resources or technical capabilities instead of environmental circumstances. This observation implies that IA implementation is profit-driven. Its extent and direction are mainly determined by the firm's internal core values and strategies instead of customers' or social actors' requirements.

Concerning the role of human-based factors, our results showed that social capital competency significantly positively affects IA implementation. This finding revealed that when employees share similar visions and ambitions regarding digital organizational transformation and have the capacity to internally and externally collaborate on driving innovation, the organization would have higher capacities to progress IA integration and extensively use this technology across the business operations. This observation further supports and extends [93]; who showed that external social capital facilitates the implementation of Industry 4.0 advanced technologies among smaller businesses. We observed a similar pattern for the role of employee socio-behavioral concerns. Results pointed out the significant but negative effect of this determinant on IA implementation, which supports comparable studies by Refs. [144,145]. This observation implies that some concerns may negatively brew in the employees' psyche due to interacting with IA. Indeed, results showed that the firm would be considered less technically and strategically willing to extend IA integration when employees believed that IA had been associated with job loss, work conflicts, or undermining their autonomy and dignity. Our results further showed that management digitalization competency significantly positively affects IA implementation, and it can be considered the most critical determinant based on the f^2 effect size values. The dominating role of management competencies is widely acknowledged in the literature [56], especially in technology adoption within smaller businesses [146]. Findings showed that resource commitment, strategic management capability, employee empowerment, and digitalization pre-assessment capability are among the capabilities that facilitate IA implementation. These observations support and extend previous studies offering similar insights within comparable technological contexts like A.I [39], blockchain [53], hospital information systems [65], and social commerce [68].

Finally, yet importantly, results pointed out the crucial implications of IA for the firm's sustainability performance. As inferred from H4, IA is a dominantly profit-driven technology, and results revealed that implementing this technology improves companies' economic sustainability performance significantly. Although none of the core components of IA functionally favor environmentalism, the operations efficiency and effectiveness implications of this technology inadvertently improve the environmental performance of implementing firms in terms of resource efficiency, emission reduction, and compliance with environmental standards. Nonetheless, results did not identify any meaningful association between IA implementation of social sustainability performance. However, assessing the moderating role of CSR strategy revealed that firms with formal CSR strategies have successfully transformed the value of IA implementation into social values. In contrast, IA has been significantly detrimental to the social values in firms with informal CSR strategies.

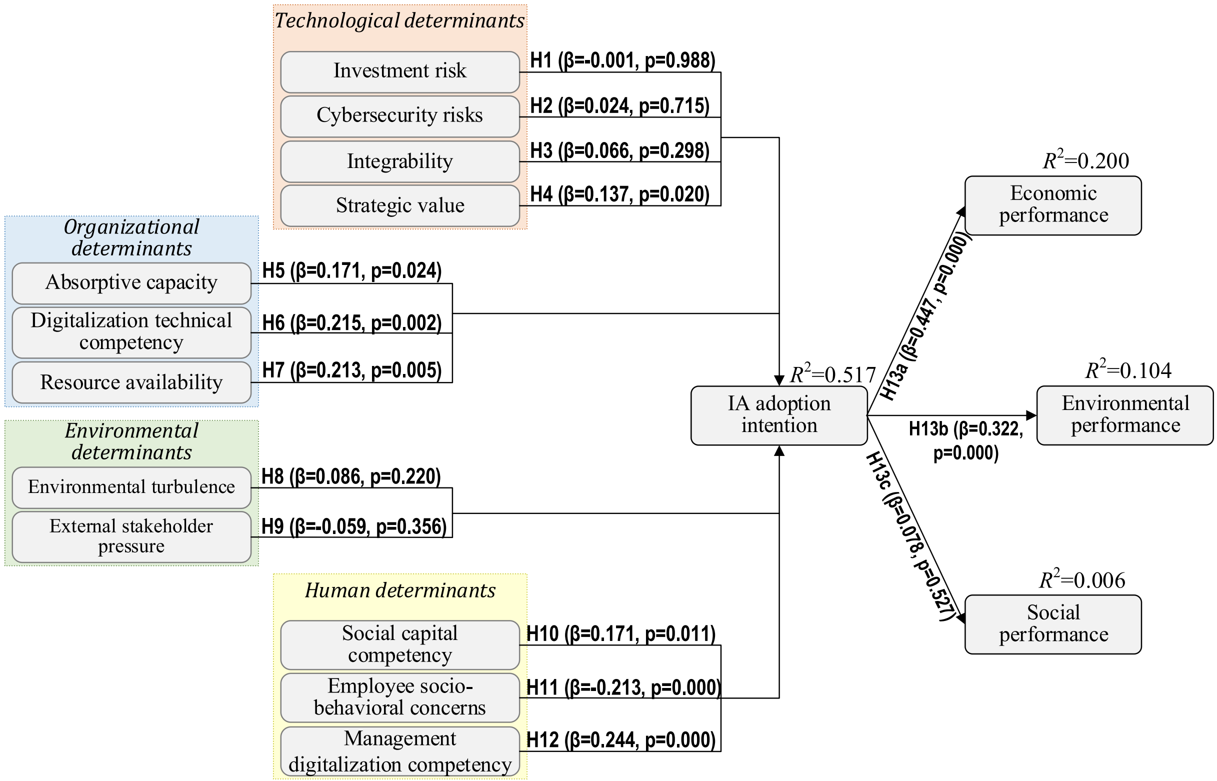

Fig. 3. The structural path model.

8. Conclusions

The study attempted to explain how various factors within and outside organizational boundaries might affect the implementation of IA. The study further strived to assess the implications of IA for corporate sustainability performance. The findings revealed that investment and cybersecurity risks did not significantly affect IA implementation, challenging previous studies that identified these factors as key determinants. However, the strategic value of IA was found to impact the implementation positively. Organizational factors such as absorptive capacity, digitalization technical competency, and resource availability were found to play critical roles in shaping IA implementation. Higher absorptive capacity, digitalization technical competencies, and resource availability positively influenced the integration of IA into business processes.

Regarding sustainability, IA implementation was found to improve economic and environmental performance but did not show a meaningful association with social performance. A formal CSR strategy enhanced the social value of IA implementation, while firms with informal CSR strategies experienced detrimental effects on social values. The study highlights the importance of considering technological, organizational, and sustainability factors in successfully implementing IA. The results of the assessment of hypothesized relationships are expected to offer important implications for the theory and practice.

8.1. Theoretical implications

Businesses worldwide strive to use automation technologies to gain exponential value. IA, which manifests in the integration of A.I, BPM, and RPA, is giving birth to a new era of automation. IA has become a near-term practical technology, and industry experts believe that most business leaders are already moving toward some variation of IA deployment. Nevertheless, IA literature is embryonic; to our knowledge, this study is the first to offer theoretical insights into the IA implementation phenomenon. IA is a disruptive technology, and its implementation significantly relies on human resources. It also radically changes the work environment, affecting the human workforce psyche. Therefore, we integrated the TOE framework with the HOT-fit theory to develop a comprehensive theoretical basis that could account for various determinants of IA implementation within the firm's technological, organizational, environmental, and human resource context. Accordingly, our extended TOE model identified 12 factors determining

Table 7
Results of PLS-MGA analysis.

Relationship	Formal CSRS			Informal CSRS			Formal CSRS vs. Informal CSRS		
	PC	t-Value	p-Value	PC	t-Value	p-Value	ΔPC	t value	p-value
IAI → EcSP	0.478	6.841	0.000	0.428	4.501	0.000	0.051	0.440	0.660
IAI → EvSP	0.397	4.580	0.000	0.261	1.972	0.000	0.136	0.899	0.370
IAI → SoSP	0.553	7.634	0.000	−0.293	4.191	0.000	0.846	8.212	0.000

Note: PC, path coefficient; CSRS, corporate social responsibility strategy; EcSP, economic sustainability performance; EvSP, environmental sustainability performance; SoSP, social sustainability performance.

