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AI Platforms as Cooperation Enablers Favoring the Development of Strategic Situating Capabilities Within Solution Delivery Ecosystems

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ABSTRACT

Academic Summary: By integrating artificial intelligence (AI) platforms into their processes, firms aim to enhance their strategic capabilities and gain a competitive advantage. This study investigates the impact of such platforms on value generation within solution-based strategies, proposing two connected mechanisms. First, AI platforms foster collaborative value systems between firms and value-chain agents across the stages of the solution delivery process (i.e., problem identification, solution development, and solution implementation). Second, such cooperation could foster the development of situating capabilities (i.e., grounding, bounding, and recasting), which are conceptually linked to the mitigation of situated agency constraints that stifle value creation within productive systems. These relationships underscore the value generation potential of AI platforms for solution providers, extending the premise of situated AI capabilities to the organizational and inter-organizational level. Data collected from 570 Spanish manufacturing firms in 2023 reveals that firms utilizing AI platforms exhibit greater cooperative and situating capability-building behavior during the problem identification and solution implementation stages. However, no significant association is found between AI platforms and the more creative stage of solution development. The study provides novel insights into the interplay between AI platforms, user cooperation, situated agency, and strategic capabilities as drivers of value generation and advancement of the AI-dominated paradigm. Theoretical and practical implications are discussed.

Managerial Summary: This study highlights the strategic role of AI platforms in enhancing collaboration between manufacturers and solution seekers throughout the solution delivery process. AI technologies facilitate collective learning, adaptation, and knowledge sharing, particularly during the diagnostic and implementation stages, where real-time data processing and predictive analytics help tailor solutions to user-specific challenges. This more effective coordination is essential for mitigating agency problems that arise due to asymmetric information or misaligned objectives within complex solution systems. However, the findings reveal that AI's influence is limited in the co-creation of solution design and development, which relies heavily on human insight, creativity, and contextual judgment. Managers should therefore not view AI as a substitute for human input, but

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rather as a complementary tool that enhances efficacy and integration. For firms seeking to strengthen their solution-oriented strategies, the key takeaway is that maintaining a balanced approach—combining AI-enabled collaboration with human ingenuity—will improve solution outcomes and sustain competitive advantage in markets increasingly shaped by personalization and customer-specific problem solving.

Summary

- Findings offer new insights into AI's role in enabling organizational and inter-organizational value creation.
- AI platforms enhance strategic capabilities by fostering cooperation in solution-based business models.
- AI-induced cooperation strengthens strategic situating capabilities during problem identification and solution implementation stages.
- AI platforms help address agency constraints by improving coordination and facilitating collective knowledge collection, sharing, and adaptation.
- A balanced AI-human approach is essential for effective solution strategies and sustained competitive advantage.

1 | Introduction

Artificial intelligence (AI) is transforming the way productive firms generate value and develop strategic capabilities (Sullivan and Wamba 2024), including enhancement of their high-value solution delivery capabilities (Kohtamäki et al. 2024). Unlike traditional standardized product business models, solution delivery allows producers to offer more targeted utility that caters to customers' specific needs and thus generates greater value differentiation and competitive advantage (Lafuente and Sallan 2024; Storbacka 2011). AI can boost firms' capacity for diagnosis, solution development, and solution implementation as they transition towards the adoption of solution-based strategies (Baden-Fuller and Morgan 2010; see also Spanjol et al. 2024 for a similar perspective in the context of new product development (NPD) stages). Solution delivery has been closely associated with the digital transformation of industries and the rise of smart production (Vendrell-Herrero et al. 2022). AI not only helps producers navigate the complexities of delivering customizable solutions (Vaillant, Vendrell-Herrero, et al. 2025), but also supports the development of industry-specific applications (Weber et al. 2024) and scalable solution business models (Leppänen et al. 2023; Sjödin et al. 2022).

AI is also transforming value generation by facilitating collaborative value systems among interoperating firms, developers, and value-chain agents that co-innovate and co-create value with unprecedented synchrony (Jia et al. 2024; Lafuente, Vaillant, and Rabetino 2023; Wamba et al. 2022), largely due to the data connectivity, sharing, storage, and processing capacity that digitization, and AI in particular, has introduced to productive ecosystems. Firms are integrating AI into their operations, either as task-specific AI software tools or through AI platforms

(Berente et al. 2021). The latter are multi-actor digital platform ecosystems designed to facilitate interaction among diverse, independent participants (Jovanovic et al. 2022; Parker et al. 2017; Schrieck et al. 2023). AI-based innovation platforms are flexible software systems that enable collaboration by providing shared functionality across interacting modules, supporting co-innovation and the development of complementary products (Cusumano et al. 2020; Lafuente, Vaillant, and Rabetino 2023; Lafuente, Vaillant, and Vendrell-Herrero 2023; Nambisan et al. 2018). Due to their accessibility, AI platforms are an increasingly popular choice for developing AI-enabled capabilities (Cusumano et al. 2020; Jovanovic et al. 2022).

AI platforms can also potentially enhance value creation within solution delivery ecosystems by stimulating collaboration, which helps mitigate the constraints of situated agency challenges. The capabilities enabled by AI platforms are regarded as "situating" because they help firms adjust to the agency constraints at play within the context of solution delivery ecosystems in which agents interact.

According to situated AI theory, grounding, bounding, and recasting capabilities are key factors of AI-generated value creation (Kemp 2024). Solution delivery ecosystems must be grounded in order to generate competitive advantages and viability, which is achieved when they can collectively learn, adjust, and calibrate activities in response to context-specific conditions and the needs of solution seekers (Kemp 2024). But these ecosystems must also be bounded, whereby they can address the risk of knowledge expropriation by establishing clear interoperational guidelines and role assignment to all agents (Heiman and Nickerson 2004). Finally, solution delivery ecosystems must be able to recast themselves by synchronously evolving their agents' conjoined routines to thus overcome the myopic stagnation that often characterizes such productive systems (Balasubramanian et al. 2022).

This article therefore addresses the following research question: Can the use of AI platforms act as a cooperation enabler that facilitates the development of these AI-driven situating capabilities?

This study responds to calls to fill gaps in the literature (Berg et al. 2023; Verganti et al. 2020) by evaluating the cooperation-enabling capacity of AI platforms within the solution delivery process. It also tests whether platform-enabled collaboration contributes to the development of key strategic AI-driven situating capabilities within the resulting solution delivery ecosystems. We do so by comparing the solution delivery process (examining the stages of problem identification, solution development, and solution implementation) of manufacturing firms that use modular AI platforms with those that do not.

The empirical research is based on a bespoke survey of 570 Spanish manufacturing firms in 2023. We find that firms

utilizing AI platforms are significantly more likely to engage in cooperative behavior with their clients during the problem identification and solution implementation stages than during solution development. Furthermore, AI-facilitated collaborations during problem identification and solution implementation positively correlate with grounding, bounding, and recasting situating capabilities, which are strategic mechanisms that support value generation in firms adopting solution business models.

Our theoretical model provides three significant insights into the role of AI platforms in cooperation with end users and the development of strategic capabilities. First, this study pioneers the exploration of the antecedents of AI-induced situating capabilities, elevating and extending the recently proposed theory of situated AI (Kemp 2024) to productive ecosystems. It also contributes to management theory by conceptualizing organizations as algorithms, following Glaser et al. (2024), and answers calls for research into AI from a strategic management perspective (Raisch and Krakowski 2021). Second, it establishes a clear connection between the utilization of innovation-based AI platforms, user cooperation, and strategic capabilities, offering a pathway for enhancing value generation and advancing the evolving AI-dominated paradigm, an area of increasing academic interest (Berg et al. 2023; Verganti et al. 2020).

