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Flipping the odds of AI-driven open innovation: The effectiveness of partner trustworthiness in counteracting interorganizational knowledge hiding

José Arias-Pérez [a,*], Thanh Huynh [b]

[a] *Department of Administrative Sciences, Universidad de Antioquia, Colombia*
[b] *Centre for Business in Society, Coventry University, United Kingdom*

A R T I C L E I N F O

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A B S T R A C T

This paper aims to analyze the negative effect of knowledge hiding on the relationship between artificial intelligence (AI) capability and open innovation (inbound and outbound) when partner trustworthiness (benevolence, integrity, and ability) is high. Structural equations were used to test this three-way interaction with survey data from a sample of 229 firms, mainly from highly digitalized sectors. The findings indicate that interorganizational knowledge hiding affects only the relationship between AI capability and outbound open innovation and that partner ability is the only factor that will counteract this negative effect. Therefore, co-exploitation of AI-based solutions with external allies is the sole scenario to encourage knowledge hiding by increasing employees' perceptions of the likelihood of AI negatively impacting their personal interests at work. Moreover, when trustworthiness is at the forefront of the intraorganizational discussion, the findings downplay the significance of benevolence and integrity as traits that significantly reduce knowledge hiding. In contrast, at the interorganizational level, knowledge hiding is lessened only when employees perceive that co-exploitation with external partners represents an opportunity to learn and capture crucial AI knowledge.

1. Introduction

The World Economic Forum's prediction that artificial intelligence will be performing 52% of tasks in firms by 2025 is becoming less plausible (WEF, 2018). AI seeks to design algorithms that endow computers with cognitive skills and competencies for decision-making and sensemaking; its various business solutions can be categorized as data analytics and autonomy (Abbass, 2019; Truong & Papagiannidis, 2022). The capacity to manage alliances under the balancing influence of data analytics powered by artificial intelligence improves the organization's operational and financial performance (Dubey, Bryde, Blome, Roubaud, & Giannakis, 2021). The field of AI also presents significant prospects for improving the systems and analytical processes used by businesses to handle a range of marketing and innovation problems (Petrescu, Krishen, Kachen, & Gironda, 2022). Surprisingly, according to the Boston Consulting Group and McKinsey, 70% of digital technology adoption projects fail in their attempt to realize benefits for the business (BSC, 2020; Li, 2022). Early indications showed the reasons underlying this low success rate are diverse. On the one hand, skill gaps in the local labour market relate to the environment, while the inability to attract specialized talent or insufficient understanding of opportunities reveals a firm's internal challenges to develop its AI capability (WEF, 2020).

In recent years, however, firm-centrism has predominantly been the main approach to study AI in firms. Recent literature reviews and the most representative works on AI capability assume its development is a product of recombining existing IT resources in the firm (Mikalef & Gupta, 2021; Wamba-Taguimdje, Fosso Wamba, Kala Kamdjoug, & Tchatchouang Wanko, 2020). By extension, this current also argues firms manage to leverage AI on their own to boost the automation and generation of insights and, as a result, they enhance operational efficiency (Dwivedi & Wang, 2022), improve the quality of decision-making (Hossain, Agnihotri, Rushan, Rahman, & Sumi, 2022) and achieve a higher rate of product and service innovation (Fosso Wamba, 2022; Rusthollkarhu, Toukola, Aarikka-Stenroos, & Mahlamäki, 2022).

In contrast, the alternative view of network-centrism is rooted in the assumption that open innovation is the only way to generate benefits from AI capability development (Gregory, Henfridsson, Kaganer, & Kyriakou, 2020; Li, Peng, Xing, Zhang, & Zhang, 2021). Open innovation is defined as the process based on the deliberate management of knowledge flows across organizational boundaries, and it is comprised of two key organizational processes: inbound and outbound (Chesbrough & Bogers, 2014). Unfortunately, this emerging current has

* Corresponding author.
E-mail addresses: jenrique.arias@udea.edu.co (J. Arias-Pérez), ad2685@coventry.ac.uk (T. Huynh).

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received less attention in the field of study. Notably, in an exploratory fashion, early qualitative studies have managed to ascertain that firms making progress in their AI capability development are more involved in inbound activities such as customer co-creation (Li et al., 2021; Sjödin, Parida, Palmié, & Wincent, 2021), and outbound activities such as the adoption of intellectual property protection mechanisms to maximize the commercial exploitation of AI-based solutions developed in-house (Yang, Chesbrough, & Hurmelinna-Laukkanen, 2022).

Nevertheless, the recent detection of opportunistic employee behaviours is redefining research priorities in the field of study of AI in the firm (Enholm, Papagiannidis, Mikalef, & Krogstie, 2021; Truong & Papagiannidis, 2022). Currently, lack of employee cooperation is viewed as the main reason AI adoption in businesses has failed (Li, 2022) since employees are the ones with in-depth knowledge of business processes and customer preferences (Mikalef & Gupta, 2021). This intangible resource is essential for the successful implementation of IA applications in creating create value by enhancing operational efficiency and customer experience (Kinkel, Baumgartner, & Cherubini, 2022; Mikalef & Gupta, 2021).

For the above reason, employees' knowledge hiding is probably the most concerning behaviour given its potential to increase the risk of failure of AI applications in the firm (Zhang, Ye, Qiu, Zhang, & Yu, 2022). Knowledge hiding is the deliberate attempt to withhold or conceal information that has been requested by a colleague (Connelly, Zweig, Webster, & Trougakos, 2012). Recent studies have found that, in an attempt to undermine the use of artificial intelligence and protect their personal interests at work, employees refuse to share key knowledge when faced with the imminent risk of being replaced by intelligent robots and losing their jobs and careers (Arias-Pérez & Vélez-Jaramillo, 2021; Shen & Kuang, 2022).

Regrettably, little progress has been made in this discussion from the network-centrism perspective. Seminal work on interorganizational knowledge hiding detected the presence of this behaviour across interactions of certain digital platforms with their customers, such as Uber and Airbnb (Khelladi, Castellano, Hobeika, Perano, & Rutambuka, 2021). Yet there is an evident lack of research works analyzing employee knowledge hiding in interactions with external partners when seeking to co-create and co-exploit AI-based solutions. Understanding the repercussions of this interorganizational phenomenon is of paramount significance as employees are still the ones setting the pace of collaborative work in AI-driven innovation with external allies due to their technical, operational or business knowledge (Petrescu et al., 2022; Sjödin et al., 2021). There is also a major methodological restriction in the subject area as there is no scale for measuring interorganizational knowledge hiding that yields conclusive results to overcome the limitations of the seminal work, which is qualitative and exploratory in nature.

Moreover, as the seriousness of the knowledge hiding issue has become evident, interest in identifying individual or organizational factors that help reduce its negative influence has been sparked in the field of study (Anand, Offergelt, & Anand, 2022). One of the most promising, potential solutions makes a case for regarding this behaviour as a problem related to a lack of management trustworthiness (Haar, O'Kane, & Cunningham, 2022), defined as the managerial conduct that supports the assumption that an actor (the organization) will act in the other's best interests (its employees) (Hodson, 2004). Management trustworthiness comprises three aspects: benevolence, integrity, and ability (Mayer, Davis, & Schoorman, 1995; Ogbeibu, Senadjki, & Gaskin, 2018). Recent studies, which are firm-centrism oriented, have revealed that knowledge hiding is reduced by management trustworthiness mainly because it helps minimize employees' stress and concern about losing their jobs (Chhabra & Pandey, 2022; Jahanzeb, De Clercq, & Fatima, 2021).

Conversely, research on knowledge hiding and trustworthiness at interorganizational level is still fairly incipient; the closest approach to this discussion is the one endeavouring to understand the role of partner trustworthiness as a driver of knowledge exchange (Carson, Madhok, Varman, & John, 2003; Chiong, Dhakal, Chaston, & Chica, 2022). Specifically, previous studies have repeatedly found that partner trustworthiness increases employees' positive attitude toward external allies (Henttonen, Hurmelinna-Laukkanen, & Blomqvist, 2020) and the intention to collaborate with them (Akinremi & Roper, 2021) while reducing the presence of opportunistic behaviours, such as knowledge leakage (Qiu & Haugland, 2019), from the parties involved (Collier, Wood, & Henderson, 2021; Judge & Dooley, 2006). Unfortunately, there is a lack of studies examining the effect of partner trustworthiness on interorganizational knowledge hiding.

Therefore, we believe the following situations are occurring in firms: 1) Interorganizational knowledge hiding is a reality with devastating effects on the relationship between AI capability and open innovation. Particularly, we believe that, as it occurs at intra-organizational level, employees will also resort to hiding knowledge from external allies to reduce the risk of being replaced by artificial intelligence at work. 2) Partner trustworthiness is the key variable to prevent employees from hindering activities carried out by the firm to co-create and co-exploit AI-based solutions and business models. Indeed, we believe employees will stop hiding knowledge from the firm's external partners when they perceive their benevolence, integrity and ability.