Table 8
The summary of findings.

Context	Factors	Findings
Technological	Investment risks	No significant impact on IA implementation
	Cybersecurity risks	No significant impact on IA implementation
	Integrability	No significant impact on IA implementation
	Strategic value	Positive impact on IA implementation
Organizational	Absorptive capacity	Positive impact on IA implementation
	Digitalization technical competency	Positive impact on IA implementation
	Resource availability	Positive impact on IA implementation
Environmental	Environmental turbulence	No significant impact on IA implementation
	External stakeholder pressure	No significant impact on IA implementation
Human-based	Social capital competency	Positive impact on IA implementation
	Employee socio-behavioral concerns	Negative impact on IA implementation
	Management digitalization competency	Positive impact on IA implementation
Sustainability	Economic performance	IA implementation improves economic sustainability
	Environmental performance	IA implementation improves environmental performance
	Social performance	No meaningful association found
Moderating effect	CSR strategy	Formal CSR strategies enhance social value of IA implementation, while informal CSR strategies have a detrimental effect on social values of IA implementation

the institutionalization of IA. The close-to-substantial predictive power of our model, manifested in the adjusted coefficient of determination for IA implementation, signifies the robustness of our extended TOE-HOT-fit model for studying this phenomenon.

Our findings revealed that technological and environmental factors, except strategic value, have no meaningful impact on IA implementation. Thus, firms build their IA digitalization plans and capabilities regardless of the technical properties of available IA solutions or environmental circumstances. Alternatively, we observed that the firms' organizational and human-based circumstances significantly determine IA implementation. These observations imply that organizations build their IA adoption strategic plan and capabilities based on their internal characteristics and in isolation from the external business environment. Our results provide empirical support for recent criticism of the negative impact of digital industrial transformation on employee psychology, mainly under the Industry 4.0 phenomenon (e.g., Ref. [13]). Critiques argue that digital industrial transformation and automation may adversely affect some aspects of social sustainability, such as job security, workplace dignity, employee privacy, and autonomy at work. Indeed, our results revealed that IA might associate with many of the said adverse effects on employees. We observed that organizations significantly slow and abandon their IA implementation project when their employees experience that the automation, continuous monitoring, and decentralization features of IA negatively affect job security, work-related stress, autonomy, and workplace dignity. This finding supports the advocate of Industry 5.0, who believe that new technology governance strategies are needed to ensure the human-centricity of emerging disruptive technologies such as IA.

Finally, results showed that IA has important implications for the sustainability performance of implementing firms. As a productivity-driven technology, IA can lead to a radical improvement in the firm's economic performance and promote firm-level sustainability values that are functions of operational efficiency and effectiveness. Nonetheless, IA is a double-edged sword for sustainability values. Indeed, we observed that firms with formal CSR could successfully leverage IA to promote social sustainability performance in terms of employee satisfaction or better engagement with social actors. Conversely, IA can harm social values among firms with informal CSR strategy.

8.2. Practical implications

We believe our findings can offer notable implications for managers and industrialists. Sitting at the intersection of A.I, BPM, and RPA, intelligent automation appears to be the future of business process smartification. IA promises various benefits throughout industries and is being adopted by most industry leaders worldwide. The strategic value of IA implementation may include employee productivity, customer satisfaction, operational flexibility, process efficiency, and organizational innovativeness. Results showed that organizations would improve their strategic digitalization competency and expedite their IA implementation agenda when they consider and experience IA solutions valuable and beneficial to improving their business operations. Assuming the IA adoption phenomenon as a 'common good,' IA stakeholders such as technology providers and governments should strive to raise firms' awareness concerning the values and benefits that IA may deliver to them.

Our results showed that, while valuable and advantageous, IA is a disruptive, integrative, and complex technology. As a result, the IA implementation is highly knowledge and resource intensive. Organizations should note that the resource intensity of IA involves affording the cost of IA hardware and software, temporary process disruption and productivity loss, employee training, and system maintenance costs. Organizations should also note that IA adoption is a knowledge-intensive phenomenon. We observed that absorptive capacity significantly facilitates IA implementation. Thus, it is imperative to note that firms interested in IA should keep themselves updated with the latest development in digital and automation technologies and identify opportunities that emerging technologies can offer for improving their adaptability and responsiveness. Since IA is a dynamic and ever-advancing technology, organizations should acquire information on the state of the art of IA to devise better strategies for involving internal and external stakeholders throughout IA implementation processes. Firms should also expand their social capital competencies to enhance internal digitalization capabilities for IA. This process should include building shared ambition and visions regarding digital transformation among employees and developing internal and external collaboration capabilities to enhance the firm's innovation capacity.

Firms interested in intelligent automation should pay special attention to the facilitating role of management digitalization competency since our results showed that this factor is arguably the most important determinant of IA implementation. The managerial competencies for IA generally involve digitalization pre-assessment capability, empowering employees for active participation in IA integration steps, and commitment to providing the necessary resources. We further observed that IA might adversely affect workplace psychology, given that employee socio-behavioral concerns acted as a significant barrier to implementation in the present study. Consistent with the emerging concept of Industry 5.0, we believe that IA solutions should complement employees' capabilities as technical assistants rather than substitute them. Therefore, firms should take a human-centric approach in adopting IA and assure employees that the automation and smartification of business processes will not replace them nor undermine their autonomy, privacy, and work dignity. The management team should further ensure that this human-centric approach to IA is openly and continuously communicated to the internal stakeholders, particularly employees.

It is also notable that firms could be pushed toward IA due to pressure from the competitive environment or stakeholders. Indeed, Industry 4.0 and the underlying industrial transformation require new business models that support product individualization, servitization, and customer orientation. The ever-intensifying market turbulence and emerging disruptions such as the Covid-19 pandemic require businesses to improve their process and product portfolio continuously to maintain competitiveness. On top of these emerging circumstances, social actors and governments may inadvertently push companies toward cognitive automation to improve their sustainability performance. Therefore, IA can be considered an emerging strategic option for addressing environmental uncertainties and maintaining competitiveness in the age of digital automation. Nonetheless, the extent of IA implementation and the business performance implications of this technology would predominantly be the firm's internal business environment.

This work's most important practical implication relates to contentious findings on the sustainability performance implications of IA within implementing firms. As expected, IA can significantly boost the economic performance of implementing firms. Interestingly, we observed that IA improves the firms' environmental sustainability performance independently of their CSR strategy. These findings imply that IA boosts the economic and environmental performance of firms with formal and informal CSR strategies in a statistically similar manner. However, the formality of CSR strategies significantly determines how IA affects social sustainability values. Indeed, IA enormously improves social values when the CSR strategy is the formal part of the management system, whereas social sustainability is negatively affected by IA within firms with informal CSR strategy. Since the economic and environmental benefits of IA are not the function of CSR strategy formality, it is safe to conclude that there is no specific trade-off associated with boosting the social values of IA via the implementation of the formal CSR strategy. Therefore, companies should note that a formal CSR strategy can serve as a governance tool for assuring the equitable contribution of IA to the triple bottom line.

8.3. Social implications

The findings of the present study may offer notable social implications in the context of implementing IA technologies. The positive impact of social capital competency on IA implementation suggests that fostering collaboration and shared vision among employees can contribute to the successful integration and widespread use of IA across business operations while addressing social concerns that employees might have about this technology. This implies that organizations should prioritize creating a supportive and collaborative work environment that encourages employee participation and engagement in the digital transformation process. By nurturing social capital, companies can enhance the adoption and utilization of IA, leading to increased productivity, innovation, and overall organizational effectiveness while preserving employees' values and well-being.

