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Research Article

Impact of artificial intelligence assimilation on firm performance: The mediating effects of organizational agility and customer agility

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ABSTRACT

In the emerging literature on artificial intelligence (AI) and other disruptive technologies, the importance of technological assimilation has been recognized for high operational and strategic organizational benefits and economic growth. AI is considered as the next productivity frontier for its high capability to transform almost all aspects of intra-and-inter-organizational operations across the industry. Yet, the literature lacks empirical studies on how AI assimilation could lead to improved organizational outcomes such as organizational agility, customer agility and firm performance. This study is an initial attempt to fill this research gap. It draws on the dynamic capability view and the available studies on AI to investigate the impacts of AI assimilation (AIASS) on firm performance (FPERF). Then, it assesses the mediating effects of organizational agility (ORGAG) and customer agility (CUSTAG) on the relationship between the AIASS and FPERF. This study uses an online survey-based approach to collect data from 205 supply chain executives in the USA to test the proposed research model. The findings confirm that AIASS is an important predictor of FPERF, CUSTAG, and ORGAG, with stronger effects on ORGAG. Moreover, ORGAG is an important predictor of CUSTAG and FPERF, with stronger effects on CUSTAG. Furthermore, CUSTAG and ORGAG were found to be complementary partial mediators of the relationship between AIASS and FPERF. These results are discussed, with implications for research and practice. Some limitations to the study are presented, which opens up future research perspectives.

1. Introduction

The core hypothesis for this research study is that the full potential of AI-related technologies to help firms achieve and sustain competitive advantage is subordinated to the full assimilation of such technologies across intra- and inter-organizational business processes (Purvis et al., 2001; Shao, 2019). This can be explained by the critical role of IT assimilation in supporting end-to-end business processes to create and sustain IT-business value (Liu et al., 2013; Shao, 2019). Evidence supporting this hypothesis exists in prior research on IT assimilation. It can be relied on to improve firm performance through absorptive capacity and supply chain agility in the supply chain context (Liu et al., 2013); advance manufacturing and boost product innovation performance (Uwizeyemungu et al., 2015); and to grasp e-government systems that help create business value (Hossain et al., 2011). It appears that the large body of literature mainly focuses only on two aspects of assimilation, namely the key determinants of IT assimilation (Chatterjee et al., 2002; Chaubey & Sahoo, 2021; Liang et al., 2007; Nam et al., 2019; Purvis et al., 2001; Shao, 2019; Wei et al., 2015; Zhu et al., 2006), and IT assimilation as an IT-based outcome (Elbashir et al., 2011; Mu et al., 2015; Purvis et al., 2001; Roberts et al., 2012; Shao, 2019).

The assimilation of artificial intelligence (AI) is a subject that also needs some studies, as so far, little has been written about AI assimilation, including for high-level operational and strategic performance, whether it is from the practitioner's perspective (McKinsey Global Institute, 2018, 2019) or from of viewpoint of scholars (Abubakar et al., 2019; Allal-Chérif et al., 2021; Alter, 2021; Chatterjee et al., 2021; Demlehner et al., 2021; Dubey et al., 2021; Dwivedi et al., 2021; Farrokhi et al., 2020; Sipior, 2020; Sung et al., 2021; Wang et al., 2021; Zhang et al., 2021). However, the emerging literature has already acknowledged the high business value potential of AI (Ashok et al., 2022; Collins et al., 2021; Doumpos et al., 2022; Duan et al., 2019; Dwivedi et al., 2021; Fosso Wamba et al., 2021; Mariani & Borghi, 2019; Mariani et al., 2022; Pereira et al., 2022; Stahl, 2022; Zeba et al., 2021), including for improved productivity and employment (Yang, 2022), organizational innovation performance (Rammer et al., 2022), climate change tracking (Leal Filho et al., 2022), macrolevel factors of entrepreneurial opportunity forcasting (Jabeur et al., 2022), manufacturing

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(Pillai et al., 2021), sustainable manufacturing and circular economy (Bag et al., 2021). Yet, in their bibliometric analysis of AI for social good, Fosso Wamba et al. (2021) found that only 0.6% of documents were directed toward AI-enabled economic empowerment, including opening access to economic resources and opportunities. Similarly, Almirall (2022) argued that "the adoption of AI itself is largely absent from most of the organizations with which we directly interact or work" (p. 1). Another study by Olan et al. (2022) found that the "implementation of AI technologies alone is not sufficient in improving organizational performance" (p. 605).

In this context, the relevance of the identified research gap is supported by recent studies from scholars (Olan et al., 2022) and industry practitioners (WEF, 2020; Forbes, 2022). For instance, McKinsey (2021), in a recent survey, highlighted that AI tool adoption continues to increase. Besides, in this survey, a significant number of executives reported that adopting AI reduced the firms' costs and improved high returns from AI. In addition, WEF (2022), in its survey about AI, found that more than half of the participants reported that they believe in profound transformations in the use of AI in the firm's services and products. Therefore, this research is an initial effort to compensate for the existing literature deficiencies. More specifically, it seeks to examine the following research questions (RQs):

RQ1. What are the direct effects of AI assimilation on organizational agility, customer agility, and firm performance?

RQ2. What are the mediating effects of organizational and customer agility on the relationship between AI assimilation and firm performance?

In order to address these research questions, this study explored the emerging literature on AI and the dynamic capability view (DCV) (Teece et al., 1997). Data were collected from 205 supply chain executives based in the United States (USA). The structure of this paper appears as follows. After the introduction, the literature review is presented in Section 2, then outline how and on which basis the hypotheses are delineated in Section 3. The research design features in Section 4, followed by the data analysis and results in Section 5. Then, Section 6 is about the discussion of the key findings of the study. The conclusions of the study are presented in Section 7.

2. Literature review

2.1. A primer of AI

AI is defined as "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (p. 5) (Haenlein & Kaplan, 2019). While first articles on AI can be traced back to the 1940s (Haenlein & Kaplan, 2019), it is only recently that this technology received much attention from both practitioners and scholars, mainly because of the availability of "big data" that enabled the emergence of the so-called "data-based AI", the development of cloud computing, the increase in computing powers of machines, and advances in deep learning (Seth, 2019). These nurtured interests in AI could be explained by its high ability to transform almost all aspects of organizational management for increased productivity and sustainability of competitive advantage.

