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Assessing the influence of emerging technologies on organizational data driven culture and innovation capabilities: A sustainability performance perspective

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A R T I C L E I N F O

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A B S T R A C T

Industry 4.0 applications can accelerate data driven decision making culture in organizations. Such data driven culture can have a profound impact on the organizational capabilities underlying product and process innovation. While there is a relatively developed body of literature on the effect of data driven culture on organizational performance, there is virtually no study that has examined how Industry 4.0 influences the data driven culture of organizations and how in its turn such culture influences both product and process innovation. Furthermore, the role of organizational data driven culture has seldom been examined in relation to organizational sustainability performance. Against this backdrop, the aim of this study is to examine the role of emerging Industry 4.0 technologies on the data driven culture of organizations and analyze if and how such data driven culture influences organizational performance ultimately translating into competitive advantage. By leveraging the Resource Based View (RBV) and Dynamic Capabilities theory, we developed a theoretical model and tested it using a PLS-SEM approach on a sample of 416 organizations. We found that adoption of industry 4.0 technologies influences organizational performance by improving social, competitive, and financial performance of the organizations relying on data driven culture and improved innovative capabilities.

1. Introduction

The rapid progress of information and communication technologies (ICTs) and more generally digital technologies has accelerated what is known as digital disruption (Alshawi et al., 2003; Soluk et al., 2023). While traditional business models relied typically on physical activities, the advent of ICTs and digital technologies has brought about digitalization of business processes and activities (Büyüközkan and Göçer, 2018; Chaudhuri et al., 2021a, 2021b, 2021c; D'Ambra et al., 2022; Mariani et al., 2023a). Such digitalization of business stems from the deployment of Industry 4.0 technologies including the Internet of Things (IoT), Artificial Intelligence (AI), Cyber Physical System (CPS), Blockchain technology (BCT), and so on (Mariani and Borghi, 2019; Qin et al., 2016). The underlying source of emerging digital technologies is data that allows to generate insights to support decision making (Li et al., 2016; Sharma et al., 2021), leading organizations to deploy a data driven culture facilitating digitalization process (Delen and Zolbanin, 2018). Such data driven culture helps organizations to support process and product innovation (Mariani and Wamba, 2020) eventually impacting the performance of the organizations (Wang et al., 2016, 2018; Thrassou et al., 2022).

Digital transformation enabled by Industry 4.0 technologies adoption supports the flow of real time intra- and inter-organizational data that can make process and product innovation smarter (Holmström et al., 2019; Mariani and Wamba, 2020; Chaudhuri, 2022). Growing scholarly debate revolves around how such digital transformation of organizational activities can lead organizations to achieve different forms of sustainability (Hohn and Durach, 2021). Challenges related to global warming, resource constraints along with compliance with different regulations have put immense pressure on the organizations to

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sustain their economic, social, and environmental commitments while achieving competitive advantage (Seuring and Müller, 2008; Wilhelm et al., 2018; Maheshwari et al., 2022). In this perspective, the adoption of industry 4.0 technologies for digital transformation plays a vital role since it can predict how organizations will influence their environmental activities and achieve sustainability performance (Elia et al., 2021; Silvestre et al., 2020). More specifically, the adoption of industry 4.0 technologies facilitates the identification and reduction of waste and can enhance the recycling processes thus lead to the improvement of organizational sustainability performance (Meindl et al., 2021). However, the role of organizational data driven culture has seldom been examined in relation to organizational sustainability performance. Against this backdrop, the aim of this study is to examine the role of emerging Industry 4.0 technologies on the data driven culture of organizations and analyze if and how such data driven culture influences organizational performance, innovative activities and ultimately translates into competitive advantage. In this vein, with the support of extant literature along with the inputs from the concepts of resource-based view (RBV) (Barney, 1991) and dynamic capability view (DCV) (Teece et al., 1997), a framework has been developed conceptually. Such framework has been validated by the help of PLS-SEM approach through analysis of data obtained from the 416 responses. The study results demonstrate that adoption of industry 4.0 technologies could improve organizational performance by establishing a conducive data driven culture and improving innovative activities in the organizations. The organizational performance duly controlled by their size, age, and variety has been able to improve social, financial, as well as competitive performance of the organizations. It is pertinent to mention here that limited studies have extensively analyzed all these issues in a single study with comprehensive manner like the present study.

2. Literature review and theories

Some studies have demonstrated that applications of industry 4.0 technologies can support the digitalization process, along with establishing a data driven culture that is considered as an important driver for innovation (Davenport and Kudyba, 2016; Wang et al., 2020; Mariani and Nambisan, 2021; Chaudhuri et al., 2021a, 2021b, 2021c). In a study authored by Akter and Wamba (2016), it has been observed that several digital technology giants such as Apple, Alibaba, Facebook, Alphabet/Google, and others could achieve enhanced competitive advantage through the support of data driven culture in their organizations. Other studies have highlighted that organizations must analyze various types of data to enhance their innovation outcomes (Mariani et al., 2023c) and improve their business models to face increasingly volatile market environments (Al-Zyoud and Mert, 2019; Chen et al., 2023; Penco et al., 2019; Chatterjee, 2019). Such arguments are supported by the framework of the Dynamic Capabilities theory (Teece et al., 1997). Thus, from the above discussion, it can be said that the adoption of industry 4.0 technologies within organizations could impact the existing data driven culture in the organizations which could eventually influence innovative activities and outcomes. Organization can achieve enhanced performance if they organizations can improve both their innovation performance and their sustainability performance which include societal, environmental, and financial dimensions (Hsu et al., 2016; Abdel-Baset et al., 2019; Wang et al., 2020; Nguyen, 2021). Thus, it can be said that applications of industry 4,0 technologies could help organizations to potentially influence their existing data driven culture and innovative activities (Chaudhuri and Vrontis, 2021; Bhattacharjee et al., 2021). Several studies also highlighted that applications of industry 4.0 technologies could help organizations improve their sustainability performance (Calabrese et al., 2023; Yang et al., 2023). However, extant literature did not simultaneously investigate how the digitalization process facilitated by the applications of emerging digital technologies could impact both innovative outcomes and practices, as well as sustainable performance. This is a clear research gap that this study bridges in a holistic way.