The research further implies that organizations need competent and digitally savvy managers who can effectively lead and guide the implementation process, aligning it with strategic objectives and allocating the necessary resources. By investing in developing management competencies in the digital realm, companies can overcome challenges and maximize the benefits of IA, ultimately improving their competitiveness and long-term sustainability. This entails top managers' competency and involvement in developing effective CSR strategies that align with corporate digitalization strategy to prioritize societal values and balance economic productivity and socio-environmental sustainability while maintaining the company's competitive position. The findings emphasize the need for top managers to possess strategic capabilities, digitalization competencies, and a proactive approach to addressing IA implementation's social implications. By integrating CSR into the overall business strategy and considering the social and environmental impacts, companies can ensure that IA implementation enhances economic sustainability and contributes positively to society and the environment, thereby achieving a competitive advantage in the long run.

8.4. Limitations and future directions

As with any scientific research, the present study has some limitations that future studies could address. First, the TOE framework does not assume any specific interrelationships among determinants of the technology adoption process. Similarly, we did not consider any particular relationships among the 12 determinants of IA implementation. Nonetheless, referring to recent studies that offer strategy roadmaps for Industry 4.0 technology adoption, some precedence relationships might exist among the determinants of IA implementation, which we could not conceivably assess within the present study. Future research can draw on experts' opinions and decision analysis methods, such as interpretive structural modeling, to explore possible interrelationships among the factors that affect IA implementation.

In addition, our sample was limited to multinational companies, which are generally considered industry leaders and pioneers in adopting new technological innovations. We expect classic companies and, notably, smaller businesses to behave differently regarding IA implementation. For example, we observed that the participating firm had built their IA implementation behavior and the underlying digitalization strategic plan and capabilities merely based on organizational and human factors and almost independent of environmental and technological determinants. Nonetheless, we expect smaller businesses and their IA implementation behavior to be significantly more prone to external environmental circumstances. Future research can extend the present work by testing the original or extended version of our research model in other industrial settings.

Author statement

Morteza Ghobskhloo: Conceptualization, Methodology, Writing- Original draft preparation, Supervision, Formal analysis, Funding acquisition, Writing - Review & Editing.

Shahla Asadi: Data Curation, Formal analysis, Visualization, Methodology.

Mohammad Iranmanesh: Writing- Original draft preparation, Writing - Review & Editing, Formal analysis, Validation.

Behzad Foroughi: Conceptualization, Methodology.

Elaheh Yadegaridehkordi: Conceptualization, Visualization, Project administration.

Muhammad Faraz Mubarak: Conceptualization, Conceptualization, Writing- Original draft preparation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

This research has been a part of a project that received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 810318.

Appendix

Constructs and their respective measurement items.

Construct	Measurement items	Sources
Economic sustainability performance (EcSP)	During the past three years, our organization has achieved improvement in … 1. Return on investment. 2. Profitability. 3. Market share.	[14,15]
Environmental sustainability performance (EvSP)	During the past three years, our organization has … 1. Achieved higher resource efficiency. 2. Enhanced its compliance with environmental standards. 3. Reduced harmful emissions.	
Social sustainability performance (SoSP)	During the past three years, our organization has achieved improvement in … 1. Employee satisfaction 2. Customer satisfaction 3. Equitable employment opportunities 4. Engaging and integrating with social actors	
IA implementation (IAI)	During the past three years … 1. Our organization has developed strategic plans to integrate IA tools progressively. 2. Our organization has always committed to the business transformation needed for IA implementation. 3. Our organization has increasingly progressed in using IA across business processes and operations.	[39,50], [66]
Investment risk (INV)	1. IA solutions' acquisition costs may not remain aligned with the projected benefits. 2. Significant uncertainties are associated with the potential costs and benefits of available IA solutions. 3. The unanticipated actions and strategies of regulatory bodies may deny the functional benefits of IA solutions. 4. Introducing more advanced IA solutions may render the IA solutions available in the market obsolete.	[70,147]
Cybersecurity risks (CYB)	1. Implementing IA in our organization can lead to ransomware-based attacks that may cause operational disruption (e.g., manufacturing automation systems disruption). 2. Implementing IA in our organization can lead to ransomware-based attacks for stealing supplier, business partner, or customer data. 3. Implementing IA in our organization can lead to the theft or breach of intellectual property (e.g., manufacturing process or product design information).	[80,148]
Integrability (INT)	1. IA solutions can integrate with our existing IT infrastructure (e.g., communication networks or cloud infrastructure). 2. IA solutions can integrate with our existing OT (e.g., industrial control systems or embedded computing technologies). 3. IA solutions can integrate with our existing business process management software and back-end systems.	[39,83]
Strategic value (STR)	1. Viewed from the perspective of our organization, implementing IA would increase the productivity of our workforce. 2. Viewed from the perspective of our organization, implementing IA would lead to a product, process, or service innovation. 3. Viewed from the perspective of our organization, implementing IA would enhance process efficiency. 4. Viewed from the perspective of our organization, implementing IA would improve customer experience. 5. Viewed from the perspective of our organization, implementing IA would enhance our scalability to adjust to changes in demand.	[39,66]
Absorptive capacity (ABS)	1. Our organization is capable of identifying and involving critical internal and external stakeholders to engage in the IA implementation process. 2. Our organization is capable of acquiring information on the state of the art of IA. 3. Our organization regularly approaches third parties (e.g., IT consultants, vendors, or universities) to gather information on emerging industrial and automation technologies. 4. Our organization can quickly identify new opportunities in technology implementation to improve its adaptability to market changes.	[89] and ul zia et al. (2022)
Digitalization technical competency (DTC)	1. Our organization has the necessary IT infrastructure to integrate IA solutions. 2. The existing ITs in our organization have the necessary integrability and interoperability to support the seamless integration of new IA solutions. 3. The existing operation technologies in our organization have the necessary integrability and interoperability to support the seamless integration of new IA solutions. 4. Our organization has the necessary information and digital technology governance capabilities to support the implementation of IA solutions.	[50,80]
Resource availability (RES)	1. Our organization has the necessary financial capital to afford the cost of IA hardware and software acquisition. 2. Our organization has the necessary financial capital to afford the indirect IA adoption costs (e.g., hiring experts, maintenance, or cybersecurity measures). 3. Our organization has the resources to provide the necessary in-house or outsourced IA training. 4. Our organization has the necessary resources to withstand the initial disruption caused by IA implementation (e.g., temporary disruption of processes or temporary productivity loss).	[88,149]
Environmental competitiveness (ENV)	1. Environmental uncertainties such as market turbulence or shifts in customer demand threaten our organization's competitiveness. 2. Digitalization and the resulting transformation of existing markets have reshaped the way our organization has to compete. 3. Our company has to improve its productivity performance continuingly to maintain competitiveness.	[50,66]
External stakeholder pressure (STA)	1. Our customers have pressured us to diversify our product portfolio. 2. Social actors such as government pressure us to reduce our carbon footprint throughout the value chain. 3. Our business partners (e.g., suppliers or distributors) require us to continuously improve our products, processes, and services.	[50,83]
Social capital (SOC)	1. In our organization, all employees share similar ambitions and visions regarding digital technological transformation.	[93,107]

(continued on next page)

(*continued*)

Construct	Measurement items	Sources
	2. In our organization, employees are skilled at internal collaboration to advance ideation or innovation. 3. Our organization actively collaborates with external actors (e.g., business partners, universities, or technology providers) to advance ideation or innovation.	
Employee socio-behavioral concerns (ESC)	1. Our employees generally believe that using digital technologies such as AI and automation leads to job loss. 2. Our employees believe that using digital technologies such as AI and automation leads to work conflict or work-related stress. 3. Our employees believe that using digital technologies such as AI and automation undermines their autonomy. 4. Our employees believe that using digital technologies such as AI and automation undermines workplace dignity.	[88,150]
Management digitalization competency (MDC)	1. In our organization, the management team has the necessary competencies to manage the implementation of new digital technological innovations strategically. 2. The management can perform the necessary digitalization pre-assessment in our organization before implementing a new digital technological innovation. 3. In our organization, the management team has the necessary competencies to empower employees to participate in various phases of digital technology implementation. 4. When the decision to implement a new digital technological innovation is made in our organization, the management team commits to providing the necessary resources.	[53,68,88]

References

[1] K.K. Ng, C.-H. Chen, C.K. Lee, J.R. Jiao, Z.-X. Yang, A systematic literature review on intelligent automation: aligning concepts from theory, practice, and future perspectives, Adv. Eng. Inf. 47 (2021), 101246.

