



Automation, augmentation, or dual AI strategies for superior product line performance: the functional subsidiarity challenge

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ABSTRACT

This study evaluates the effectiveness of AI strategy implementation within the solution delivery process of products by analyzing the associations between such strategies (i.e., automation, augmentation, and dual) and the market performance of product lines. The analysis uses a unique sample of 667 distinct product lines from 2023 and applies Kernel-based propensity score matching to ensure that AI-enhanced smart products are comparable to their non-AI-enhanced counterparts. The core findings reveal that, irrespective of their AI capacity, a product's smart capabilities must align with the specific functional needs of the task at hand to optimize outcomes, a principle termed functional subsidiarity. The results show that neither automation nor augmentation alone has a significant impact on market performance; instead, only a dual AI strategy demonstrates a positive effect. By analyzing the effectiveness of smart product lines within strategic processes rather than isolated tasks, the findings highlight the importance of adopting a flexible dual AI strategy to navigate the complexities of solution delivery processes, specifically across its problem identification, solution development, and solution implementation stages. Theoretical and practical implications are discussed.

1. Introduction

A growing number of products are being enhanced with added sensors and connectivity that increase their value-creation potential through dimensions of remote adaptability, reactivity, multi-functionality, autonomy, and humanlike interaction abilities; transforming them into so-called smart products (Rijdsdijk and Hultink, 2009; Porter and Heppelmann, 2014, 2015). To be truly 'smart' and achieve these benefits, products need more than just sensors and data collection; they require artificial intelligence (AI)-enabled capabilities that allow them to provide functionalities that can replace, complement, or improve the cognitive capacity and task performance of their users (Opazo Basáez et al., 2024; Rabetino et al., 2024).

The demand for AI chips and applications has surged (Vendrell-Herrero et al., 2025), driven in part by the rapid and profound transformation in how organizations adopt AI technologies to enhance their products (Cooper, 2024; Gama and Magistretti, 2025). However, this shift has exposed several challenges that, if left unresolved, could undermine the transformative potential of AI by failing to realize its full

benefits (Floridi, 2024; Johnson and Menzies, 2024). Because many managers hold high expectations of AI (Sullivan and Wamba, 2024), it is important for manufacturers to implement the technology effectively when enhancing their products. Otherwise, they risk poor value generation and weak market response (Wörsdörfer, 2024). Research must keep pace with these changes by offering evidence-based, rather than hype-based, guidelines for effective product-level AI implementation (Lagrandeur, 2024; Markelius et al., 2024).

While prior research has extensively explored issues such as ethical considerations (Bankins and Formosa, 2023) and data quality (Berente et al., 2021), this paper focuses on a critical yet underexamined challenge linked to AI strategies: functional subsidiarity. Borrowed from the corporate governance (Abländer, 2011) and regional science literature (Begg, 2008; Moodie et al., 2022), we define this concept as the alignment between a product's AI-enabled capacities and the specific functional requirements of the tasks in which these capabilities are employed.

AI strategies in organizations generally follow two approaches: automation and augmentation (Raisch and Fomina, 2025). Automation

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involves machines independently taking over routine, structured tasks to enhance efficiency, consistency, and cost-effectiveness (Davenport and Kirby, 2016). In contrast, augmentation emphasizes close collaboration between humans and machines, leveraging the unique strengths of both—such as human intuition and reasoning paired with machine precision and processing capabilities (Daugherty and Wilson, 2018). The choice of approach depends on the nature of the task¹: well-structured, routine tasks lend themselves to automation, while complex, more variable tasks benefit from augmentation (Brynjolfsson and McAfee, 2014; Davenport and Kirby, 2016; Daugherty and Wilson, 2018). Both strategies offer distinct advantages. Therefore, viewing them as complementary, with their integration serving as a source of synergies rather than conflict, could potentially enhance organizational outcomes (Krakowski et al., 2023; Raisch and Fomina, 2025; Raisch and Krakowski, 2021). This link is conceptually grounded in the principle of agility (Hoonsopon and Puriwat, 2019; Weber and Tarba, 2014), that emerge as a key aspect of the dynamic capability view (Eisenhardt and Martin, 2000; Teece et al., 1997). AI can significantly improve a product's competitive edge by enabling functional agility allowing it to quickly adapt to task specific conditions (Vaillant et al., 2025a,b,c). Such AI functional agility is at the basis of the functional subsidiarity that aligns smart products to the specificities of the tasks being addressed through a dual (automation-augmentation) AI strategy.

Effective AI strategy implementation is a practical challenge faced by many firms and is one that demands greater academic attention (Dagnino and La Bruna, 2023; Peretz-Andersson et al., 2024; Usman et al., 2024). Management scholars have a vital role to play in advancing the AI debate by revisiting managerial prescriptions and developing more nuanced, comprehensive frameworks to guide organizations in balancing automation and augmentation. For a product line, AI strategy implementation refers to the design decision to embed such capabilities—whether for automation, augmentation, or both—into a product for customer use. The objective of this study is therefore to evaluate which AI strategy generates greater product market performance, defined as a product line's attainments in terms of customer-centricity, agility when responding to markets, and sales growth (Smulowitz et al., 2020). Our proposed principle of functional subsidiarity helps to better determine the AI strategy to adopt.

To meet this objective and evaluate the associations between AI strategies and product market performance, we employ two complementary empirical strategies using a unique self-collected sample of 667 product lines. First, we address endogeneity by estimating treatment effects through Kernel-based propensity score matching (PSM). Second, we estimate a series of linear regression models that enable a more consistent comparison of AI strategic choices across firms. These models examine product market performance as a function of AI decisions made within the product's solution delivery process—the multi-stage sequence through which complex customer challenges are addressed, comprising problem identification, solution development, and solution implementation (Baden-Fuller and Morgan, 2010; Brady et al., 2005; Vaillant et al., 2025a,b,c). As a complementary analysis informing the discussion, we further decompose the solution delivery process into its three stages to explore how functional heterogeneity shapes the need for a dual AI strategic approach.

This study makes significant contributions to both academic research on AI strategy and its practical application. First, it advances the ongoing academic debate on automation versus augmentation by empirically

validating the benefits of integrating both strategies, aligning with the “both/and” approach advocated by the hybrid perspective proposed by Raisch and Krakowski (2021) and recently analyzed by Johnson et al. (2022), Guo et al. (2025), and Raisch and Fomina (2025). The automation-augmentation dichotomy has traditionally been discussed in the context of smart manufacturing—technology used within production processes. This study shifts the context to smart products, where AI capabilities are embedded in the product itself and may provide value to both suppliers and customers. Although the analysis is purely from the manufacturer/supplier perspective, it detects whether the observed smart products were designed to be used by customers in a flexible dual format, or only in an autonomous or augmented one.

Second, our findings underscore the importance of adopting a dual AI strategy at the product-line or strategic business unit level, rather than exclusively at the broader corporate level (Gadepalli et al., 2025). This significant methodological contribution reflects the practical reality that distinct AI strategies are often tailored to specific product lines. Although sub-organizational levels of analysis are gaining prominence in the management literature, existing research has predominantly focused on subsidiaries, departments, teams, or individual employees (e.g., Felin et al., 2015). In contrast, and although there are a few notable exceptions (e.g., Salvato, 2009), quantitative investigations that examine units of analysis linked to product lines—particularly those that explore capabilities, functions, and performance—remain relatively limited, despite repeated calls for such research (e.g., Helfat and Raubitschek, 2000; Pentland and Feldman, 2005). This is especially relevant for journals concerned with advancing the study of product strategy and innovation management. Our research design offers a valuable methodological contribution by addressing this gap.

Third, the concept of functional subsidiarity, which is based on agility from dynamic capabilities and derived from the policy literature (Abländer, 2011; Begg, 2008; Moodie et al., 2022), is applied to AI strategy, highlighting the importance of aligning a product's smart capabilities with specific functional tasks to optimize outcomes. For example, tractors equipped with AI-enabled autonomous capabilities should not necessarily be operated in autonomous mode for every agricultural task, for some jobs may require that this feature be switched off. The functional subsidiarity principle demonstrates that capability-functionality alignment in AI strategy occurs not at the organizational level but at a sub-organizational one (in our case, the product-solution delivery process; but potentially also in projects, organizational routines, assembly lines, or specific supply chains). This framework not only clarifies the study's results but also sets the stage for future research in business and management.

Finally, from a practical viewpoint, the study underscores the importance of viewing smart products as integral to dynamic processes rather than isolated tasks, advocating for a flexible, dual AI strategy to navigate the complexities of multistage solution delivery processes. Firms need to understand the synergetic effects of combining automation and augmentation, tailored to functional requirements, to maximize product performance. Consequently, the results suggest that, instead of uniform applications across all tasks, AI capabilities should be selectively applied to specific ones for optimal results, in a manner consistent with the principle of functional subsidiarity. This provides a roadmap for practitioners to better leverage AI in complex operational contexts. By addressing functional subsidiarity, researchers and practitioners alike can help unlock the full potential of AI in business and management contexts.

2. Background literature

We build on two complementary literature streams. First, the dynamic capability view explains how AI enhances product-level agility by enabling rapid sensing, adaptation, and reconfiguration. Second, research on smart products and solution delivery highlights how AI capabilities vary across product functions and stages, underscoring the

¹ Both in the context of augmentation (Jia et al., 2024) and automation (Acemoglu et al., 2022), the impact of AI on employment is increasingly analyzed at the task rather than the job level. This perspective recognizes that AI does not affect all aspects of a job equally but targets specific tasks within broader occupational roles. We adopt a similar lens in our study—whereby capabilities parallel the notion of jobs, and functions correspond to individual tasks.

need to analyze AI strategy at the product-line level. Together, these perspectives ground our theorization of how AI strategies shape performance. We discuss each of these perspectives in turn.

2.1. AI-enabled agility and the dynamic capability view

The theoretical foundation of this study is grounded in the premise of agility, that emerge as a key aspect of the dynamic capability view (Weber and Tarba, 2014). The dynamic capability view highlights the importance of sensing, seizing, and reconfiguring resources and capabilities to navigate changing business environments successfully to build and maintain competitive advantage (Eisenhardt and Martin, 2000; Teece et al., 1997). Agility is a manifestation of such dynamic skills in action, as it entails the capacity to rapidly adapt and respond to change (Hoopeson and Puriwat, 2019; Weber and Tarba, 2014).