To interpret how adoption of industry 4.0 technologies could impact organizational innovative activities, data driven culture, and business sustainability performance, this work has combined the resource-based view (RBV) (Barney, 1991) and the dynamic capability view (DCV) (Teece et al., 1997). RBV suggests that not all the in-house resources and competencies can lead to improved innovative activities, data driven culture, and sustainability. Indeed, only those resources that possess valuable, rare, inimitable, and non-substitutable (VRIN) characteristics can translate into competitive advantage (Bhatt and Grover, 2005; Sheshadri, 2015; Shen et al., 2022). In this context, organizational competitiveness can be achieved when organizations have internally (within the organizational boundaries) VRIN resources (Wójcik, 2015; Chuang et al., 2016). However, RBV alone are not sufficient to support strategies in an increasingly volatile and dynamic business environment (Žitkienė et al., 2015). This limitation has been duly addressed by theorists that have initiated and developed the dynamic capability view (DCV) framework (Teece et al., 1997; Karimi and Walter, 2015). DCV tries to provide an interpretation of how and why organizations can adapt themselves and technologies to rapid changes in a turbulent economic environment (Nair et al., 2014). More specifically, dynamic capabilities help organizations sense, seize, and redesign external opportunities to revivify existing in-house opportunities (Sheshadri, 2020). In the context of this work, the exploration and exploitation of industry 4.0 technologies lead organizations to be prepared to react and respond to dynamic changes in the market by improving their data driven culture. This could improve innovation capabilities as well as could enhance sustainability performance of the organizations (Kaur and Mehta, 2016; Vidgen et al., 2017).

Moreover, organizations looking to digitally transform their business activities must ascertain how best to integrate applications of industry 4.0 technologies and could reestablish their operating business model using a more developed way of doing business. There has been a paradigm shift towards business strategy owing to the emergence of industry 4.0 applications and the performance of the organizations towards data driven decision making process which in turn could enhance the innovation ability and competitive advantage of the organizations. In such context, Nadeem et al. (2018) conducted a systematic literature review and found that the digitalization of the organizations by the applications of industry 4.0 technology is intricately linked with cross functional integration of processes and systems, structural changes of the organizations, along with organizational dynamic capabilities which can successfully address the volatile business environment. This concept corroborates dynamic capability view (Teece et al., 1997).

In terms of the above discussions, the study aims at addressing the following research questions (RQs).

RQ1: How can emerging digital technologies influence organizational data driven culture and innovation capabilities?
RQ2: Do applications of emerging technologies to organizations improve the sustainability performance of the organizations?

The aforementioned research questions were addressed by developing a model based on the conjoint deployment of the Resource Based View (RBV) (Barney, 1991) and Dynamic Capabilities theory (Teece et al., 1997). The model was tested on a sample of 416 organizations displaying different size, age, and reference industry. The rest of the paper is organized as follows. Section 2 reviews the literature and most relevant theories. In section 3 we develop our research hypotheses. Section 4 illustrates the methods. Section 5 elucidates the main findings of the analysis while the sixth section offers a holistic discussion of the key findings, provides conclusions, and offers a research agenda.

3. Hypotheses development and proposed conceptual model

The review of relevant studies and theories carried out in the previous section has helped us identify the factors that are likely to influence how industry 4.0 adoption can translate into innovativeness, data driven culture, and sustainability performance. Several hypotheses have been developed and formulated in the ensuing subsections.

3.1. Adoption of industry 4.0 applications

Adoption of industry 4.0 technologies is an essential step to develop smart applications (Maheshwari et al., 2022). These smart applications empower human-machine interactions throough the help of emerging technologies like AI, BCT, IoT, CPS, and so on. These technologies can also improve the creativity of employees within organizations (Schumacher et al., 2016). Relatedly, business models have undergone a notable change due to the emergence of various applications backed by multiple emerging technologies. Such smart applications help the organizations to analyze various types of data faster and in an accurate manner that support decision making processes (Lin et al., 2017). Such applications of emerging technologies including AI (Oyekan et al., 2017), IoT (Bibri, 2018), BCT (Li et al., 2018), and so on have stimulated organizations to digitalize their business activities. Such digitalization of business processes has helped employees to be more creative and helped employees to share their views and knowledge with others, which has supported product and service innovation (Kanarachos et al., 2018). Digital technologies can help the organizations to manage capability deficiencies and could also leverage external resources. Digital technologies could help to formulate appropriate planning for expanding businesses in new markets (Bibri, 2018). Such digitalization process ensures consistency across all the functionalities of the organizations ensuring better financial efficiency and profitability of the organizations (Yu et al., 2021). Digitalization process of the organizations supports in acquiring new competencies, skills, knowledge, and expertise which are all antecedents of the organizational innovative activities (Ardito et al., 2021; Dubey et al., 2022). Application of emerging technologies has allowed organizations to effectively analyze various types of data and accelerate the growth of a data driven culture within the organizations. The data driven culture has enhanced employees' creativity leading to innovation in both products, processes, and practices (Sheshadri, 2019; Yu et al., 2021; Dubey et al., 2022). The adoption of different emerging technologies such as industry 4.0 has supported innovative activities and helped ensure more revenues to achieve better profitability (Enrique et al., 2022). This discussion leads to the development of the following hypothesis.