[2] M. Lacity, L. Willcocks, Becoming strategic with intelligent automation, MIS Q. Exec. 20 (2) (2021) 1–14.

[3] N. Jha, D. Prashar, A. Nagpal, Combining artificial intelligence with robotic process automation—an intelligent automation approach, in: K.R. Ahmed, A. E. Hassanien (Eds.), Deep Learning and Big Data for Intelligent Transportation: Enabling Technologies and Future Trends, Springer International Publishing, 2021, pp. 245–264, https://doi.org/10.1007/978-3-030-65661-4_12.

[4] C. Coombs, D. Hislop, S.K. Taneva, S. Barnard, The strategic impacts of Intelligent Automation for knowledge and service work: an interdisciplinary review, J. Strat. Inf. Syst. 29 (4) (2020), 101600, https://doi.org/10.1016/j.jsis.2020.101600.

[5] S. Anagnoste, The road to intelligent automation in the energy sector, Manag. Dyn. the Knowl. Econ. 6 (3) (2018) 489–502.

[6] C. Coombs, Will COVID-19 be the tipping point for the Intelligent Automation of work? A review of the debate and implications for research, Int. J. Inf. Manag. 55 (2020), 102182, https://doi.org/10.1016/j.ijinfomgt.2020.102182.

[7] S. Ghosh, The future is both automated and intelligent. Forbes technology council, Retrieved July 16, 2022 from, https://www.forbes.com/sites/forbestechcouncil/2021/04/08/the-future-is-both-automated-and-intelligent/?sh=45cdfcfa5664, 2021.

[8] S.S. Josyula, M. Suresh, R. Raghu Raman, How to make intelligent automation projects agile? Identification of success factors and an assessment approach, Int. J. Organ. Anal. (2021), https://doi.org/10.1108/IJOA-05-2021-274.

[9] M. Attaran, The impact of 5G on the evolution of intelligent automation and industry digitization, J. Ambient Intell. Hum. Comput. 14 (5) (2023) 5977–5993.

[10] M. Dahl, C. Larsen, E. Eros, K. Bengtsson, M. Fabian, P. Falkman, Interactive formal specification for efficient preparation of intelligent automation systems, CIRP J. Manuf. Sci. Technol. 38 (2022) 129–138, https://doi.org/10.1016/j.cirpj.2022.04.013.

[11] O. Kjoersvik, A. Bate, Black swan events and intelligent automation for routine safety surveillance, Drug Saf. 45 (5) (2022) 419–427, https://doi.org/10.1007/s40264-022-01169-0.

[12] W.H. DeLone, E.R. McLean, The DeLone and McLean model of information systems success: a ten-year update, J. Manag. Inf. Syst. 19 (4) (2003) 9–30.

[13] A. Grybauskas, A. Stefanini, M. Ghobakhloo, Social sustainability in the age of digitalization: a systematic literature Review on the social implications of industry 4.0, Technol. Soc. 70 (2022), 101997, https://doi.org/10.1016/j.techsoc.2022.101997.

[14] S.H. Abdul-Rashid, N. Sakundarini, R.A. Raja Ghazilla, R. Thurasamy, The impact of sustainable manufacturing practices on sustainability performance, Int. J. Oper. Prod. Manag. 37 (2) (2017) 182–204, https://doi.org/10.1108/IJOPM-04-2015-0223.

[15] L. Fok, S. Zee, Y.-C.T. Morgan, Green practices and sustainability performance: the exploratory links of organizational culture and quality improvement practices, J. Manuf. Technol. Manag. 33 (5) (2022) 913–933, https://doi.org/10.1108/JMTM-11-2021-0439.

[16] A. Rydzik, C.S. Kissoon, Decent work and tourism workers in the age of intelligent automation and digital surveillance, J. Sustain. Tourism 30 (12) (2022) 2860–2877.

[17] B. Feng, X. Hu, I.J. Orji, Multi-tier supply chain sustainability in the pulp and paper industry: a framework and evaluation methodology, Int. J. Prod. Res. (2021) 1–27.

[18] M. Wade, J. Hulland, The resource-based view and information systems research: review, extension, and suggestions for future research, MIS Q. (2004) 107–142.

[19] B. Wernerfelt, A resource-based view of the firm, Strat. Manag. J. 5 (2) (1984) 171–180.

[20] R. Chandrakant, R. Rajesh, Social sustainability, corporate governance, and sustainability performances: an empirical study of the effects, J. Ambient Intell. Hum. Comput. (2022), https://doi.org/10.1007/s12652-022-04417-4.

[21] R. Rajesh, Predicting environmental sustainability performances of firms using trigonometric grey prediction model, Environ. Dev. 45 (2023), 100830, https://doi.org/10.1016/j.envdev.2023.100830.

[22] L. Lamberti, E. Lettieri, CSR practices and corporate strategy: evidence from a longitudinal case study, J. Bus. Ethics 87 (2009) 153–168.

[23] IBM, Differentiating between Intelligent Automation and Hyperautomation. IBM Cloud Education, 2021. Retrieved July 18, 2022 from, https://www.ibm.com/cloud/learn/intelligent-automation.

[24] A.K. Tyagi, T.F. Fernandez, S. Mishra, S. Kumari, Intelligent Automation Systems at the Core of Industry 4.0. International Conference on Intelligent Systems Design and Applications, 2020.

[25] J. Wirtz, W. Kunz, S. Paluch, The service revolution, intelligent automation and service robots, Eur. Bus. Rev. 29 (5) (2021) 909.

[26] A. Haleem, M. Javaid, R.P. Singh, S. Rab, R. Suman, Hyperautomation for the enhancement of automation in industries, Sens. Int. 2 (2021), 100124, https://doi.org/10.1016/j.sintl.2021.100124.

[27] K. Huysentruyt, O. Kjoersvik, P. Dobracki, E. Savage, E. Mishalov, M. Cherry, E. Leonard, R. Taylor, B. Patel, D. Abatemarco, Validating intelligent automation systems in pharmacovigilance: insights from good manufacturing practices, Drug Saf. 44 (3) (2021) 261–272.

[28] IBM, Intelligent automation. IBM cloud education, Retrieved July 15, 2022 from, https://www.ibm.com/cloud/learn/intelligent-automation, 2021.

[29] M. Indihar Štemberger, B. Buh, L. Milanović Glavan, J. Mendling, Propositions on the interaction of organizational culture with other factors in the context of BPM adoption, Bus. Process Manag. J. 24 (2) (2018) 425–445, https://doi.org/10.1108/BPMJ-02-2017-0023.