For example, AI could be used to achieve deep market engagement and sense critical events related to business activities (Farrokhi et al., 2020), support and create value to a firm's operations (Fosso Wamba et al., 2022), facilitate competitive advantage (Baabdullah et al., 2021; Chatterjee et al., 2021), enhance firm performance (e.g., financial performance and non-financial performance) (Baabdullah et al., 2021; Wamba-Taguimdje et al., 2020), support the responsible digital health (Fosso Wamba & Queiroz, 2021) and help unveil employees' turnover intention (Li et al., 2019). It can also improve customer services and experience (Samala et al., 2020), foster environmental governance (Nishant et al., 2020), play an essential role in fighting pandemics (e.g., COVID-19) (Sipior, 2020), and enhance patient flows in healthcare settings by streamlining administrative tasks and optimizing the allocation of resources (Dawoodbhoy et al., 2021). Other essential advantages of AI include the optimization of end-to-end business processes, the facilitation of automation (Wamba-Taguimdje et al., 2020), its ability to enhance efficiency (e.g., space optimization, labor productivity) and effectiveness (e.g., error reduction) (Zhang et al., 2021) in business value creation.

Trocin et al. (2021) demonstrated the ability of AI-enabled organizational digital innovation to transform digital processes and services and thus improve organizational performance (e.g., a higher degree of perceived fairness, less biased decision-making, transparent feedback, increased communication) (p. 8). Wang et al. (2021) showed that the effective use of AI-enabled voice robots could lead to procedural justice and enhance perceived public service value. Samala et al. (2020) argued that AI enables automated, customized, and insightful travel services. According to these authors, travelers can rely on AI to deepen their knowledge about their own behaviors and their inclination and preference interests while customizing the experience they offer (p. 1). Upon an empirical investigation of applications of AI algorithms in wind power technology innovation from 1980 to 2017, Lee and He (2021) found that AI had accelerated the automation of wind power systems. And when combined with advanced data analytics, AI proved to significantly "increase the efficiency of wind power systems and to optimize wind farm operations," they concluded (p. 1).

Wong et al. (2022) drew on the RBV to examine the impact of AI on supply chain risk management for SMEs. They found that using AI for risk management could lead to improved supply chain re-engineering capabilities and supply chain agility. Spanaki et al. (2021) discussed AI applications-enabled data sharing in agriculture 4.0. Demlehner et al. (2021), through a Delphi study, were able to identify twenty different high-level use cases where AI adoption and use could enhance the car manufacturing sector (e.g., production forecasting and planning, reduction of robot energy consumption, object labeling and tracking) (p. 6). Sung et al. (2021) concluded that interactive AI and mixed reality technology could improve consumer engagement. Samuel et al. (2022) investigated AI-enabled improved human performance. Mariani and Borghi (2021) discussed some implications of AI-enabled hotel service interactions. Mariani and Fosso Wamba (2020) argued that AI could be used for improved customer service, including sales prediction on an item-by-item basis. In a study that assesses the firm level of AI's impact on productivity and employment, Yang (2022) found that AI has a positive relationship between productivity and employment. Rammer et al. (2022) revealed a positive link between AI and organizational innovation performance. Mariani et al. (2021) presented an example of AI-enabled tourist arrivals prediction. Johnson et al. (2022) argued that informed AI (IAI) is a suitable tool for product defect identification. In addition, IAI could be used to sense customers' needs and thus assist managers in the decision-making process toward improving quality and customer satisfaction.

In the B2B and supply chain contexts, combining AI with customer management systems (CRM) could foster the automation of B2B relationship activities, thus improving organizational performance and competitive advantage (Chatterjee et al., 2021). Also, AI can foster the emergence of intelligent, augmented, predictive 4.0 purchasing (Allal-Chérif et al., 2021). These researchers argued that "buyers who employ AI can become faster, more reactive, and more efficient" before adding that "selecting a supplier and signing a contract becomes an affair of weeks, rather than months" (p. 74). Moreover, AI could foster the innovative development processes of new products (Paschen et al., 2019), mitigate supply chain risks, and automate the decision-making process (Nayal et al., 2021). Akter et al. (2021) found that AI climate could significantly affect new service offerings and market performance in B2B markets.

2.2. IT assimilation

Purvis et al. (2001: 121) defined AI assimilation as the scope of using technology across the organizational dimensions of projects and work processes and the resulted technology's routinization in the activities related to such projects and processes (p. 121) (Purvis et al., 2001). It has become an important research topic, considering its potential role in enhancing operational efficiency and competitive agility for the long-term survival of organizations (Chatterjee et al., 2002; Gunasekaran et al., 2017; Liu et al., 2013; Zhu et al., 2006). While IT assimilation is an essential indicator of IT implementation success, IT-enabled business value creation, and enhanced organizational performance (Ing-Long & Cheng-Hung, 2010; Liang et al., 2007; Liang et al., 2019), it also shows whether IT infrastructure investments made by a given organization have succeeded (Liu et al., 2013) and have led to the expected improvements in organizational efficiency and effectiveness (Abdul-Gader & Kozar, 1995; Liu et al., 2013). To assess the impact of investments in the implementation of a new strategic technological innovation, including their contribution to IT-enabled end-to-end digital processes (Chaubey & Sahoo, 2021; Gunasekaran et al., 2017)—for improved operational and strategic benefits (Elbashir et al., 2011; Liu et al., 2013)—the assimilation of the established ITs remains the critical barometer. But also, IT assimilation is a viable organizational mechanism to verify that IT tools are aligned with firms' strategic decisions on inter-organizational collaborations (e.g., customer relationship management and supply chain integration). Furthermore, IT assimilation could act as a bridge between organizational functions and channel partners, therefore leading to "the development of dynamic capability and operational capability" (p. 1455) (Liu et al., 2013). For some scholars, IT assimilation appears as a set of rare, valuable, and imperfectly imitable IT capabilities that firms most need to achieve competitive advantage in a changing and hostile environment (Liu et al., 2013).

3. Research model and hypotheses development

This study is drawn from the emerging literature on AI and the dynamic capability view (DCV) to propose the research model presented in Fig. 1.

3.1. Dynamic capability view

To Teece et al. (1997), the dynamic capability view (DCV) refers to an extension of the resource-based view (RBV) and represents a viable approach for assessing how organizations create and capture business value to gain and sustain competitive advantage in a dynamic environment (Teece et al., 1997). In this research stream, scholars argued that DCV could help explain performance differences of firms within a given industry (Barreto, 2010; Liu et al., 2013) while providing the best opportunity to firms to build and adapt their resources (Eisenhardt & Martin, 2000; Schilke, 2014). Of course, the expected outcomes would be creating and modifying organizational operating routines and significant improvements in organization effectiveness (Mitsuhiro, 2015; Zollo & Winter, 2002). Various organizational capabilities have been classified in line with DCV to determine the superior level of firm performance. Such organizational capabilities include ordinary, operational, or zero-order capabilities and dynamic or high-order capabilities (Helfat & Winter, 2011; Teece et al., 2016; Winter, 2003).