H1. Adoption of industry 4.0 applications (AOI) positively influences the organizational data driven culture (ODC).

3.2. Data driven culture and innovation

In the digital era, different types of data in huge volume are generated within and outside of the organizations. These data can be accurately analyzed by using different applications of emerging technologies (Wang et al., 2018). The emergence of different digital technologies has accelerated innovation activities in organizations and has triggered the development of new ideas, concepts and business models (Ransbotham and Kiron, 2017; Mariani and Nambisan, 2021). Efficient and fast analysis of huge volumes of data has helped organizations make accurate decisions which could help influence innovative activities. Such an approach has also helped organizations revamp their business processes and develop smart products in relation to customer needs, eventually leading to increased profitability (Vidgen et al., 2017). Thus, the improvement of the organizational data driven culture could lead employees to be more creative and generate novel ideas that could lead to the creation of new products to cater to the needs of dynamic markets (Duan et al., 2018). This phenomenon can be better understood by mobilizing the DCV (Teece et al., 1997). Data driven culture is interpreted as "a pattern of behaviors and practices by a group of people who share a belief that having, understanding, and using certain kinds of data and information plays a crucial role in the success of their organizations" (Kiron et al., 2013, p.18). A study has demonstrated that organizations must improve their data driven culture to enhance their performance (Hindle and Vidgen, 2018). All these observations lead to postulating the following hypotheses.

H2a. Organizational data driven culture (ODC) positively influences the process innovation capability (PIN) of the organization.

H2b. Organizational data driven culture (ODC) positively influences the product innovation capability (PIC) of the organization.

H2c. Organizational data driven culture (ODC) positively influences the organization performance (ORP).

The deployment of emerging technologies helps organizations analyze the various types of data that can be used to quickly respond to an external dynamic market environment (Cosic et al., 2015). Data driven culture influences business models and provides ways through which organizations develop their operations to secure higher profits (Klatt et al., 2011). A study has demonstrated that there is a relation between adoption of industry 4.0 technologies and business process innovation of the organizations (Troilo et al., 2016). More specifically, organizations need to achieve their goals through systematic, cost-effective, and methodical processes. Applications of emerging technologies help organizations promote innovation by embracing new business processes that can engender higher revenue (Chen et al., 2014). Business process innovation is conceptualized as the understanding of new methodologies, technologies, and business strategies deployed in the organizations (Marcon et al., 2022). However, for an effective development of innovative business processes, organizations need to improve their in-house competencies to appropriately use emerging technologies, as implicitly suggested by the RBV theoretical framework (Barney, 1991). Changes made in the business process to make them leaner and more effective are closely associated with business process innovation capability which is supported by digitalization of the existing legacy processes. Such changes can enhance the performance of the organizations (Duman and Akdemir, 2021).

Moreover, data driven culture also supports product innovation (Almodóvar and Nguyen, 2022). The new idea generation is closely associated with the innovation capability of the organizations (Kiron and Shockley, 2011). The creative capability of the employees of the organizations helps in generating new ideas to create new products befitting with the changing needs of the customers in the dynamic market environment (Ramanathan et al., 2017; Chatterjee et al., 2021). Thus, product innovation ability of the organizations would help develop new products based on the ever-changing needs of customers. This influences organizational profitability. This phenomenon is tightly linked to the DCV framework (Teece et al., 1997). Accordingly, organizations need to understand the pulse of volatile market environments that influence organizations towards the development of new products that could enhance organizational performance (Kiron et al., 2013; Duman and Akdemir, 2021). This discussion helps to develop and formulate the following hypotheses.

H3. Process innovation capability (PIN) positively influences organization performance (ORP).

H4. Product innovation capability (PIC) positively influences organization performance (ORP).

3.3. Organizational performance

It has been argued that operational activities need to be improved by using different emerging technologies (Chatterjee et al., 2023; Wamba et al., 2018; Mariani and Borghi, 2023; Wamba and Queiroz, 2020). That body of literature has emphasized that usage of digital technologies can reduce the operational costs and improve the quality of the products along with development of new product delivery systems (Wamba et al., 2019). To make that possible organizations need to strengthen their data driven cultural abilities (Srinivasan and Swink, 2018) also by adopting big data capabilities. More specifically, Gunasekaran et al. (2017) have found that organizations which possess better in-house capability can generate better revenue resulting in higher profits. This finding is corroborated by the core tenets of the RBV framework. While several decades ago most scholars were traditionally focusing on financial performance, today they focus mostly on social and environmental performance (Barbaglia et al., 2023; Jia and Sun, 2023; Mariani and Borghi, 2022). Over the last three decades an increasing number of organizations have engaged in social practices (Yang and Wu, 2016) and in corporate social responsibility (CSR) initiatives that could eventually ensure profitability in the long run (Li et al., 2018; Mariani et al., 2023b). There are both costs and benefits associated to organizational engagement with CSR: on one hand, organizations have to make investments in CSR initiatives; on the other hand, CSR is positively evaluated by organizational stakeholders and therefore can bring to improved overall performance (other things being equal in terms of economic performance) (Baah et al., 2021). Hence, we develop the following hypotheses.

H5a. Better organizational performance (ORP) positively impacts the social performance (SOC) of organizations.