Thus, the present work aims to analyze the effect of interorganizational knowledge hiding –moderated by partners' benevolence, integrity and ability– on the relationship between AI capability and inbound and outbound open innovation processes. This moderated moderation model was tested through survey data with a sample of 229 firms, the vast majority of which belong to highly digitized sectors. This type of model, better known as three-way interaction, helps to establish the rate of change of the independent variable's effect (AI capability) on the dependent variable (both inbound and outbound processes) as the primary moderator (interorganizational knowledge hiding) changes when the secondary moderator (partner trustworthiness) varies (Hayes, 2018).

2. Theoretical framework and hypothesis statement

2.1. AI capabilities and inbound and outbound processes

AI capabilities can be defined as a company's capacity to assemble organizational, human, and AI resources for the creation and capture of business value (Wamba-Taguimdje et al., 2020). Tangible and human resources are the two main dimensions of AI capability (Mikalef & Gupta, 2021). The tangible dimension is composed of three subdimensions: 1) Data, or the processing of large amounts of structured and unstructured data; 2) Technology, referring to the technology infrastructure for the company's use of intelligent robots; 3) Basic resources, i.e., sufficient resources for developing and implementing AI-based solutions. Meanwhile, human resources refer to the technical and business knowledge to operate and take advantage of this digital technology.

Open innovation is the innovation process based on the intentional management of knowledge flows across organizational boundaries (Chesbrough & Bogers, 2014; Markovic, Bagherzadeh, Vanhaverbeke, & Bogers, 2021). The first open innovation process is inbound, which alludes to the flow of external knowledge coming in and arising from joint activities with external allies, such as outsourcing technology services, customer involvement, or inward IP licensing (Tang, Fisher, & Qualls, 2021; van de Vrande, de Jong, Vanhaverbeke, & de Rochemont, 2009). The second open innovation process is outbound, which relates to managing the flow of knowledge from the inside out, especially with the commercial co-exploitation of technologies or their applications through mechanisms including joint-venturing, technology spin-offs and outward IP licensing (Cheah & Ho, 2021; Lau, Lee, Lai, & Lee, 2018).

Firms that have been successful at developing their AI capability are more involved in open innovation (Keegan, Canhoto, & Yen, 2022; Yang et al., 2022), particularly in inbound activities that help enhance products and services such as collaboration with customers (Sjödin et al., 2021) and technology providers (Li et al., 2021). The reason behind the increase in these activities is that AI capability increases routine-task automation and helps to overcome restrictions regarding the processing of large amounts of data (Fosso Wamba, 2022; Kushwaha, Kumar, & Kar, 2021). Both aspects allow employees to have better insights about changes in customer preferences and a way to create value through artificial intelligence (Rusthollkarhu et al., 2022) and, above all, to have more free time for creative and innovative work (Mikalef & Gupta, 2021). These conditions increase employee interest and participation in co-creation activities to improve their innovation ideas and accelerate their implementation within the company with the support of external partners (Kohtamäki, Rabetino, Parida, Sjödin, & Henneberg, 2022).

AI capability development also increases the degree of firm engagement with outbound process activities. It particularly boosts the search for protection mechanisms for AI-based solutions developed in-house (Yang et al., 2022). For example, in the local context, some firms have developed AI applications for analyzing data capable of predicting work disabilities, anticipate churn, or predict customer's propensity to buy, which they deliberately protect through copyright and trademark with the support of the actors and mechanisms provided by the local innovation ecosystem. In this way, the company seeks to maintain its AI-based competitive advantages (Krakowski, Luger, & Raisch, 2022). In parallel, the company becomes more interested in commercially co-exploiting these developments with other actors such as Fintech, e-commerce firms, or other firms in the sector (Arias-Pérez, Velez-Ocampo, & Cepeda-Cardona, 2021).

Additionally, the intention to share the knowledge associated with internally developed AI applications with the innovation ecosystem is strengthened by the development of AI capability. With the help of external partners, these solutions will be more scalable and less likely to conflict with other applications or technological standards (Kohtamäki et al., 2022; Sjödin et al., 2021). The firm also becomes more interested in new ventures, many of which are born-digital that extensively exploit the new business models emerging as a result of AI capability development (Chatterjee, Chaudhuri, Vrontis, & Basile, 2022). The following hypotheses are hence put forward:

H1a. AI capability positively influences the inbound process.

H1b. AI capability positively influences the outbound process.

2.2. Moderating role of interorganizational knowledge hiding

Knowledge hiding emerges in the firm in three ways: playing dumb, evasive hiding and rationalized hiding (Connelly et al., 2012). In terms of interorganizational hiding, playing dumb occurs when an employee acts in front of a coworker or an external ally as though they are ignorant of the information or knowledge that they possess. Evasive hiding refers to employees' elusive behaviour toward any knowledge exchange commitment required by external allies, either delaying its delivery or providing information that is incomplete or different from what was requested. By comparison, rationalized hiding occurs when employees argue false reasons to disregard an external ally's information request; for example, the employee may claim they are not permitted to share the information or that the information is extremely confidential, when in fact there is no such restriction (Xiong, Zheng, Germon, Susini, & Chang, 2021).

Uncertainty in the business environment is a trigger for knowledge hiding (Caputo, Magni, Papa, & Corsi, 2021). Such uncertainty is exacerbated by AI in the digital age a threat to employees' jobs and careers (Braganza, Chen, Canhoto, & Sap, 2021; Rampersad, 2020). AI prompts them to opportunistically resort to the three types of hiding to protect their personal interests at work (Arias-Pérez & Vélez-Jaramillo, 2021; Shen & Kuang, 2022). Consequently, activities conducted by the firm with external allies to co-create and co-exploit AI-based solutions and business models will be sabotaged by employees. Notably, they will resort to hiding in all its forms. In other words, they will avoid sharing key knowledge with external partners to prompt the failure of any joint development aimed at boosting work automation, fully-digitized products and services and the launch of AI-based new ventures, all with the purpose of lessening the risk of being replaced by intelligent robots at work (Zhang et al., 2022).

For example, an employee agrees to share key documents such as a process flowchart or a product or service technical sheet required by the external partner to support its automation or to help turn it into a new business model or spin-off. The employee then delays submitting these files as long as possible, shares an incomplete flowchart or technical sheet or one about a different product or process. The employee may even hide behind a false concern about a potential, non-existent leak of sensitive information (Arias-Pérez & Vélez-Jaramillo, 2021; Shen & Kuang, 2022) to close the door to knowledge exchange beyond organizational boundaries. Therefore, the following hypotheses are proposed:

H2a. The positive impact of AI capability on inbound process will be reduced when knowledge hiding is present.

H2b. The positive impact of AI capability on outbound process will be reduced when knowledge hiding is present.

2.3. Moderating effect of partner trustworthiness

Partner trustworthiness is derived from management trustworthiness and is defined as the managerial behaviour that supports the expectation that an actor (the organization) will act in the other's best interests (its employees) (Hodson, 2004). Employees view managers as trustworthy to the extent that they perceive them to have good intentions (benevolence), to subscribe to and act in accordance with a set of valued or acceptable principles (integrity), and to be able to meet expectations (ability) (Mayer et al., 1995; Ogbeibu et al., 2018). Partner trustworthiness as an offshoot of this classic concept refers to the behaviour that supports the expectation that an actor (the external partner) will act in the interests of the other (Akinremi & Roper, 2021; Carson et al., 2003), particularly of employees who, due to their technical or business knowledge, continue to be the ones setting the pace of collaborative work in AI-driven innovation with external allies (Petrescu et al., 2022; Sjödin et al., 2021).

Partner trustworthiness has long been considered a key variable in interorganizational knowledge exchange (Jiang, Bao, Xie, & Gao, 2016). It intensifies employees' positive attitude toward external allies (Henttonen et al., 2020) and the intention to collaborate with them (Akinremi & Roper, 2021), especially in receiving and sharing key knowledge (Jiang et al., 2016; Qiu & Haugland, 2019) while reducing the presence of opportunistic behaviours from the involved parties (Judge & Dooley, 2006). Consequently, partner trustworthiness enhances value co-creation (Ferguson, Schattke, & Paulin, 2016) and the overall outcomes of collaborative work (Choi, Özer, & Zheng, 2020). For instance, firms are more open to experimenting with new digital technologies proposed by an external ally when the latter is perceived as having integrity and competence (Falcone, Steelman, & Aloysius, 2021).