[30] G. Meroni, P. Plebani, Artifact-driven monitoring for human-centric business processes with smart devices: assessment and improvement, in: J. Carmona, G. Engels, A. Kumar (Eds.), Business Process Management Forum. BPM 2017, Lecture Notes in Business Information Processing, vol. 297, Springer, Cham, 2017, https://doi.org/10.1007/978-3-319-65015-9_10.

[31] Y. He, W. Wang, BPM software adoption in enterprises based on TOE framework and IS success model, Comput. Model. N. Technol. 18 (12C) (2014) 195–200.

[32] R. Gabryelczyk, N. Roztocki, Business process management success framework for transition economies, Inf. Syst. Manag. 35 (3) (2018) 234–253, https://doi.org/10.1080/10580530.2018.1477299.

[33] A. Van Looy, J.V. Bergh, The effect of organization size and sector on adopting business process management, Business Inf. Syst. Eng. 60 (6) (2018) 479–491, https://doi.org/10.1007/s12599-017-0491-3.

[34] W.P. Wong, M.-L. Tseng, K.H. Tan, A business process management capabilities perspective on organisation performance, Total Qual. Manag. Bus. Excel. 25 (5–6) (2014) 602–617, https://doi.org/10.1080/14783363.2013.850812.

[35] C. Flechsig, F. Anslinger, R. Lasch, Robotic Process Automation in purchasing and supply management: a multiple case study on potentials, barriers, and implementation, J. Purch. Supply Manag. 28 (1) (2022), 100718, https://doi.org/10.1016/j.pursup.2021.100718.

[36] J. Kokina, S. Blanchette, Early evidence of digital labor in accounting: innovation with robotic process automation, Int. J. Account. Inf. Syst. 35 (2019), 100431.

[37] D. Pramod, Robotic process automation for industry: adoption status, benefits, challenges and research agenda, Benchmark Int. J. 29 (5) (2022) 1562–1586, https://doi.org/10.1108/BIJ-01-2021-0033.

[38] M. Cubric, Drivers, barriers and social considerations for AI adoption in business and management: a tertiary study, Technol. Soc. 62 (2020), 101257.

[39] S. Chatterjee, N.P. Rana, Y.K. Dwivedi, A.M. Baabdullah, Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model, Technol. Forecast. Soc. Change 170 (2021), 120880, https://doi.org/10.1016/j.techfore.2021.120880.