H5b. Better organizational performance (ORP) positively impacts the competitive performance (COP) of organizations.

H5c. Better organizational performance (ORP) positively impacts the financial performance (FIN) of organizations.

3.4. Business sustainability performance

An organization that is highly committed to CSR and social initiatives can get reputational gains and the latter ones can help organizations penetrate in the surrounding markets (Martin-de Castro et al., 2020). However, to commit to CSR, organizations need adequate investment at the initial stage of any socially oriented projects, be related to healthcare, educational programs and more (Li et al., 2018). Social projects also need strict compliance with ethical, legal, and local norms. Those social projects also help introduce better and green production capabilities that can minimize production costs (Yavari and Ajalli, 2021). On the benefits side, organizations engaging with social projects can achieve enhanced financial performance in the long run and translate into competitive advantage (Baah et al., 2021). By addressing economic, social, and environmental issues organizations are more likely to gain a competitive edge. Hence, with the help of the above discussion, we develop the following hypotheses.

H6. Social performance (SOP) of the organization positively influences the competitive performance (COP) of the organizations.

H7. Financial performance (FIN) of the organization positively influences the competitive performance (COP) of the organizations.

In addition to the effects included in the hypotheses developed above, this study has also considered organizational age, size, and type as three control variables which could impact organizational performance.

To sum up the above discussion, we have developed a conceptual model that is represented in Fig. 1.

4. Research design

To validate the model, a survey was conducted among managers. The survey consists of two stages: preparation of the questionnaire and data collection. The survey method has been deemed to be suitable because it aims at testing the hypotheses, developing the measurement scales along with describing the population (Lee and Shim, 2007; Wamba et al., 2019).

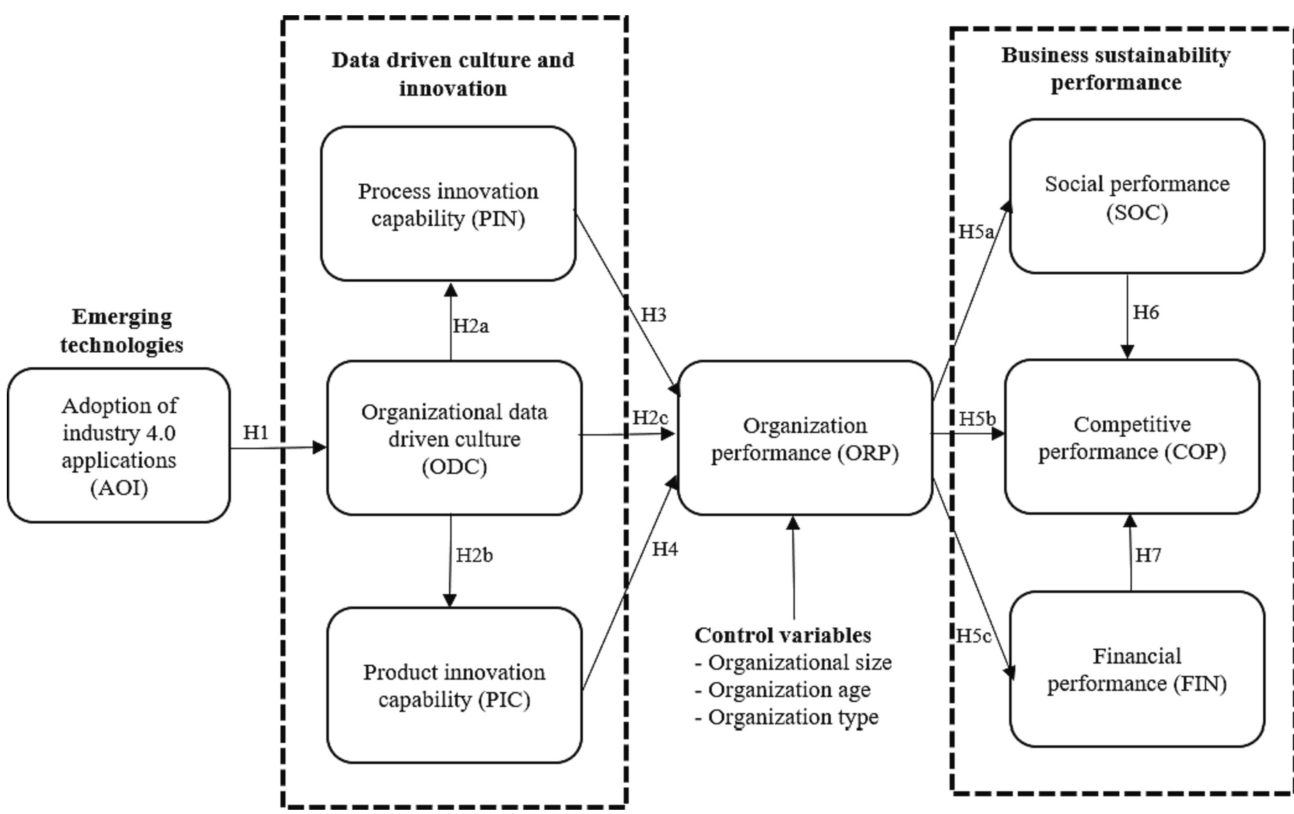

Fig. 1. Conceptual model.

4.1. Preparation of the instruments

A set of questions was developed by adopting relevant measures with the support of extant literature and theories (Barney, 1991; Teece et al., 1997). The recitals of the questions were adjusted according to the context of this study. Each questionnaire item was endowed with a 5-point Likert scale assigning a mark of 1 for Strongly Disagree (SD) and 5 for Strongly Agree (SA).