Operational capability is known as an organizational "ability to execute and coordinate the various tasks required to perform operational activities, such as distribution logistics and marketing campaigns" (p. 4153) (Liu et al., 2013). It plays a crucial role in producing and selling products and services (Helfat & Winter, 2011; Teece et al., 2016), which allows the firm to make a living in the present (Fainshmidt et al., 2016). In contrast, dynamic capability (DC) designates the strengths that a firm can put in to develop and adjust not only its internal skills but also external competencies that are remodeled and integrated to respond to business landscape changes (p. 516) (Teece et al., 1997). Therefore, it epitomizes the firm's ability to innovate and adapt according to changes and foster transformative actions in favor of its customers and unknown to its competitors. Relying on its own dynamic capability, a firm can extend, modify, improve, protect or create ordinary capabilities (Ambrosini & Bowman, 2009; Fainshmidt et al., 2016; Helfat & Winter, 2011; Roberts et al., 2016; Winter, 2003) to alter and adjust its strategy for sustainability (p. 1244) (Helfat & Winter, 2011) while developing new strategies geared toward creating values (Liu et al., 2013) to support long-term competitive advantage (Protogerou et al., 2012; Teece, 2014).

3.2. Organizational agility

In today's hypercompetitive environment, agility is emerging as a critical organizational asset (Ferraris et al., 2022; Gligor et al., 2015; Shams et al., 2021) to innovate and achieve competitive advantage (Bresciani et al., 2022). Agility is considered an adequate means of ensuring quickness and effectiveness during business model adjustments by firms (Ferraris et al., 2022; Giacosa et al., 2022). This entails

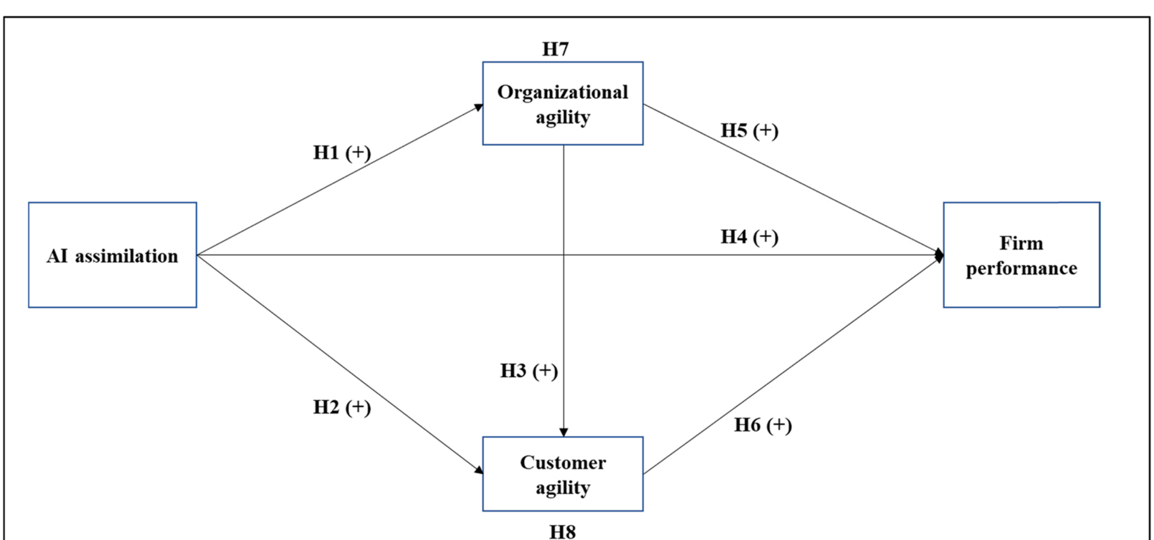

Fig. 1. Proposed research model.

designing and implementing a range of value-creation activities in this hyper-competitive environment (Shams et al., 2021). Agility has also been viewed as the firm's ability to explore new business opportunities for market arbitrage and exploit the same (Sambamurthy et al., 2003). Such actions may be deployed, for instance, through experimentation with new alternatives and the development and use of already known knowledge and acquisitions utilizing existing competencies, technologies, and know-how. Organizational agility enables firms to rely on their various assets to respond to industry progress, which is sometimes unforeseeable and requires velocity and proactiveness in operational actions, should the firm aspire to seize opportunities and take the lead (p. 933) (Lu & Ramamurthy, 2011). Moreover, it is increasingly viewed as an essential asset that is leveraged by firms/organizations to generate the information needed to inform management decision-making (Zain et al., 2005), upgrade organizational performance (Chatfield & Reddick, 2018; Ravichandran, 2018; Sambamurthy et al., 2003) and competitive advantage (Cheng et al., 2020; Lee et al., 2015; Mathiassen & Pries-Heje, 2006; Sambamurthy et al., 2003) in hypercompetitive environments (Roberts & Grover, 2012a). For example, organizational agility is required to search for and retrieve relevant knowledge from the business ecosystem in order to develop improved products and services (Cegarra-Navarro et al., 2016; Sambamurthy et al., 2003), establish market channels, and segment trade outlets. (Sambamurthy et al., 2003). Organizational agility is also instrumental in adequately responding to new competitors within a given market (Cegarra-Navarro et al., 2016). To sense and adapt quickly to changing customer needs and behaviors (Chatfield & Reddick, 2018; Holmqvist & Pessi, 2006; Tallon & Pinsonneault, 2011), any organization should make proof of agility in a competitive environment. So goes with organizations' ambition to quickly and easily detect and seize innovation threats and opportunities and then pool all required assets, knowledge, and business relationships (Hovorka & Larsen, 2006; Richardson et al., 2014; Sambamurthy et al., 2003).

3.3. Customer agility

Customer agility is defined as a "firm's capability to not only sense but also to respond in expeditious way to customer-based opportunities for innovation, and competitive action is of great importance" (p. 136) (Hajli et al., 2020). It is an organizational "ability to leverage the voice of the customer for gaining market intelligence and detecting competitive action opportunities" (p. 245) (Sambamurthy et al., 2003). This essential organizational capability plays a vital role in the firm's strategy to rapidly catch business opportunities and boost its innovation-oriented spirit and competitiveness (Roberts & Grover, 2012b). It enables firms not only to quickly uncover their customers' behaviors and preferences by monitoring their data but also to track potential customers in real-time (Giacosa et al., 2021), thereby improving customers' experiences and interactions with and among them, while facilitating real-time monitoring of customer data (Giacosa et al., 2022), and personalized information collection (Huang et al., 2021). Sambamurthy et al.(2003) argued that customer agility is the "co-opting of customers in the exploration and exploitation of opportunities for innovation and competitive action moves" (p. 245). Customer agility allows the firm to capitalize on customer voices to achieve market intelligence and explore competitive action opportunities, enabling organizational survival and prosperity (Giacosa et al., 2022; Huang et al., 2021). This study follows the views of (Cheng et al., 2020) on organizational agility and argues that both organizational agility and customer agility may serve as bridges between AI assimilation and firm performance.