Third, our study distinguishes between different stages of the solution delivery process involving end users, highlighting the critical role of AI platforms in enabling cooperation during the problem identification and solution implementation stages of solution delivery. However, it also acknowledges the limitations of AI platforms in processes requiring inventiveness, such as solution development and design, thereby corroborating recent claims that human intervention remains important in AI platform management (Jia et al. 2024).¹ In doing so, this article complements recent research on the complementarity between machine and human input in AI platforms, and the role that the latter could potentially play in addressing the “intra” and “inter” organizational agency challenges that often obstruct value generation (Bouschery et al. 2023; Gama and Magistretti 2023; Kemp 2024).

Our quantitative study is based on a rigorous two-stage If-Then model (Dorobantu et al. 2024; Zhang and Shaw 2012). Specifically, “if” the observed manufacturers are making use of AI platforms, “then” they are significantly more likely to engage in collaboration during their solution delivery process. Moreover, “if” they do so, “then” they are more likely to develop situating capabilities that unlock value generation within productive systems. Innovation-based AI platforms, even those not purposefully designed to foster collaboration, can nevertheless facilitate such behavior among actors within the same solution delivery system.

The findings provide a solid foundation for future process studies to build on to analyze how and which innovation-based AI platforms best serve value creation within productive systems.

The article is structured as follows. Section 2 presents the theoretical background; Section 3 develops the hypotheses; Section 4 addresses the methodological issues; Section 5 presents the

results; Section 6 discusses the findings and identifies promising avenues for future inquiry, and Section 7 concludes.

2 | Background

“Artificial intelligence” refers to a computer system that is proficient in integrating external data, extracting valuable insights, and utilizing those insights to accomplish specific objectives (Haenlein and Kaplan 2019). This includes its inherent ability to autonomously learn, make decisions, and perform tasks, many of which have traditionally been associated with human cognition. This study focuses on firms that adopt externally-developed AI and do not necessarily conduct R&D activities of their own in this specific field (Li et al. 2023). AI adoption can enhance firm productivity “by automating tasks, enhancing creativity, improving accuracy and efficiency, and streamlining development processes” (Ebert and Louridas 2023, 34), which can be achieved by introducing AI to the productive process either as task-specific AI tools, or as AI platforms. This research focuses exclusively on the latter.

2.1 | AI Platforms

Digital platforms are multi-actor, supra-organizational ecosystems engineered to foster interactions among diverse, autonomous participants, each pursuing their own agendas (Jovanovic et al. 2022; Parker et al. 2017; Rojas-Segura et al. 2023; Schrieck et al. 2023). The literature distinguishes between two main types: transaction and innovation platforms (Nambisan et al. 2018; Cusumano et al. 2019; Cusumano et al. 2020). This study only focuses on the latter and hence does not address platforms like Etsy and eBay, which facilitate exchanges between consumers and producers for a fee (Nambisan et al. 2018), its sub-categories such as e-commerce platforms (e.g., Temu), content distribution platforms (e.g., Spotify), social media platforms (e.g., TikTok), or search engines (e.g., Google Search) (Parker et al. 2017).

Innovation platforms “consist of common technological building blocks that the owner and ecosystem partners can share in order to create new complementary products and services” (Cusumano et al. 2019, 18). AI platforms like OpenAI’s ChatGPT, Google’s Gemini, and Microsoft’s Copilot, together with cloud-based AI services such as Microsoft’s Azure AI, are categorized as innovation platforms because they foster interaction, establishing an environment conducive to innovation, where partners can develop complementary products (Cusumano et al. 2020; Nambisan et al. 2018). They also amplify the externalities of analogue platforms, such as technological spillovers (Jacobides et al. 2024; Wamba et al. 2023), and promote compatibility of third-party applications and modules through standardization and modular separation (Weber et al. 2024).

AI-based innovation platforms can thus be defined as adaptable software systems that enable interaction by providing essential functionality that is shared across cooperating modules (Tiwana et al. 2010). By expanding their users’ capabilities, these platforms offer resourcing and securing advantages through this

core functionality, which is shared by interoperating modules and complementary offerings (Jovanovic et al. 2022; Parker et al. 2017). Thus, access to AI platforms allows resource-constrained actors to tap into the transformative potential of powerful AI technologies (Nambisan et al. 2018; Wamba et al. 2022).

2.2 | AI Platforms and Cooperation

Cooperation is a defining feature of AI platforms as they are designed to encourage interaction (Cusumano et al. 2019). At their core lies the cooperation among the community of complementors, developers, and the platform coordinator. However, AI platforms can also potentially facilitate user collaboration by enabling coordinated activities between multiple actors (Davidsson et al. 2020; Jacobides et al. 2018).

AI platforms tend to be much more user-friendly and cost-effective than task-specific AI or digital tools, which reduces the skill threshold required for firms to use and benefit from them (Davidsson and Sufyan 2023; Wamba et al. 2023). The modular structure of many such platforms enables customization and hence better alignment with the user's business (Hsuan et al. 2021; Sullivan and Wamba 2024). Users of AI platforms can also access the potential advantages of AI software whilst also benefiting from their conservation (less input) and compression (less time) mechanisms (Davidsson et al. 2020; Davidsson and Sufyan 2023).

AI platforms often provide infrastructure for data sharing and integration, enabling users to collaborate by exchanging data and insights (Springer et al. 2025; von Briel et al. 2018), which, when leveraged collaboratively, means businesses can better identify opportunities, mitigate risks, and optimize strategies (Wamba 2022). AI platforms can also enable resource pooling, allowing users to access capabilities that might otherwise be prohibitively expensive or too complex to develop independently (Nambisan et al. 2018). By sharing knowledge, expertise, and resources, AI platform users can accelerate innovation and co-create new value-added solutions that benefit all participants.

Furthermore, AI platforms enable novel forms of collaborative intelligence. According to Weber et al. (2024), they support cooperation not only through infrastructural connectivity but also by facilitating the co-creation of shared datasets and the implementation of federated learning systems, meaning multiple users and organizations can jointly train AI models without directly sharing proprietary data—thus fostering trust, maintaining privacy, and promoting more distributed and inclusive knowledge generation (Springer et al. 2025).

Most importantly, AI platforms can act as cooperation enablers by establishing standardized systems and applications, allowing for greater interoperability through seamless data and communication exchange (Escribá-Carda et al. 2024; Nambisan et al. 2017; Tiwana et al. 2010). This AI-enabled cooperation is key to the solution delivery process and supports the situating capabilities that are so crucial for alleviating common agency constraints on interorganizational collaboration within solution-based value generation ecosystems.

3 | Theoretical and Hypothesis Development

3.1 | Solution Delivery Process

Among the most important contributions of digitization to production strategies is its ability to deliver greater value-added through personalized solutions in response to specific problems (Brady et al. 2005; Lafuente and Sallan 2024). Compared to standardized production, digital tools, and AI in particular, allow for greater scalability and cost-efficient customization of supply. This supports the competitive and customer-oriented virtues of adopting a solution business model, while mitigating many of its disadvantages (Shleha et al. 2023; Storbacka et al. 2013; Vendrell-Herrero et al. 2022).

An optimal solution delivery process is typically composed of three consecutive stages (Baden-Fuller and Morgan 2010): identifying the problem, developing a customized solution, and implementing it effectively. AI can make an important contribution to all three of these stages, and AI platforms make them more collaborative and, therefore, more effective.