The questionnaire was pretested with 20 business professionals and academicians. This was done to enhance the readability of the questions. Out of these 20 experts, 12 experts came from industry, each having >10 years of professional experience and the remaining 8 experts came from academia each having >15 years of research experience in the domain of the present study. This improved the readability and understandability of the questions so that the potential respondents could respond without misunderstandings. After the pretest, the questions were piloted with the help of analysis of responses from 25 respondents selected through convenience sampling techniques. These 25 respondents were not included in the main survey, though the criteria of selection of these 25 respondents in the pilot test were the same as those used in the main survey. The input of the respondents helped to rectify the questions and some of the formulations. In this way, it was possible to fine-tune 27 questions.

4.2. Data collection

For this study, India was selected for data collection. There are multiple reasons why the country was chosen. First, there are convenience reasons as some authors of this study are based in India where data collection took place. Second, India is the fifth largest economy in the world and one of the members of BRICS countries. Third, an increasing number of organizations in India are willing to engage in sustainable development goals by adopting different emerging technologies. To collect the data, a list of organizations was retrieved from the Bombay Stock Exchange (BSE) since BSE is known to have been promoting sustainability and CSR initiatives among the organizations (Spulbar et al., 2019). Initially, a list of 900 organizations were selected at random. Out of these 900 organizations, it was observed that 711 organizations used emerging technologies and engaged in improving sustainability performance. Since the unit of analysis of this study is the organization, one of the top executives of each of these 711 organizations was contacted with a request to take part in the survey. All these 711 top executives of 711 organizations were appraised that the aim of the survey was purely academic, and they were assured that their identities will not be disclosed. They were contacted several times over telephone and emails to get them involved in the survey. After that, 532 top executives of 532 organizations agreed to participate in the survey. All of them were provided with response sheets, each containing 27 questions in the form of statements. Each of the top executives was informed by describing how to fill up the response sheet. They were given three months' time (October to December 2022) to respond by appropriately filling up the response sheets. With the scheduled time window responses of 428 top executives of 428 organizations were received. All 428 responses were scrutinized, and it was found that out of 428 responses, 12 responses were incomplete. These were not considered. The analysis of the 416 responses received (representing 416 organizations) was conducted. The details of the 416 organizations are provided in Table 1.

Table 1
Details of the organizations (N = 416).

Particulars	Characteristics	Frequency	Percentage
Organization size	Large (>10,000 employees)	175	42.0
	Medium (1000–10,000 employees)	130	31.3
	Micro and small (<1000)	111	26.7
Organization age	Older (>20 years of establishment)	200	48.1
	Younger (5–20 years of establishment)	140	33.6
	Newly created (<5 years of establishment)	75	18.3
Organization type	Service oriented	255	61.3
	Manufacturing	161	38.7
Industry sector	Automotive	58	13.9
	Pharmaceuticals	70	16.8
	Chemical and petrochemical	33	8.0
	Consumer goods and retail	80	19.2
	Telecommunication	98	23.6
	Information technology	45	10.8
	Transportation and logistics	32	7.7
Profile of respondent	President/Vice Presidents	75	18.2
	Owners	84	20.2
	CXOs	58	13.9
	Sr. Director/Director	91	21.8
	Sr. Managers/Managers	108	25.9

5. Data analysis along with results

To analyze the data, the study deployed PLS-SEM technique. This technique has been preferred since it provides accurate results by analyzing any complex model (Wetzels et al., 2009). Here, PLS3.2.3 software was used with consideration of bootstrapping procedure assuming 5000 resamples (Ringle et al., 2015). The PLS-SEM approach can analyze data that are not normally distributed whereas through the CB-SEM technique, the data which are normally distributed can only be analyzed (Akter et al., 2017).

5.1. Measurement property and discriminant validity test

To examine the convergence validity of each of the items, the loading factor (LF) of each item was measured. To ascertain the validity of the constructs, reliability of the constructs and internal consistency of the constructs, average variance extracted (AVE) of the construct, composite reliability (CR) of the construct and internal Cronbach's alpha (α) of the construct have been computed. All the estimated values are within the allowable range. Table 2 shows the results.

The square roots of all the AVEs were estimated. They were found to be greater than the corresponding bifactor correlation coefficients. This confirms the Fornell and Larcker criteria (Fornell and Larcker, 1981). Hence, discriminant validity of the constructs is also confirmed. The results are shown in Table 3.

5.2. Common method bias (CMB)

The findings of this study depend on survey-based data. Hence, there exists potential for common method bias (CMB). To mitigate the risk of CMB, some procedural steps have been taken. The questionnaire has been made simpler by the help of pretest and pilot test. The respondents were also assured that their anonymity and confidentiality will not be disclosed so that they may provide the responses in an unbiased manner. Also, to verify the risk of CMB, Harman's single factor test (SFT) has been conducted and it was found that the first factor only accounts for 20.62 % of the variance. It is less than the recommended highest value of 50 % as is observed by Podsakoff et al. (2003). Since Harman's SFT is considered not a robust and conclusive test for CMB as opined by Ketokivi and Schroeder (2004), marker correlation ratio test has also been conducted (Lindell and Whitney, 2001). The results also did not provide any evidence of CMB. Hence, it can be safely inferred that CMB cannot distort the data.

5.3. Hypotheses testing

To test our hypotheses, a bootstrapping procedure was adopted by considering 5000 resamples. Assuming separation distance of 7, cross

Table 2
Measurement properties.