3.4. The relationships between AI assimilation, organizational agility, and customer agility

In firms and organizations, chief operating officers (CIOs) have consistently ranked IT-enabled organizational agility as a top priority (Tallon et al., 2019). They know for a fact that IT-based innovations are a critical enabler of firm agility (Felipe et al., 2016; Gao et al., 2020; Huang et al., 2012; Lu & Ramamurthy, 2011; Mariani & Nambisan, 2021; Mathiassen & Pries-Heje, 2006; Richardson et al., 2014; Tallon et al., 2019). For example, information technologies (ITs) produce digital options enabling organizations to respond quickly to changes in hypercompetitive environments (Ravichandran, 2018); apart from facilitating the efficient and effective communication and sharing of specialized knowledge among the firm's internal and external stakeholders (Nazir & Pinsonneault, 2012), they enhance both the competency needed for the development of organizational agility (Chakravarty et al., 2013) and the organizational agility that is required to sense and seize operational opportunities, while responding to internal and external emergent changes (Lee et al., 2016). While there is a strong direct effect of IT on organizational agility (Lee et al., 2016; Lu & Ramamurthy, 2011; Zain et al., 2005), Overby et al. (2006) argue that organizational agility also depends on the volume of firms' investments in information technologies. Prior studies have demonstrated the ability of IT-enabled agility to improve the decision-making process (e.g., speed and quality), internal and external organizational communication, and to rapidly respond to changes in the market (Lu & Ramamurthy, 2011). If AI assimilation helps to foster the organizational ability to sense and seize business opportunities, respond to threats, and quickly adapt to and face internal and external changes, this study hypothesizes the following:

H1. AI assimilation positively influences organizational agility.

Once again, organizations rely on ITs to sense customer opportunities and threats (Roberts & Grover, 2012a, 2012b) and respond to them effectively (Lu & Ramamurthy, 2011; Ravichandran, 2018). IT has long been viewed as an important means to build and enhance online customer communities and thus enhance customer agility. These customer communities could enhance interactions between organizations and their customers during information collection for product design, evaluation, or testing (Sambamurthy et al., 2003). For example, Giacosa et al.(2022) argued that advanced IT infrastructures could be instrumental in improving customer agility. And for Zhou et al. (2018), the organizational ability is essential to capture insights from customers' online reviews and thus foster customer agility. For example, Chatfield and Reddick (2018) have found that the assimilation of big data and big data analytics positively influenced customer agility (p. 336). AI enhances customer predictive insights that could be used to empower organizational capabilities, allow for personalized offers and services, anticipate and reduce customer churn, and improve leads scoring and generation for sales or cross-sales (Comdata, 2021). For example, firms are leveraging AI capabilities to enhance customer agility worldwide. Netflix is capitalizing on AI to personalize recommendations to its vast subscriber base worldwide. Like Amazon, the same Netflix is increasingly relying on AI-enabled individualized product recommendations to improve its agility toward its customers (McKinsey and Company, 2019). Therefore, this study hypothesizes the following:

H2. AI assimilation positively influences customer agility.

In the same light of thought, organizational agility enables a firm not only to quickly sense changing customer requirements (Felipe et al., 2020; Lee & Yang, 2014), but also to easily and quickly adapt its strategy to such changes (Tallon & Pinsonneault, 2011). For example, agile organizations will be able to quickly leverage digital technologies to create online customers communities and multiple channels that will support and facilitate customer interactions for market intelligence, improved customer service, and satisfaction (Hadjielias et al., 2022). Moreover, scholars argued that customer agility could be considered as a manifestation of the firm agility in terms of quickly perceiving and responding to "customer relative innovative competitive and opportunities actions" (p. 102) (Liu et al., 2018). Therefore, the following hypothesis can be formulated:

H3. Organizational agility positively influences customer agility.

3.5. The relationships between AI assimilation, organizational, customer agility, and firm performance

The relationship between IT investments and firm performance has been found to be positive by a good number of studies (Kim et al., 2009; Sambamurthy et al., 2003; Zhu et al., 2021). For example, Kim et al. (2009) investigated the impact of IT investment on the financial performance of firms in the Chinese electronic industry and found a positive effect. Wu et al. (2016) found that IT-enabled resources enhance organization performance in the healthcare sector. Similarly, Zhu et al. (2021) established the positive influence of big data and analytics on the creation of business value when it comes to enhancing operational efficiency and business growth. Dubey et al. (2020) identified a positive and significant interplay between big data analytics powered by AI and operational performance. Taguimdje Wamba et al. (2020) found that AI adoption and use could lead to improved business processes and organizational performance (e.g., financial, marketing and administrative). Similarly, Chen et al. (2022) suggested a positive link between AI capability and firm performance in the context of e-commerce firms. Rammer et al. (2022) used firm-level data from Germany to reveal a positive link between AI and organizational innovation performance. This enables us to propose the following hypothesis:

H4. AI assimilation positively influences firm performance.

Organizational agility is henceforth known to impact firm performance significantly, as demonstrated by the available literature (Cegarra-Navarro et al., 2016; Lee & Yang, 2014; Tallon & Pinsonneault, 2011). According to (Lee & Yang, 2014), firms showing proof of agility can easily enhance their operational niche, respond quickly to market uncertainty, meet customers' requirements and create new opportunities, all of which improve their overall competitiveness. Ravichandran (2018) also demonstrated the strong positive influence of organizational agility on the performance of firms. In addition, Rozak et al. (2022), in the context of Indonesian small and medium enterprises (SMEs), which are using digital technologies in different processes, including the relationship with customers, reported a positive effect of organizational agility on firm performance. Puriwat and Hoonsopon (2022) highlighted that organizational agility supports the firm's performance in the context of radical innovation as well as in contexts with technological turbulence. As a result, the following hypothesis can be formulated:

H5. Organizational agility positively influences firm performance.

Prior studies have found that customer agility could predict new product success (Hajli et al., 2020) and product performance (Zhou et al., 2018), and facilitate the way and pace with which firms sense and seize innovation opportunities (Hajli et al., 2020) to develop new products and services for improved firm performance and competitive advantage. Felipe et al. (2020) argued that "customer agility allows organizations to proactively react to customer-based opportunities by acting creatively and introducing new products, promotions, or services to enhance profits, competitive advantage, and industry position" (p. 586). Similarly, Huang et al. (2021) believed that organizations with high customer agility could match customer needs with their services and products, with a real impact on customer satisfaction. For example, firms such as Netflix and Amazon use AI-enabled individual recommendations on their products while personalizing promotions combined with dynamic pricing to enhance customer agility and thus increase sales (McKinsey and Company, 2019). Therefore, the following hypothesis emerges:

H6. Customer agility positively influences firm performance.