3.1.1 | Problem Identification

This is a crucial starting point on which the success of the subsequent phases depends. It can be addressed passively by the solution provider, with the client itself diagnosing the specific issue (Davies et al. 2007) and turning to the solution provider to request a remedy. However, clients are often better at identifying symptoms, rather than the underlying causes (Storbacka 2011). Alternatively, the solution provider can take an active role by identifying the root cause through observation and diagnostic research. Both client-based and provider-based problem identification are unilateral processes. However, clients are not always properly equipped or knowledgeable enough to self-diagnose their problems, separate need from want, or even determine what exactly it is that requires resolution (Storbacka 2011). Meanwhile, solution providers, even when endowed with experience and expertise, may lack the capacity to diagnose their clients' problems independently (Schaffhausen and Kowalewski 2015). Hence, needs-finding is much more effective when undertaken bilaterally or multilaterally (Patnaik and Becker 1999). The data and communication exchange possibilities offered by the interoperability of AI platforms can potentially facilitate this process (Nambisan et al. 2017).

3.1.2 | Solution Development

Once the problem has been clearly defined, an adapted and effective solution must be developed. This can be done unilaterally by the solution provider, either as a fully customized response to the specific client and problem at hand or by offering suitably structured alternatives. Otherwise, the client handles the development process, with the solution providers merely supplying different market-ready modules and components, which the client picks and chooses in a self-customization exercise tailored to the specific nature of the identified problem (Leng and Zhao 2023). AI software interfaces can potentially facilitate both of these approaches by improving the alignment between

the solution provider and seeker, with the modular nature of AI platforms particularly enhancing the effectiveness of (self-)customization capabilities (Hsuan et al. 2021).

Such collaboration between providers, seekers, and users fosters creativity in solution development (Grant and Berry 2011), and ultimately better aligned and more functional solutions (Lafuente, Vaillant, and Vendrell-Herrero 2023). This will enhance customer embeddedness, integration, operational adaptability, and organizational networking, all of which are key continuums that contribute to solution-based value creation (see Storbacka et al. 2013 for a detailed discussion). Hence, AI platforms are likely to play an important role in the solution development stage of the delivery process.

3.1.3 | Solution Implementation

This final stage is often under-emphasized, despite its critical role in successful problem-solving and value creation (Kot and Leszczyński 2022). It is frequently left in the hands of the client, but very high failure rates have been documented, largely due to them being unable or unwilling to implement the proposed solution effectively (Cândido and Santos 2015; De Mast 2013). When solutions are misaligned with the resources and capabilities of their seekers, implementation is often outsourced to third-party providers (Sayed et al. 2021), but these may not be sufficiently familiar with the solution seeker's specific context, the problem requiring resolution, and/or the proposed solution (Leng and Zhao 2023).

To ensure effective implementation of long-term solutions to core problems, the continued involvement of solution providers or developers during the implementation stage is usually essential (Paiola et al. 2013), especially in cases of highly customized solutions (Lafuente and Sallan 2024; Vendrell-Herrero et al. 2022). The context in which a solution was developed often changes over time, raising the danger of obsolescence due to a growing mismatch between the solution and the problem it was meant to address (Storbacka 2011; Storbacka et al. 2013). Long-term relationships between solution providers and seekers are therefore needed in order to ensure the delivery of truly complete and effective solutions (Lafuente, Vaillant, and Rabetino 2023; Vendrell-Herrero et al. 2022). Such collaboration helps to build the required relational capital, and ongoing interaction will foster mutual adaptation and hence the right alignment between solutions and the evolving nature of the problems they are designed to address (Lafuente and Vaillant 2023; Vendrell-Herrero et al. 2025).

As enablers of cooperation and facilitators of interoperability, AI platforms play a crucial role in developing this relational capital throughout the implementation stage. By standardizing data and communication flows, they are better equipped to enhance cooperation than isolated AI or digital tools (Nambisan et al. 2017; Tiwana et al. 2010), offering real-time communication channels, data sharing, and feedback loops between solution providers and seekers. This ensures continuous monitoring and adjustment during implementation, enabling both parties to adapt to evolving conditions and unexpected challenges. For example, in manufacturing, AI platforms leverage

predictive analytics and machine learning to optimize equipment installation and operational adjustments, ensuring seamless integration into existing systems (Sjödin et al. 2022). This proactive approach not only minimizes the risk of implementation failure but also fosters deeper engagement, leading to more effective and durable solutions.

Drawing on the above arguments, the following hypothesis is proposed:

H1. *The use of AI platforms stimulates greater cooperation during the solution delivery process.*

3.2 | Collaborative Solution Delivery and AI-Driven Capabilities

As discussed in the previous section, collaboration with partners allows organizations to leverage collective strengths, resources, and capabilities, leading to more innovative, efficient, and competitive solutions (Lafuente, Vaillant, and Vendrell-Herrero 2023; Nambisan et al. 2018; von Briel et al. 2018), even when participants have different goals, technological expertise, or infrastructure.

AI-facilitated cooperation throughout the solution delivery process can therefore be linked to strong competitive advantages, largely due to better orchestrated ecosystemic activities that can be more reliably leveraged to create and capture solution-based value (Winter 2000, 2003; Majchrzak et al. 2023). The theory of situated AI, which draws on the conceptual foundations of agency (Kemp 2024; Westphal and Zajac 2013), posits that AI-enabled capabilities are “situating” when they adapt to the agency constraints within the context in which agents act. In our study, the solution delivery ecosystem constitutes such a context and shapes agent behavior and interactions, ultimately leading to the co-generation of solution-based value.

Such value creation requires “situating capabilities,” which are purposeful and concerted actions across the entire solution delivery ecosystem. When this occurs through AI platforms, three AI-induced situating capabilities are potentially delivered, namely grounding, bounding, and recasting. As described by Kemp (2024), these are the constituents of AI-driven competitive advantages² because they help address the generic, articulate, and myopic agency constraints in such contexts (Moser et al. 2024). While firms cannot always directly control systemic agency, they can strategically structure the context using AI-induced situating capabilities, particularly through platforms, to make better sense of problems and more effectively apply solutions (Murray et al. 2021). Each situating capability results from a constellation of coordinated, interorganizational tactical moves that synchronously optimize the capabilities of one ecosystem, laying the foundations for competitive advantage (Grant 1991; Porter 1985).

Grounding capabilities are situating abilities that steer the ecosystem's value creation through reflexive and deliberate learning from experience (Kemp 2024; Vaillant, Mora-Esquivel, and Alvarado 2025). Unlike generic, ad-hoc problem-solving and indiscriminate data analytics, grounding capabilities fine-tune

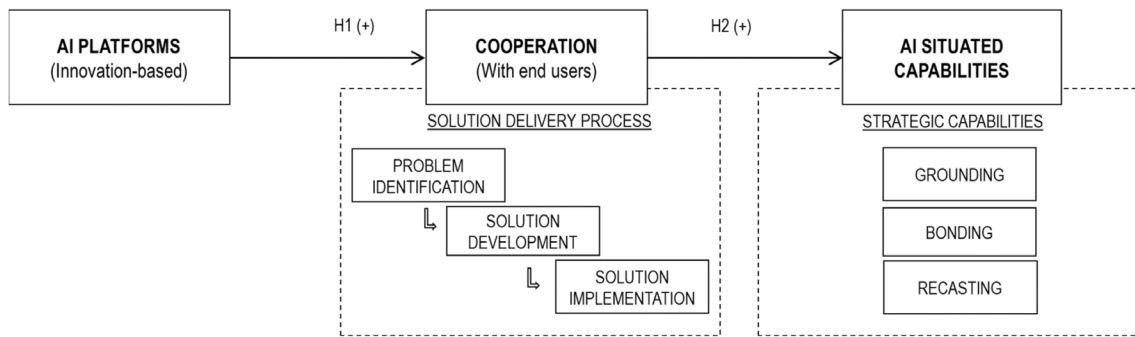


FIGURE 1 | Model of hypothesized conceptual framework.

the solution delivery process to the specific context and needs of solution seekers. Firms intentionally orchestrate data collection and deployment to address unique problems, and AI platforms support this process by guiding collaboration, thus helping to customize the ecosystem's output (Vendrell-Herrero et al. 2025). As a result, AI platforms are far more effective for fostering grounding capabilities than AI-driven tools used in isolation, and ultimately produce greater solution-based value.