Constructs/items	LF	AVE	CR	α	t-Values
AOI		0.75	0.79	0.83	
AOI1	0.91				22.11
AOI2	0.78				26.07
AOI3	0.85				25.77
AOI4	0.97				20.21
AOI5	0.90				19.06
ODC		0.81	0.83	0.87	
ODC1	0.90				20.17
ODC2	0.85				22.19
ODC3	0.95				31.11
PIN		0.79	0.82	0.86	
PIN1	0.80				26.92
PIN2	0.92				31.91
PIN3	0.95				23.77
PIC		0.74	0.81	0.85	
PIC1	0.80				29.11
PIC2	0.87				27.34
PIC3	0.90				32.77
ORP		0.80	0.84	0.87	
ORP1	0.91				29.08
ORP2	0.93				26.21
ORP3	0.89				24.52
ORP4	0.85				26.17
SOC		0.68	0.72	0.83	
SOC1	0.87				29.51
SOC2	0.82				24.17
SOC3	0.79				34.18
FIN		0.78	0.81	0.86	
FIN1	0.90				32.77
FIN2	0.85				29.92
FIN3	0.80				24.45
COP		0.76	0.84	0.88	
COP1	0.80				26.17
COP2	0.85				35.21
COP3	0.95				27.07

validated redundancy was assessed by estimating the Stone-Geisser Q^2 value (Stone, 1974; Geisser, 1975). The Q^2 value came out to be 0.058, which is positive. This confirms that the model has predictive relevance (Mishra et al., 2018). To ascertain the model fit, the standardized root mean square residual (SRMR) was considered as the standard index and its values emerged as 0.064 for PLS and 0.033 for PLSc, both of which are less than the accepted highest cutoff value of 0.08 (Hu and Bentler, 1999). Hence, it can be said that the model is in order. The structural equation modelling technique could help to estimate the path coefficients (β-values) of different linkages along with the corresponding probability values (p-values). Also, coefficients of determination (R^2) have were assessed in respect of all the endogenous variables. The effects of the control variables on the organization performance were also computed. The results are provided in Table 4.

With all these inputs, the model after validation is provided in Fig. 2.

5.4. Results

In this study, the authors have formulated and tested 11 hypotheses that were accepted. The results highlight that AOI impacts ODC significantly and positively since the concerned path coefficient is 0.12 with level of significance as $p < 0.001$(***). The study results highlight that ODC significantly and positively influences PIN, PIC, ORP to the tune of 0.17, 0.28, and 0.22 respectively with levels of significance at $p < 0.05$(*), $p < 0.01$(**), and $p < 0.001$(***). The results of this study show that PIN and PIC significantly and positively impact ORP as the concerned path coefficients are 0.21 and 0.26 with levels of significance at $p < 0.001$(***) and $p < 0.001$(***). The study results also demonstrate that ORP positively and significantly influences SOC, COP, and FIN since the path coefficients concerned are 0.18, 0.24, and 0.29 respectively, with levels of significance as $p < 0.05$(*), $p < 0.01$(**), and $p < 0.001$(***). The results of this study also highlight that SOC and PIN significantly and positively impact COP separately as the concerned path coefficients are 0.41 and 0.44 with respective levels of significance at $p < 0.001$(***) and $p < 0.001$(***). The study results also reveal that the effects of the control variables such as organization size, age, and type on ORP are insignificant since the concerned path coefficients are 0.04, 0.02, and 0.03 respectively each having level of non-significance at $p > 0.5$(ns). As far as the coefficient of determination (R^2) are concerned, ODC can be predicted by AOI to the tune of 45 %, PIN and PIC can be predicted by ODC to the tune of 47 % and 49 % respectively whereas ORP could be predicted by PIN, ODC, and PIC simultaneously to the tune of 42 %. The results of this study also highlight that SOC and PIN could be explained separately by ORP to the tune of 51 % and 56 % respectively whereas COP could be predicted simultaneously by SOC, FIN, and ORP to the extent of 69 % which is the explanatory power of the proposed theoretical model.

6. Discussion and conclusion

6.1. Discussion

This study demonstrates that the adoption of industry 4.0 technologies helps organizations to be more innovative by improving their product and process innovation capabilities, with the active support of

Table 4
Structural equation modelling.

Linkages	Hypotheses	β-Values	p-Values	Remarks
AOI → ODC	H1	0.12	$p < 0.001$(***)	Supported
ODC → PIN	H2a	0.17	$p < 0.05$(*)	Supported
ODC → PIC	H2b	0.28	$p < 0.01$(**)	Supported
ODC → ORP	H2c	0.22	$p < 0.001$(***)	Supported
PIN → ORP	H3	0.21	$p < 0.001$(***)	Supported
PIC → ORP	H4	0.26	$p < 0.001$(***)	Supported
ORP → SOC	H5a	0.18	$p < 0.05$(*)	Supported
ORP → COP	H5b	0.24	$p < 0.01$(**)	Supported
ORP → FIN	H5c	0.29	$p < 0.001$(***)	Supported
SOC → COP	H6	0.41	$p < 0.001$(***)	Supported
FIN→COP	H7	0.44	$p < 0.001$(***)	Supported
Control variables				
Impact of organization size on ORP		0.04	$p > 0.05$(ns)	Not supported
Impact of organization age on ORP		0.02	$p > 0.05$(ns)	Not supported
Impact of organization type on ORP		0.03	$p > 0.05$(ns)	Not supported

Table 3
Discriminant validity test.