3.6. The mediating effects of organizational and customer agility on the relationship between AI assimilation and firm performance

Sambamurthy et al. (2003) argue that IT investments impact organizational performance through three significant organizational capabilities, namely agility, digital options, and entrepreneurial alertness. According to Werder et al. (2021), agility has generally been described as a firm ability to mediate the impact of IT investment on firm performance. Lee et al. (2016) and Felipe et al. (2020) rather note that organizational agility is an important mediator of the relationship between IT and firm performance. For example, "IT-enabled operation-level agility allows the firm to seize operational opportunities, respond to internal and external emerging changes, and sustain its competitive operational edge, which, in turn, lead to its superior firm performance" (p. 13) (Lee et al., 2016). This leads to the following hypothesis:

H7. Organizational agility serves as a mediator in the relationship between AI assimilation and firm performance.

Prior studies have identified customer analytics as an important mediator of the relationship between IT capability and firm performance (Felipe et al., 2020; Lee et al., 2016; Roberts & Grover, 2012b). For example, Roberts and Grover (2012b) argued that customer agility is enabled by IT, which, in turn, generates competitive activity (p. 231). They added that agility is an intermediate concept that "lead[s] to economic outcomes and provides a different understanding of how IT indirectly contributes to firm value" (p. 254). In this line of thought, Heredia et al. (2022) reported a full mediation that technological capabilities exert in the relationship between digital capabilities and firm performance. Accordingly, the firm's performance is improved when the technological capabilities support the firm's digital strategies. Moreover, Bahrami and Shokouhyar (2022) found that big data analytics capabilities substantially indirectly affect a firm's performance. Therefore, the following hypothesis emerges:

H8. The relationship between AI assimilation and firm performance is mediated by customer agility.

4. Research design

Data were collected from USA-based firms' senior managers and mid-level managers of supply chains through a web-based survey. The study targeted respondents where AI tools and systems were already deployed across various organizational and inter-organizational operations. More precisely, the following constructs AI assimilation, organizational agility, customer agility, and firm performance, were adapted respectively from Liu et al. (2016), Tallon and Pinsonneault (2011), Roberts and Grover (2012a), and Queiroz et al. (2018). A seven-point Likert scale (ranging from 1 "strongly disagree" to 7 "strongly agree") was used (see Appendix 1). Before the final data collection, four (4) professors of information systems and supply chain operations who had experience in artificial intelligence and two data scientists pretested the survey questionnaire to ensure the intelligibility of the various questions (Dillman, 2000). The final data collection was conducted by a global market research firm called Bilendi (https://www.bilendi.fr/) in September 2021, using who relied on supply chain executives of its USA panel with proven experiences in both AI and business analytics.

Data collection was conducted through an online survey encompassing multiple filters (e.g., attention check) to ensure that only the required respondents were targeted (Abbey & Meloy, 2017). These included supply chain managers and mid-level managers of firms with established business analytics and artificial intelligence (AI)-based application systems who understand the needs of their firms in terms of technical and non-technical capabilities in the area of business analytics and AI). The final online survey also included questions to avoid random responses from respondents. Bilendi sent an invitation to participate in the study to 1924 of its panel members, indicating the study's objectives, the survey duration, and the link to the online questionnaire. A total of 1586-panel members agreed to participate in the survey, and 205 final good responses were finally received (a response rate of 13%). The final sample is made of various profiles, including Vice-President, Director of Operations, Director of Global Procurement, Operations Manager, Director of Supply Management, Distribution Manager, Director of Logistics & Distribution, Supply Chain Manager, across various industries.

5. Data analysis and results

Table 1 presents the main demographic characteristics of the sample. The age distribution shows that the respondents in the range 31–43 were the majority, accounting for 52.20%. Regarding gender, male participants were 67.30%, while females achieved 32.70%. Regarding the highest education level, participants with bachelor's and master's degrees accounted for 46.83% and 24.88%, respectively. The participants came from a variety of industries. However, the most expressive fraction was represented by the computers/software sector (24.39%) and manufacturing (23.90%). Finally, considering the position of the participants, VP, and director of operations were the most popular occupations, accounting for 19.02% and 17.56%, respectively.

Table 1
Demographic profile of the respondents.

	N = 205	*Percentage*
Age		
18–30	34	16.58
31–43	107	52.20
44–56	38	18.54
57–69	18	8.78
70–82	8	3.90
Gender		
Male	138	67.30
Female	67	32.70
Education		
High school	12	5.85
Bachelors' degree	96	46.83
Masters' degree	51	24.88
Postgraduate	29	14.15
Ph.D.	17	8.29
Industry		
Banking/finance	27	13.17
Computers/software	50	24.39
Consulting	10	4.88
Insurance	6	2.93
Manufacturing	49	23.90
Medicine/health	13	6.34
Publishing/communications	5	2.44
Hotel/restaurants	6	2.93
Transportation	5	2.44
Construction	8	3.90
Education	7	3.41
Retail and wholesale trade	6	2.93
Others	13	6.34
Position		
Vice-President	39	19.02
Director of Operations	36	17.56
Business Analyst	21	10.24
Project Manager	17	8.29
Operations Manager	14	6.83
Director of Supply Management	8	3.90
Distribution Manager	8	3.90
Director of Logistics & Distribution	7	3.40
Supply Chain Manager	6	2.93
Director of Global Procurement	6	2.93
Logistics Analyst	4	1.95
Demand Planning Manager	4	1.95
Production Planner	3	1.46
Global Sourcing Manager	2	0.98
Process Improvement Manager	2	0.98
Purchasing Manager	2	0.98
Sourcing Specialist	2	0.98
Transportation Specialist	2	0.98
Import/Export Specialist	1	0.49
Quality Systems Auditor	1	0.49
Strategic Procurement Manager	1	0.49
Transportation Planner Manager	1	0.49
Others	18	8.78

For this study, the following statistical analysis tools were used: IBM SPSS Statistics 24.0 (IBM, 2018), and two well-known PLS-based SEM tools, namely SmartPLS 3.0 (Ringle et al., 2015) and WarpPLS 7.0 (Kock, 2021). The PLS approach to SEM has proved to be appropriate for model estimation in various contexts (Hair et al., 2017; Ringle et al., 2015), including for the analysis of big data analytics quality (Akter et al., 2017) and trustworthiness in mobile health information services (Akter et al., 2011).