AI technologies enable products to collect and analyze large volumes of data, allowing for more precise and fast needs discovery, solution development, and solution implementation (Vaillant et al., 2025a,b,c). The insights generated by AI have been identified as being important in improving resource allocation, forecasting market trends, and modifying solution delivery to match personalized and evolving customer needs (Ameen et al., 2021; Petrescu et al., 2022). But at the same time, the enhancement of a product's functional capability through the adoption of AI can significantly improve its competitive edge by enabling functional agility allowing it to quickly adapt to task specific conditions (Vaillant et al., 2025a,b,c). Such AI functional agility is at the basis of the functional subsidiarity that aligns smart products to the specificities of the tasks being addressed.

2.2. Smart products within a solution delivery process

Much emphasis has been placed on the big data generated by smart products (Hopp et al., 2018; Reinartz et al., 2019), as well as on the scalable customization capacity that such product-based intelligence can offer users (Berente et al., 2021; Raff et al., 2020; Vendrell-Herrero et al., 2021). However, AI-enabled capabilities are required to allow smart products to achieve functionalities that can replace, complement, or improve the cognitive capacity and task performance of their users (Opazo Basáez et al., 2024; Rabetino et al., 2024).

To study how AI-enabled capabilities fulfill these functions, research must focus on the product itself. Whereas many studies of AI strategies have been conducted at the corporate or firm level (Bahoo et al., 2023; Kemp, 2024), it is important for research on smart products to specify such analysis at the product-line level. This is because organizations do not, nor should they, implement a single universal AI strategy across their different strategic business units or product lines. Despite falling under the same corporate structure, independent product lines based on different competitive business strategies are likely to necessitate distinct AI strategies. Therefore, analyzing the AI strategy of smart products at the product-line level is likely to yield more accurate and nuanced results.

This study therefore adopts the product line as the unit of analysis in order to differentiate the specific AI capabilities of each analyzed product. Similarly, the study distinguishes the AI strategy applied across different functions of certain products. Specifically, the functionality of smart products is examined in relation to their implementation across different tasks within the solution delivery process. Moreover, one of the most important strategic contributions of smart products has been mass personalization and the ability of firms to offer added value through tailored solution delivery in response to specific customer problems (Brady et al., 2005; Kulkov, 2023). An integral solution delivery process is composed of three consecutive stages. First, the problem that requires a solution must be identified. Second, a customized solution must be developed. Finally, the solution must be effectively implemented (Baden-Fuller and Morgan, 2010). For all three of these stages, AI strategies can make different contributions to the functionality of smart

products.

3. Hypotheses development

3.1. Strategic AI approaches: automation vs. augmentation

Rather than mechanical work, smart products equipped with AI technologies can perform cognitive work that has traditionally been limited to the human domain (Berente et al., 2021; Rabetino et al., 2024). With clear rules in place, tasks can be delegated to automation-capable smart products, which draw on codified domain expertise to program rules into the system in the form of algorithms specifying the relationships between the conditions ("if") and the consequences ("then") (Gillespie et al., 2014; Raisch and Krakowski, 2021).

An example of an AI-enhanced smart product with autonomous capabilities is the John Deere 8R(x) and 9R(x) tractors equipped with autonomy packs, presented by the manufacturer at the 2025 Consumer Electronics Show (CES).² These intelligent agricultural machines are equipped with advanced connectivity, video, and lidar technologies allowing remote operation, and also integrate a sophisticated Nvidia-based machine learning processing system that enables relatively more efficient, effective, and precise autonomous operation. These tractors not only learn and improve their autonomous operation with use, but also have the ability to communicate and learn from the data accessible in other systems (irrigation, weather data, seed optimization, and other farm equipment), as well as from other similar autonomous machinery operating worldwide (Jahmy Hindman-CTO John Deere, 2025³; The FarmCast, 02/25/2025).

In a similar fashion, organizations addressing a well-structured solution delivery process can opt for an automation-based AI strategy for their products. AI can substitute human cognitive capabilities, enabling products to learn and act autonomously (Balasubramanian et al., 2022). AI-enabled products make autonomous predictions for strategic decision-making and problem-solving tasks that traditionally relied solely on human cognitive capabilities (Choudhury et al., 2020; Shrestha et al., 2019). AI can potentially allow smart products to perform a wide variety of optimization and automation tasks, replacing time-consuming human activity with processes that improve accuracy, efficiency, or effectiveness (Langley and Simon, 1995; Vaillant et al., 2025a,b,c).

Beyond the zero-sum substitution aspect, automation-enabled products can also generate capacity beyond human abilities (Vaillant et al., 2025a,b,c). This is achieved by handling and analyzing far greater volumes of data through faster and more accurate computation from a much wider landscape of possible options than humans or products not equipped with such capabilities. Unlike humans, products with AI-induced autonomous capabilities may have virtually unlimited information-processing capacity (Raisch and Krakowski, 2021), whose accuracy is likely to overshadow the value of products dependent on traditional human prediction, or even make them obsolete (Agrawal et al., 2022). The application of an automation-based AI strategy means that a firm's products face far less information-processing limitations (Davenport and Kirby, 2016). Because humans' domain-specific cognitive capabilities are difficult to transfer to unrelated domains, path dependencies can be broken and greater novelty achieved if humans are replaced by integrating automation-based AI (Raisch and Krakowski, 2021). From a dynamic capability lens, the adoption of an automation-based AI strategy allows the product to develop new capabilities that allow it to expand its capacity frontier, enabling it to

² <https://www.futurefarming.com/tech-in-focus/john-deere-unveils-electric-tractor-at-ces-2025/><https://www.reuters.com/technology/deere-boosts-bet-autonomous-tractors-with-new-machines-2025-01-06/>.

³ <https://www.agritechtomorrow.com/news/2025/03/18/john-deeres-chief-technology-officer-jahmy-hindman-and-rdo-equipment-co-leaders-share-insights-from-autonomous-and-machine-learning-field-partnerships-16457/>.

generate greater value when used (Lafuente et al., 2023).

The autonomous capacity of John Deere's tractors means farm labor can be repurposed. In a context of shortages in skilled labor and an aging workforce, the use of autonomous tractors for routine and time-consuming tasks such as tillage allows farm operators to shift to more value-adding agricultural work. Moreover, optimal farm operations often require the ability to face sudden hectic periods when multiple tasks need to be performed at the same time. Compared to human labor limitations, autonomous tractors can operate 24 h a day, maximizing operation time within short opportunity windows, thereby boosting yields and providing farm management optimization alternatives. The connected intelligence that characterizes such tractors allows for real-time customization to the specific conditions of a client's operations, developing and implementing personalized solutions based on access to large data libraries from connected systems. This enables tractors to employ vicarious learning to deliver the optimal solutions for every specific situation. In most farm operations, the added cost of AI-enhancing the autonomy of farm equipment is more than compensated by efficiency and effectiveness gains for manufacturers and customers alike (Jahmy Hindman-CTO John Deere, 2025³; The FarmCast, 02/25/2025).

Products with automation properties can generate superior value by increasing their output potential and gaining competitive advantage over rival products that do not utilize an automation-based AI strategy. As a result, it is hypothesized that.

H1. *Automation-based AI strategies in a product's solution delivery process enhance product market performance.*

Technological and social barriers continue to hinder the complete automation of certain organizational processes. This is particularly evident in tasks that involve significant levels of ambiguity, complexity, or infrequent occurrence, which restrict the practical application of deterministic approaches (Davis and Marcus, 2015). Such technical limitations hinder a smart product's ability to entirely take over certain decision-making or problem-solving tasks (Raisch and Krakowski, 2021).

AI-enabled products lack a sense of self and purpose, requiring humans to clearly define their objectives in order for them to function effectively (Braga and Logan, 2017). While these products can consider multiple scenarios by relaxing certain real-world constraints, they are unable to fully account for ambiguous predictors such as cultural fit or interpersonal relations due to the limited availability of codified data. Additionally, smart products are usually confined to the specific tasks for which they have been trained and lack human senses, perceptions, emotions, and social skills (Braga and Logan, 2017; Davenport and Kirby, 2016). As a result, the relationship between humans and smart products is not dichotomous but is evolving toward machine augmentation of human capabilities, where such products complement rather than replace human decision-making and performance (Raisch and Krakowski, 2021).

Airbus implements such AI-enhanced augmentation capabilities within many of its most advanced aircraft. Following a human-centric approach, its engineers are working to bring AI-augmented processes into cockpits to enhance safety, increase efficiency, and reduce pilot workload. With the help of AI, pilot-assistance technology has evolved from simple devices that maintain an aircraft's altitude to highly independent flight control systems. According to Airbus, the integration of AI in aviation must focus on safety, security, assurance, human factors, and ethical considerations, which are only attainable from an augmentation-based, human-centric approach (Airbus FCAS, 2025⁷; Weitering, 2023).

AI-enabled products have the potential to augment, rather than replace, humans within solution delivery processes. By shifting to an augmentation approach, many limitations of smart products can be addressed, as human capabilities—such as holistic thinking and intuitive information processing—are leveraged to interpret options and apply broader contextual understanding beyond the confines of specific tasks

(Brynjolfsson and McAfee, 2014). This collaborative interaction between human cognition and smart products allows for more nuanced decision-making and adaptability in the real-world scenarios common to most solution delivery processes. Many of these entail significant complexity, where the underlying rules and models are not well-defined or readily accessible, making traditional rule-based automation impractical. Instead, products adopting an augmentation approach allow users to delve deeper into the problem while maintaining an active role in the process (Holzinger, 2016). By leveraging this approach, users can work collaboratively with the product, combining computational efficiency with human judgment and creativity to navigate and address complex challenges more effectively. From a dynamic capability lens, the adoption of an augmentation-based AI strategy allows the product to complement the users existing resources in order to reach value generation capacities that would be unreachable without such an additive mutualization (Ameen et al., 2025).

For example, in its defense aviation division, Airbus relies heavily on the AI-enhanced Future Combat Air System (FCAS) to offer pilots of its new generation fighters augmented defense and security capabilities as part of its broader Next Generation Weapons System (NGWS) based on collaborative combat. This system allows pilots to integrate enhanced platforms using AI, big data, and human-machine interaction to connect with other systems in space, in the air, on the ground, at sea and in cyberspace, thereby enabling agile decision-making and rapid, real-time situational awareness, ultimately ensuring mission success (Airbus FCAS, 2025⁷; Weitering, 2023).