Partner trustworthiness is hence crucial to reducing the negative effect of interorganizational knowledge hiding for the following reasons. First, benevolence and integrity minimize knowledge hiding by lessening employee stress and worry about losing their jobs (Chhabra & Pandey, 2022; Jahanzeb et al., 2021). As an example, several digital transformation attempts in the local context failed after employees hid key knowledge upon realizing that the true purpose of the collaboration requested by technology providers hired by the firm to automate certain organizational processes was intended to replace them in the workplace with an intelligent robot. Viewed in another way, when external allies act with good intentions and following shared principles, there is increased employee perception that the AI-based solutions they are co-creating and co-exploiting with external allies do not represent a threat to their personal interests in the job. Therefore, once these concerns implying great emotional wear and tear are alleviated, employees no longer need to resort to knowledge hiding as a strategy to safeguard their interests (Chhabra & Pandey, 2022).

Nonetheless, benevolence and integrity are not the only two partner characteristics that help mitigate interorganizational knowledge hiding; ability also plays a relevant role for less emotional reasons. Specifically, another type of cognition-based trust is boosted when employees perceive their partners' high level of competence (Henttonen et al., 2020), that is, they perceive that the partner possesses the knowledge and experience required for collaborative work to be successful and that the need to act opportunistically is redundant (Akinremi & Roper, 2021; Tomlinson, Schnackenberg, Dawley, & Ash, 2020). That kind of trust, resulting from the partner's ability, immediately reduces knowledge hiding as it helps employees perceive collaborative work as an opportunity to learn and capture key knowledge from external sources that is useful for achieving their individual goals and objectives both at work and in the industry (Nadeem, Liu, Ghani, Younis, & Xu, 2020). In this scenario, employees' perception that there is a high risk of knowledge appropriation by third parties also thus decreases, mitigating knowledge hiding (Hadjielias, Christofi, & Tarba, 2021). In consequence, the following hypotheses are proposed:

H3a. The negative impact of interorganizational knowledge hiding on the relationship between AI capability and inbound process will be reduced when partner benevolence is stronger.

H3b. The negative impact of interorganizational knowledge hiding on the relationship between AI capability and inbound process will be reduced when partner ability is stronger.

H3c. The negative impact of interorganizational knowledge hiding on the relationship between AI capability and inbound process will be reduced when partner integrity is stronger.

H4a. The negative impact of interorganizational knowledge hiding on the relationship between AI capability and outbound process will be reduced when partner benevolence is stronger.

H4b. The negative impact of interorganizational knowledge hiding on the relationship between AI capability and outbound process will be reduced when partner ability is stronger.

H4c. The negative impact of interorganizational knowledge hiding on the relationship between AI capability and outbound process will be reduced when partner integrity is stronger. Fig. 1. Three-way interaction.

3. Methodology

3.1. Sample and data collection

The three-way interaction was tested on a sample of service and manufacturing companies which have succeeded in advancing their digital transformation (Butner & Ho, 2019) and belong mainly to highly digitized sectors (Manyika et al., 2015). These companies are located in Colombia and, together with their Brazilian counterparts, make the largest investments in emerging digital technologies in South America (Portulans Institute, 2019). There were two main work fronts for the data collection, which took place between March 2021 and August 2021. First, the most renowned polling company in the nation was hired to distribute the questionnaire to 200 business executives that had previously reported using new digital technologies. Second, the questionnaire was sent to 100 managers of companies from the local cluster of information and communications technologies. This second dataset is completely different from the first one.

Although 257 valid responses were received, the final sample size was 229 after excluding through a cluster analysis a small group of companies that reported very low values in the tangible dimension of AI capability. According to the minimum R-squared method used in this

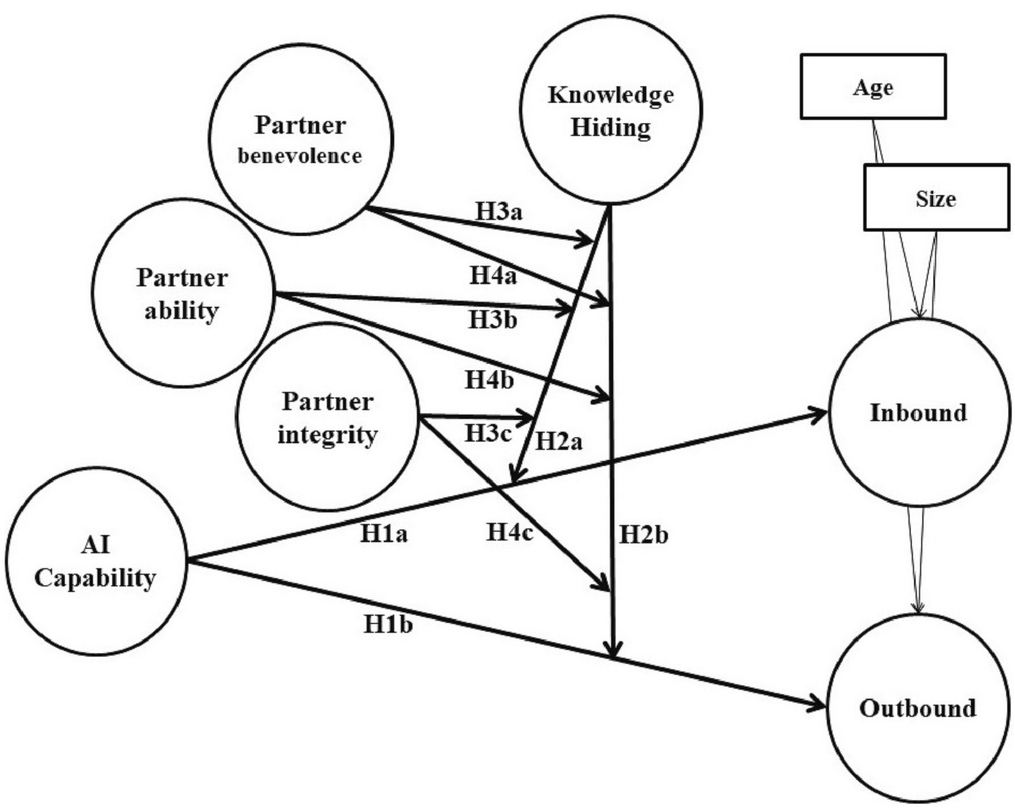

Fig. 1. Three-way interaction.

work to calculate the minimum sample size, this number of companies allowed for a statistical power higher than 80%, sufficient to ensure that the statistical test performed was able to recognize a path coefficient as statistically significant ($P < 0.05$) (Hair, Risher, Sarstedt, & Ringle, 2019).

As for the firms' characteristics, 46% are large and 54% are SMEs. The majority of the service sector companies in the sample belong to information services (32%), computer programming (16%), wholesale and retail trade (7%), education (6%), financial and insurance services (5%), human health (2%), other knowledge-intensive services (14%), and other less knowledge-intensive services (8%). The manufacturing sector companies in the sample belong to food products (6%), pharmaceuticals (1%), and other low-and-medium technology manufacturing sectors (3%). Furthermore, 24% of the executives surveyed are general managers; the remaining executives belong to different functional areas in the following proportion: Systems and Technology (55%), Research and Development (8%), Finances (6%), Human Resources (5%), Other Areas (2%).

3.2. Measurement scales

The scale developed by Mikalef and Gupta (2021) was used to measure AI capability and the scale by Cheng and Shiu (2015) was employed for measuring inbound and outbound processes. Partner trustworthiness was measured with the scale of Becerra, Lunnan, and Huemer (2008), recently used in another key study on the subject (Qiu & Haugland, 2019). For the measurement of interorganizational knowledge hiding the scale of Connelly et al. (2012) was adapted, which is the most widely used in this field of study (Appendix A). A Likert scale going from *totally disagree* (1) to *totally agree* (5) was used.

3.3. Control variables

In our study we incorporate two control variables: size and age, which have been considered in previous works on open innovation (Harison & Koski, 2010; Seo & Park, 2022).

3.4. Reliability and validity

The validity and reliability of the measuring model, which includes formative and reflective constructs, were assessed with structural equations by the partial least squares (PLS) method (Hair, Hult, Ringle, & Sarstedt, 2021). In the case of the only formative construct of the model (AI capability), it was verified that the second- and first-order constructs had significant weights and that their variance inflation factor (VIF) was below 5 (Hair et al., 2019) (see Table 1).

As for the reflective constructs, it was verified that all of them had an average variance extracted (AVE) >0.5, and a Cronbach's alpha (CA) and a composite reliability index (CR) above 0.7. (see Table 2). The items' individual reliability was also assessed and all their loadings were confirmed to be significant and higher than 0.7. (Hair et al., 2021).

3.5. Discriminant validity

To establish discriminant validity (see Table 3), it was verified that all the Heterotrait-Monotrait (HTMT) correlations of the reflective constructs were below the 0.85 threshold (Hair et al., 2021).

3.6. Three-way interaction test procedure

A three-way interaction or moderate moderation model allows to establish the rate of change of the independent variable's (AI capability) effect on the dependent variable (inbound and outbound) as the primary moderator (interorganizational knowledge hiding) changes when the secondary moderator (partner trustworthiness) varies. To assess the three-way interaction, we estimated three structural equation models:

Table 1
Reliability and validity of AI capability.