5.1. *Measurement model*

This study followed the steps proposed by (Hair et al., 2017) to evaluate the measurement model. Both SmartPLS 3.0 (Ringle et al., 2015) and WarpPLS 7.0 (Kock, 2021) were used for analysis.

5.1.1. *Internal consistency*

Cronbach's Alpha (α) and composite reliability (CR) were used to evaluate internal consistency reliability. Both the values of α and CR stood between 0.825 and 0.939, thus greater than the required threshold of 0.7 for all the constructs (Table 2), which is a satisfactory level of internal consistency reliability (Hair et al., 2017).

5.1.2. *Convergent validity*

The outer loadings and the average variance extracted (AVE) were used to assess the convergent validity (Hair et al., 2017). All the outer loadings values were equal to or higher than 0.7, while the AVEs values were greater than 0.5 (Table 2). As a result, the convergent validity of the constructs was ensured (Hair et al., 2012; Hulland, 1999).

5.1.3. *Discriminant validity*

This study assessed the discriminant validity using the Fornell-Larcker criteria (Table 3) and the heterotrait-monotrait ratio (HTMT) (Table 4) (Hair et al., 2017; Henseler et al., 2015). Table 3 clearly indicates that all the values in bold on the diagonal or the square root of AVEs values are higher than the inter-construct correlations' values, thus satisfying the Fornell-Larcker criteria (Fornell & Larcker, 1981; Hair et al., 2017).

In Table 4, it can be noticed that all the values in the HTMT matrix are smaller than 0.90 (Hair et al., 2017; Henseler et al., 2015), which means that the HTMT requirements are met. Therefore, the study can conclude that the results from the Fornell-Larcker criteria and the HTMT assessment strongly support the discriminant validity of all the constructs included in the proposed model.

5.2. *Common method bias*

Common method biases (CMB) represent an important threat for survey-based studies, especially when using a single-informant (Guide & Ketokivi, 2015). This study tried to reduce this threat by targeting key respondents with the highest level of expertize required to answer the questionnaire: supply chain executives. Also, it conducted the full collinearity variance inflation factors (VIFs) test as proposed by Kock (2015) to identify CMB. The author suggests the VIF threshold of 3.3 that is used in CMB tests when factor-based PLS-SEM algorithms are employed or the threshold of 5 when using algorithms that integrate a measurement error. Table 5 shows the value of the full VIF for each construct. It can be clearly seen that these values are less than 3.3, thus suggesting that the proposed research model could be considered free of CMB (Kock, 2021).

Table 6 points out the model fit and quality indices. In this regard, all indices are according to the literature threshold (Kock, 2021). According

Table 2
Outer loadings, Cronbach's Alpha, CR and AVE.

Constructs	Items	Outer loadings	Cronbach's Alpha (α)	Composite Reliability (CR)	Average Variance Extracted (AVE)
AI assimilation	AIASSI1	0.863	0.825	0.895	0.741
	AIASSI2	0.874			
	AIASSI3	0.844			
Customer agility	CUSTAG1	0.850	0.891	0.920	0.696
	CUSTAG2	0.839			
	CUSTAG3	0.834			
	CUSTAG4	0.802			
	CUSTAG5	0.847			
Firm performance	FPERF1	0.800	0.875	0.909	0.667
	FPERF2	0.834			
	FPERF3	0.825			
	FPERF4	0.843			
	FPERF5	0.781			
Organizational agility	ORGAG1	0.846	0.925	0.939	0.658
	ORGAG2	0.785			
	ORGAG3	0.822			
	ORGAG4	0.858			
	ORGAG5	0.774			
	ORGAG6	0.858			
	ORGAG7	0.838			
	ORGAG8	0.700			

Table 3
Discriminant validity assessment using the Fornell-Larcker test.

	FPERF	CUSTAG	ORGAG	AIASS
FPERF	**0.817**			
CUSTAG	0.689	**0.834**		
ORGAG	0.684	0.636	**0.811**	
AIASS	0.723	0.607	0.569	**0.861**

Table 4
Discriminant validity assessment using the HTMT test.

	FPERF	CUSTAG	ORGAG	AIASS
FPERF				
CUSTAG	0.780			
ORGAG	0.759	0.699		
AIASS	0.851	0.708	0.649	

Table 5
Full collinearity statistics (VIF).

	VIF
FPERF	3.006
CUSTAG	2.180
ORGAG	2.096
AIASS	2.216

Table 6
Model fit and quality indices.

Model fit and quality indices	Value	Thresholds and acceptable values
Average path coefficient (APC)	0.386, P<0.001	p < 0.05
Average R-squared (ARS)	0.529, P<0.001	p < 0.05
Average block VIF (AVIF)	2.152	Acceptable if <= 5, ideally <= 3.3
Average full collinearity VIF (AFVIF)	~2.37	Acceptable if equal to or higher than 5, and is ideal when equal to or lower than 3.3
Tenenhaus GoF (GoF)	~0.60	Small if equal to or higher than 0.1, medium if >= 0.25, large if >= 0.36
Nonlinear bivariate causality direction ratio (NLBCDR)	1.000	Acceptable if >= 0.7

to (Kock, 2021), these indices present some particularities in the interpretation. For example, if the main objective is to test hypotheses (our case), the model fit and the indices are less important than the use to test the performance of different models. However, one of our most important indices is the NLBCDR to assess the construct causality, which is considered an essential aspect to be addressed before any hypotheses testing, especially when using cross-sectional surveys (Fosso Wamba et al., 2020; Guide & Ketokivi, 2015). More precisely, the study assessed the nonlinear bivariate causality direction ratio (NLBCDR), which is "a measure of the extent to which bivariate nonlinear coefficients of association provide support for the hypothesized directions of the causal links in a model." (p. 81) (Kock, 2021). This ratio should be >= 0.7, as suggested by Kock (2021). In this study, the NLBCDR has a value of 1.000, which is greater than the threshold of 0.7, thus confirming that causality is not a significant issue for this study. In addition, the study provided the model fit and quality indices based on the PLS-SEM analysis (see Table 6).

5.3. Assessment of the structural model

The results of the structural model evaluation are presented in Table 7. From the Table, it can be concluded that all the proposed research hypotheses are supported. More precisely, while AIASS could be considered as a good predictor of FPERF (β=0.367, $p < 0.001$), CUSTAG (β=0.267, $p < 0.001$) and ORGAG (β=0.571, $p < 0.001$), AIASS effects are stronger on ORGAG (β=0.571), followed by FPERF (β=0.367), and finally by CUSTAG (β=0.267). These results provide strong support for **H1, H2, and H4**. In addition, ORGAG is an important predictor of CUSTAG (β=0.564, $p < 0.001$), and FPERF (β=0.342, $p < 0.001$), with stronger effects on CUSTAG (β=0.564). These final results provide strong support for **H3 and H5**. Finally, CUSTAG has a significant positive effect on FPERF (β=0.207, $p = 0.001$), thus providing support for H6.