Construct	AOI	ODC	PIN	PIC	ORP	SOC	FIN	COP	AVE
AOI	0.87								0.75
ODC	0.29	0.90							0.61
PIN	0.22	0.19	0.89						0.79
PIC	0.26	0.31	0.22	0.86					0.74
ORP	0.31	0.24	0.36	0.39	0.89				0.80
SOC	0.34	0.30	0.24	0.26	0.29	0.82			0.68
FIN	0.29	0.33	0.18	0.21	0.25	0.23	0.88		0.78
COP	0.17	0.29	0.38	0.27	0.21	0.20	0.26	0.87	0.76

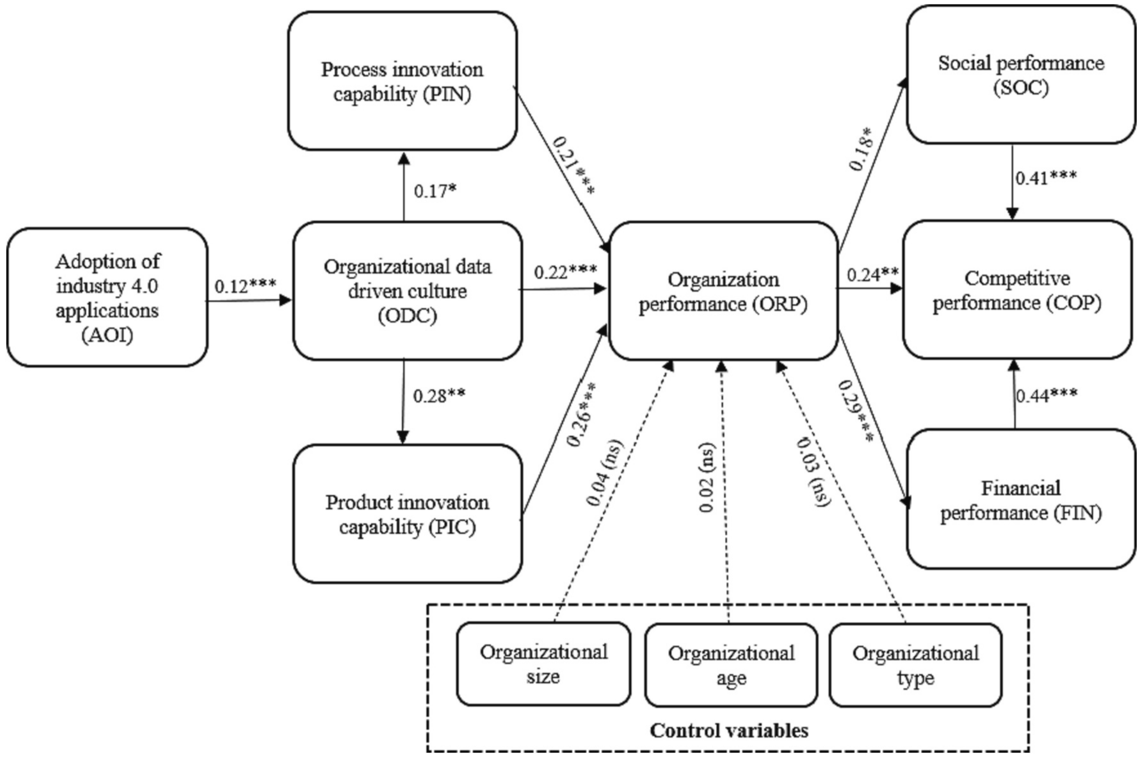

Fig. 2. Model after validation.

data driven culture of the organization. This idea is in line with other studies (Noori and Chen, 2003; Chen et al., 2014; Duan et al., 2018). The study of Noori and Chen (2003) has highlighted how scenario-driven strategy could help the organizations to integrate environmental management and product design processes. The present study has lent the concepts from Noori and Chen (2003) and demonstrated how data driven culture and adoption of industry 4.0 technologies could improve organizational performance. Moreover, another study of Chen et al. (2014) has highlighted that by improving IT capability, the business process agility and environmental management system of the organizations can be enhanced. The present study with the concept of the study of Chen et al. (2014) has demonstrated that adoption of industry 4.0 technologies could help the organizations to enhance their performance by improving the intermediate contextual factors like data driven culture as well as process and product innovation activities. Again, another study of Duan et al. (2018) has recommended that use of business analytics tool could improve innovation ability of the organizations. However, the present study has demonstrated that apart from use of business analytics tools, other industry 4.0 technologies such as blockchain technology, artificial intelligence, and so on could also improve the innovation activities and could facilitate the data driven culture of the organizations which in turn can enhance the sustainable performance of the organizations. This study also suggests that adoption of industry 4.0 applications can improve organizational performance which also in turn, can enhance sustainability performance of the organizations. This idea seems to extend other studies (Birkel and Müller, 2020; Ebinger and Omondi, 2020). Here, the study of Birkel and Müller (2020) has highlighted that the applications of industry 4.0 technologies could improve the sustainability of the organizations especially through the improvement of supply chain system. The concept of this study has helped the present study to develop a comprehensive framework which advocates that adoption of industry 4.0 technologies could improve the organizational process and product innovation activities as well as can establish a conducive atmosphere of data driven culture which help the organizations to improve their sustainability performance. Another study of Ebinger and Omondi (2020) has demonstrated that digitalization can ensure improvement of sustainable supply chain system of the organizations. The concept of this study has supported the present study to highlight that applications of industry 4.0 technologies accelerate the digitalization process of the organizations that in turn could strengthen the innovative abilities thereby supporting data driven culture of the organizations and improving overall sustainable performance.