Construct	Loadings
Artificial intelligence capability (Third-order)	
Tangible (Second-order) (Weight = 0.605*; VIF = 4.925)	
Data (First-order; Weight = 0.158; VIF = 2.397)*	
ArtIntellCap1	0.768
ArtIntellCap2	0.895
ArtIntellCap3	0.877
ArtIntellCap4	0.791
ArtIntellCap5	0.917
ArtIntellCap6	0.902
Technology (First-order; Weight = 0.321; VIF = 2.958)*	
ArtIntellCap7	0.821
ArtIntellCap8	0.828
ArtIntellCap9	0.759
ArtIntellCap10	0.916
ArtIntellCap11	0.882
ArtIntellCap12	0.854
ArtIntellCap13	0.900
Basic Resources (First-order; Weight = 0.617; VIF = 2.244)*	
ArtIntellCap14	0.938
ArtIntellCap15	0.949
ArtIntellCap16	0.939
Human Skills (Second-order) (Weight = 0.422; VIF = 4.925)*	
ArtIntellCap17	0.843
ArtIntellCap18	0.878
ArtIntellCap19	0.866
ArtIntellCap20	0.834
ArtIntellCap21	0.869
ArtIntellCap22	0.867
ArtIntellCap23	0.904
ArtIntellCap24	0.888
ArtIntellCap25	0.867
ArtIntellCap26	0.888
ArtIntellCap27	0.878
ArtIntellCap28	0.893
ArtIntellCap29	0.870
ArtIntellCap30	0.889

direct, moderation, and moderate moderation. In the first one we incorporated the control variables (age and size) and tested the direct effects of AI capability on the inbound and outbound activities (H1a and H1b). In the second model, we introduced the first moderating variable and tested its effect on the direct relationships that were positive and significant in the previous model (H2a and H2b). If the results show the existence of a first moderating effect, the third model is tested, in which the second moderating variable is included and the changes in the combined effect of the independent variable and the first moderator on the independent variable are estimated (H3a, H3b, H3c, H4a, H4b, H4c) (Hayes, 2018).

4. Results

Table 4 shows that AI capability has a significant positive effect in the direct model on both inbound (0.24) and outbound (0.41) activities, therefore validating H1a and H1b. In the moderation model, it is observed that only inter-organizational knowledge hiding has a significant negative effect on the relationship between AI capability and outbound activities (−0.17), thereby accepting H2b but rejecting H2a. Since this first moderator does not affect the relationship between AI capability and inbound activities, it was not possible to test H3a, H3b, and H3c. In the third model, only partner ability was found to have a significant positive effect on the combined effect of inter-organizational knowledge hiding and AI capability on outbound activities (0.16). Therefore, H4b is accepted but H4a and H4c are rejected. The control variables had no significant influence on any of the three models.

The f^2 value of 0.13 indicates that the size of the moderating effects is far from the low level (0.02), close to the medium level (0.15), and far from the high level (0.35) (Hair et al., 2021). Therefore, its importance in AI-driven open innovation cannot be underestimated. Moreover,

Table 2
Reliability and validity of the reflective constructs.

Constructs	Loadings
Partner trustworthiness	
Benevolence (CA = 0.903; CR = 0.927; AVE = 0.718)	
Benev1	0.885
Benev2	0.865
Benev3	0.827
Benev4	0.834
Benev5	0.824
Ability(CA = 0.930; CR = 0.947; AVE = 0.782)	
Abil1	0.860
Abil2	0.897
Abil3	0.889
Abil4	0.896
Abil5	0.879
Integrity(CA = 0.884; CR = 0.970; AVE = 0.735)	
Integ1	0.841
Integ2	0.908
Integ3	0.819
Integ4	0.859
Open innovation / Inbound (CA = 0.790; CR = 0.853; AVE = 0.539)	
Inbound1	0.652
Inbound2	0.736
Inbound3	0.772
Inbound4	0.815
Inbound5	0.686
Open innovation / Outbound (CA = 0.867; CR = 0.904; AVE = 0.654)	
Outbound1	0.761
Outbound2	0.864
Outbound3	0.794
Outbound4	0.803
Outbound5	0.818
Interorganizational knowledge hiding (CA = 0.884; CR = 0.917; AVE = 0.505)	
Evasive hiding (CA = 0.791; CR = 0.877; AVE = 0.705)	
Evasive1	0.756
Evasive2	0.899
Evasive3	0.858
Playing dumb (CA = 0.938; CR = 0.956; AVE = 0.844)	
Dumb1	0.899
Dumb2	0.932
Dumb3	0.930
Dumb4	0.914
Rationalized hiding (CA = 0.846; CR = 0.908; AVE = 0.765)	
Rationalized1	0.852
Rationalized2	0.901
Rationalized3	0.870

Table 3
Discriminant validity.

Constructs	HTMT				
	1	2	3	4	5
1. Partner benevolence					
2. Partner ability	0.703				
3. Partner integrity	0.847	0.635			
4. Inbound	0.289	0.374	0.225		
5. Outbound	0.198	0.267	0.126	0.473	
6. Interorganizational knowledge hiding	0.192	0.120	0.184	0.201	0.210

Fig. 2 shows to what extent interorganizational knowledge hiding weakens the relationship between AI capability and outbound activities, and to what extent partner ability reduces the negative effects of knowledge hiding.

5. Discussion

Our results confirm that AI capability development increases firm engagement with open innovation processes: inbound (Sjödin et al., 2021) and outbound (Yang et al., 2022). However, the positive influence of AI capability is greater in the outbound ($\beta = 0.41$) than in the inbound ($\beta = 0.24$) process, which may be linked to the fact that the firms in the sample belong mostly to highly digitized sectors with sufficient knowledge to take advantage of the opportunities provided by artificial intelligence (Fosso Wamba, 2022; Mikalef & Gupta, 2021). These firms are therefore interested in engaging in activities such as customer co-creation to maximize the use of intelligent robots, yet do not depend on the inbound process to create value from this digital technology. Instead, there is a greater concern with adopting protection mechanisms for AI-based solutions developed in-house and maximizing commercial co-exploitation with the support of external allies (Kohtamäki et al., 2022; Yang et al., 2022).

This is probably the reason why knowledge hiding does not reduce the positive effect of AI ability on the inbound process. The fact that the firms in the sample have a good resource and internal knowledge base regarding AI, as most of them are highly digitized, could be a supporting factor for employees to anticipate the possible risk of inbound processes and become involved in those types of activities that are strictly necessary (Akinremi & Roper, 2021). As a result, contrary to expectations, co-creation would not pose a threat to employees' personal interests at work in this scenario.

In contrast, when it comes to co-exploiting with external allies, knowledge hiding is evident ($\beta = -0.17$), especially because this is the activity that could offer the most learning experiences for highly digitized firms and create changes both in their current technological standard and business models (Arias-Pérez et al., 2021); this would increase the company's use of intelligent robots while also maximizing value creation through the use of digital technologies (Yang et al., 2022). In this scenario, employee perception of the likelihood of being replaced by artificial intelligence at work grows, which explains the presence of knowledge hiding in outbound activities.

However, the most interesting result of the study is that, of the three partner trustworthiness aspects, only ability ($\beta = 0.16$) contributes to reducing the negative effect of knowledge hiding on the relationship between AI ability and the outbound process. External partners' exhibition of benevolence and integrity is thus of little interest to employees; what matters is that they generate cognition-based trust (Henttonen et al., 2020). In other words, partners should be perceived as possessing key knowledge and experience; in this way, co-exploitation will be successful and collaborative work will be an opportunity for employees to learn and capture key AI knowledge useful for achieving their individual goals and their objectives both at work and in the industry (Akinremi & Roper, 2021; Tomlinson et al., 2020). Moreover, the f^2 value of 0.13 indicates that the size of *ability*'s moderating effect is of a considerable magnitude so that its role in reducing interorganizational knowledge hiding cannot be downplayed.

6. Conclusions

6.1. Theoretical implications

This study has several academic implications. First, the work contributes to moving the discussion on AI-driven open innovation beyond the exploratory domain. Unlike previous studies that have identified a relationship between AI capability and open innovation (Sjödin et al., 2021; Yang et al., 2022), the present findings show there is greater interest in the outbound process rather than in the inbound process, that is, the concern for maximizing the commercial co-exploitation of AI-based solutions developed in-house prevails, particularly in firms that have attained a certain degree of maturity in the adoption and use of artificial intelligence. This result also constitutes a departure from

Table 4
Results.