Table 7
Hypothesis testing.

Hypothesis	Path	β	P-values	Results
H1	AIASS -> ORGAG	0.571	<0.001	Supported
H2	AIASS -> CUSTAG	0.267	<0.001	Supported
H3	ORGAG -> CUSTAG	0.564	<0.001	Supported
H4	AIASS -> FPERF	0.367	<0.001	Supported
H5	ORGAG -> FPERF	0.342	<0.001	Supported
H6	CUSTAG -> FPERF	0.207	0.001	Supported

In addition to testing direct effects in the proposed research model, the study also tested various mediating effects (Table 8). Mediation testing was carried out using various techniques (Baron & Kenny, 1986; Nirino et al., 2022). In this paper, we used the guidelines proposed by (Zhao et al., 2010), which are synthesized in (Hair et al., 2017). More precisely, the study first looked at the significance of the indirect effects, followed by that of the direct effects (Table 8). The table shows that the two specific indirect effects are significant, as is also the direct effect. For the two paths, the positive value of all beta products (direct and indirect effects) is ensured, implying the complementarity of partial mediation (Hair et al., 2017) and thus supporting hypotheses H7 and H8.

Also, this study assessed the model's explanatory power by evaluating the explained variance (R-square) of all endogenous constructs (Table 9). R-square values could be considered substantial (0.75), medium (0.50), or weak (0.25) (Hair et al., 2017). The table shows the following values: FPERF (0.666), CUSTAG (0.594), and ORGAG (0.327).

In addition, the effect size of each predictor was assessed using Cohen's f-square formula and compared to the proposed threshold values of 0.35 or large, 0.15 or medium, and 0.02 or small (Cohen, 2013). From the analysis (Table 10), different effect sizes can be noticed: CUSTAG on FPERF, 0.143; ORGG on FPERF, 0.255; ORGAG on CUSTAG, 0.420; AIASS on FPERF, CUSTAG, and ORGAG: 0.268, 0.174 and 0.327, respectively (Table 10). Furthermore, it was evaluated the model's predictive relevance using Stone-Geisser's Q-square value (Stone, 1974) for all the endogenous constructs (Table 9) (Hair et al., 2017). The table shows the following values: FPERF (0.668); CUSTAG (0.594); ORGAG (0.330). They are all larger than zero and therefore suggest that all the exogenous constructs have acceptable predictive relevance for the dedicated endogenous constructs selected for the proposed research model (Hair et al., 2017).

6. Discussion

The purpose of this paper was to examine the direct effects of AI assimilation on organizational agility, customer agility, and firm performance. The mediating effects of both organizational and customer agility on the AI assimilation/firm performance link were also studied. The results obtained provide strong support to all the proposed hypotheses. More precisely, the proposed nomological network showed that AIASS is an important predictor of FPERF (β=0.367, p-value < 0.001), CUSTAG (β=0.267, p-value < 0.001), and ORGAG (β=0.571, p-value < 0.001), with stronger effects on ORGAG (β=0.571), followed by FPERF (β=0.367), and finally by CUSTAG (β=0.267). In addition, CUSTAG has a significant positive effect on FPERF (β=0.207, p-value = 0.001). Moreover, ORGAG is an important predictor of CUSTAG (β=0.564, p-value < 0.001), and FPERF (β=0.342, p-value < 0.001), with stronger effects on CUSTAG (β=0.564). Furthermore, CUSTAG and ORGAG were found to be complementary partial mediators of the relationship between AIASS and FPERF. Finally, FPERF, CUSTAG, and ORGAG r-square values are 66.6%, 59.4%, and 32.7%, respectively.

The findings of this study are in line with the extant literature exploring IT assimilation. For example, our result for AIASS reinforces the importance and contribution of AI to FPERF (Dubey et al., 2020). In this regard, similar to Taguimdje Wamba et al. (2020), our findings suggest that AIASS can improve different business processes and capabilities of the organizations, hence organizational agility and customer agility. In that perspective, concerning ORGAG, this study's findings support previous studies that reported the power of IT-enabled agility for organization's operations (Lu & Ramamurthy, 2011). Besides, the revealed positive effect of AIASS on CUSTAG is similar to results from previous studies highlighting the influence of IT tools on the creation of customer agility Giacosa et al. (2022).

Table 8
Mediation testing (SmartPLS).

Path	β	P-values
Specific indirect effects		
AIASS -> ORGAG -> FPERF	0.171	0.001
AIASS -> CUSTAG -> FPERF	0.092	0.042

Table 9
R-square and Q-square.

Construct	R-square	Q-square
FPERF	0.666	0.668
CUSTAG	0.594	0.594
ORGAG	0.327	0.330

Table 10
F-square.

FPERF	CUSTAG	ORGAG	AIASS
	0.143	0.255	0.268
		0.420	0.174
			0.327

Furthermore, our findings show that ORGAG is a predictor of CUSTAG and FPERF, which is consistent with previous IT-related studies. For instance, the positive effect of ORGAG on CUSTAG was already reported in other IT contexts (Felipe et al., 2020; Tallon & Pinsonneault, 2011). Similarly, Ravichandran (2018) demonstrated the impact of organizational agility on firm performance, and specifically that of ORGAG on FPERF. In addition, the positive influence of CUSTAG on FPERF is in line with other studies that reported the influence of customer agility on support to firms' products (Hajli et al., 2020). Finally, our results regarding the mediation analysis corroborate findings from previous IT literature. We found that ORGAG is mediating the relationship between AIASS and FPERF. This is consistent with previous literature highlighting the influence of organizational agility on the relationship between IT and firm performance (Felipe et al., 2020). Moreover, it has been demonstrated that CUSTAG mediates the relationship between AIASS and FPERF, which is in line with relevant IT literature (Felipe et al., 2020; Lee et al., 2016; Roberts & Grover, 2012b).

6.1. Theoretical contributions and implications

This research has several theoretical implications for the emerging literature on AI. This study extends the IS literature by providing a nomological network of AI assimilation that links AI assimilation to two levels of organizational outcomes. For instance, it features among the first studies to draw on the dynamic capability view to assess the impact of AI assimilation on firm performance as well as the mediation effects of organizational and customer agility on this relationship; this is a notable contribution to the emerging literature on AI, with empirical evidence on the importance of AI assimilation for improving firm performance.