[40] L. Chen, L. Zhang, J. Huang, H. Xiao, Z. Zhou, Social responsibility portfolio optimization incorporating ESG criteria, J. Manag. Sci. Eng. 6 (1) (2021) 75–85, https://doi.org/10.1016/j.jmse.2021.02.005.
[41] L. Chen, M. Jiang, F. Jia, G. Liu, Artificial intelligence adoption in business-to-business marketing: toward a conceptual framework, J. Bus. Ind. Market. 37 (5) (2022) 1025–1044, https://doi.org/10.1108/JBIM-09-2020-0448.
[42] A. Molla, P.S. Licker, Perceived e-readiness factors in e-commerce adoption: an empirical investigation in a developing country, Int. J. Electron. Commer. 10 (1) (2005) 83–110.
[43] S. Bag, J.H.C. Pretorius, S. Gupta, Y.K. Dwivedi, Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities, Technol. Forecast. Soc. Change 163 (2021), 120420, https://doi.org/10.1016/j.techfore.2020.120420.
[44] R. Dubey, A. Gunasekaran, S.J. Childe, D.J. Bryde, M. Giannakis, C. Foropon, D. Roubaud, B.T. Hazen, Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: a study of manufacturing organisations, Int. J. Prod. Econ. 226 (2020), 107599.
[45] L.G. Tornatzky, M. Fleischer, A.K. Chakrabarti, Processes of Technological Innovation, Lexington books, 1990.
[46] E. Yadegaridehkordi, M. Nilashi, M.H.N.B.M. Nasir, O. Ibrahim, Predicting determinants of hotel success and development using Structural Equation Modelling (SEM)-ANFIS method, Tourism Manag. 66 (2018) 364–386.
[47] H. Chen, L. Li, Y. Chen, Explore success factors that impact artificial intelligence adoption on telecom industry in China, Journal of Management Analytics 8 (1) (2021) 36–68.
[48] R. Pillai, B. Sivathanu, Adoption of artificial intelligence (AI) for talent acquisition in IT/ITeS organizations, Benchmark Int. J. 27 (9) (2020) 2599–2629, https://doi.org/10.1108/BIJ-04-2020-0186.
[49] H. Ahmadi, M. Nilashi, O. Ibrahim, Organizational decision to adopt hospital information system: an empirical investigation in the case of Malaysian public hospitals, Int. J. Med. Inf. 84 (3) (2015) 166–188.
[50] R. Pillai, B. Sivathanu, M. Mariani, N.P. Rana, B. Yang, Y.K. Dwivedi, Adoption of AI-empowered industrial robots in auto component manufacturing companies, Prod. Plann. Control (2021) 1–17, https://doi.org/10.1080/09537287.2021.1882689.
[51] K. Nam, C.S. Dutt, P. Chathoth, A. Daghfous, M.S. Khan, The adoption of artificial intelligence and robotics in the hotel industry: prospects and challenges, Electron. Mark. 31 (3) (2021) 553–574, https://doi.org/10.1007/s12525-020-00442-3.
[52] P. Maroufkhani, W.K. Wan Ismail, M. Ghobakhloo, Big data analytics adoption model for small and medium enterprises, J. Sci. Technol. Policy Manag. 11 (4) (2020) 483–513, https://doi.org/10.1108/JSTPM-02-2020-0018.
[53] T. Clohessy, T. Acton, Investigating the influence of organizational factors on blockchain adoption, Ind. Manag. Data Syst. 119 (7) (2019) 1457–1491, https://doi.org/10.1108/IMDS-08-2018-0365.
[54] V. Christiansen, M. Haddara, M. Langseth, Factors affecting cloud ERP adoption decisions in organizations, Procedia Comput. Sci. 196 (2022) 255–262.
[55] C.-C. Yeh, Y.-F. Chen, Critical success factors for adoption of 3D printing, Technol. Forecast. Soc. Change 132 (2018) 209–216, https://doi.org/10.1016/j.techfore.2018.02.003.
[56] T. Oliveira, M.F. Martins, Literature review of information technology adoption models at firm level, Electron. J. Inf. Syst. Eval. 14 (1) (2011) p110–121.
[57] F.D. Davis, Perceived usefulness, perceived ease of use, and user acceptance of information technology, MIS Q. 13 (3) (1989) 319–340.
[58] H. Ahmadi, M. Nilashi, L. Shahmoradi, O. Ibrahim, Hospital Information System adoption: expert perspectives on an adoption framework for Malaysian public hospitals, Comput. Hum. Behav. 67 (2017) 161–189.
[59] J.-W. Lian, D.C. Yen, Y.-T. Wang, An exploratory study to understand the critical factors affecting the decision to adopt cloud computing in Taiwan hospital, Int. J. Inf. Manag. 34 (1) (2014) 28–36.
[60] M.M. Yusof, J. Kuljis, A. Papazafeiropoulou, L.K. Stergioulas, An evaluation framework for Health Information Systems: human, organization and technology-fit factors (HOT-fit), Int. J. Med. Inf. 77 (6) (2008) 386–398.
[61] F. Alharbi, A. Atkins, C. Stanier, Understanding the determinants of Cloud Computing adoption in Saudi healthcare organisations, Complex Intell. Syst. 2 (3) (2016) 155–171, https://doi.org/10.1007/s40747-016-0021-9.
[62] Y. Suseno, C. Chang, M. Hudik, E.S. Fang, Beliefs, anxiety and change readiness for artificial intelligence adoption among human resource managers: the moderating role of high-performance work systems, Int. J. Hum. Resour. Manag. 33 (6) (2022) 1209–1236, https://doi.org/10.1080/09585192.2021.1931408.
[63] L. Zheng, N. Montargot, Anger and fear: effects of negative emotions on hotel employees' information technology adoption, Int. J. Prod. Perform. Manag. 71 (5) (2022) 1708–1727, https://doi.org/10.1108/IJPPM-01-2020-0013.
[64] P. Christou, E. Hadjielias, A. Simillidou, O. Kvasova, The use of intelligent automation as a form of digital transformation in tourism: towards a hybrid experiential offering, J. Bus. Res. 155 (2023), 113415.
[65] M. Nilashi, H. Ahmadi, A. Ahani, R. Ravangard, O.b. Ibrahim, Determining the importance of hospital information system adoption factors using fuzzy analytic network process (ANP), Technol. Forecast. Soc. Change 111 (2016) 244–264, https://doi.org/10.1016/j.techfore.2016.07.008.
[66] M. Ghobakhloo, T.C. Ng, Adoption of digital technologies of smart manufacturing in SMEs, J. Ind. Inf. Integr. 16 (2019), 100107, https://doi.org/10.1016/j.jii.2019.100107.
[67] B. Sivathanu, Adoption of industrial IoT (IIoT) in auto-component manufacturing SMEs in India, Inf. Resour. Manag. J. 32 (2) (2019) 52–75.
[68] S.S. Abed, Social commerce adoption using TOE framework: an empirical investigation of Saudi Arabian SMEs, Int. J. Inf. Manag. 53 (2020), 102118, https://doi.org/10.1016/j.ijinfomgt.2020.102118.
[69] Y. Pan, F. Froese, N. Liu, Y. Hu, M. Ye, The adoption of artificial intelligence in employee recruitment: the influence of contextual factors, Int. J. Hum. Resour. Manag. 33 (6) (2022) 1125–1147, https://doi.org/10.1080/09585192.2021.1879206.
[70] M. Benaroch, Managing information technology investment risk: a real options perspective, J. Manag. Inf. Syst. 19 (2) (2002) 43–84.
[71] M. Sony, J. Antony, G. Tortorella, O. McDermott, L. Gutierrez, Determining the critical failure factors for industry 4.0: an exploratory sequential mixed method study, IEEE Trans. Eng. Manag. (2022) 1–15, https://doi.org/10.1109/TEM.2022.3159860.
[72] K.W. Prewett, G.L. Prescott, K. Phillips, Blockchain adoption is inevitable—barriers and risks remain, J. Corp. Account. Finance 31 (2) (2020) 21–28.
[73] R. Syed, S. Suriadi, M. Adams, W. Bandara, S.J. Leemans, C. Ouyang, A.H. ter Hofstede, I. van de Weerd, M.T. Wynn, H.A. Reijers, Robotic process automation: contemporary themes and challenges, Comput. Ind. 115 (2020), 103162.
[74] G. Smith, The intelligent solution: automation, the skills shortage and cyber-security, Comput. Fraud Secur. 2018 (8) (2018) 6–9.
[75] G. Culot, F. Fattori, M. Podrecca, M. Sartor, Addressing industry 4.0 cybersecurity challenges, IEEE Eng. Manag. Rev. 47 (3) (2019) 79–86.
[76] A. Bécue, I. Praça, J. Gama, Artificial intelligence, cyber-threats and Industry 4.0: challenges and opportunities, Artif. Intell. Rev. 54 (5) (2021) 3849–3886.
[77] B.D. Deebak, A.-T. Fadi, Privacy-preserving in smart contracts using blockchain and artificial intelligence for cyber risk measurements, J. Inf. Secur. Appl. 58 (2021), 102749.
[78] A. Corallo, M. Lazoi, M. Lezzi, Cybersecurity in the context of industry 4.0: a structured classification of critical assets and business impacts, Comput. Ind. 114 (2020), 103165, https://doi.org/10.1016/j.compind.2019.103165.
[79] A.G. Khanzode, P. Sarma, S.K. Mangla, H. Yuan, Modeling the industry 4.0 adoption for sustainable production in micro, small & medium enterprises, J. Clean. Prod. 279 (2021), 123489.
[80] M. Ghobakhloo, M. Iranmanesh, M. Vilkas, A. Grybauskas, A. Amran, Drivers and barriers of Industry 4.0 technology adoption among manufacturing SMEs: a systematic review and transformation roadmap, J. Manuf. Technol. Manag. (2022), https://doi.org/10.1108/JMTM-12-2021-0505 ahead-of-print(ahead-of-print).
[81] V.M. Tabim, N.F. Ayala, A.G. Frank, Implementing vertical integration in the industry 4.0 journey: which factors influence the process of information systems adoption? Inf. Syst. Front (2021) https://doi.org/10.1007/s10796-021-10220-x.
[82] M. Sanchez, E. Exposito, J. Aguilar, Industry 4.0: survey from a system integration perspective, Int. J. Comput. Integrated Manuf. 33 (10–11) (2020) 1017–1041.
[83] S. Parhi, K. Joshi, T. Wuest, M. Akarte, Factors affecting Industry 4.0 adoption – a hybrid SEM-ANN approach, Comput. Ind. Eng. 168 (2022), 108062, https://doi.org/10.1016/j.cie.2022.108062.
[84] M. Prause, Challenges of industry 4.0 technology adoption for SMEs: the case of Japan, Sustainability 11 (20) (2019) 5807. https://www.mdpi.com/2071-1050/11/20/5807.
[85] M. Iranmanesh, K.H. Lim, B. Foroughi, M.C. Hong, M. Ghobakhloo, Determinants of Intention to Adopt Big Data and Outsourcing Among SMEs: Organisational and Technological Factors as Moderators. Management Decision, 2022, https://doi.org/10.1108/MD-08-2021-1059 ahead-of-print(ahead-of-print).
[86] T. Coito, M.S.E. Martins, J.L. Viegas, B. Firme, J. Figueiredo, S.M. Vieira, J.M. C. Sousa, A middleware platform for intelligent automation: an industrial prototype implementation, Comput. Ind. 123 (2020), 103329, https://doi.org/10.1016/j.compind.2020.103329.
[87] A.K. Kar, A.K. Kushwaha, Facilitators and barriers of artificial intelligence adoption in business – insights from opinions using big data analytics, Inf. Syst. Front (2021), https://doi.org/10.1007/s10796-021-10219-4.
[88] M. Ghobakhloo, M. Iranmanesh, Digital transformation success under Industry 4.0: a strategic guideline for manufacturing SMEs, J. Manuf. Technol. Manag. 32 (8) (2021) 1533–1556, https://doi.org/10.1108/JMTM-11-2020-0455.
[89] J.M. Müller, O. Buliga, K.-I. Voigt, The role of absorptive capacity and innovation strategy in the design of industry 4.0 business Models - a comparison between SMEs and large enterprises, Eur. Manag. J. 39 (3) (2021) 333–343, https://doi.org/10.1016/j.emj.2020.01.002.
[90] S. Chatterjee, R. Chaudhuri, D. Vrontis, Examining the impact of adoption of emerging technology and supply chain resilience on firm performance: moderating role of absorptive capacity and leadership support, IEEE Trans. Eng. Manag. (2022) 1–14, https://doi.org/10.1109/TEM.2021.3134188.
[91] F. Arcidiacono, A. Ancarani, C. Di Mauro, F. Schupp, The role of absorptive capacity in the adoption of Smart Manufacturing, Int. J. Oper. Prod. Manag. 42 (6) (2022) 773–796, https://doi.org/10.1108/IJOPM-09-2021-0615.
[92] S. Khin, D.M.H. Kee, Factors influencing Industry 4.0 adoption, J. Manuf. Technol. Manag. 33 (3) (2022) 448–467, https://doi.org/10.1108/JMTM-03-2021-0111.
[93] L. Agostini, A. Nosella, The adoption of Industry 4.0 technologies in SMEs: results of an international study, Manag. Decis. 58 (4) (2020) 625–643, https://doi.org/10.1108/MD-09-2018-0973.
[94] D. Horváth, R.Z. Szabó, Driving forces and barriers of Industry 4.0: do multinational and small and medium-sized companies have equal opportunities? Technol. Forecast. Soc. Change 146 (2019) 119–132.