Bounding situating capabilities are the orchestrated capacity to manage agency within a solution delivery ecosystem (Kemp 2024). The participants in such processes are expected to manage the distribution of the generated benefits, and clear bounding capabilities prevent hazards such as knowledge expropriation, where collectively generated value is sequestered by a particular party (Heiman and Nickerson 2004). In the absence of such safeguards, insecurities may discourage participation. In contrast to individual AI tools, AI platforms facilitate collaboration by establishing clear inter-operational guidelines that define roles and responsibilities within the ecosystem, making interactions more predictable and reducing concerns about opportunistic behavior.

Recasting capabilities refer to a solution delivery ecosystem's dynamic situating capability to adapt its internal procedures and technologies by synchronously evolving, updating, and contextualizing operational, relational, and strategic interdependencies (Kemp 2024) to address misalignments that emerge over time. Recasting potentially necessitates discussion and engagement from all parties involved in the solution delivery ecosystem, as any change to any single routine can ripple through the entire system. The complexity of concerted adaptation, especially when it is proactive and strategic in nature, often leads to myopic stagnation (Balasubramanian et al. 2022; Vaillant, Vendrell-Herrero, et al. 2025). Compared to isolated AI or digital tools, the collaboration facilitated by AI platforms potentially helps to develop recasting capabilities, which in turn make the solution ecosystem more dynamic, better aligned, and competitively advantageous.

Taken together, these arguments suggest that user cooperation throughout the solution delivery process strengthens all three AI-driven situating capabilities. Consequently, we propose the following hypothesis:

H2. *Cooperation during the solution delivery process leads to greater AI-driven situating capabilities.*

Figure 1 presents the conceptual framework used to theorize the study's hypotheses for the different stages of the solution delivery process and different AI-driven situating capabilities.

4 | Empirical Design

4.1 | Sample

The target population comprises manufacturing businesses, and the data used to test the proposed hypotheses were drawn from two sources. First, accounting and organizational data for the selected businesses were obtained from the Spanish SABI (Sistema de Análisis de Balances Ibéricos) database, from which an initial sample was drawn of 9413 small and medium-sized (number of employees ≤ 250) and large (> 250) firms operating in manufacturing industries.

Second, a specifically designed questionnaire was administered (see Section 4.2 for full details). The firm is the unit of analysis, and the respondents were limited to executives and top managers familiar with their firm's strategic and technological operations. The survey was conducted by a professional market research and public opinion firm, and the process was directly monitored by the researchers. Data collection (between June and September 2023) involved structured interviews based on closed-ended questions (both dichotomous and Likert-based).

A total of 626 responses were received. After removing observations with missing data (50 cases) and firms with no employment data for the survey year (6), the final sample included 570 manufacturing firms, representing an effective response rate of 6.06%. At a 95% confidence level ($Z=1.96$), the sample is representative of the target population, with a sampling margin of error of 3.98%, which is deemed acceptable for quantitative research (Juslin et al. 2007).

The geographic and organizational diversity further supports the validity of the sample. The respondent firms are well distributed across Spain's autonomous communities (Catalonia = 16.32%, Valencia = 12.63%, Andalusia = 11.93%, Madrid = 9.47%, Galicia = 7.72%, Murcia = 7.54%, Castile-La-Mancha = 7.37%, Basque Country = 6.84%, Castile Leon = 5.26%, Aragon = 3.86%, Navarra = 3.51%, Asturias = 1.75%, Extremadura = 1.40%, La Rioja = 1.40%, Canary Islands = 1.23%, Balearic Islands = 1.05%, and Cantabria = 0.70%). Average firm size—in terms of employees—is 35.57, ranging between 21 and 411 workers. Industry

breakdown figures are presented in Table 1 and verify the diversity of economic activity among the sampled firms.

4.2 | Dependent Variables: Measurement and Psychometric Properties (Scale Reliability and Validity) of AI-Induced Situating Capabilities

Based on Kemp's (2024) framework, our questionnaire included three sets of questions corresponding to each of the three AI-driven situating capabilities analyzed in this study: grounding, bounding, and recasting. For each set of questions, respondents were asked to rate the importance of various items related to each situating capability on a 7-point Likert scale (1 = completely disagree, 7 = completely agree). These questions are detailed in Table A1.

Factor analysis was used to verify that the instrument correctly measures these situating capabilities, as summarized in Table 2. Diagnostic statistics—namely Cronbach's alpha, the KMO measure of sampling adequacy, and Bartlett's test of sphericity—validate our approach (Nunnally and Bernstein 1994) and corroborate that the constructs extracted from the factor model are reliable and internally consistent.

We also used Loevinger's H coefficients to test the scalability (i.e., homogeneity) of the set of items included in each latent construct (Goodman and Kruskal 1979). For the three AI-driven situating capabilities, the coefficients are above the

common threshold of 0.50 (grounding = 0.76; bounding = 0.75; and recasting = 0.80). These results confirm that the items and scales are reliable for capturing highly homogeneous, unidimensional latent constructs related to situating capabilities (Hemker et al. 1995).

Two procedures were carried out to verify the convergent and discriminant validity of the items used to measure the three AI-induced situating capabilities. The first test is based on the correlations among the situating capabilities' items and the computed factor scores. As shown in Table 3, all items have a correlation coefficient with a factor score of their own latent construct greater than 0.67, which is strong evidence of convergent validity, as the items within each situating capability are highly correlated. Table 3 also shows that, for the nine analyzed variables, each item's correlation with its own latent factor is greater than it is with the other factors, evidencing discriminant validity, as the three situating capabilities are unrelated (Henseler et al. 2015).

The second validity test involved a descriptive inspection of the correlation matrix among the estimated constructs related to the AI-driven situating capabilities and their average variance extracted (AVE, computed via SEM modeling). As shown in

TABLE 1 | Industry distribution of the sampled firms.

Industry	NACE codes	Number of cases	Proportion of total
Food processing	10–12	149	26.14%
Textile	13	22	3.86%
Chemicals	20–21	39	6.84%
Plastic	22–23	60	10.53%
Metal	24–25	117	20.53%
Electronic and machinery	26–28	82	14.39%
Furniture	31	19	3.33%
Other	14–18, 29	82	14.39%
Total		570	100.00%

TABLE 2 | Factor analysis: Summary results for the analyzed situating capabilities.

Construct	Number of items	Cronbach's alpha	Variance explained	Bartlett's test	KMO test
Grounding capabilities	3	0.8937	0.8236	997.41***	0.7209
Bounding capabilities	3	0.8802	0.8035	991.32***	0.7099
Recasting capabilities	3	0.9215	0.8644	1197.78***	0.7524

Note: *, **, *** = significant at the 10%, 5%, and 1% levels, respectively.

TABLE 3 | Correlation matrix for the items related to the study's strategic AI-driven capabilities and the extracted constructs.