As such, the application of an augmentation-based AI strategy for smart products has been found to potentially increase productivity, improve service quality, and foster innovation (Krakowski et al., 2023). Moreover, it is assumed that the combination of complementary human and smart product capabilities will increase the quality, speed, and extent of learning in organizations (Brynjolfsson and McAfee, 2014; Davenport and Kirby, 2016; Daugherty and Wilson, 2018). Brynjolfsson and McAfee (2014) suggest that organizations should prioritize augmentation, which they relate to superior performance. According to Raisch and Krakowski (2021), augmentation drives competitive advantage when the superior predictive capabilities of AI-enabled smart products complement human cognitive, creative ideation, large-scale contextualization, and social interaction capabilities. Based on these arguments, the following hypothesis is proposed.

H2. *Augmentation-based AI strategies in a product's solution delivery process enhance product market performance.*

3.2. Functional subsidiarity through dual AI strategy

When it comes to effective use of smart products, a distinction must be made between the AI capacity of a specific product in terms of automation or augmentation, and the actual functional application of the product to a specific task. A smart product exhibiting a certain AI capacity will not necessarily use that capability for every task for which it is employed. We propose that functional subsidiarity is likely to lead to more effective applications of such smart products.

The principle of functional subsidiarity refers to the deployment of a product's smart capability at the functional level that is most coherent with the task at hand, where the resulting actions produce optimal outcomes. To achieve functional subsidiarity, a smart product will not necessarily use all of its AI-enabled capabilities at every point, but will instead adjust to optimize their deployment according to the task. For example, an operator may manually or remotely switch off a tractor's autonomous function to take control if need be. Likewise, smart products designed for augmentation may still carry out certain tasks autonomously, such as pilots of AI-enhanced aircraft switching on autopilot during routine cruising.

Functional subsidiarity builds on the principle of subsidiarity from territorial business and policy, which holds that effective decision-

making must occur at the level best suited to the affected actions and outcomes (Abländer, 2011; Begg, 2008; Moodie et al., 2022). For smart products, functional subsidiarity refers to the adequate implementation of capabilities adjusted to the requirements of tasks. For their optimal use, smart products may not necessarily make full usage of their AI-enabled capabilities at every single task where they are employed. Raisch and Krakowski (2021) made a similar observation, suggesting the need for differentiation in AI implementation strategies to “allow organizations to recognize and appreciate automation and augmentation’s distinctive benefits and leverage them separately.” They argue that managers should purposefully iterate between automation and augmentation tasks, enabling long-term dual engagement across both strategies.

Overemphasizing either augmentation or automation can fuel reinforcing cycles that harm organizational performance (Raisch and Krakowski, 2021). A non-flexible, one-sided AI strategy leads to ineffective implementation and suboptimal performance because it fails to address the frequent conflict between a product’s smart capacity and the specific functional requirements of a given task. Subsidiarity therefore calls for the dual application of AI strategies within a product’s solution delivery process.

In such processes, AI is often deployed within open systems that blur traditional organizational boundaries (Panait and Luke, 2005). Such systems facilitate widespread data collection, with diverse stakeholders continuously and collaboratively contributing updates (Gregory et al., 2021). The dynamic interplay of inputs from both internal and external agents shapes the processes of automation and augmentation, ultimately influencing subsidiarity and organizational performance with potentially far-reaching impacts.

The mechanisms that lead to superior outcomes from a dual AI strategy are based on the synergistic advantages attained through functional subsidiarity. The integration of augmentation and automation leverages their distinct strengths, offering greater versatility and better adaptation to immediate functional needs. A smart product guided by a dual AI strategy can hypothetically achieve more. Augmentation excels at identifying patterns within vast datasets, thus enhancing decision-making, while automation ensures cost-effective design and processes. Their combined application generates complementary benefits that neither can achieve alone, resulting in enhanced performance within the solution delivery process.

The enhancement of a product’s functional capability through the adoption of a dual-AI strategy can significantly improve its competitive edge by enabling functional agility allowing it to quickly adapt to task specific conditions (Vaillant et al., 2025a,b,c). From a dynamic capability lens (Eisenhardt and Martin, 2000; Teece et al., 1997), the agility to reconfigure resources and capabilities to achieve responsiveness and flexibility enhances a smart products capacity for customized solution delivery and therefore its value, competitive advantage, and potential market performance (Ameen et al., 2021, 2025; Mikalef et al., 2021; Mikalef and Gupta, 2021). Such AI functional agility is at the basis of the functional subsidiarity that aligns smart products to the specificities of the tasks being addressed when adopting a dual-AI strategy.

For example, John Deere’s tractors equipped with autonomy packs retain cabs, allowing an operator to climb aboard and assume control while benefiting from AI-enhanced capacity. This increases the tractor’s capacity and value when higher-order operations are required to manage unusual solutions or ambiguous settings requiring human intervention (The FarmCast, 02/25/2025). Similarly, Airbus’ AI-enhanced pilot augmentation systems are able to autonomously handle problem-identification tasks through simultaneous real-time data processing, leaving pilots to focus on solution development and implementation in accordance with functional subsidiarity (Airbus FCAS, 2025⁷). Fig. 1 summarizes these cases by visually mapping how each system shifts between autonomous and augmented modes across the solution-delivery process, illustrating their dual AI strategy profiles.

Together, the dual applications of AI within smart products provide users with a comprehensive range of advantages, achieving functional

subsidiarity and delivering superior outcomes (Raisch and Krakowski, 2021). We therefore hypothesize as follows.

H3. *Compared to AI strategies based on automation or augmentation alone, dual AI strategies in a product’s solution delivery process enhance market performance the most.*

4. Data, variables, and method

4.1. Data

In this study, the product line is the unit of analysis, defined here as a fundamentally distinct business unit nested within the organizational structure that uses specific technology (production process), competes in a differentiated industrial sector (competitors), and targets a concrete market segment (customers) (Dowell, 2006; Govindarajan and Fisher, 1990; McFarland et al., 2024).

We created a questionnaire to collect information about the use of digital technologies (Internet of Things (IoT) and AI). Details of the instrument are provided in Section 4.2. The questionnaire was pilot-tested by three technology experts and academics to ensure that the questions related to product lines and digital technologies were clear and appropriate for achieving the study’s objectives.

In parallel, we collected financial and organizational data from the Spanish ORBIS database, provided by Moody’s Investors Service (<https://www.informa.es/en/business-risk/sabi/orbis>), for an initial target population of product lines from 9413 manufacturers with more than 10 employees.

We administered the survey through a professional market research firm. Data were collected between June and September 2023 via computer-assisted telephone interviews. Respondents—i.e., executives and senior managers familiar with the products’ operational and digital strategy—were asked to answer essentially closed-ended questions about the production and sales of their two most representative product lines.

A total of 570 valid responses were received, of which 97 reported producing more than one product. The final sample consists of 667 observations, each corresponding to a distinct product line. Among the sampled firms, manufacturers producing a single product line were significantly smaller (mean number of employees = 32.90) than those producing more than one (mean = 48.59) (t -test = 6.25, p -value < 0.001). The relatively small number of manufacturers producing multiple product lines is consistent with the notion that larger organizations are more likely to diversify their product portfolios (Bernard et al., 2011; Goldberg et al., 2010).

With a 95 % confidence level ($Z = 1.96$), the collected responses are representative of the targeted population, with a sampling margin error of 3.98 %, which falls within acceptance levels for quantitative studies (Juslin et al., 2007). The diversity of the sampled product lines, in terms of location and economic activity, further validates the final sample.

The geographic spread of Spain’s manufacturing sector, as reported by the Spanish Statistics Institute (INE), is consistent with the distribution in the study’s sample.⁴ For example: the proportion of sampled product lines manufactured in Catalonia = 16.32 % (Spain = 17.70 %), Valencia = 12.63 % (Spain = 12.35 %), Andalusia = 11.93 % (Spain = 14.70 %), and Madrid = 9.47 % (Spain = 10.78 %). Finally, the industry breakdown of the studied product lines supports the diversity of their economic activity: food processing (NACE: 10–12) = 27.44 %, metal (NACE: 24–25) = 20.09 %, electronic and machinery (NACE: 26–28) = 14.09 %, plastic (NACE: 22–23) = 10.79 %, chemicals (NACE: 20–21) = 7.20 %, textile (NACE: 13) = 3.45 %, furniture (NACE: 31) = 3 %, and others (NACE: 14–18 and 29) = 13.64 %.

⁴ See: www.ine.es/jaxiT3/Tabla.htm?t=36176.

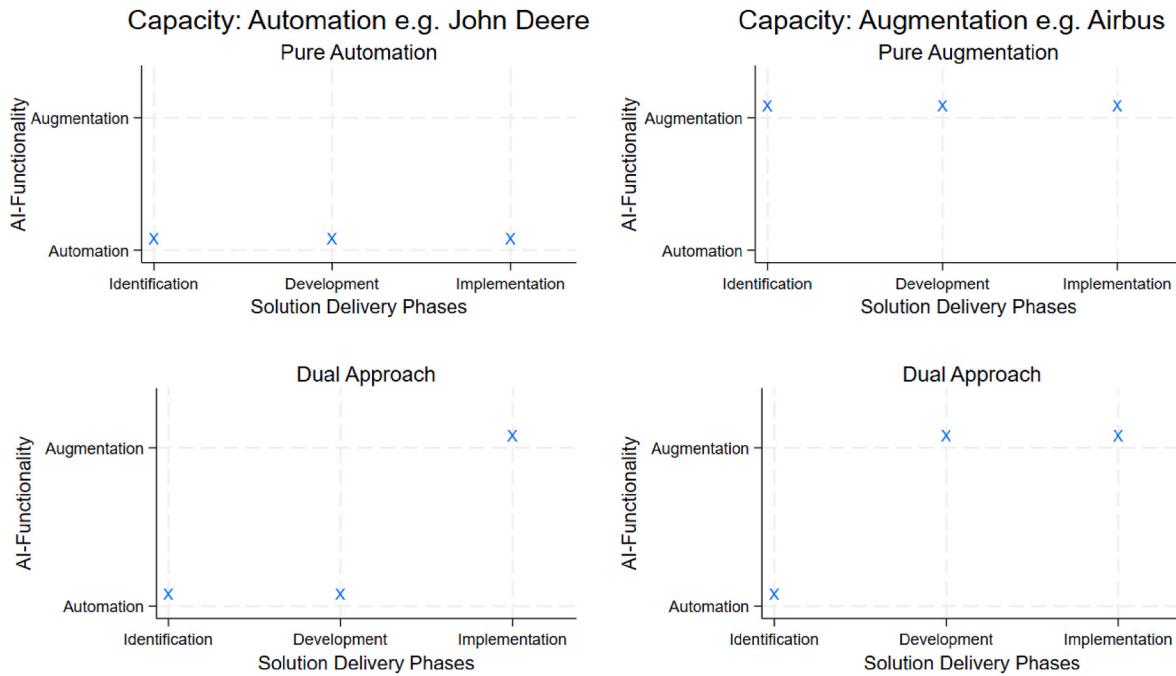


Fig. 1. Misalignment between AI Capacity and Functionality: A Dual Approach. **Note:** This figure illustrates how misalignment between AI capacity and functionality can create the need for a dual approach. For instance, John Deere's fully automated tractors can also function with its automatic features intermittently switched off, necessitating augmented functionality during solution delivery (e.g., implementation). Conversely, Airbus's pilot assistance system does not always require augmented operation; it employs automated AI functions, such as problem identification, to enhance overall product performance.