Models	Paths	Coeficients	Conclusions
	Direct effects		
	H1a. AI capability - > Inbound (R^2 =)	0.24**	Accepted
	H1b. AI capability - > Outbound ($R^2 = 0.17$)	0.41**	Accepted
	Control variables		
Direct	Age - > Inbound	−0.06	
	Age - > Outbound	−0.03	
	Size - > Inbound	−0.08	
	Size - > Outbound	−0.05	
	Direct effects		
	AI capability - > Inbound	0.25**	
	AI capability - > Outbound	0.40**	
	Interorg. knowledge hiding (Interkhiding) > Inbound	−0.05	
	Interkhiding - > Outbound	0.11	
	Interaction effects		
	H2a. AI capabilityxInterkhiding - > Inbound	0.23	Rejected
	H2b. AI capabilityxInterkhiding - > Outbound ($R^2 = 0.21$; $f^2 = 0.05$)	−0.17*	Accepted
	Control variables		
	Age - > Inbound	−0.05	
	Age - > Outbound	0.00	
	Size - > Inbound	−0.11	
Moderation	Size - > Outbound	−0.01	
	Direct effects		
	AI capability - > Outbound	0.30**	
	Interkhiding - > outbound	0.15*	
	Benevolence - > Outbound	0.21*	
	Ability - > Outbound	0.06	
	Integrity - > Outbound	−0.09	
	Interaction effects		
	AI capabilityxInterkhiding - > Outbound	−0.17*	
	AI capabilityxBenevolence - > Outbound	−0.09	
	AI CapabilityxAbility - > Outbound	0.09	
	AI CapabilityxIntegrity - > Outbound	0.02	
	InterkhidingxIntegrity - > Outbound	0.05	
	InterkhidingxBenevolence - > Outbound	−0.11	
	InterkhidingxAbility - > Outbound	−0.01	
	H4a. AI capabilityxInterkhidingxBenevolence - > Outbound	−0.05	Rejected
	H4b. AI capabilityxInterkhidingxAbility - > Outbound ($R^2 = 0.30$; $f^2 = 0.13$)	0.16*	Accepted
	H4c. AI capabilityxInterkhidingxIntegrity - > Outbound	−0.10	Rejected
	Control variables		
	Age - > Outbound	0.01	
Three-way interaction	Size - > Outbound	−0.02	

* $p < 0.05$.
** $p < 0.001$.

mainstream open innovation research, which has traditionally favoured the inbound process more prominently over the outbound process in the pre-digital and digital eras (Keegan et al., 2022; Li et al., 2021; Tang et al., 2021).

Second, a new study perspective on knowledge hiding in the digital age is provided by strictly placing this behaviour at the interorganizational level, namely in the context of the firm's collaborative work with external allies to co-create and co-exploit AI-based solutions. This approach evinces a departure in the discussion initiated by seminal work which identified the presence of this behaviour, albeit in another context –in the interaction of certain digital platforms such as Uber and Airbnb with their customers (Khelladi et al., 2021). Our analysis demonstrates that external allies, particularly those who support the firm in outbound activities, should be listed among those who are affected by knowledge hiding. This finding is key as it broadens research horizons beyond knowledge hiding between the employees and their colleagues, which has traditionally been the approach followed by the most relevant, previous studies conducted in the context of digital transformation (Arias-Pérez & Vélez-Jaramillo, 2021; Ghasemaghaei & Turel, 2021; Shen & Kuang, 2022).

There is also a methodological contribution as the present study provides an adaptation of the knowledge-hiding scale that has been widely used to measure this phenomenon between employees and their colleagues (Anand et al., 2022). This adaptation of the scale by Connelly et al. (2012) for measuring interorganizational knowledge hiding yields good reliability and validity indicators. In this way, the research helps to overcome one of the main limitations of this area of study and will enable the completion of studies that go beyond the exploratory level at which they are now being conducted (Khelladi et al., 2021). Additionally, our findings suggest expanding the list of opportunistic employee behaviours that hinder the implementation of intelligent robots in the firm (Enholm et al., 2021; Truong & Papagiannidis, 2022) and considering a possible redefinition of research priorities in the subject area by including interorganizational knowledge hiding.

Nevertheless, the main academic contributions of our work are concerned with the discussion on partner trustworthiness. Firstly, our results show this variable continues to be crucial to counteracting opportunistic behaviours in knowledge exchange, not only in the pre-digital era, as has been thought until now (Collier et al., 2021; Qiu & Haugland, 2019), but also in the digital era. Secondly, our results dismiss the significance of benevolence and integrity, the traits that have significantly reduced knowledge hiding, given the emotional relief they produce when trustworthiness is at the centre of the intraorganizational discussion (Chhabra & Pandey, 2022; Jahanzeb et al., 2021). Contrariwise, rational reasons matter more at the interorganizational level since ability is the only external partner's trait that weakens knowledge hiding. This indicates that employees are willing to share knowledge only when they perceive co-exploitation with the external partner offers a chance to learn and capture key AI knowledge that is useful for achieving their individual goals and objectives at work and in the

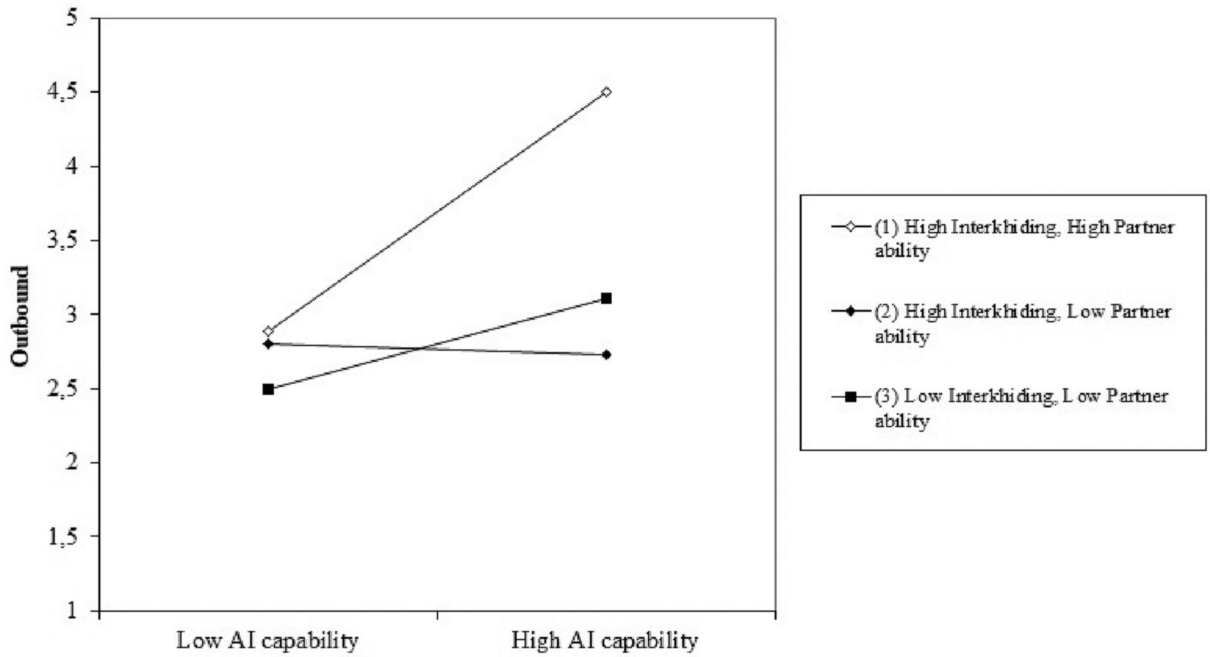

Fig. 2. The three-way interaction of AI capability, interorganizational knowledge hiding and partner ability in outbound activities.

industry (Akinremi & Roper, 2021; Tomlinson et al., 2020).

6.2. Practical implications

Regarding the practical implications of the study. Businesses are generally aware of the value and benefits of implementing AI technology, but they usually fail to approach it strategically on a regular basis. This requires a thorough comprehension of the goals and objectives of all facets of AI operations, from data collection to the dissemination of the uncovered insights to the workforce. The answer to this question is quite simple: organizations must always have a plan in place before investing time and resources in launching costly and resource-intensive AI initiatives and pilots without a clear understanding of the benefits they can deliver. Businesses must ensure that their AI initiatives are clearly linked to business performance objectives, prioritized by their strategic goals, and that every stakeholder understands what success or failure will look like for a given initiative.

The study's main practical suggestion, however, is to put more effort into making co-exploitation with external partners a genuine learning opportunity in order to discourage employees from hiding knowledge. Employees should view co-exploitation as a strategy to develop new AI technical and business skills so that they can be reassigned to other roles within the organization as they will inevitably be replaced by an IA application. For this purpose, the company should refrain from signing restrictive confidentiality agreements that slow down knowledge flows between the parties. Second, in order for employees to understand their dual mission—co-exploitation and capture of key knowledge—the organization should prioritize mapping key knowledge from external partners and, to the greatest extent possible, establish knowledge gaps with them. Third, to maximize knowledge transfer to employees, alliances with external partners should plan for their participation in specific activities of the company's training programs from the beginning.