	Panel A: Grounding capabilities	Panel B: Bounding capabilities	Panel C: Recasting capabilities
Panel A: Grounding capabilities			
GR1	0.715	0.597	0.707
GR2	0.843	0.602	0.697
GR3	0.826	0.580	0.734
Panel B: Bounding capabilities			
BD1	0.552	0.824	0.612
BD2	0.646	0.809	0.666
BD3	0.587	0.679	0.633
Panel C: Recasting capabilities			
RC1	0.731	0.592	0.837
RC2	0.781	0.696	0.869
RC3	0.728	0.688	0.814

Note: The full description of the analyzed items is presented in Table A1.

Table 4, all AVE values are higher than 0.50, and the correlation of any focal situating capability with other constructs is lower than the square root of its AVE, further corroborating the convergent and discriminant validity of the study (Henseler et al. 2015).

4.3 | Independent Variables

4.3.1 | Cooperation During the Solution Delivery Process

The surveyed firms were asked to describe their interaction with users during different stages of the solution delivery process (i.e., problem identification, solution development, and solution implementation). Specific questions were added to the survey instrument to identify firms that collaborate with users in “problem identification” (“Does the business directly and actively interact with customers to identify the problem(s) that the offered product aims to solve?”). Similarly, respondents were asked whether they collaborate with users during the “solution

development” stage (“In your firm, is R&D investment in collaboration with customers the main product development method used to solve the client’s identified problems?”) and the “solution implementation” stage (“Is active collaboration with customers the main approach adopted by the firm to implement the client’s developed solution?”).

Descriptive statistics presented in Table 5 show that 50% of the sampled firms collaborate with customers during problem identification, while 24% and 18% do so during the solution development and solution implementation stages, respectively.

4.3.2 | Use of AI Platforms

Managers were asked whether AI platforms are fully integrated into the firm’s operations (“Does your business use artificial intelligence (AI) platforms such as SAS, Watson (IBM), Azure (Microsoft), TensorFlow, Google AI Platform, or similar?”). The figures in Table 5 indicate that 8% of firms report the use of AI platforms in their production processes. This figure is aligned with previous research on AI adoption (McElheran et al. 2024; OECD/BCG/INSEAD 2025).

4.3.3 | Control Variables

We control for firm size, firm age, location, and industry in all model specifications. Firm size is measured by the number of employees, while business age is expressed in years, with both of these variables logged to reduce skewness. Finally, we included a set of regional and industry dummy variables to rule out potential territorial and industry-specific effects.

TABLE 4 | Correlation matrix among latent constructs and average variance extracted (AVE).

Variables	1	2	3
1. Grounding capabilities	0.86		
2. Bounding capabilities	0.62	0.85	
3. Recasting capabilities	0.78	0.68	0.90

Note: For each latent construct, the square root of the average variance extracted (AVE) is on the diagonal of the matrix. AVE values: grounding = 0.74, bounding = 0.72, recasting = 0.81. All correlations are significant at the 1% level.

TABLE 5 | Descriptive statistics and bivariate correlations (sample = 570 firms).

	Variables	Mean	Std. dev.	1	2	3	4	5	6	7	8
1	Grounding capabilities	0.00	1.00	1.00							
2	Bounding capabilities	0.00	1.00	0.62***	1.00						
3	Recasting capabilities	0.00	1.00	0.78***	0.68***	1.00					
4	Use of AI platforms	0.08	0.28	0.30***	0.19***	0.28***	1.00				
5	Cooperation with users for problem identification	0.50	0.50	0.07	0.04	0.04	0.05	1.00			
6	Cooperation with users for solution development	0.24	0.43	0.12***	0.07*	0.09**	0.01	0.28***	1.00		
7	Cooperation with users for solution implementation	0.18	0.39	0.16***	0.16***	0.11***	0.10**	0.18***	0.32***	1.00	
8	Firm size (employees)	35.57	25.45	−0.03	−0.02	−0.02	0.00	−0.06	−0.01	−0.02	1.00
9	Firm age (years)	30.91	16.19	−0.04	−0.03	−0.02	0.03	0.00	−0.03	−0.02	0.11***

Note: *, **, and *** are significant at the 10%, 5%, and 1% levels, respectively.

4.4 | Test of Non-Response Bias, Early Response Bias, and Common Method Bias

We then tested for the potential presence of bias in the study data. For non-response bias, we examined whether the 56 firms excluded from the final sample (due to incomplete surveys or missing employment data) differed significantly from the 570 firms included in the final sample, in terms of employment (50 cases), use of AI platforms (33), and cooperation with users (24). The results of the Mann–Whitney U test suggest that the excluded firms are slightly larger (average number of employees = 42.41) than those included in the final sample (35.57) (Mann–Whitney U test = 1.92, p value = 0.056); however, no significant differences were observed in relation to the use of AI platforms (Mann–Whitney U test = 0.139, p value = 0.889) and cooperation with users (Mann–Whitney U test = -0.101, p value = 0.915). These results suggest that non-response bias does not contaminate the findings.

Following the temporal separation approach (Podsakoff et al. 2012), we used the non-parametric Mann–Whitney U test to evaluate whether the distribution of responses by early (first 10%) and late (last 10%) respondents is drawn from the same sample, that is, whether the two response vectors share the same distribution. This procedure was applied to the variables for firm size, use of AI platforms, and cooperation with users, as well as the items measuring AI-driven situating capabilities: grounding (3 items), bounding (3), and recasting (3). As shown in Table A2, of the 14 analyzed variables, a significant difference in response distribution was only found in two cases (the employment variable and the first question used to measure recasting AI capabilities). Therefore, the comparisons between early and late respondents corroborate that the distribution of the main variables does not raise early-response bias concerns.

Finally, we ran Harman's single factor test to verify the potential presence of common method bias (Podsakoff et al. 2003; Fuller et al. 2016), which, according to this test, occurs if the solution of a factor model including all variables produces a single factor that accounts for more than 50% of the variance in the measurement items (Fuller et al. 2016). We ran an exploratory factor analysis with the 13 variables related to AI-driven situating capabilities, cooperation during the solution delivery process, and the use of AI platforms. The factor model produced four factors with eigenvalues > 1, and the first factor with the highest eigenvalue accounts for 29.02% of the total variance for the key study variables. Although the KMO test suggests that the sample is factorable (KMO = 0.7140), the Cronbach's alpha (0.6444) indicates that the proposed factor model is not internally consistent; that is, the outcome is not reliable. Therefore, the results of Harman's one-factor test do not raise common method bias concerns.

4.5 | Method

Following the arguments supporting our theoretical framework (Section 2), managers engage in collaborative solution delivery processes based on the expectation of greater competitiveness. Nevertheless, without first modeling the decision to cooperate with users in this process, any model explaining the effect of

this strategy on competitive capabilities would produce biased results, even if it controls for covariates linked to AI-driven situating capabilities (Wooldridge 2002).

All firms can engage in collaborative solution delivery, and we argue that this process is driven by, among other things, the use of AI platforms (see Section 2). This introduces a self-selection problem (Angrist 1998; Heckman and Robb Jr 1985). Therefore, we use regression models with an endogenous treatment to analyze the effect of collaborative solution delivery on the development of AI-driven situating capabilities. This method—originally proposed by Rubin (1974) and further developed by Imbens and Angrist (1994) and Angrist et al. (1996)—controls for self-selection by modeling the outcome variable (in our case, AI-driven situating capabilities) as a function of an endogenous dummy variable (i.e., the treatment) linked to the three types of collaboration that firms can engage in during the solution delivery process.