4.2. Variables

Dependent variable (product market performance). We used four items based on a 7-point Likert scale (1 = totally disagree, 7 = totally agree) to measure the market performance of product lines. The items, described in Table 1, emphasize customer-centricity (additional services offered and long-term relationships with customers), market agility (time-to-market response), and sales growth (Smulowitz et al., 2020).

We employed confirmatory factor analysis (CFA) to verify that the instrument's questions correctly measure the market performance construct. The results, presented in Table 1, confirm that the four items load into a single factor that accurately measures market performance: Cronbach's alpha = 0.8422, KMO test of sampling adequacy = 0.7594, Bartlett test of sphericity = 1209.52 (p-value <0.001), composite reliability = 0.8454, and average variance extracted = 0.5829.

AI strategies. The surveyed managers were asked about the specific characteristics of their product lines. The decision tree used to categorize the study's main independent variable (automation, augmentation, or dual AI strategy) is presented in Fig. 2. First, product lines that integrated some form of connectivity allowing data transmission were identified (53.8 % of surveyed product lines were connected). Among connected products, those with AI or machine learning capabilities were identified and separated from those without such attributes (24.1 % of surveyed product lines were AI-enhanced).⁵

For the product lines with AI attributes, respondents were asked a series of questions to identify which AI strategic capacity was dominant (automation or augmentation). Specifically, to identify autonomous

capacity, respondents indicated whether the product has self-diagnostic, self-correcting, and autonomous decision-making capacities. To identify augmentation capacity, respondents were asked whether their products use sensors, software, or algorithms to complement human capabilities and potential. From this information, we created two dummy variables to identify the automation and augmentation capacity of the analyzed product lines.

To adequately capture AI strategy in the study's model, it was not sufficient to simply observe a product line's dominant AI capacity; we also had to include the functional application of AI-enhanced products. Accordingly, we analyzed the functional implementation of product lines with dominant automation or augmentation capacity across the different stages of the solution delivery process (i.e., problem identification, solution development, and solution implementation), as part of each product lines' strategic orientation.

For the functional application of a product to a specific task, questions were added to the instrument to detect whether AI technologies were fully integrated into each stage of the solution delivery process. Concretely, for the problem-identification stage, managers of the producers or suppliers of the smart products were asked: "What is the primary means used by the product to identify the problem it attempts to solve?" Similarly, respondents were asked whether the product fully relied on AI technologies during the solution-development stage: "What is the primary means used to generate the product and the solution to the identified problem?" Finally, for the solution-implementation stage, they were asked: "What is the primary means used to implement the developed solution?" In each case, the possible answers were (A) Autonomous analysis based on AI technology, or (B) In collaboration with internal or external users.

As discussed in Section 2, a smart product will not necessarily deploy all of its AI-enabled capabilities in every function. A dual strategy emerges when adjustments are introduced. Thus, a dual automation-augmentation strategy is identified by a dummy variable when a distinction is observed between the product's AI capacity in terms of automation or augmentation, and its actual functional application in a specific task.

⁵ Despite encountering a significant proportion of firms with neither connected nor AI-enhanced products, our sample reveals a higher adoption rate compared to recent studies with slightly older datasets. For example, Vendrell-Herrero et al. (2021) reported that 36.2 % of products were connected in 2019, and McElheran et al. (2024) reported AI adoption in 6.2 % of firms in 2018. Our 2023 data show a notable increase, with 53.8 % of products connected and 24.1 % of firms adopting AI.

Table 1
Market performance: Results of the Confirmatory Factor Analysis (CFA).

Construct items	Mean (S.D.)	Factor loading (t-value)	R2	Composite reliability	Average variance extracted	Cronbach's alpha
Market performance				0.8454	0.5829	0.8422
Offer customers additional services that improve their experience with the product	4.9085 (2.0531)	0.5701 (18.89)	0.3250			
Improve response time to changes in the product proposed by the customer	5.2534 (1.7234)	0.7651 (36.46)	0.5854			
Extend the contractual relationship with customers (contract period)	5.6327 (1.6408)	0.8597 (53.53)	0.7391			
Increase the number of units (volume) sold to customers	5.6807 (1.5773)	0.8258 (48.49)	0.6820			

Note: KMO test of sampling adequacy = 0.7594, and Bartlett test of sphericity = 1209.52 (p-value <0.001).

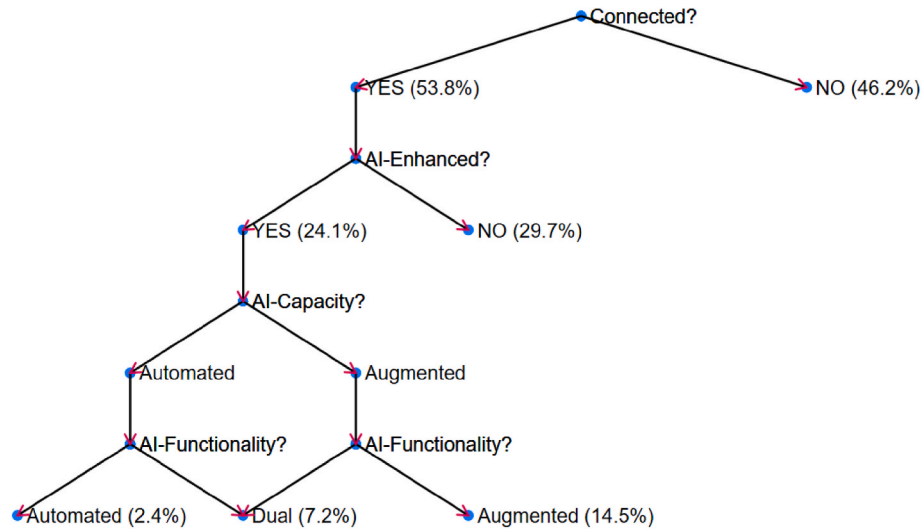


Fig. 2. Decision Tree for constructing AI functional strategies.

The three variables linked to AI strategies are mutually exclusive. The descriptive statistics in Table 2 indicate that 2.40 % and 14.5 % of product lines follow automation and augmentation strategies, respectively. Also, 7.20 % of the sampled product lines report the use of a dual automation-augmentation strategy.

Control variables. The proposed models control for the product line's corporate status, location, industry, and manufacturer's size and age. To measure corporate status, we created a dummy variable equal to one for oneling products made by manufacturers having no other product lines. A set of regional (Spain's autonomous communities) and industry (two-digit NACE codes) dummy variables were included to control for geographic and industry-specific effects. Finally, all regression models include two controls linked to the manufacturer: the number of employees in 2022 to measure firm size, and age expressed in years of market experience. Both size and age variables were logged to reduce skewness. Table 2 presents the descriptive statistics and bivariate correlations for the variables used in the study, while a summary of their definitions and measurement scales is provided in Appendix 1.

4.3. Tests of non-response bias and common method bias

To assess potential measurement bias, we tested for non-response bias and common method bias. First, we compared early (first 10 %) and late (last 10 %) responses for the four items to measure product line market performance. The results of the mean comparisons (t-test) presented in Table 3 reveal that, out of the four analyzed items, a weak but statistically significant difference appeared in only one case ('Increase the number of units (volume) sold to customers'). Although early vs. late comparisons only capture systematic differences across response waves

and might not detect other patterns of non-response bias in single-informant surveys (Guide Jr and Ketokivi, 2015), the evaluation indicates that the distribution of item responses does not suggest major non-response bias concerns.

Second, we examined the potential presence of common method bias (Fuller et al., 2016; Podsakoff et al., 2012). Because our study relies on single-informant data, such bias cannot be fully eliminated (Dubey et al., 2024; Guide Jr and Ketokivi, 2015). To minimize this risk, we followed a two-step approach. First, as indicated in Section 4.1, we pre-tested the instrument with three experts and academics to avoid ambiguous questions and improve response accuracy by ensuring clarity in survey wording, consistent with the recommendations of MacKenzie and Podsakoff (2012).

Second, we conducted a post-hoc diagnostic based on Harman's single-factor technique. Exploratory factor analysis was applied to the four market-performance items and the variables linked to the three AI strategies (automation, augmentation, and duality). The unrotated model produced three factors with eigenvalues >1, and the first factor with the highest eigenvalue accounted for 39.34 % of the total variance. Although the KMO test suggests that the sample is factorable (KMO test = 0.7572), Cronbach's alpha (0.6307) indicates that the resulting model is not internally consistent. Taken together, these findings suggest that the potential impact of common method bias in our study is limited and unlikely to compromise the validity of the results.

4.4. Empirical strategy

To evaluate the associations between AI strategies and product market performance, we followed a two-stage empirical design that

Table 2
Descriptive statistics and bivariate correlations.

	Mean	S.D.	1	2	3	4	5	6
1 Market performance	0.0000	1.0000	1.0000					
2 Automated	0.0240	0.1531	-0.0613	1.0000				
3 Augmented	0.1454	0.3528	-0.0180	-0.0647*	1.0000			
4 Dual strategy	0.0720	0.2586	0.1120***	-0.0437	-0.1149***	1.0000		
5 Oneling product	0.2909	0.4545	-0.0159	0.0290	0.0448	0.0260	1.0000	
6 Firm size	37.46	30.27	-0.0329	0.1169***	0.0240	-0.0298	0.3483***	1.0000
7 Firm age	31.50	16.50	-0.0546	-0.0021	0.0372	0.0070	0.1284***	0.1296***

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

Table 3
Early response bias test: Mean comparison for items related to market performance (early respondents vs. late respondents).