It is only through the effective integration of AI into end-to-end organizational processes that firms will be able to create and capture business value from AI-related technologies. Future studies could build on these findings to integrate some critical organizational's external factors (e.g., environmental dynamism) to account for the dynamic nature of the external environment (Fosso Wamba et al., 2021). This study also contributes to the research stream focusing on the dynamic capability view while enriching the emerging literature on AI. This goal is achieved through the identification of two important mediators of the relationships between AI assimilation and firm performance. Another contribution is that it responds to the recent call by many scholars (Dwivedi et al., 2021; Fosso Wamba et al., 2021; Huang et al., 2021) to assess the actual impacts of artificial intelligence (AI). In addition, this study drives important implications for the literature on AI and related technologies. The assimilation of AI represents a distinct and valuable capability that needs constant exploration by the emerging literature on AI (Ashok et al., 2022; Alter, 2021; Duan et al., 2019; Dwivedi et al., 2021; Fosso Wamba et al., 2021), especially for the digital transformation of the organizations.

6.2. Implications for practice

The findings of this study could provide essential guidance to professionals, consultants, and managers who plan to invest in AI-enabled business value projects. Investing in AI assimilation across end-to-end organizational processes and in complementary capabilities such as organizational and customer agility is the only way for firms' managers to create and capture the full value of organizational performance enabled by artificial intelligence. In this regard, this study attempts to disclose the mechanisms firms will need to assess and assimilate AI in order to improve their performance.

The results of this study should lead practitioners to pay more attention to how AI assimilation is built. It means that they should think about the required resources for AI assimilation in order to upgrade their capabilities. Such resources include IT infrastructure, the workers' digital literacy, the organization's digital culture, and so on. Understanding the contributions of these and other types of resources can impact the rules of the game in terms of AI assimilation capability.

Regarding AI assimilation and its contribution to the organization's internal and external activities, the results suggest that practitioners should invest in different strategies to leverage this capability, cognizant of the fact that its distinct features can help to create value and competitive advantage for the organizations (Liu et al., 2013). As the development of digital transformation projects is still in its infancy, AI assimilation can suffer from a lack of workers with AI skills to support the adoption and assimilation of different organizations' activities.

On the other hand, the fact that AI assimilation positively impacts the agility of both organizations and customers should lead practitioners to deploy efforts to grasp better how AI tools can be deployed in support of agility, mainly in turbulent and complex environments. The assimilation of AI can be decisive in facing unprecedented disruptions in the contemporary world. Similarly, organizations relying on a well-articulated plan of AI assimilation can better reap the benefits of customer agility (McKinsey and Company, 2019) and consequently acquire more value for themselves and their customers.

In addition, the results emphasize the importance of managers paying attention to the direct and indirect effects of AI assimilation. It implies that the use of different AI tools and approaches (i.e., machine learning, deep learning, neural networks, etc.) and their combination with other cutting-edge technologies (e.g., big data analytics, simulation, blockchain, etc.) should be used to maximize the business value added by the firms. Accordingly, the AI assimilation needs to be supported by the top managers of the firms to speed up the routinization across the organization's functions and consequently achieve faster benefits (i.e., agility and firm performance) of the adoption and routinization. Considering this, managers and decision-makers should invest time in strategies to maximize AI assimilation to develop new services and products that can contribute to the firm's performance and social good.

Finally, our results invite practitioners and managers to consider agility (organizational and customer) as a central capability for business value creation and firm performance. The efforts to be made include collaborations and partnerships at the intra-organizational and inter-organizational levels and deploying different strategies supporting agility practices and AI tools among business partners and key stakeholders.

6.3. Limitations and future research directions

This research has some limitations. First, it uses a cross-sectional survey to validate the proposed research model. Indeed, survey-based studies have limitations, including endogeneity issues (Guide & Ketokivi, 2015) and self-report bias (Akter et al., 2020; Fosso Wamba et al., 2017). Therefore, future studies may consider using case studies or longitudinal survey studies to assess the proposed research model. Secondly, the data were collected in the specific context of AI adoption and use in the USA, an English-speaking developed country. The adopted model may be tested and validated through other geographical and linguistic parameters, using data from non-English-speaking countries, other developed nations, and under-developed countries. Thirdly, this study relies on perceptual performance measures only, a weakness that additional studies should address by integrating objective measures to improve understanding of the real impact of AI assimilation on firm performance.

7. Conclusion

This study conceptualized and tested the impact of AI assimilation on firm performance as well as the mediation effects of organizational and customer agility on this relationship. The findings suggest that AI assimilation is an important predictor of firm performance, organizational and customer agility, with varied intensity (e.g. stronger effects on organizational agility). Besides, this research also identified customer agility as a predictor of firm performance, while organizational agility was found to be an important predictor of both customer agility and firm performance, with stronger effects on the former. Finally, the results showed that both organizational and customer agility were found to be complementary partial mediators of the relationship between AI assimilation and firm performance. These are important contributions to the emerging literature on AI impact at the organizational level.

Appendix 1. Survey measurements and their sources

AI assimilation (Liu et al., 2016)

On a 1 to 7 scale (1 = strongly disagree, 7 = strongly agree), please indicate whether you agree/disagree with the following statement.

1. AI tools are used across all our business units.
2. AI tools are used for decision-making across all our business units.
3. AI tools are used to support the development of new products and services.

Customer agility (Roberts & Grover, 2012a)

On a 1 to 7 scale (1 = strongly disagree, 7 = strongly agree), please indicate whether you agree/disagree with the following statement.

1. We respond rapidly if something important happens with regard to our customers.
2. We quickly implement our planned activities with regard to customers.
3. We quickly react to fundamental changes with regard to our customers.
4. When we identify a new customer need, we are quick to respond to it.
5. We are fast to respond to changes in our customers' product or service needs.

Organizational agility (Tallon & Pinsonneault, 2011)

How easily and quickly can your firm perform the following actions? (1 = strongly disagree; 7 = strongly agree)

1. Respond to changes in aggregate consumer demand.
2. Customize a product or service to suit an individual customer.
3. React to new product or service launches by competitors.
4. Introduce new pricing schedules in response to changes in competitors' prices.
5. Expand into new regional or international markets.
6. Change (i.e., expand or reduce) the variety of products/services available for sale.

7. Adopt new technologies to produce better, faster and cheaper products and services.
8. Switch suppliers to avail of lower costs, better quality, or improved delivery times.

Firm performance (Queiroz et al., 2018)

To what extent do the following statements reflect the current situation in your firm in the last 18 months?

1. We are more profitable than our competitors
2. Our sales growth exceeds that of our competitors
3. Our revenue growth exceeds that of our competitors
4. Our market share growth exceeds that of our competitors
5. Overall, our performance is better than our competitors.

Author statement

I am the sole author of this paper.

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