[95] S. Kinkel, M. Baumgartner, E. Cherubini, Prerequisites for the adoption of AI technologies in manufacturing – evidence from a worldwide sample of manufacturing companies, Technovation 110 (2022), 102375, https://doi.org/10.1016/j.technovation.2021.102375.

[96] Deloitte, Calculating Real ROI on Intelligent Automation (IA), 2020. https://www2.deloitte.com/content/dam/Deloitte/us/Documents/technology-media-telecommunications/blue-prism-white-paper-final.pdf.

[97] E.S. Knudsen, L.B. Lien, B. Timmermans, I. Belik, S. Pandey, Stability in turbulent times? The effect of digitalization on the sustainability of competitive advantage, J. Bus. Res. 128 (2021) 360–369, https://doi.org/10.1016/j.jbusres.2021.02.008.

[98] M. Savastano, H. Zentner, M. Spremić, N. Cucari, Assessing the relationship between digital transformation and sustainable business excellence in a turbulent scenario, Total Qual. Manag. Business Excellence (2022) 1–22, https://doi.org/10.1080/14783363.2022.2063717.

[99] Y. Lai, H. Sun, J. Ren, Understanding the determinants of big data analytics (BDA) adoption in logistics and supply chain management, Int. J. Logist. Manag. 29 (2) (2018) 676–703, https://doi.org/10.1108/IJLM-06-2017-0153.

[100] A. Pizam, A.B. Ozturk, A. Balderas-Cejudo, D. Buhalis, G. Fuchs, T. Hara, J. Meira, M.R.G. Revilla, D. Sethi, Y. Shen, O. State, A. Hacikara, S. Chaulagain, Factors affecting hotel managers' intentions to adopt robotic technologies: a global study, Int. J. Hospit. Manag. 102 (2022), 103139, https://doi.org/10.1016/j.ijhm.2022.103139.

[101] J. Moretz, C.C. Giapponi, Stakeholders and business strategy: a role-play negotiation themed exercise, Organization Management Journal 16 (1) (2019) 14–26, https://doi.org/10.1080/15416518.2019.1573130.

[102] A.G. Frank, G.H. Mendes, N.F. Ayala, A. Ghezzi, Servitization and Industry 4.0 convergence in the digital transformation of product firms: a business model innovation perspective, Technol. Forecast. Soc. Change 141 (2019) 341–351.

[103] M.A.P. Pinheiro, D. Jugend, A.B. Lopes de Sousa Jabbour, C.J. Chiappetta Jabbour, H. Latan, Circular economy-based new products and company performance: the role of stakeholders and Industry 4.0 technologies, Bus. Strat. Environ. 31 (1) (2022) 483–499.

[104] I. Kazancoglu, M. Sagnak, S. Kumar Mangla, Y. Kazancoglu, Circular economy and the policy: a framework for improving the corporate environmental management in supply chains, Bus. Strat. Environ. 30 (1) (2021) 590–608.

[105] N.T. Ching, M. Ghobakhloo, M. Iranmanesh, P. Maroufkhani, S. Asadi, Industry 4.0 applications for sustainable manufacturing: a systematic literature review and a roadmap to sustainable development, J. Clean. Prod. 334 (2022), 130133, https://doi.org/10.1016/j.jclepro.2021.130133.

[106] M.A. Hoque, R. Rasiah, F. Furuoka, S. Kumar, Critical determinants and firm performance of sustainable technology adoption in the apparel industry: the stakeholder approach, J. Fash. Mark. Manag.: Int. J. (2022), https://doi.org/10.1108/JFMM-06-2021-0147 ahead-of-print(ahead-of-print).

[107] A. Ganguly, A. Talukdar, D. Chatterjee, Evaluating the role of social capital, tacit knowledge sharing, knowledge quality and reciprocity in determining innovation capability of an organization, J. Knowl. Manag. 23 (6) (2019) 1105–1135, https://doi.org/10.1108/JKM-03-2018-0190.

[108] K.S. Al-Omoush, V. Simón-Moya, J. Sendra-García, The impact of social capital and collaborative knowledge creation on e-business proactiveness and organizational agility in responding to the COVID-19 crisis, J. Innov. Knowl. 5 (4) (2020) 279–288, https://doi.org/10.1016/j.jik.2020.10.002.

[109] Y. Gao, B. Liu, L. Yu, H. Yang, S. Yin, Social capital, land tenure and the adoption of green control techniques by family farms: evidence from Shandong and Henan Provinces of China, Land Use Pol. 89 (2019), 104250, https://doi.org/10.1016/j.landusepol.2019.104250.

[110] F. Galati, Blockchain adoption in supply networks: a social capital perspective, Supply Chain Manag.: Int. J. 27 (7) (2022) 17–32, https://doi.org/10.1108/SCM-12-2019-0448.

[111] A. Michna, R. Kmieciak, Open-mindedness culture, knowledge-sharing, financial performance, and industry 4.0 in SMEs, Sustainability 12 (21) (2020) 9041. https://www.mdpi.com/2071-1050/12/21/9041.

[112] N. ul zia, L. Burita, Y. Yang, Inter-organizational social capital of firms in developing economies and industry 4.0 readiness: the role of innovative capability and absorptive capacity, Rev. Manag. Sci. (2022), https://doi.org/10.1007/s11846-022-00539-3.

[113] N. O'Donovan, From knowledge economy to automation anxiety: a growth regime in crisis? New Polit. Econ. 25 (2) (2020) 248–266, https://doi.org/10.1080/13563467.2019.1590326.

[114] J. Howard, Artificial intelligence: implications for the future of work, Am. J. Ind. Med. 62 (11) (2019) 917–926, https://doi.org/10.1002/ajim.23037.

[115] P.K. McClure, "You're fired," says the robot: the rise of automation in the workplace, technophobes, and fears of unemployment, Soc. Sci. Comput. Rev. 36 (2) (2018) 139–156.

[116] T.-F. Kummer, J. Recker, M. Bick, Technology-induced anxiety: manifestations, cultural influences, and its effect on the adoption of sensor-based technology in German and Australian hospitals, Inf. Manag. 54 (1) (2017) 73–89, https://doi.org/10.1016/j.im.2016.04.002.

[117] J.E. Boritz, J. Efendi, J.-H. Lim, The impact of senior management competencies on the voluntary adoption of an innovative technology, J. Inf. Syst. 32 (2) (2018) 25–46.

[118] D. Hradecky, J. Kennell, W. Cai, R. Davidson, Organizational readiness to adopt artificial intelligence in the exhibition sector in Western Europe, Int. J. Inf. Manag. 65 (2022), 102497, https://doi.org/10.1016/j.ijinfomgt.2022.102497.

[119] A. Moeuf, S. Lamouri, R. Pellerin, S. Tamayo-Giraldo, E. Tobon-Valencia, R. Eburdy, Identification of critical success factors, risks and opportunities of Industry 4.0 in SMEs, Int. J. Prod. Res. 58 (5) (2020) 1384–1400, https://doi.org/10.1080/00207543.2019.1636323.