Items	Early wave	Late wave	t-test (p-value =)
	(first 10 %)	(last 10 %)	
Offer customers additional services that improve their experience with the product	5.0390 (1.8313)	5.1228 (2.0272)	-0.2503 (p-value = 0.80)
Improve response time to changes in the product proposed by the customer	5.2597 (1.5079)	5.6140 (1.4609)	-1.3626 (p-value = 0.18)
Extend the contractual relationship with customers (contract period)	5.5844 (1.5248)	5.8421 (1.5094)	-0.9714 (p-value = 0.33)
Increase the number of units (volume) sold to customers	5.4805 (1.3535)	5.9123 (1.5501)	-1.7158 (p-value = 0.09)

Standard deviation is shown in parentheses.

mitigates potential endogeneity concerns related to the adoption of the studied AI strategies (automation, augmentation, and dual). In the first stage, we computed Kernel-based PSM estimations to identify comparable groups of treated (i.e., with AI strategies) and untreated (i.e., without AI strategies) product lines and estimate the treatment effect of AI strategies, i.e., the difference in product market performance between product lines that adopt AI strategies and those within the same industry that do not. In the second supplementary stage, we ran a series of OLS model, incorporating the estimated propensity scores as a covariate to account for any potential residual imbalance between the treatment and control groups, thereby ensuring that the treatment effects are not confounded by systematic differences across product lines.

4.4.1. Propensity score estimation

The decision to implement a particular AI strategy is inherently non-random and might be influenced by product-line characteristics that also affect market performance. For instance, product lines in industries with greater technological intensity or developed by larger firms might be more likely to invest in specific AI strategies, creating the possibility of endogenous relations that can obscure the results obtained from canonical methods. To address this issue, we rely on a PSM model originally developed by Rosenbaum and Rubin (1983).

Propensity scores—i.e., the probability that a product line adopts a given treatment (AI strategy) conditional on a set of predetermined covariates—are computed for each AI strategy (i.e., automation,

augmentation, and dual) using a logit model. The vector of covariates used to predict the adoption of the analyzed AI strategies includes the product line's corporate status, industry, and manufacturer's size and age (section 4.2).

In this study we used the Kernel matching estimator with a caliper of 0.0125.⁶ This method has attractive advantages over alternative propensity score approaches (e.g., Mahalanobis or nearest-neighbor matching) (e.g., Dehejia and Wahba, 2002; Caliendo and Kopeinig, 2008; Abadie and Imbens, 2016). The Kernel matching method retains a larger control group of untreated observations by assigning weights based on their similarity in propensity scores. In addition, this estimation method ensures efficient use of information in contexts where the proportion of treated units is small, as in our subsamples of product lines adopting an AI automation strategy, and it reduces sensitivity to random fluctuations in the support of the propensity score. These characteristics align well with the properties of our product-level dataset and make the Kernel matching a suitable method for studying the role of different AI strategies on product market performance.

From the results of the Kernel PSM we obtain, for each AI strategy, an estimate of the average treatment effect which allows us to compare the product market performance level of product lines implementing any of the studied AI strategies with those that do not (Abadie and Imbens, 2016).

To assess the quality of the propensity score estimations, Table 4 presents the results of the bias reduction analysis. This analysis is based on the mean differences between treated and untreated product lines before and after matching for the variables used in the PSM model (Dhanorkar, 2019; Vendrell-Herrero et al., 2023). For the three analyzed AI strategies, the results show that the average reduction bias is 61.67 % and that a fall in bias is reported for all variables. These findings, which indicate that successful balancing outcomes are achieved through the PSM model, corroborate that the generated control group is suitable for a counterfactual analysis.

Finally, using the matched sample, we compute the average treatment effects (Abadie and Imbens, 2016). Specifically, the average treatment effect on the treated (ATT) estimates market performance gains (or loses) of product lines that adopted a given AI strategy relative to similar product lines that did not adopt the analyzed AI strategy. The estimated treatment effects will be used to individually test the study's hypotheses relating AI strategies (automation, augmentation, and dual) to product market performance.

Therefore, in terms of our hypotheses we expect a significant result for the ATT associated to the automation (H1), augmentation (H2), and

⁶ Following Stuart and Rubin (2008), we set the caliper size (i.e., the maximum tolerated difference in propensity scores between two product lines to consider these a match) to one-quarter of the standard deviation of the propensity score estimated through a logit model. In our analysis, the standard deviation of propensity scores range between 0.0502 (augmentation) and 0.1509 (automation) and, for enhanced robustness, we chose the lowest value to set the caliper (i.e., caliper = 0.0502/4 = 0.0125).

⁷ <https://www.airbus.com/en/products-services/defence/future-combat-air-system-fcas>

Table 4
Propensity score matching (PSM): Bias reduction analysis.

	Before matching Difference in mean values (t-test value)	After matching Difference in mean values (t-test value)	Bias reduction (%)
Panel A: Automation AI strategy			
Oneling product	-0.0862 (0.7494)	-0.0165 (0.1187)	80.86 %
Firm size	-0.2829 (3.0367)***	-0.0257 (0.1341)	90.92 %
Firm age	0.0080 (0.0532)	0.0028 (0.0201)	65.00 %
Industry: agrofood	-0.0391 (0.3231)	-0.0106 (0.0797)	72.89 %
Industry: chemical products	-0.0543 (0.8301)	0.0259 (0.2547)	52.30 %
Industry: plastic products	-0.0175 (0.2222)	-0.0068 (0.0971)	61.14 %
Industry: metal product	-0.0503 (0.4955)	0.0142 (0.1113)	71.77 %
Industry: computer and optics	0.0163 (0.1851)	0.0107 (0.1051)	34.36 %
Panel B: Augmentation AI strategy			
Oneling product	-0.0578 (1.7572)*	-0.0036 (0.0619)	93.77 %
Firm size	-0.0253 (0.6182)	-0.0051 (0.1385)	79.84 %
Firm age	-0.0624 (0.9588)	-0.0163 (0.2244)	73.88 %
Industry: agrofood	0.0074 (0.1507)	-0.0046 (0.0848)	37.84 %
Industry: chemical products	-0.0123 (0.4327)	0.0039 (0.1025)	68.29 %
Industry: plastic products	0.0177 (0.5199)	-0.0099 (0.2842)	44.07 %
Industry: metal product	0.0662 (1.9045)*	0.0166 (0.3715)	74.92 %
Industry: computer and optics	-0.1126 (2.9600)***	-0.0517 (1.0443)	54.09 %
Panel C: Dual AI strategy			
Oneling product	-0.0458 (0.6719)	0.0428 (0.5111)	6.55 %
Firm size	0.0428 (0.7684)	0.0273 (0.4964)	36.21 %
Firm age	-0.0159 (0.1794)	0.0151 (0.1445)	5.03 %
Industry: agrofood	0.0038 (0.0568)	0.0023 (0.0305)	39.47 %
Industry: chemical products	0.0551 (2.0229)**	0.0067 (0.2436)	87.84 %
Industry: plastic products	0.1079 (1.7526)*	0.0109 (0.2449)	89.90 %
Industry: metal product	-0.0081 (0.1332)	-0.0025 (0.0363)	69.14 %
Industry: computer and optics	-0.1624 (3.1338)***	-0.0164 (0.2100)	89.90 %

dual automation-augmentation (H3) AI strategy.

4.4.2. Regression analysis

To complement the PSM analysis, we evaluate the associations between AI strategies and product-line market performance using a set of linear models (OLS) with robust errors clustered by manufacturer to account for potential manufacturer-specific effects. The full model takes the following form:

$$\begin{aligned}
 \text{Product market performance}_i = & \beta_0 + \beta_1 \text{Automation}_i + \beta_2 \text{Augmentation}_i \\
 & + \beta_3 \text{Dual}_i + \beta_4 \text{Oneling product}_i + \beta_6 \text{Region}_i + \beta_7 \text{Industry}_i + \beta_8 \text{Size}_i \\
 & + \beta_9 \text{Age}_i + \beta_{10} \delta_i + \varepsilon_i
 \end{aligned}
 \tag{1}$$

where i indexes products, β_j is the vector of coefficients, and ε is the normally distributed error term. For the three mutually exclusive variables linked to AI strategies, the reference group consists of products without AI technologies or connectivity (unconnected products). For the location dummy variables Andalusia is the reference region, while other manufacturing (NACE sectors 14–18 and 29) is the omitted industry category in all model specifications.

Notice that all estimated models incorporate the estimated propensity scores from the Kernel-based PSM as an additional covariate (δ) (Upadhayay et al., 2024). By introducing the propensity score directly into the regression models we account for potential residual differences between treatment and control groups. In addition, this approach reduces the risk that treatment effects capture latent strategic or organizational characteristics rather than the direct impact of adopting the studied AI strategies. Therefore, this approach enables us to identify associations between AI strategies and product market performance after controlling for potential covariate imbalances.

Similar to the logic followed in the PSM estimation, we expect $\beta_1 > 0$ to verify that automation enhances product market performance (H1). Additionally, a positive coefficient for the augmentation-based AI strategy ($\beta_2 > 0$) would corroborate hypothesis H2. Finally, a positive coefficient for the dual automation-augmentation AI strategy ($\beta_3 > 0$) would corroborate hypothesis H3.

5. Empirical results

This section presents the primary tests of the study's hypotheses. Subsection 5.1 offers the empirical evaluation of the proposed theoretical framework, Subsection 5.2 expands on these results with additional analysis, and Subsection 5.3 provides robustness checks.

5.1. Main analysis

Table 5 reports the results of the Kernel-based propensity score matching estimations, including the outcome of the logit model used to compute the probability of treatment for each AI strategy (Panel A) and the corresponding average treatment effects (Panel B). Table 6 presents the findings for the regression analysis that integrates the propensity score directly into the models to account for potential residual differences between products adopting the analyzed AI strategies and the control groups. In this table, specifications (1)–(3) evaluate the individual effect of adopting each of the three analyzed AI strategies (automation, augmentation, and dual), while model (4) reports the results for the full model, which includes the three AI strategies (with unconnected products as the base category) once controlling for propensity scores, product characteristics, and contextual effects (industry and region).