This work has a few limitations. First, our study sample is mainly made up of highly digitized firms (Manyika et al., 2015) which do not depend on the inbound process to create value from artificial intelligence. Hence, extrapolating our results to firms with a low degree of digitization would present some challenges since this is why they rely heavily on both this open innovation process and external partners, namely suppliers and customers, to reach a certain degree of digital maturity (Sjödin et al., 2021). We assume that the influence of partner trustworthiness on this type of firms would be completely different, while benevolence and integrity may be relevant, unlike in our study.

6.3. Limitations and future directions for research

Furthermore, our study focuses on the knowledge employees hide from external partners but the phenomenon is not addressed in the opposite direction, that is to say, from external partners to employees who partake in collaborative work with them. In the literature, there are some initial indications external partners also exhibit this opportunistic behaviour when collaborating around the use of artificial intelligence (Grewal, Guha, Satornino, & Schweiger, 2021). This would therefore be a second limitation of the present research, as it cannot establish the impact of this other type of knowledge hiding on the relationship between AI capability and the outbound process. We believe its effect on the commercial co-exploitation of AI-based solutions developed in-house would be devastating.

Consequently, future studies should analyze AI-driven open innovation in the context of firms with a low degree of digitization (Manyika et al., 2015) or which have just started venturing into digital transformation. We believe that the inbound process could be more relevant in that context than it was in our study, while knowledge hiding could have a significant, negative impact on the relationship between AI capability and inbound processes for less rational reasons (Chhabra & Pandey, 2022; Jahanzeb et al., 2021), unlike those identified in our work. Additionally, the subject area would greatly benefit from the analysis of the effect of external partners' knowledge hiding on their trustworthiness and whether it has a contagion effect on employees; in other words, to what extent it leads employees to incur the same behaviour. Lastly, future studies should look into identifying determining factors for employees to perceive a high degree of ability in external partners (Akinremi & Roper, 2021; Tomlinson et al., 2020).

Data availability

Data will be made available on request.

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Appendix A. Scale items

Constructs	Items
Partner trustworthiness	
Benevolence	
Benev1	When making important decisions, the partner firm is concerned about our company's welfare
Benev2	The partner would not knowingly do anything to hurt our company
Benev3	Our firm's needs are important to the partner firm
Benev4	The partner firm looks out for what is important to our firm in the alliance
Benev5	This partner firm will go out of its way to help our firm
Ability	
Abil1	The partner firm is very capable of performing its role in the alliance
Abil2	The partner firm is well qualified for the alliance
Abil3	The partner firm has much knowledge about the work that needs to be done in the alliance
Abil4	We are very confident about the partner firm's skills
Abil5	The partner firm has specialized capabilities that add value to the alliance
Integrity	
Integ1	The partner firm has a strong sense of justice
Integ2	The partner firm is fair in business dealings with us
Integ3	This alliance partner stands by its words
Integ4	Sound principles seem to guide the partner firm's actions
AI capability (Third-order)	
Tangible (Second-order)	
Data (First-order)	
ArtIntellCap1	We have access to very large, unstructured, or fast-moving data for analysis
ArtIntellCap2	We integrate data from multiple internal sources into a data warehouse or mart for easy access
ArtIntellCap3	We integrate external data with internal to facilitate high-value analysis of our business environment
ArtIntellCap4	We have the capacity to share our data across business units and organizational boundaries
ArtIntellCap5	We are able to prepare and cleanse AI data efficiently and assess data for errors
ArtIntellCap6	We are able to obtain data at the right level of granularity to produce meaningful insights
Technology (First-order)	
ArtIntellCap7	We have explored or adopted cloud-based services for processing data and performing AI and machine learning
ArtIntellCap8	We have the necessary processing power to support AI applications (e.g. CPUs, GPUs)
ArtIntellCap9	We have invested in networking infrastructure (e.g. enterprise networks) that supports efficiency and scale of applications (scalability, high bandwidth, and low-latency)
ArtIntellCap10	We have explored or adopted parallel computing approaches for AI data processing
ArtIntellCap11	We have invested in advanced cloud services to allow complex AI abilities on simple API calls (e.g. Microsoft Cognitive Services, Google Cloud Vision)
ArtIntellCap12	We have invested in scalable data storage infrastructures
ArtIntellCap13	We have explored AI infrastructure to ensure that data is secured from to end to end with stateof-the-art technology
Basic Resources (First-order)	
ArtIntellCap14	The AI initiatives are adequately funded
ArtIntellCap15	The AI project has enough team members to get the work done
ArtIntellCap16	The AI project is given enough time for completion
Human Skills (Second-order)	
ArtIntellCap17	The organization has access to internal and external talent with the right technical skills to support AI work
ArtIntellCap18	Our data scientists are very capable of using AI technologies (e.g. machine learning, natural language processing, deep learning)
ArtIntellCap19	Our data scientists have the right skills to accomplish their jobs successfully
ArtIntellCap20	Our data scientists are effective in data analysis, processing, and security
ArtIntellCap21	Our data scientists are provided with the required training to deal with AI applications
ArtIntellCap22	We hire data scientists that have the AI skills we are looking for
ArtIntellCap23	Our data scientists have suitable work experience to fulfill their jobs
ArtIntellCap24	Our managers are able to understand business problems and to direct AI initiatives to solve them
ArtIntellCap25	Our managers are able to work with data scientists, other employees and customers to determine opportunities that AI might bring to our organization
ArtIntellCap26	Our managers have a good sense of where to apply AI
ArtIntellCap27	The executive manager of our AI function has strong leadership skills
ArtIntellCap28	Our managers are able to anticipate future business needs of functional managers, suppliers and customers and proactively design AI solutions to support these needs
ArtIntellCap29	Our managers are capable of coordinating AI-related activities in ways that support the organization, suppliers and customers
ArtIntellCap30	We have strong leadership to support AI initiatives and managers demonstrate ownership of and commitment to AI projects
Open innovation / Inbound	
Inbound1	External partners, such as customers, competitors, research institutes, consultants, suppliers, government, or universities, are directly involved in all our innovation
Inbound2	All our innovation projects are highly dependent upon the contribution of external partners, such as customers, competitors, research institutes, consultants, suppliers, government, or universities
Inbound3	Our firm often buys R&D related products from external partners
Inbound4	Our firm often buys intellectual property, such as patents, copyrights, or trademarks, belonging from external partners to be used in our innovation projects

(*continued on next page*)

(*continued*)

Constructs	Items
Open innovation / Outbound	
Outbound1	Our firm often sells licenses, such as patents, copyrights, or trademarks, to other firms to better benefit from our innovation efforts
Outbound2	Our firm often offers royalty agreements to other firms to better benefit from our innovation efforts
Outbound3	Our firm strengthens every possible use of our own intellectual properties to better benefit our firm
Outbound4	Our firm founds spin-offs to better benefit from our innovation efforts
Outbound5	We often co-exploit technology with external organizations
Interorganizational knowledge hiding	
Evasive hiding	When it comes to sharing information and knowledge with external partners, our employees…
Evasive1	agreed to help them but instead gave them information different from what they wanted
Evasive2	told them that they would help them out later but stalled as much as possible
Evasive3	offered them some other information instead of what they really wanted
Playing dumb	
Dumb1	pretended that they did not know the information
Dumb2	said that they did not know, even though they did
Dumb3	pretended they did not know what external partners was talking about
Dumb4	said that they were not very knowledgeable about the topic
Rationalized hiding	
Rationalized1	explained that they would like to tell them, but were not permitted by some other people
Rationalized2	told them that their boss would not let anyone share this knowledge
Rationalized3	said that they would not answer their questions

References

Abbass, H. A. (2019). Social integration of artificial intelligence: Functions, automation allocation logic and human-autonomy trust. *Cognitive Computation, 11*(2), 159–171. https://doi.org/10.1007/s12559-018-9619-0

Akinremi, T., & Roper, S. (2021). In G. Fernandes, L. Dooley, D. O'Sullivan, & A. Rolstadås (Eds.), *The collaboration paradox: Why small firms fail to collaborate for innovation BT - Managing collaborative R&D projects: Leveraging open innovation knowledge-flows for co-creation*. https://doi.org/10.1007/978-3-030-61605-2_8

Anand, A., Offergelt, F., & Anand, P. (2022). Knowledge hiding – A systematic review and research agenda. *Journal of Knowledge Management, 26*(6), 1438–1457. https://doi.org/10.1108/JKM-04-2021-0336

Arias-Pérez, J., & Vélez-Jaramillo, J. (2021). Understanding knowledge hiding under technological turbulence caused by artificial intelligence and robotics. *Journal of Knowledge Management*. https://doi.org/10.1108/JKM-01-2021-0058. ahead-of-p (ahead-of-print).