[120] N. Tsolakis, D. Zissis, S. Papaefthimiou, N. Korfiatis, Towards AI driven environmental sustainability: an application of automated logistics in container port terminals, Int. J. Prod. Res. 60 (14) (2022) 4508–4528.

[121] X. Wang, X. Lin, B. Shao, How does artificial intelligence create business agility? Evidence from chatbots, Int. J. Inf. Manag. 66 (2022), 102535.

[122] H.O. Khogali, S. Mekid, The blended future of automation and AI: examining some long-term societal and ethical impact features, Technol. Soc. 73 (2023), 102232, https://doi.org/10.1016/j.techsoc.2023.102232.

[123] O. Nasir, R.T. Javed, S. Gupta, R. Vinuesa, J. Qadir, Artificial intelligence and sustainable development goals nexus via four vantage points, Technol. Soc. 72 (2023), 102171, https://doi.org/10.1016/j.techsoc.2022.102171.

[124] P. Dauvergne, The globalization of artificial intelligence: consequences for the politics of environmentalism, Globalizations 18 (2) (2021) 285–299, https://doi.org/10.1080/14747731.2020.1785670.

[125] A. Tuomi, M.P. Ascenção, Intelligent automation in hospitality: exploring the relative automatability of frontline food service tasks, J. Hospit. Tour. Insights 6 (1) (2023) 151–173.

[126] A. Shaukat, Y. Qiu, G. Trojanowski, Board attributes, corporate social responsibility strategy, and corporate environmental and social performance, J. Bus. Ethics 135 (2016) 569–585.

[127] N. Orazalin, M. Baydauletov, Corporate social responsibility strategy and corporate environmental and social performance: the moderating role of board gender diversity, Corp. Soc. Responsib. Environ. Manag. 27 (4) (2020) 1664–1676, https://doi.org/10.1002/csr.1915.

[128] S.L. Gillan, A. Koch, L.T. Starks, Firms and social responsibility: a review of ESG and CSR research in corporate finance, J. Corp. Finance 66 (2021), 101889, https://doi.org/10.1016/j.jcorpfin.2021.101889.

[129] D.C. Broadstock, R. Matousek, M. Meyer, N.G. Tzeremes, Does corporate social responsibility impact firms' innovation capacity? The indirect link between environmental & social governance implementation and innovation performance, J. Bus. Res. 119 (2020) 99–110, https://doi.org/10.1016/j.jbusres.2019.07.014.

[130] V. Naciti, Corporate governance and board of directors: the effect of a board composition on firm sustainability performance, J. Clean. Prod. 237 (2019), 117727.

[131] B. Yuan, X. Cao, Do corporate social responsibility practices contribute to green innovation? The mediating role of green dynamic capability, Technol. Soc. 68 (2022), 101868.

[132] M.P. Miles, L.S. Munilla, J. Darroch, The role of strategic conversations with stakeholders in the formation of corporate social responsibility strategy, J. Bus. Ethics 69 (2006) 195–205.

[133] A. Russo, A. Tencati, Formal vs. informal CSR strategies: evidence from Italian micro, small, medium-sized, and large firms, J. Bus. Ethics 85 (2009) 339–353.

[134] S.M. Wagner, C. Rau, E. Lindemann, Multiple informant methodology: a critical review and recommendations, Socio. Methods Res. 38 (4) (2010) 582–618.

[135] P.M. Podsakoff, S.B. MacKenzie, J.-Y. Lee, N.P. Podsakoff, Common method biases in behavioral research: a critical review of the literature and recommended remedies, J. Appl. Psychol. 88 (5) (2003) 879.

[136] M.K. Lindell, D.J. Whitney, Accounting for common method variance in cross-sectional research designs, J. Appl. Psychol. 86 (1) (2001) 114–121, https://doi.org/10.1037/0021-9010.86.1.114.

[137] J.F. Hair, J.J. Risher, M. Sarstedt, C.M. Ringle, When to use and how to report the results of PLS-SEM, Eur. Bus. Rev. 31 (1) (2019) 2–24, https://doi.org/10.1108/EBR-11-2018-0203.

[138] C.M. Ringle, S. Wende, J.-M. Becker, SmartPLS 3, Boenningstedt: SmartPLS GmbH, 2015. http://www.smartpls.com.

[139] J. Henseler, G. Hubona, P.A. Ray, Using PLS path modeling in new technology research: updated guidelines, Ind. Manag. Data Syst. 116 (1) (2016) 2–20, https://doi.org/10.1108/IMDS-09-2015-0382.

[140] W.W. Chin, How to write up and report PLS analyses, in: V. Esposito Vinzi, W. W. Chin, J. Henseler, H. Wang (Eds.), Handbook of Partial Least Squares: Concepts, Methods and Applications, Springer Berlin Heidelberg, 2010, pp. 655–690, https://doi.org/10.1007/978-3-540-32827-8_29.

[141] J. Henseler, C.M. Ringle, R.R. Sinkovics, The use of partial least squares path modeling in international marketing, in: R.R. Sinkovics, P.N. Ghauri (Eds.), New Challenges to International Marketing, vol. 20, Emerald Group Publishing Limited, 2009, pp. 277–319, https://doi.org/10.1108/S1474-7979(2009)0000020014.

[142] M. Aboelmaged, G. Hashem, Absorptive capacity and green innovation adoption in SMEs: the mediating effects of sustainable organisational capabilities, J. Clean. Prod. 220 (2020) 853–863, https://doi.org/10.1016/j.jclepro.2019.02.150.

[143] A.M. Henao Ram-rez, E. López-Zapata, Analysis of the factors influencing adoption of 3D design digital technologies in Colombian firms, J. Enterprise Inf. Manag. 35 (2) (2022) 429–454, https://doi.org/10.1108/JEIM-10-2020-0416.

[144] N. Leesakul, A.-M. Oostveen, I. Eimontaite, M.L. Wilson, R. Hyde, Workplace 4.0: exploring the implications of technology adoption in digital manufacturing on a sustainable workforce, Sustainability 14 (6) (2022) 3311.

[145] N. Malik, S.N. Tripathi, A.K. Kar, S. Gupta, Impact of artificial intelligence on employees working in industry 4.0 led organizations, Int. J. Manpow. 43 (2) (2022) 334–354, https://doi.org/10.1108/IJM-03-2021-0173.

[146] T.H. Nguyen, Information technology adoption in SMEs: an integrated framework, Int. J. Entrepreneurial Behav. Res. 15 (2) (2009) 162–186, https://doi.org/10.1108/13552550910944566.

[147] E. Raguseo, Big data technologies: an empirical investigation on their adoption, benefits and risks for companies, Int. J. Inf. Manag. 38 (1) (2018) 187–195, https://doi.org/10.1016/j.ijinfomgt.2017.07.008.
[148] A. Corallo, M. Lazoi, M. Lezzi, P. Pontrandolfo, Cybersecurity challenges for manufacturing systems 4.0: assessment of the business impact level, IEEE Trans. Eng. Manag. (2021) 1–21, https://doi.org/10.1109/TEM.2021.3084687.
[149] K. Zhu, K.L. Kraemer, J. Dedrick, Information technology payoff in E-business environments: an international perspective on value creation of E-business in the financial services industry, J. Manag. Inf. Syst. 21 (1) (2004) 17–54, https://doi.org/10.1080/07421222.2004.11045797.
[150] C. Yoon, D. Lim, C. Park, Factors affecting adoption of smart farms: the case of Korea, Comput. Hum. Behav. 108 (2020), 106309.