Before discussing the findings, we computed the variance inflation factor (VIF) for all models to test whether coefficients were amplified due to correlations across the explanatory variables. The average VIFs for the estimated models range between 1.73 (model 1 in Table 6) and 5.68 (model 2 in Table 6). The results of this test suggest that the model specifications do not suffer from collinearity problems.

In addition, we assessed the distributional properties of the residuals for the models reported in Tables 5 and 6. We first inspected the quantile–quantile (Q–Q) plot to visually evaluate whether the estimated errors follow a normal distribution (Loy et al., 2016). To complement this visual analysis, we employed two additional normality tests (Midway and White, 2025; Yuan and Gomer, 2021). On the one hand, we applied

Table 5
Estimation of propensity scores and average treatment effects.

	Automation AI strategy	Augmentation AI strategy	Dual AI strategy
Panel A: Logit estimates			
Oneling product	-0.0696 (0.2490)	0.1069 (0.1397)	0.3484 (0.3281)
Size (ln employees)	0.6049 (0.2468)**	0.0684 (0.1796)	-0.5160 (0.5461)
Age (ln years)	-0.0400 (0.1864)	0.1003 (0.1071)	0.1214 (0.3279)
Industry: agrofood	0.2952 (0.4284)	0.0343 (0.1837)	0.3586 (0.4637)
Industry: chemical products	0.7319 (0.4892)	0.1386 (0.2581)	-1.0269 (1.0838)
Industry: plastic products	0.5730 (0.4757)	-0.0230 (0.2366)	-0.3213 (0.7139)
Industry: metal products and structures	0.5980 (0.4213)	-0.1178 (0.2022)	0.3524 (0.5049)
Industry: computer and optics	0.4956 (0.4624)	0.4578 (0.1989)**	1.1110 (0.4798)**
Intercept	-4.4461 (1.1139)***	-1.7391 (0.7023)**	-1.5728 (1.7778)
Log likelihood	-70.91	-270.84	-166.11
LR chi2	19.16***	21.52***	21.99***
Pseudo R2	0.0607	0.0289	0.0373
Observations	667	667	667
Panel B: Average treatment effects			
ATT (AI strategy)	-0.2740 (0.1670)	0.0272 (0.1016)	0.5661 (0.2018)***
Control group effect	-0.1858 (0.1901)	0.0157 (0.1366)	0.4821 (2.0677)
Observations	631	641	647

Dependent variable: Product market performance. Propensity score matching computed using the Kernel method (Epanechnikov kernel function). A dummy including products in NACE sectors 14–18 and 29 is the omitted industry category. Robust standard errors are presented in parentheses. *, **, and *** indicate significance at the 10 %, 5 %, and 1 %, respectively.

Table 6
Regression results.

	(1)	(2)	(3)	(4)
Automation AI strategy	-0.4960 (0.3198)			-0.4595 (0.3011)
Augmentation AI strategy		0.0010 (0.1236)		0.0253 (0.1252)
Dual automation-augmentation AI strategy			0.4779*** (0.1480)	0.4672*** (0.1495)
Oneling product	-0.0254 (0.1094)	-0.0739 (0.1958)	-0.0067 (0.1632)	-0.1332 (0.2110)
Size (ln employees)	0.1709 (0.2695)	-0.0832 (0.1734)	-0.0168 (0.1836)	0.1351 (0.4561)
Age (ln years)	-0.0968 (0.0793)	-0.1492 (0.1570)	-0.0877 (0.0838)	-0.1868 (0.1805)
Propensity score as covariate	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes
Regional effects	Yes	Yes	Yes	Yes
Intercept	0.0219 (0.8007)	0.7085 (0.4969)	0.5847 (0.8115)	-0.0410 (1.4990)
F test	3.51***	2.97***	3.32***	3.24***
Adjusted R2	0.0561	0.0822	0.1251	0.0670
Mean VIF	1.73	5.68	3.01	4.04
Cases (product lines)	631	641	647	631

Robust standard errors clustered by manufacturer are shown in parentheses. For the regional effects Andalusia is the reference territory, while a dummy including products in NACE sectors 14–18 and 29 is the omitted industry category. *, **, *** = significant at 10 %, 5 %, and 1 %, respectively.

the Anderson–Darling test—a method based on the empirical distribution function (EDF)—which emphasizes the tails of the distribution, thus improving sensitivity to deviations from normality and enabling detection of violations that visual inspection alone may overlook. On the

other hand, we computed the Kolmogorov–Smirnov test—a distribution-free method—that measures the maximum distance between the empirical and theoretical cumulative distribution functions. The results of the two normality tests are presented in Fig. 3. Overall, the graphical evidence (Q-Q plot) and the results of both tests indicate that the residuals for the study's main models (Tables 5 and 6) are probably normally distributed, thus supporting the validity of our regression analysis.

Concerning the key findings, the results of the Kernel PSM model in Table 5 indicate that adoption of either an automation-based or augmentation-based AI strategy is not significantly associated with product market performance (the estimated treatment effects for these two AI strategies are not significant). Therefore, hypotheses H1 and H2, which propose a relationship between these strategies and product market performance, are not supported. This suggests inefficiencies stemming from the inappropriate use of a smart product's AI capacity in ways that mismatch the functional requirements of the tasks for which this product is used. The potential added value from AI-enhanced automation or augmentation at certain stages of the solution delivery process may be offset by losses resulting from inadequate implementation at other stages (Kanter, 2006). This zero-sum effect can explain the lack of significant positive impact over product market performance of a uniform automation- or augmentation-based AI strategy throughout the solution delivery process.

Hypothesis H3, which proposes that the application of a dual automation-augmentation AI strategy within the product line's solution delivery process generates superior market performance, is confirmed by the results of the Kernel PSM model. Table 5 shows that the treatment effect linked to the adoption of a dual automation-augmentation AI strategy is positive and significantly correlated with product market performance (0.5661, p -value <0.01). This result suggests additional gains, in terms of product market performance, for product lines adopting a dual AI strategy, relative to comparable non-treated product lines.

Table 6 presents the results of the complementary analysis based on OLS models. The coefficients linked to automation and augmentation strategies are not statistically significant, confirming the findings of the PSM model. In contrast, the dual automation–augmentation strategy consistently shows a positive and statistically robust association with market performance (model 4 in Table 6: 0.4672, p -value <0.01). Given that the propensity scores are included in the models as covariates, the findings indicate that the contribution of a dual AI strategy to products' market performance is not explained by unobserved differences between adopting and non-adopting product lines.

To verify that this reported effect is greater than that of the other two AI strategies (automation and augmentation), we compared the estimated coefficients in column (4). The results indicate that the parameter linked to the dual automation-augmentation strategy is significantly greater than that for both the automation-based (F-test = 12.84, p -value = 0.0004) and augmentation-based strategy (F-test = 5.90, p -value = 0.0154). Overall, these findings are consistent with PSM estimations, thus further confirming H3.

These findings indicate that a uniform AI strategy applied throughout a product line's solution delivery process is ineffective for optimizing a smart product's market performance. A homogeneous approach, whether automation- or augmentation-based, implies ignoring potential variations in the configuration of tasks within this process. The principle of functional subsidiarity supports the need for more heterogeneous and adaptive application of AI capacities to processes and tasks, rather than relying on uniform use of their innate capabilities.

5.2. Additional analysis and expansion of results

In a product line's solution delivery process, AI is often deployed within collaborative systems, where diverse stakeholders interact to

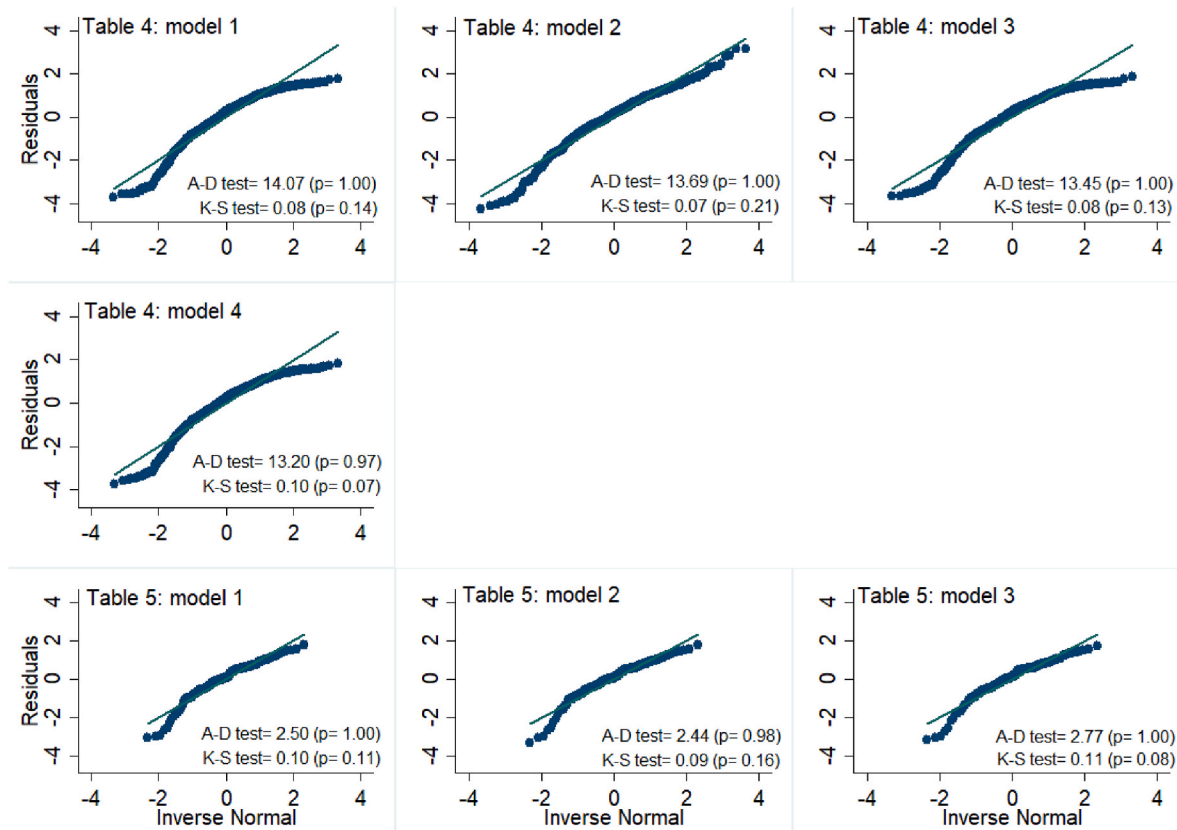


Fig. 3. Normality tests of residuals (models reported in Tables 4 and 5). Note: A-D = Anderson-Darling normality test, and K-S= Kolmogorov-Smirnov test.

tackle tasks through joint actions (Gregory et al., 2021). The dynamic interplay of inputs from internal and external agents influences automation and augmentation, ultimately shaping subsidiarity and organizational performance. Our study finds that a more flexible functional approach, adopting a dual automation-augmentation AI strategy, has a significant positive impact on a product's market performance. This is not the case when a rigid strategy tied solely to the product's smart capacity is implemented, whether automation or augmentation.