6.2. Conclusion

This study has been able to demonstrate how the use of emerging technologies can improve both innovative abilities of the organizations with the support of data driven culture along with improvement of sustainability performance of the organizations. Overall, the proposed conceptual framework that was tested has provided an insight to understand how adoption of industry 4.0 technologies can improve process and product innovation capabilities based on a data driven culture and can ultimately improve the societal as well as financial performance of the organizations that eventually translates into competitive advantage. The present study has been able to develop a framework with the help of RBV and DCV. This study has extended the concepts of RBV and DCV through profound analysis of their synergistic effects explaining how use of emerging technologies could improve the overall performance of the organizations with the help of data driven culture of the organizations. Moreover, the proposed framework is expected to support the leaders of the organizations to be able to extract best potentials in using the industry 4.0 technologies helpful to improve the overall performance of the organizations.

7. Implications, limitations, and future scope

7.1. Theoretical contributions

The present study has made several theoretical contributions that we hope will enrich extant literature. First, this study has demonstrated that by adopting Industry 4.0 technologies, organizations could establish a strong data driven culture which has effectively improved product and process innovation capability along with overall performance of the organizations. This extends other studies that have found that Industry 4.0 and generally digital technologies can support product/process innovation (Mariani and Wamba, 2020) as well as innovation performance. Secondly, this study has found that, to be successful in dynamic markets, organizations that deploy emerging (digital) technologies should also focus on strengthening their sustainability performance. This seems to extend recent works at the nexus of emerging technologies and sustainability (Chaudhuri et al., 2021a, 2021b, 2021c: Wamba and Queiroz, 2020). Third, to the best of our knowledge, no other studies have extensively analyzed all these salient factors simultaneously and holistically to investigate how they can improve the competitive performance of organizations. Fourth, this work has also contributed to extending the RBV (Barney, 1991) and DCV (Teece et al., 1997) by analyzing their synergistic effects in the context of emerging (digital) technologies. More specifically, the study suggests that for successful use of emerging technologies and improving the data driven culture of the organizations, in-house VRIN resources and competencies of the organizations need to be improved so that organizations can use proficiently emerging technologies to become more innovative and improve their sustainability performance. As the market is always undergoing rapid changes, organizations need to develop their dynamic abilities to effectively sense and size external opportunities, as well as reconfigure their business models by integrating the seized external opportunities with the in-house capabilities of the organizations. Apparently, this will enable organizations to improve their innovative practices along with improving the organizational data driven culture that will eventually enhance the sustainability performance of the organizations. This extends other studies (Duan et al., 2018; Mariani and Wamba, 2020) that found that the use of several of these technologies (e.g., digital business analytics) could influence innovation activities and performance.

. More generally, our study seems to highlight that various applications of emerging technologies with a strong data driven culture can positively influence product and process innovation capabilities as well as innovation practices. Last, this study has highlighted that the applications of emerging technologies could also improve the sustainability performance of organizations including improvement of social and financial performance to achieve a better competitive advantage. This extends previous studies that have focused either on one or the other dimension.

7.2. Practical implications

The findings of this study also generated implications useful for business leaders or managers who consider making investments in industry 4.0 technologies within their organizations. First, before making investments, managers should carefully evaluate the in-house competencies of the organizations to appropriately sense the rapid dynamic market changes in the external business environment. Second, managers should also weigh the internal competencies of the organizations and whether organizations can appropriately seize the sense of external opportunities and whether the organizations could reconfigure their intangible and tangible assets to improve the innovation capabilities and enhance the sustainability performance. Third, apart from performing routine tasks, managers need to possess foresight to decide when and how to develop organizational capabilities and how it is possible to explore and exploit the capabilities to accomplish better competitive performance. Fourth, to appropriately and efficiently use the emerging technologies to achieve business outcomes, managers need to invest in appropriate training for employees so that the employees' skills and expertise in using the emerging technologies could be improved. Fifth, from the perspective of upholding social commitments through CSR activities and to enhance the sustainability performance, managers need to assess if organizations have adequate resources for this purpose. Sixth, to improve the awareness of employees of social issues that can be addressed through emerging technologies, business leaders should regularly interact with the employees and conduct social awareness programs inside the organizations. This will help the employees to realize that investing in solving social issues could eventually benefit the organizations financially as well as intangibly as improving goodwill and reputation of the organizations.

7.3. Limitations and future scope

The present study is not without limitations. First, the study result depends on cross-sectional data that might display causality issues between the relationships of the constructs. Such issues also give rise to endogeneity flaws. Future research should conduct longitudinal studies to eliminate these issues. Second, this study has built on the DCV (Teece et al., 1997). However, the DCV suffers from issues related to context insensitivity (Ling-Yee, 2007). DCV cannot identify the correct circumstances in which adoption of industry 4.0 technologies could yield best organizational performance (Dubey et al., 2019). It is suggested that future research might explore the optimal conditions under which applications of emerging technologies could provide the best performance of the organizations. Third, the findings of this work depend on the analysis of the respondents who are based in India. This gives rise to external validity issues. To eliminate these issues, it is suggested that future researchers should collect data from organizations spread across the world to increase generalizability. Fourth, the study results also depend on the analysis of inputs of only 416 organizations. This limits generalization as well. Future research should focus on a higher number of organizations. Fifth, the explanatory power of the model is 69 %. It is suggested that future researchers might include other constructs and boundary conditions, to increase the explanatory power of the model.

CRediT authorship contribution statement

Ranjan Chaudhuri: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sheshadri Chatterjee:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Marcello M. Mariani:** Writing – review & editing, Writing – original draft. **Samuel Fosso Wamba:** Writing – review & editing, Writing – original draft.

Declaration of Generative AI and AI-assisted technologies in the writing process

NO AI systems was used to prepare this manuscript.

Data availability

The data that has been used is confidential.

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