Arias-Pérez, J., Velez-Ocampo, J., & Cepeda-Cardona, J. (2021). Strategic orientation toward digitalization to improve innovation capability: Why knowledge acquisition and exploitation through external embeddedness matter? *Journal of Knowledge Management*. https://doi.org/10.1108/JKM-03-2020-0231. ahead-of-p(ahead-of-print).

Becerra, M., Lunnan, R., & Huemer, L. (2008). Trustworthiness, risk, and the transfer of tacit and explicit knowledge between alliance partners. *Journal of Management Studies, 45*(4), 691–713. https://doi.org/10.1111/j.1467-6486.2008.00766.x

Braganza, A., Chen, W., Canhoto, A., & Sap, S. (2021). Productive employment and decent work: The impact of AI adoption on psychological contracts, job engagement and employee trust. *Journal of Business Research, 131*, 485–494. https://doi.org/10.1016/j.jbusres.2020.08.018

BSC. (2020). *Flipping the odds of digital transformation success*.

Butner, K., & Ho, G. (2019). How the human-machine interchange will transform business operations. *Strategy & Leadership, 47*(2), 25–33. https://doi.org/10.1108/SL-01-2019-0003

Caputo, F., Magni, D., Papa, A., & Corsi, C. (2021). Knowledge hiding in socioeconomic settings: Matching organizational and environmental antecedents. *Journal of Business Research, 135*, 19–27. https://doi.org/10.1016/j.jbusres.2021.06.012

Carson, S. J., Madhok, A., Varman, R., & John, G. (2003). Information processing moderators of the effectiveness of trust-based governance in interfirm R&D collaboration. *Organization Science, 14*, 45–56. https://doi.org/10.1287/orsc.14.1.45.12811

Chatterjee, S., Chaudhuri, R., Vrontis, D., & Basile, G. (2022). Digital transformation and entrepreneurship process in SMEs of India: A moderating role of adoption of AI-CRM capability and strategic planning. *Journal of Strategy and Management, 15*(3), 416–433. https://doi.org/10.1108/JSMA-02-2021-0049

Cheah, S. L.-Y., & Ho, Y.-P. (2021). Commercialization performance of outbound open innovation projects in public research organizations: The roles of innovation potential and organizational capabilities. *Industrial Marketing Management, 94*, 229–241. https://doi.org/10.1016/j.indmarman.2021.02.012

Cheng, C. C. J., & Shiu, E. C. (2015). The inconvenient truth of the relationship between open innovation activities and innovation performance. *Management Decision, 53*(3), 625–647. https://doi.org/10.1108/MD-03-2014-0163

Chesbrough, H., & Bogers, M. (2014). Explicating open innovation: Clarifying an emerging paradigm for understanding innovation. In H. Chesbrough, W. Vanhaverbeke, & J. West (Eds.), *New frontiers in open innovation* (pp. 3–28). https://doi.org/10.1093/acprof:oso/9780199682461.003.0001

Chhabra, B., & Pandey, P. (2022). Job insecurity as a barrier to thriving during COVID-19 pandemic: A moderated mediation model of knowledge hiding and benevolent leadership. *Journal of Knowledge Management*. https://doi.org/10.1108/JKM-05-2021-0403. ahead-of-p(ahead-of-print).

Chiong, R., Dhakal, S., Chaston, T., & Chica, M. (2022). Evolution of trust in the sharing economy with fixed provider and consumer roles under different host network structures. *Knowledge-Based Systems, 236*, Article 107496. https://doi.org/10.1016/j.knosys.2021.107496

Choi, E. W., Özer, Ö., & Zheng, Y. (2020). Network trust and trust behaviors among executives in supply chain interactions. *Management Science, 66*(12), 5823–5849. https://doi.org/10.1287/mnsc.2019.3499

Collier, Z. A., Wood, M. D., & Henderson, D. A. (2021). Balancing risk and trust for strategic alliance formation decisions. *Journal of Strategy and Management*. https://doi.org/10.1108/JSMA-03-2021-0067. ahead-of-p(ahead-of-print).

Connelly, C., Zweig, D., Webster, J., & Trougakos, J. P. (2012). Knowledge hiding in organizations. *Journal of Organizational Behavior, 33*(1), 64–88. https://doi.org/10.1002/job.737

Dubey, R., Bryde, D. J., Blome, C., Roubaud, D., & Giannakis, M. (2021). Facilitating artificial intelligence powered supply chain analytics through alliance management during the pandemic crises in the B2B context. *Industrial Marketing Management, 96*, 135–146. https://doi.org/10.1016/j.indmarman.2021.05.003

Dwivedi, Y. K., & Wang, Y. (2022). Guest editorial: Artificial intelligence for B2B marketing: Challenges and opportunities. *Industrial Marketing Management, 105*, 109–113. https://doi.org/10.1016/j.indmarman.2022.06.001

Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2021). Artificial intelligence and business value: A literature review. *Information Systems Frontiers*. https://doi.org/10.1007/s10796-021-10186-w

Falcone, E. C., Steelman, Z. R., & Aloysius, J. A. (2021). Understanding managers' reactions to blockchain technologies in the supply chain: The reliable and unbiased software agent. *Journal of Business Logistics, 42*(1), 25–45. https://doi.org/10.1111/jbl.12263

Ferguson, R., Schattke, K., & Paulin, M. (2016). The social context for value co-creations in an entrepreneurial network. *International Journal of Entrepreneurial Behavior & Research, 22*(2), 199–214. https://doi.org/10.1108/IJEBR-04-2015-0100

Fosso Wamba, S. (2022). Impact of artificial intelligence assimilation on firm performance: The mediating effects of organizational agility and customer agility. *International Journal of Information Management, 67*, Article 102544. https://doi.org/10.1016/j.ijinfomgt.2022.102544

Ghasemaghaei, M., & Turel, O. (2021). Possible negative effects of big data on decision quality in firms: The role of knowledge hiding behaviours. *Information Systems Journal, 31*(2), 268–293. https://doi.org/10.1111/isj.12310

Gregory, R. W., Henfridsson, O., Kaganer, E., & Kyriakou, S. H. (2020). The role of artificial intelligence and data network effects for creating user value. *Academy of Management Review, 46*(3), 534–551. https://doi.org/10.5465/amr.2019.0178

Grewal, D., Guha, A., Satornino, C. B., & Schweiger, E. B. (2021). Artificial intelligence: The light and the darkness. *Journal of Business Research, 136*, 229–236. https://doi.org/10.1016/j.jbusres.2021.07.043

Haar, J., O'Kane, C., & Cunningham, J. A. (2022). Firm-level antecedents and consequences of knowledge hiding climate. *Journal of Business Research, 141*, 410–421. https://doi.org/10.1016/j.jbusres.2021.11.034

Hadjielias, E., Christofi, M., & Tarba, S. (2021). Knowledge hiding and knowledge sharing in small family farms: A stewardship view. *Journal of Business Research, 137*, 279–292. https://doi.org/10.1016/j.jbusres.2021.08.042

Hair, J., Risher, J., Sarstedt, M., & Ringle, C. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Hair, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2021). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Los Angeles: Sage Publications.

Harison, E., & Koski, H. (2010). Applying open innovation in business strategies: Evidence from Finnish software firms. *Research Policy, 39*(3), 351–359. https://doi.org/10.1016/j.respol.2010.01.008

Hayes, A. F. (2018). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach.* New York, NY, USA: Guilford publications.

Henttonen, K., Hurmelinna-Laukkanen, P., & Blomqvist, K. (2020). Between trust and control in R&D alliances. *VINE Journal of Information and Knowledge Management Systems, 50*(2), 247–269. https://doi.org/10.1108/VJIKMS-02-2019-0027

Hodson, R. (2004). Organizational trustworthiness: Findings from the population of organizational ethnographies. *Organization Science, 15*(4), 432–445. Retrieved from http://www.jstor.org/stable/30034747.