These results can also be explained by the multistage, iterative nature of solution delivery processes, which involve a variety of tasks with heterogeneous functional needs. As Bergstein (2019) observed in the case of Symrise, the optimal functional requirement of one task can be influenced by the AI strategy adopted in other tasks of the same stage of the process (Raisch and Krakowski, 2021). For example, applying an automation strategy to a particular task may increase the need for augmentation in preceding or succeeding tasks at the same stage. This 'spillover' effect underscores the value of a dual AI strategy, which permits flexible adjustment across tasks.

The level of functional heterogeneity or homogeneity within solution delivery processes may also vary across the problem identification, solution development, and solution implementation stages (Baden-Fuller and Morgan, 2010). Because our study has found that functional heterogeneity across the entire process is sufficient to support a dual AI strategy, it seemed useful to break the process into these three stages to examine whether this heterogeneity is consistent at each.

To do so, we analyzed a sub-sample of 161 smart product lines that use AI technologies in at least one stage of the solution delivery process. Table 7 shows the impact of a dual automation-augmentation AI strategy in each separate stage. The results indicate that a dual AI strategy improves market performance in the problem-identification and solution-development stages, but not in the solution-implementation stage. We can speculate that the heterogeneity across tasks at the implementation stage is insufficient to necessitate a dual strategy to attain superior

Table 7

Regression results: Dual automation-augmentation AI strategy and market performance across products' solution delivery process (sample = 161 smart product lines).

	Problem identification	Solution development	Solution implementation
Dual automation-augmentation AI strategy	0.3778** (0.1876)	0.3807** (0.1822)	0.2486 (0.1759)
Oneling product	-0.1972 (0.3506)	-0.2037 (0.3085)	-0.2103 (0.3548)
Size (ln employees)	0.0959 (0.3517)	0.0546 (0.3508)	0.0584 (0.3635)
Age (ln years)	0.1502 (0.1759)	0.1659 (0.1924)	0.1657 (0.1784)
Propensity score as covariate	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes
Regional effects	Yes	Yes	Yes
Intercept	-0.5517 (1.5653)	-0.4103 (1.5541)	-0.4208 (1.5928)
F test	2.23***	2.24***	2.11***
Adjusted R2	0.1507	0.1511	0.1362
Mean VIF	4.27	4.27	4.27
Cases (product lines)	161	161	161

Dependent variable: market performance. Sample: 161 smart product lines. Robust standard errors clustered by manufacturer are shown in parentheses. The regression model includes a set of both regional dummies (Andalusia is the reference territory) and industry dummies (NACE sectors 14–18 and 29 is the omitted industry category). *, **, *** = significant at 10 %, 5 %, and 1 %, respectively.

market performance. Although this deduction is consistent with the principle of functional subsidiarity, further research is needed to confirm it.

5.3. Robustness checks

We ran two additional tests to verify our assumption that the unit of analysis for AI effectiveness is smaller than the organization itself—specifically, at the product line level. First, we replicated the full model in [Table 6](#), including interaction terms between the variable identifying oneling products and the three variables linked to the studied AI strategies. This approach—based on isolating the effect on product market performance of different AI strategies in oneling products vis-à-vis products from manufacturers with more than one product line—effectively controls for potential confounding factors arising from the use of the product as the unit of analysis. It also provides more robust evidence that the interplay between automation and augmentation strategies is better understood at a more granular level.

The regression model presented in [Appendix 2](#) indicates that the positive effect of a dual automation-augmentation AI strategy on product market performance is unaffected by the type of product (oneling or non-oneling): coefficient for oneling products = -0.0766 (p -value = 0.73), coefficient for dual automation-augmentation AI strategy = 0.5069 (p -value < 0.01), and interaction between the oneling product dummy and the dual AI strategy dummy = -0.1322 (p -value = 0.66). All variables related to alternative AI strategies (automation and augmentation), as well as their interaction with the oneling dummy, are not statistically significant ([Appendix 2](#)). A further verification based on the Chow test ([Chow, 1960](#)) validates that there is no structural break in the model, that is, the estimated coefficients and error terms are the same across product types (Chow test = 1.29 , p -value = 0.1562). Therefore, the proposed model is adequate to capture the analyzed relationships.

However, this analysis applied to the pooled dataset is based on the assumption that the variance of both types of products (oneling and non-oneling) is homogeneous. To address common variance concerns in pooled models ([Greene, 2003](#)), we replicated the full model in [Table 6](#) for the two sub-samples of oneling and non-oneling products separately. The findings presented in [Appendix 3](#) corroborate that dual automation-augmentation is the only AI strategy that positively influences products' market performance: coefficient for the sub-sample of oneling products = 0.4666 (p -value = 0.012), and coefficient for the sub-sample of non-oneling products = 0.3760 (p -value = 0.076).

Overall, from a theoretical perspective the findings confirm the consistency of our argument that the automation-augmentation paradox operates not at the organizational level, as has been suggested in the literature, but at a sub-organizational level—in this case, the product level. This observation aligns with the principle of functional subsidiarity, emphasizing that firms should tailor AI applications to the specific demands and characteristics of their products to optimize performance.

From a practical point of view, the findings presented in this subsection reinforce the logic that manufacturers can expect performance benefits from a dual AI strategy, irrespective of whether they produce a single product or a diverse portfolio. These results underscore the importance of flexible AI strategies that adjust to heterogeneous functional needs within solution delivery processes.

6. Discussion

As AI technologies become increasingly prevalent (e.g., [McElheran et al., 2024](#)), determining how and when to effectively leverage their core functionalities presents a complex challenge. This research addresses this issue by providing insights into the optimal integration of AI within organizational contexts. Specifically, it examines the strategic adoption of AI in product lines to tackle the longstanding automation-augmentation dilemma.

Central to our findings is the principle of functional subsidiarity, a concept borrowed from corporate governance ([Abländer, 2011](#)) and regional science ([Begg, 2008](#); [Moodie et al., 2022](#)) that emphasizes the alignment of AI capabilities with specific task demands for optimal

results. Our findings suggest that neither automation nor augmentation alone is sufficient; instead, a dual AI strategy that dynamically employs both approaches to adapt to task-specific requirements most effectively enhances product market performance. From the lens of dynamic capabilities, dual-AI strategies give smart products potential functional agility. This extends the framework proposed by [Raisch and Krakowski \(2021\)](#) by showing that a single product can serve dual purposes depending on contextual needs, thereby optimizing resource management across tasks and functions ([Guo et al., 2025](#)).

This perspective marks a significant shift in strategic thinking, moving beyond the traditional “substituting vs complementing” debate (e.g., [Balasubramanian et al., 2022](#)). Rather than treating automation and augmentation as competing strategies, our findings establish the value of a hybrid approach that maximizes AI potential by tailoring applications to each product's unique needs and operational context. This refined understanding challenges existing academic discourse and illustrates the need for flexibility and adaptability in AI deployment ([Ayala et al., 2025](#)). The benefits of the dual AI strategy stem from its versatile implementation, matching AI-enhanced automation or augmentation capacities to task-specific needs. Our empirical evidence contributes to the broader academic conversation, signaling a shift from dichotomous to more adaptive views of AI implementation.

6.1. Academic implications

From an academic perspective, the study makes several contributions. It is one of the first empirical studies of the recent hybrid dual view, contributing an applied perspective to the topical automation-augmentation debate. It also does so from a product-centric lens, which has rarely been adopted in previous research despite its suitability for studying innovation management and particularly AI in business. Doing so allows the study to introduce the principles of functional subsidiarity and their potential to offer a much more granular analysis of AI implementation and the mechanisms influencing its impact on market performance.

The theoretical premise of agility, that emerges as a key aspect of the dynamic capability view ([Teece et al., 1997](#); [Weber and Tarba, 2014](#)), has been conceptualized at different levels and applied to help explain different AI-induced business and managerial mechanisms. AI enhanced organizational agility is found to foster market innovation by optimizing organizational structure and operational management to cater to market change ([Ravichandran, 2018](#); [Petrescu et al., 2022](#)); business agility is intensified by AI, which leads to the active adaptation of procedures and routines necessary to proactively respond to environmental changes ([Gao et al., 2020](#); [Mikalef et al., 2021](#)); and strategic agility can be digitally amplified to develop innovative ways to create value and to help companies' remain strategically flexible in the face of new market or industry developments ([Tarba et al., 2023](#); [Weber and Tarba, 2014](#)). The study in this paper adds to this conceptualization the notion of AI-functional agility. By focusing in on the product and the tasks that these are designed to accomplish, functional agility is the product's ability to reconfigure resources and capabilities to achieve responsiveness and flexibility that enhances its capacity for customized solution delivery and therefore its value, competitive advantage, and potential market performance. Such AI functional agility, in our study, is at the basis of the functional subsidiarity that aligns smart products to the specificities of the tasks being addressed when adopting a dual-AI strategy.

The study also provides evidence that contributes to the ongoing substituting vs. complementing debate in the AI strategy literature ([Balasubramanian et al., 2022](#); [Krakowski et al., 2023](#); [Raisch and Krakowski, 2021](#)). Its findings support the conceptual propositions of [Raisch and Krakowski \(2021\)](#), who called for joint implementation of automation and augmentation rather than an either-or approach. This aligns with the more recent hybrid view advocating an integrated dual approach to AI strategy that promotes a more holistic perspective on

product value creation (Raisch and Fomina, 2025). Our study contributes to this line of research by developing one of the first empirical applications of these theoretical propositions (Guo et al., 2025; Raisch and Fomina, 2025).

Our study differs from previous research on the dual use of AI. Earlier authors have argued that dual AI works by automating lower-level tasks, thereby freeing resources for higher-value human augmentation (Chowdhury et al., 2024; Hillebrand et al., 2025; Raisch and Krakowski, 2021). However, this approach assumes uniform implementation of AI and does not allow for the adaptation to the real-time needs of specific tasks or functions.