In treatment effect models, the outcome variable is observed for all firms, and the endogenous dummy variable indicating the treatment condition enters into the outcome equation (Wooldridge 2002). In this study, the treatment model takes the following form:

$$\text{Cooperation}_i = \beta_0 + \beta_1 \text{AIplatforms}_i + \beta_2 \text{Controls}_i + \varepsilon_i \quad (1)$$

$$\text{Situating capability}_i = \delta_0 + \delta_1 \text{Cooperation}_i + \delta_2 \text{Controls}_i + \gamma_i \quad (2)$$

Equation (1) is the endogenous treatment probit model, where i indexes the sampled firms ($N=570$), β_j is the vector of coefficients, and “AI platforms” is the instrument variable used to model the endogenous treatment variables, that is, the set of dummies linked to the three types of collaboration during solution delivery, and which are our dependent variables.

For the outcome model presented in Equation (2), “situating capability” refers to the factor scores computed via factor analysis for the three AI-driven situating capabilities (grounding, bounding, and recasting), while δ_w is the vector of parameter estimates for the linear models. Control variables include logged firm size (employees), logged firm age (years), and two sets of dummy variables that account for the potential geographic and industry-specific effects among the sampled firms. Finally, ε and γ are the normally distributed errors of the binary-choice and linear regression models respectively.

As for the study's hypotheses, we expect $\beta_1 > 0$ to confirm that the use of AI platforms leads to greater cooperation during the solution delivery process (H1). A significant coefficient for the cooperation variable in Equation (2) ($\delta_1 > 0$) would also corroborate that cooperation with end customers during the three stages of the solution delivery process generates greater AI-induced situating capabilities (H2).

5 | Results

This section presents the findings of the treatment regressions modeling AI-driven situating capabilities as a function of endogenous collaborative solution delivery processes. In Table 6, the first column shows the results for the probit model evaluating

TABLE 6 | Results of regression models with endogenous treatment (sample = 570 firms).

	(1) First stage (Equation 1)	(2) Second stage (Equation 2): Situating capabilities		
	Cooperation with users	Grounding capabilities	Bounding capabilities	Recasting capabilities
Panel A: Problem identification				
Use of AI platforms (H1)	0.49 (0.20)**			
Cooperation with users (H2)		1.28 (0.13)***	1.10 (0.17)***	1.23 (0.14)***
Firm size (in employees)		-0.15 (0.08)*	-0.11 (0.09)	-0.09 (0.09)
Firm age (in years)		-0.03 (0.05)	-0.03 (0.06)	0.01 (0.05)
Industry dummies	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes
Intercept	-0.34 (0.11)***	0.15 (0.39)	0.15 (0.37)	-0.15 (0.35)
Inverse Mills ratio (lambda)		-0.75 (0.09)***	-0.65 (0.13)***	-0.74 (0.10)***
Pseudo R ²	0.0530	0.4749	0.4057	0.4721
Log likelihood	-374.14	-1035.91	-1048.21	-1025.53
Wald test (chi2)	40.79*** (df = 34)	124.56*** (df = 36)	66.12*** (df = 36)	123.05*** (df = 36)
Test of independent eqs. (chi2) (df = 1)		82.93***	28.63***	72.83***
Average VIF	1.27	1.41	1.50	1.39
Panel B: Solution development				
Use of AI platforms (H1)	-0.02 (0.21)			
Cooperation with users (H2)		-0.18 (0.32)	-0.07 (0.22)	-0.11 (0.33)
Firm size (in employees)		0.15 (0.09)*	-0.13 (0.09)	-0.11 (0.09)
Firm age (in years)		-0.02 (0.06)	-0.03 (0.06)	0.02 (0.05)
Industry dummies	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes
Intercept	-0.94 (0.13)***	0.65 (0.44)	0.64 (0.41)	0.37 (0.40)
Inverse Mills ratio (lambda)		0.26 (0.15)*	0.17 (0.10)*	0.16 (0.09)*
Pseudo R ²	0.0506	0.3393	0.3251	0.2782
Log likelihood	-298.20	-973.01	-980.38	-966.03
Wald test (chi2)	28.58** (df = 34)	63.32*** (df = 36)	57.88** (df = 36)	68.86*** (df = 36)
Test of independent eqs. (chi2) (df = 1)		4.20*	3.52*	4.97*
Average VIF	1.27	1.85	4.06	2.74
Panel C: Solution implementation				
Use of AI platforms (H1)	0.57 (0.21)***			
Cooperation with users (H2)		1.44 (0.16)***	1.39 (0.17)***	1.39 (0.14)***
Firm size (in employees)		-0.15 (0.09)*	-0.14 (0.09)	-0.11 (0.09)
Firm age (in years)		-0.02 (0.05)	-0.01 (0.06)	0.04 (0.05)
Industry dummies	Yes	Yes	Yes	Yes

(Continues)

TABLE 6 | (Continued)

	(1) First stage (Equation 1)	(2) Second stage (Equation 2): Situating capabilities		
	Cooperation with users	Grounding capabilities	Bounding capabilities	Recasting capabilities
Regional dummies	Yes	Yes	Yes	Yes
Intercept	−1.11 (0.21)***	0.38 (0.41)	0.39 (0.37)	0.07 (0.36)
Inverse Mills ratio (lambda)		−0.66 (0.10)***	−0.63 (0.12)***	−0.71 (0.09)***
Pseudo R ²	0.0711	0.2764	0.2203	0.2816
Log likelihood	−249.48	−910.73	−914.75	−894.89
Wald test (chi2)	32.92*** (df = 34)	106.52*** (df = 36)	93.62*** (df = 36)	121.97*** (df = 36)
Test of independent eqs. (chi2) (df = 1)		42.96***	22.88***	70.50***
Average VIF	1.27	1.85	2.14	1.84

Note: Robust standard errors in parentheses. All models include a set of regional (Andalusia is the reference region) and industry dummies ('Food processing' is the reference industry). *, **, and *** are significant at the 10%, 5%, and 1% levels, respectively.

the effect of AI platforms on the three stages of collaborative solution delivery (Panel A: problem identification, Panel B: solution development, and Panel C: solution implementation (Equation 1)). The model specifications in columns 2, 3, and 4 report the findings for the linear models testing the role of collaborative solution delivery in the three situating capabilities analyzed in this study (Equation 2).

We computed the variance inflation factor (VIF) for all models to test whether coefficients are amplified due to correlations across the explanatory variables. The average VIF value for the probit model in column 1 of Table 6 is 1.27 (range = 1.02–2.07). In the treatment models, the average VIFs range between 1.39 when estimating the effect of collaborations with users for problem identification on AI-driven recasting capabilities (Table 6: column 4 of Panel A), and 4.06 for the model analyzing the impact of collaborations for solution development on AI-driven bounding capabilities (Table 6: column 3 of Panel B). In all outcome equations, the highest VIF values—including those exceeding the generally accepted cutoff value of 10 for collinearity assessment—were observed for the endogenous treatment effect. This term is estimated from equation (1), which explains its correlation with the exogenous covariates in Equation (2) (Greene 2003; Heckman 1990). We also computed VIFs, including only the strictly exogenous variables used in the outcome models and the dummy variables linked to collaborative solution delivery. For the outcome models, the resulting average VIFs are 1.29 for the model that includes the dummies linked to collaboration for problem identification (column 2 of Panel A) and solution implementation (column 4 of Panel C), and 1.28 for the specification analyzing collaborations for solution development (column 3 of Panel B). In all models, VIF values range between 1.05 and 2.08. Overall, these results suggest that the model specifications do not suffer from collinearity problems, thereby further validating our empirical approach.