Hossain, M. A., Agnihotri, R., Rushan, M. R. I., Rahman, M. S., & Sumi, S. F. (2022). Marketing analytics capability, artificial intelligence adoption, and firms' competitive advantage: Evidence from the manufacturing industry. *Industrial Marketing Management, 106*, 240–255. https://doi.org/10.1016/j.indmarman.2022.08.017

Jahanzeb, S., De Clercq, D., & Fatima, T. (2021). Organizational injustice and knowledge hiding: The roles of organizational dis-identification and benevolence. *Management Decision, 59*(2), 446–462. https://doi.org/10.1108/MD-05-2019-0581

Jiang, X., Bao, Y., Xie, Y., & Gao, S. (2016). Partner trustworthiness, knowledge flow in strategic alliances, and firm competitiveness: A contingency perspective. *Journal of Business Research, 69*(2), 804–814. https://doi.org/10.1016/j.jbusres.2015.07.009

Judge, W. Q., & Dooley, R. (2006). Strategic alliance outcomes: A transaction-cost economics perspective. *British Journal of Management, 17*(1), 23–37. https://doi.org/10.1111/j.1467-8551.2005.00441.x

Keegan, B. J., Canhoto, A. I., & Yen, D. A. (2022). Power negotiation on the tango dancefloor: The adoption of AI in B2B marketing. *Industrial Marketing Management, 100*, 36–48. https://doi.org/10.1016/j.indmarman.2021.11.001

Khelladi, I., Castellano, S., Hobeika, J., Perano, M., & Rutambuka, D. (2021). Customer knowledge hiding behavior in service multi-sided platforms. *Journal of Business Research*. https://doi.org/10.1016/j.jbusres.2021.11.017

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

Kohtamäki, M., Rabetino, R., Parida, V., Sjödin, D., & Henneberg, S. (2022). Managing digital servitization toward smart solutions: Framing the connections between technologies, business models, and ecosystems. *Industrial Marketing Management, 105*, 253–267. https://doi.org/10.1016/j.indmarman.2022.06.010

Krakowski, S., Luger, J., & Raisch, S. (2022). Artificial intelligence and the changing sources of competitive advantage. *Strategic Management Journal*. https://doi.org/10.1002/smj.3387. n/a(n/a).

Kushwaha, A. K., Kumar, P., & Kar, A. K. (2021). What impacts customer experience for B2B enterprises on using AI-enabled chatbots? Insights from big data analytics. *Industrial Marketing Management, 98*, 207–221. https://doi.org/10.1016/j.indmarman.2021.08.011

Lau, A. K. W., Lee, L. W. Y., Lai, K.-H., & Lee, P. K. C. (2018). Adopting an open innovation program with supply chain management in China: A case study. *Engineering Management Journal, 30*(1), 24–41. https://doi.org/10.1080/10429247.2017.1408387

Li, L. (2022). Digital transformation and sustainable performance: The moderating role of market turbulence. *Industrial Marketing Management, 104*, 28–37. https://doi.org/10.1016/j.indmarman.2022.04.007

Li, S., Peng, G., Xing, F., Zhang, J., & Zhang, B. (2021). Value co-creation in industrial AI: The interactive role of B2B supplier, customer and technology provider. *Industrial Marketing Management, 98*, 105–114. https://doi.org/10.1016/j.indmarman.2021.07.015

Manyika, J., Ramaswamy, S., Khanna, S., Sarrazin, H., Pinkus, G., Sethupathy, G., & Yaffe, A. (2015). *Digital America: A tale of the haves and have-mores* (pp. 1–120). McKinsey Global Institute.

Markovic, S., Bagherzadeh, M., Vanhaverbeke, W., & Bogers, M. (2021). Managing business-to-business open innovation: A project-level approach. *Industrial Marketing Management, 94*, 159–163. https://doi.org/10.1016/j.indmarman.2021.02.009

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. *Academy of Management Review, 20*(3), 709–734. https://doi.org/10.5465/amr.1995.9508080335

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management, 58*(3), Article 103434. https://doi.org/10.1016/j.im.2021.103434

Nadeem, M. A., Liu, Z., Ghani, U., Younis, A., & Xu, Y. (2020). Impact of shared goals on knowledge hiding behavior: The moderating role of trust. *Management Decision*. https://doi.org/10.1108/MD-09-2019-1197

Ogbeibu, S., Senadjki, A., & Gaskin, J. (2018). The moderating effect of benevolence on the impact of organisational culture on employee creativity. *Journal of Business Research, 90*, 334–346. https://doi.org/10.1016/j.jbusres.2018.05.032

Petrescu, M., Krishen, A. S., Kachen, S., & Gironda, J. T. (2022). AI-based innovation in B2B marketing: An interdisciplinary framework incorporating academic and practitioner perspectives. *Industrial Marketing Management, 103*, 61–72. https://doi.org/10.1016/j.indmarman.2022.03.001

Portulans Institute. (2019). *Network readiness index 2019. Washington D.C., USA*.

Qiu, X., & Haugland, S. A. (2019). The role of regulatory focus and trustworthiness in knowledge transfer and leakage in alliances. *Industrial Marketing Management, 83*, 162–173. https://doi.org/10.1016/j.indmarman.2019.03.014

Rampersad, G. (2020). Robot will take your job: Innovation for an era of artificial intelligence. *Journal of Business Research, 116*, 68–74. https://doi.org/10.1016/j.jbusres.2020.05.019

Rusthollkarhu, S., Toukola, S., Aarikka-Stenroos, L., & Mahlamäki, T. (2022). Managing B2B customer journeys in digital era: Four management activities with artificial intelligence-empowered tools. *Industrial Marketing Management, 104*, 241–257. https://doi.org/10.1016/j.indmarman.2022.04.014

Seo, R., & Park, J.-H. (2022). When is interorganizational learning beneficial for inbound open innovation of ventures? A contingent role of entrepreneurial orientation. *Technovation, 116*, Article 102514. https://doi.org/10.1016/j.technovation.2022.102514

Shen, B., & Kuang, Y. (2022). Assessing the relationship between technostress and knowledge hiding—A moderated mediation model. *Data and Information Management, 6*(1), Article 100002. https://doi.org/10.1016/j.dim.2022.100002

Sjödin, D., Parida, V., Palmié, M., & Wincent, J. (2021). How AI capabilities enable business model innovation: Scaling AI through co-evolutionary processes and feedback loops. *Journal of Business Research, 134*, 574–587. https://doi.org/10.1016/j.jbusres.2021.05.009

Tang, T.(. Y.)., Fisher, G. J., & Qualls, W. J. (2021). The effects of inbound open innovation, outbound open innovation, and team role diversity on open source software project performance. *Industrial Marketing Management, 94*, 216–228. https://doi.org/10.1016/j.indmarman.2021.02.013

Tomlinson, E. C., Schnackenberg, A. K., Dawley, D., & Ash, S. R. (2020). Revisiting the trustworthiness–trust relationship: Exploring the differential predictors of cognition- and affect-based trust. *Journal of Organizational Behavior, 41*(6), 535–550. https://doi.org/10.1002/job.2448

Truong, Y., & Papagiannidis, S. (2022). Artificial intelligence as an enabler for innovation: A review and future research agenda. *Technological Forecasting and Social Change, 183*, Article 121852. https://doi.org/10.1016/j.techfore.2022.121852

van de Vrande, V., de Jong, J. P. J., Vanhaverbeke, W., & de Rochemont, M. (2009). Open innovation in SMEs: Trends, motives and management challenges. *Technovation, 29*(6), 423–437. https://doi.org/10.1016/j.technovation.2008.10.001

Wamba-Taguimdje, S.-L., Fosso Wamba, S., Kala Kamdjoug, J. R., & Tchatchouang Wanko, C. E. (2020). Influence of artificial intelligence (AI) on firm performance: The business value of AI-based transformation projects. *Business Process Management Journal, 26*(7), 1893–1924. https://doi.org/10.1108/BPMJ-10-2019-0411

WEF. (2018). *The future of jobs report 2018.* Geneva: World Economic Forum.

WEF. (2020). *The future of jobs report 2020. Geneva*.

Xiong, C., Zheng, L. J., Germon, R., Susini, J.-P., & Chang, V. (2021). Telling "white lies" within the entrepreneurial firm: How rationalized knowledge hiding between founder CEO and founder CTO influences new product development. *Journal of Business Research, 136*, 431–439. https://doi.org/10.1016/j.jbusres.2021.07.039

Yang, J., Chesbrough, H., & Hurmelinna-Laukkanen, P. (2022). How to appropriate value from general-purpose technology by applying open innovation. *California Management Review, 64*(3), 24–48. https://doi.org/10.1177/00081256211041787

Zhang, Z., Ye, B., Qiu, Z., Zhang, H., & Yu, C. (2022). Does technostress increase R&D employees' knowledge hiding in the digital era? *Frontiers in Psychology, 13*. https://doi.org/10.3389/fpsyg.2022.873846. Retrieved from.

Jose Arias-Pérez, PhD., is a full professor of innovation management of the Department of Administrative Science at the Universidad de Antioquia, Colombia. His research interests include knowledge management, digital transformation and big data analytics capability and their impacts on innovation performance. His research has been published in journals such as *Technological Forecasting and Social Change, Journal of Knowledge Management, IEEE Transactions on Engineering Management, International Journal of Innovation Management, Multinational Business Review,* and *Baltic Journal of Management.*

Thanh Huynh is the Deputy Director of Coventry University's International Centre for Transformational Entrepreneurship. He has spent the majority of his career in the fields of entrepreneurship and open resources. His work has been published in a number of prestigious journals, including the *Journal of Business Research, Venture Capital, and the International Journal of Innovation Management*, among others. Huynh's recent research is closely related to dynamic capabilities, open innovation, and crowdsourcing, all of which aim to advance our understanding of entrepreneurship in practice and theory.