Concerning the key findings of the study, the results of the probit model estimating collaborative solution delivery (column 1 of Table 6) indicate that, unlike the case of collaborations for

solution development (Panel B), the coefficient linked to the adoption of AI platforms is positive and statistically significant for collaborations in problem identification (Panel A) and solution implementation (Panel C). That is, among the sampled firms, AI platforms are instrumental in supporting the development of relational capital between firms and the users of their solutions. This effect particularly emerges in collaborations that are most effective during the problem identification and solution implementation stages. Therefore, hypothesis 1 (H1) that using AI platforms stimulates greater cooperation during the solution delivery process is confirmed for collaborations during problem identification and solution implementation, but not in the case of solution development.

Hypothesis (H2) proposes that cooperation during the solution delivery process leads to greater AI-induced situating capabilities. This hypothesis is partially confirmed. Table 6 shows that the coefficient for the cooperation variable is positive and significant when such collaborations between solution providers and users are designed to enhance needs-finding practices (Table 6: Panel A) and to more effectively implement the customized solution (Table 6: Panel C). These results suggest that the effect of platform-induced cooperation during the diagnostic and implementation stages contributes to the creation of AI-driven situating capabilities.

Overall, by introducing AI platforms into their operations, businesses can leverage the infrastructures and potential of this technology for sharing data, thus generating valuable information and knowledge with value-creation and innovation potential (e.g., Lafuente, Vaillant, and Rabetino 2023; Nambisan et al. 2017). While the AI-powered connection between businesses and solution users proves effective for generating collaborations in problem identification and solution implementation, this association is insignificant when such collaboration involves the development of customized solutions. Collaboration is nonetheless important during solution development; indeed, this finding implies that AI platforms are not inherently tied to collaboration at this key stage of the solution delivery process. These results suggest possible

limitations of AI platforms in influencing processes that require creativity, such as solution development/design, thereby emphasizing the importance of human intervention in AI platform management.

6 | Discussion

6.1 | Summary

The study presented in this article addresses the issue of whether the use of AI platforms could act as a cooperation enabler that fosters the development of AI-driven situating capabilities within solution-based value generation ecosystems. To do so, the solution delivery processes of manufacturing firms that use modular AI platforms were compared to those of firms that do not. It was found that such usage does indeed facilitate cooperation during the problem identification and solution implementation stages, and, as predicted by the theory of situated AI, this cooperation leads solution ecosystems towards greater AI-driven situating capabilities, namely, those attained through grounding, bounding, and recasting.

6.2 | Theoretical Contributions and Implications

Our results have multiple theoretical implications. By addressing the growing demand for research on the rapidly evolving AI-dominated paradigm (Berg et al. 2023; Verganti et al. 2020), this is one of the first studies to empirically apply the situated AI theory. This recently published conceptual framework linking AI-driven situating capabilities to competitive advantages (Kemp 2024) is derived from the consolidated premises of situated agency and highlights the role that AI potentially plays in surmounting agency challenges within organizations to facilitate the development of competitive advantages. Along with the well-documented analytical advantages of digitization and AI for industrial organizations (Abdel-Karim et al. 2023; Kohtamäki et al. 2024; Lafuente and Sallan 2024; Weber et al. 2024), the situated AI theory proposes that: (i) with AI-driven grounding capabilities, the organization can avoid the difficulties inhibiting shared experiential learning across the organization, which can otherwise lead to ad-hoc problem solving (Nayak et al. 2020; Vaillant, Mora-Esquivel, and Alvarado 2025); (ii) through AI-driven bounding capabilities, knowledge expropriation hazards (Heiman and Nickerson 2004) can be avoided within the organization; and (iii) the use of AI-driven recasting capabilities can help avert myopic stagnation (Balasubramanian et al. 2022) across inter-organizational value interdependencies (Kemp 2024). Extrapolating from these concepts, multi-item constructs were designed to faithfully capture the essence of the theory's situating capabilities, as conceptually described in Kemp (2024). The questionnaire was tested and found to adequately capture the nature of the designed constructs. Consequently, the modeled constructs meant that our study could indeed find evidence of the role AI plays in driving the development of value-inducing situating capabilities.

However, our study also extended the situated AI theory. While the premises of this theory were conceptualized with

“intra”-organizational agency challenges in mind, the current study has elevated its application to the “inter”-organizational level of value-generating ecosystems. Our approach aligns with Glaser et al.'s (2024) view that organizations should be regarded as algorithms, wherein “agency exists in assemblages, not just in humans or artifacts” (p. 2755). The situated agency challenges that AI-driven situating capabilities are meant to address are found to be particularly relevant across multi-organizational, interoperative, and conjoined value ecosystems (Dhanaraj and Parkhe 2006; Longo and Giaccone 2017). Conceptually and empirically, as identified in our results, the AI-driven grounding, bounding, and recasting capabilities that address situated agency problems are correlated at the value-ecosystem level with AI platform-induced cooperation.

As such, confirmation of the importance of AI platform-enabled cooperation in solving ecosystemic situated agency challenges is another important contribution of the study. The situated AI theory gives no indication of the possible pre-determinants of the situating capabilities that lead to AI-driven competitive advantages. Our results clearly establish a link, in terms of solution value ecosystems, between AI platform-enabled cooperation and the presence of grounding, bounding, and recasting.

The setting adds to the theoretical and practical implications of these results. Solution delivery is an increasingly common, albeit complex, value-generating strategy adopted by many productive industries (Storbacka et al. 2013). The advent of AI has enabled manufacturing firms to increase the value of their products by better catering to the specific needs of their clients through the adoption of solution business models (Kohtamäki et al. 2024; Lafuente and Sallan 2024; Vendrell-Herrero et al. 2022). However, the multi-stage solution delivery process (problem identification, solution development, solution implementation), together with the scalable customization requirements needed to successfully transition towards solution delivery, is often best addressed collaboratively (von Briel et al. 2018). Our results highlight the cooperation-enabling virtues of AI platforms within the solution delivery process. In turn, the resulting cooperation is tied to the key strategic situating capabilities mentioned above.

6.3 | Practical Implications

The practical implications of the study arise from the clear connection made between the utilization of AI-based innovation platforms, user cooperation, and strategic capabilities, offering a pathway for enhanced value generation and smoother agency within value ecosystems. Distinguishing between the different stages of the solution delivery process and the importance of involving solution users at each stage highlights the critical role that AI platforms play in inducing cooperation, surmounting agency challenges, and systematizing various interdependent procedures across the solution delivery process.

However, the correlation between the use of AI platforms and the consequent cooperation was primarily observed in the diagnostic and implementation stages of the process. For the development stage, although one in every four firms in our sample co-created their solutions with their clients, these firms did

not use AI platforms to do so, unlike in the other stages. This may point to possible limitations of AI platforms in influencing processes requiring creativity, such as solution development/design, thereby emphasizing the importance of human intervention in AI platform management. As such, our results contribute to a better understanding of the complementarity between machine and human intervention in AI platforms, adding to recent progress in this area (Bouschery et al. 2023; Gama and Magistretti 2023).

6.4 | Future Research Avenues

Our study highlights promising avenues for future inquiry. Although it is by no means intended to be confirmatory, it is nevertheless a pioneering work on the empirical application of the principles of the situated AI theory. However, replication studies are needed to further validate and contextualize its findings (Bonett 2021). Kemp's model of AI-driven situating capabilities has also faced criticism for potentially undermining other core firm capabilities and overall competitiveness (see Moser et al. 2024; Lindebaum et al. 2024). Although we presented a supplementary analysis connecting the development of situating capabilities to labor productivity, we primarily focused on the generation of these capabilities, rather than their outcomes. Therefore, future research should evaluate the impact of developing these capabilities on core competencies, organizational values, and other financial performance metrics.

As our main research question focuses on variance, future process-oriented qualitative research could offer valuable insights to complement those already obtained. The specific quantitative methodology used in the study allowed us to determine the sequence of the relationship between AI platform use, solution delivery cooperation, and greater situating capabilities. Through qualitative research, future studies could extend the analysis by exploring the specific micro-foundations at play within these relationships and further emphasizing the importance of governance in interorganizational networks, particularly in relation to AI-driven situating capabilities. In this context, our focus on solution delivery stages can readily be extended or applied to other stage-based models in innovation management, such as New Product Development (Spanjol et al. 2024).

The cross-sectional nature of our data does not allow for longitudinal heterogeneity analyses, which seem necessary to better understand the temporal evolution of the links between AI platform use and the generation of situating capabilities that drive value creation within a productive ecosystem. We found that AI platforms make firms more likely to collaborate during the solution delivery process, which in turn is correlated with situating capabilities that help mitigate intra-organization agency challenges. A more in-depth longitudinal study is needed to answer the how, why, which, and what research questions that fall beyond the scope of our research but could build upon its findings. Furthermore, qualitative research could tell us much more about causation, system dynamics, and the potential reinforcing loops that could be at play within this chain of events.

Similarly, the conclusions generated by this study are drawn from Spanish manufacturing companies. Although we believe

that our findings and recommendations can be extended to organizations and solution delivery ecosystems in different geographic settings, culture has a strong influence on collaborative behavior and is likely to impact the situated agency challenges and the necessary resolve at the foundation of the theoretical model guiding this study and its results. We encourage researchers to engage in new studies exploring both “intra” and “inter” organizational scenarios to further support and consolidate the premise of the novel situated AI theory and the implications of our study's results. Our findings also indicate that most firms are currently unprepared to engage with AI platforms for innovation, with only 8% of our sample adopting this technology. Currently, it is only early adopters who seriously consider the use of AI platforms. However, as adoption rates continue to rise, further analysis will shed light on their relationship with user cooperation, strategic capabilities, and other significant organizational outcomes, including internal R&D investment and innovation.

Finally, this study focuses on the role of AI in building strategic situating capabilities; however, AI platforms can also lead to stronger systemic connections between participating agents. Therefore, to further explore the strategic value of AI technologies, future work should consider analyzing AI-driven capabilities among firms participating in interorganizational networks.

7 | Conclusion

This article highlights the role of AI platforms in enhancing cooperation and developing strategic AI situating capabilities within solution delivery ecosystems. By analyzing Spanish manufacturing firms, we show that AI platforms facilitate cooperation during the problem identification and solution implementation phases by fostering key situating capabilities that mitigate common agency constraints on interorganizational collaboration, yet highlight the need for human intervention during the more inventive solution development stage. The results of the study underscore the value generation potential of AI platforms for solution providers, extending the premise of situated AI to the organizational and interorganizational level. Our findings contribute to a better understanding of both the potential and the limitations of AI platforms in driving cooperation and strategic capabilities in value ecosystems.

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Ethics Statement

The authors have read and agreed to the Committee on Publication Ethics (COPE) international standards for authors.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Endnotes

¹Recent research has recognized that AI can enhance creativity in human innovation teams (Bouschery et al. 2023). However, our focus is on the observation that while AI platforms can effectively support operational improvements, major creative breakthroughs still require human intervention. Thus, we propose that AI platforms may be more proficient at facilitating operational solutions than driving highly creative outcomes without human involvement.

²It should be noted that while Kemp (2024) referred to ‘AI-driven situating activities’, we call them ‘capabilities’ in our study. Kemp sought to explain increased competitive advantages, implying that AI-driven situating capabilities have been ‘acted upon’ to generate such competitive advantage. Our focus, on the other hand, is centered on the role of AI platforms as cooperation enablers, which in turn supports the development of the aforementioned situating capabilities within solution delivery ecosystems. We do not consider whether these capabilities have been acted upon (becoming activities rather than capabilities) to improve the firm’s competitive performance, which was the primary focus of Kemp’s model (see Moser et al. 2024).

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Appendix A

TABLE A1 | AI-driven situating capabilities: Questions in the study questionnaire.

Panel A: Grounding capabilities	
GR1	Your firm processes collected data for learning purposes to develop its competitive strategies
GR2	Your firm feeds its management control systems with specific customer intelligence data
GR3	Your firm feeds its management control systems with historical organizational data
Panel B: Bounding capabilities	
BD1	The firm takes steps to prevent competitors from expropriating shared value
BD2	The firm takes steps to prevent collaborating firms from appropriating shared value
BD3	The firm participates in actions aimed at influencing government regulation of AI
Panel C: Recasting capabilities	
RC1	The firm uses analytical tools to help establish future strategic paths
RC2	The firm uses analytical tools to better align with internal and external changes
RC3	The firm's AI algorithms are updated frequently

TABLE A2 | Early response bias test: Mean comparison of items related to the study's AI-driven situating capabilities (early respondents vs. late respondents).

Variables		Early wave (first 10%)	Late wave (last 10%)	Mann-Whitney <i>U</i> test
Item	Panel A: Grounding capabilities			
GR1	Your firm processes collected data for learning purposes to develop its competitive strategies	1.67 (1.29)	1.42 (1.13)	1.16 (<i>p</i> value = 0.24)
GR2	Your firm feeds its management control systems with specific customer intelligence data	1.63 (1.38)	1.33 (1.04)	1.38 (<i>p</i> value = 0.17)
GR3	Your firm feeds its management control systems with historical organizational data	1.85 (1.64)	1.54 (1.36)	0.98 (<i>p</i> value = 0.33)
	Panel B: Bounding capabilities			
BD1	The firm takes steps to prevent competitors from expropriating shared value	1.34 (0.89)	1.18 (0.59)	0.87 (<i>p</i> value = 0.39)
BD2	The firm takes steps to prevent collaborating firms from appropriating shared value	1.28 (0.76)	1.38 (1.19)	-0.12 (<i>p</i> value = 0.91)
BD3	The firm participates in actions aimed at influencing government regulation of AI	1.25 (0.70)	1.31 (1.13)	-0.51 (<i>p</i> value = 0.61)
	Panel C: Recasting capabilities			
RC1	The firm uses analytical tools to help establish future strategic paths	1.57 (1.26)	1.27 (1.06)	1.90 (<i>p</i> value = 0.06)
RC2	The firm uses analytical tools to better align with internal and external changes	1.54 (1.22)	1.40 (1.26)	1.09 (<i>p</i> value = 0.27)
RC3	The firm's AI algorithms are updated frequently	1.48 (1.29)	1.18 (0.77)	1.41 (<i>p</i> value = 0.16)
	Panel D: Use of AI platforms, cooperation with users, and firm size			
	Use of AI platforms	0.11 (0.31)	0.07 (0.26)	0.63 (<i>p</i> value = 0.53)
	Cooperation with users for problem identification	0.43 (0.49)	0.47 (0.51)	-0.47 (<i>p</i> value = 0.64)
	Cooperation with users for solution development	0.30 (0.46)	0.20 (0.40)	1.25 (<i>p</i> value = 0.21)
	Cooperation with users for solution implementation	0.18 (0.39)	0.20 (0.40)	-0.29 (<i>p</i> value = 0.27)
	Firm size (employees)	52.18 (62.41)	22.11 (15.74)	4.16 (<i>p</i> value < 0.00)

Note: Standard deviations in parentheses. *, **, *** = significant at the 10%, 5%, and 1% levels, respectively (Mann-Whitney *U* test).