In contrast, we find that dual AI yields greater output when adapted dynamically at the product-line level to task-specific needs (Boussioux et al., 2024; Raisch and Fomina, 2025; Guo et al., 2025). Guided by the principles of functional subsidiarity, this means applying automation or augmentation when its use is most coherent with the needs of any particular moment. Our findings show that smart products incapable of such versatility generally achieved zero-sum outcomes (in terms of market performance) from the uniform adoption of either an automation- or augmentation-based AI strategy. This is because the benefits from AI-enhanced capacity are offset by forfeitures from inadequate functional implementation (Kanter, 2006).

As such, our study has potentially valuable implications for subsequent product innovation management research into AI strategy. It is among the first to narrow the level of analysis to the product line, or strategic business unit, rather than the entire corporation. A product-line level of analysis is more appropriate for the study of AI-enabled products because organizations rarely employ a single universal AI strategy across all lines. Independent lines based on different strategies necessitate distinct AI-strategies. The product-centric lens adopted here enables a more granular understanding of how AI shapes strategic choices and value generation at the product level, where users directly experience the benefits of AI-enhanced products. Therefore, the analysis of smart product AI strategies at the product line level, such as the one presented in this study, is likely to better inform optimization of the complex interrelations between digital technologies and product capacities.

Another key contribution of the study is the introduction of the principle of functional subsidiarity to the field of AI strategy, adapted from territorial policy and its notion that effective decision-making must occur at the level best suited to the affected actions and outcomes (Abländer, 2011; Begg, 2008; Moodie et al., 2022). For smart products, this study proposes that functional subsidiarity refers to the adequate implementation of their capabilities in line with the requirements of specific functional tasks. Adopting this perspective allows us to better explain and understand the results obtained in this paper and provides a framework for further contributions in business and management research on AI strategy.

6.2. Practical implications

The study and its findings help to develop a more nuanced, comprehensive framework to guide organizations in balancing automation and augmentation. This helps address the frequently ineffective implementation of AI strategies that is posing such a challenge to many firms (Dagnino and La Bruna, 2023; Peretz-Andersson et al., 2024; Usman et al., 2024). Our findings indicate that the functional heterogeneity of the many tasks underlying the multistage solution delivery process requires a more flexible dual AI strategy to maximize product market performance. This also suggests that firms should recognize the synergetic impact of implementing a dual AI strategy from a functional subsidiarity perspective. Rather than adopting the traditional either-or approach to automation versus augmentation in AI strategy, functional subsidiarity highlights that, for optimal use, smart products do not necessarily need to deploy their AI-enabled capabilities fully for every task. Instead, smarter products will allocate AI capabilities appropriately, making targeted use of them rather than constantly operating at

full capacity.

Expanding on these practical implications, our results advance the role of AI-enhanced smart products as part of multifunctional processes (Inaganti et al., 2020) rather than only for single-task use (Porter and Heppelmann, 2015; Raff et al., 2020). The creation and design of smart products that offer multitasking solutions and deliver versatility across processes is key for manufacturers to provide customized, multifunctional value (Vaillant et al., 2025a,b,c). This can create more durable competitive advantages through greater process integration within clients' operations (Vendrell-Herrero et al., 2022). Viewing AI-enhanced products as part of multifunctional processes provides a more holistic perspective on their use (Inaganti et al., 2020), recognizing AI as a dynamic and integrated strategy that interacts across tasks and undergoes multiple iterations. Consequently, to achieve optimal performance, a flexible dual AI strategy is required for AI-enhanced smart products, rather than single-function tactics (Ahmed et al., 2020).

The higher potential for market performance from an adaptive dual AI strategy stems from its ability to alternate between autonomous and augmented functionality depending on the needs of the task at hand. For example, motor vehicles such as cars are increasingly developing smart capabilities from the multiple sensors that they are being equipped with and the AI software that is used to process the real time data collected by these devices (Lafuente et al., 2024). This product intelligence being gathered is not utilized for just any one unique purpose but becomes input for a multitude of different ends that helps the 'smart' vehicles become more performing, more fuel-efficient, more comfortable, as well as safer, among many other functions. For the car manufacturer, this helps them generate and optimize the value potential of such a smart product for its clients (Ayala et al., 2025; Tredinnick, 2017).

The study and its results also testify to the role of AI and AI-enhanced smart products in the transition toward solution-based, highly-personalized value provision (Vaillant et al., 2025a,b,c). One of the most significant ways digitization has reshaped production is by enabling firms to deliver customized, value-rich solutions tailored to specific customer challenges (Brady et al., 2005; Lafuente and Sallan, 2024). Unlike conventional production methods, AI-enhanced products offer greater tractability, allowing companies to scale personalized offerings efficiently and at reduced costs (Vaillant et al., 2025a,b,c). This advancement strengthens the competitiveness and customer responsiveness of solution-based business models, while also helping to overcome some of the traditional limitations tied to customization, such as complexity and resource intensity (Shleha et al., 2023; Storbacka et al., 2013; Vendrell-Herrero et al., 2022). An example is Nvidia, which has evolved from designing single-purpose products to offering customizable bundled smart solutions (Vendrell-Herrero et al., 2025), thanks to which the company has achieved 66 % gross margins (NVIDIA Annual Reports, 2006–2025). Although primarily a chip designer, its key differentiation lies in the system platforms and AI software built on top of this hardware (Jensen Huang, Stanford Talk, 2024)⁸. Nvidia's ultimate ambition is to bring accelerated computing to everyone by providing solutions for any computing workload to run as efficiently as possible (Vendrell-Herrero et al., 2025).

6.3. Limitations and future research avenues

The findings indicate that smart products implementing a dual AI strategy across tasks in business processes can enhance operational performance. Nevertheless, the study has several methodological limitations: its cross-sectional design, reliance on a prescriptive solution delivery framework, and omission of direct financial performance metrics.

First, the cross-sectional nature of the research constrains the ability to capture dynamic effects over time. Ideally, the effectiveness of a dual

⁸ <https://www.youtube.com/watch?v=IXLBTBbil2U>

AI strategy should be examined using a longitudinal design, in which strategic choices in one period are evaluated in relation to the evolving functional requirements of subsequent tasks (Raisch and Krakowski, 2021).

Second, the identification of AI strategies was anchored in the sequential stages of the solution delivery process. While this approach ensured consistency in analysis, it may not fully account for the functional heterogeneity of product-related tasks. Future studies should incorporate task-specific functional variations when assessing AI deployment and its performance implications.

Third, the study operationalized product performance through a multi-item construct combining sales and market indicators, without directly incorporating financial outcomes (e.g., operating margin, market share, etc.). Integrating such measures in future research would provide a more comprehensive assessment of strategic effectiveness. Furthermore, applying the dual AI framework to other business and management processes—beyond the solution delivery context—could broaden its theoretical and practical relevance.

Beyond these gaps, the study suggests further research opportunities aligned with its core contributions. As one of the first empirical validations of integrating automation and augmentation into a dual AI strategy, replication studies are needed to confirm and contextualize the results (Bonett, 2021). Moreover, the principle of functional subsidiarity—central to our theoretical framing—not only clarifies our findings but also offers a promising conceptual avenue for AI strategy research. The notion remains underdeveloped and could be further refined with applications extending beyond smart product performance to areas such as project management, organizational routines, and supply chains.

Given that evidence on AI's effectiveness in business has often been underwhelming (Wamba, 2022), deeper investigation into the functional subsidiarity challenge could yield insights to enhance AI implementation. This could involve multi-method studies, experimental designs, and cross-industry comparisons to assess how different contexts influence the optimal balance between automation and augmentation.

Appendix 1. Definition and measurement scale of the study's variables

Variable	Definition	Measurement Scale
Product market performance	Extent to which a product line achieves customer-centricity, market responsiveness agility, and sales growth (Smulowitz et al., 2020).	Four items on a 7-point Likert scale (1 = totally disagree, 7 = totally agree). Items: (1) additional services offered, (2) long-term relationship with customers, (3) time-to-market response, and (4) increase in number of units sold.
Automation AI strategy	Strategy where AI capacities allow products to autonomously perform self-diagnostics, self-correcting, and autonomous decision-making tasks.	Dummy variable = 1 if product line displays autonomous AI capacity, 0 otherwise.
Augmentation AI strategy	Strategy whereby products incorporate sensors, software, or algorithms to complement human decision-making and performance.	Dummy variable = 1 if product line displays augmentation AI capacity, 0 otherwise.
Dual AI strategy	Strategy where both automation and augmentation capacities are deployed across different stages of the solution delivery process (functional subsidiarity).	Dummy variable = 1 if a mismatch exists between dominant AI capacity (automation or augmentation) and functional application across tasks, 0 otherwise.
Oneling product	Manufacturers producing a single-product or multiple product lines.	Dummy variable = 1 for oneling products, 0 otherwise.
Firm size	Scale of manufacturer's, in terms of the number of employees	Log of number of employees (2022).
Firm age	Market experience of the firm.	Log of years since start-up.
Location	Geographic location of the manufacturer.	Regional dummy variables (Spain's autonomous communities).
Industry	Industry classification of the product line.	Dummy variables (two-digit NACE codes).

Appendix 2. Regression results: AI strategies in oneling vis-à-vis non-oneling products

	(1)	(2)
Automation AI strategy	-0.4595 (0.3011)	-0.4430 (0.3149)
Augmentation AI strategy	0.0253 (0.1252)	0.1624 (0.1558)
Dual automation-augmentation AI strategy	0.4672*** (0.1495)	0.5069*** (0.1922)
Oneling product	-0.1332 (0.2110)	-0.0766 (0.2211)

(continued on next page)

7. Conclusion

This study highlights the transformative potential of a dual AI strategy that combines automation and augmentation through the lens of functional subsidiarity. Our findings challenge the traditional divide between these approaches by demonstrating that aligning AI capabilities with specific task demands enhances resource management and market performance. This contributes to theory by proposing a more adaptable AI framework, and also provides practical insights for organizations aiming to enhance competitiveness through flexible AI deployment. By tailoring AI applications to contextual needs, firms can drive both innovation and efficiency. Future research should investigate the broader implications of this strategy across industries, further exploring how contextual adaptability in AI impacts organizational success.

CRedit authorship contribution statement

Yancy Vaillant: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Esteban Lafuente:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ferran Vendrell-Herrero:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis.

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(continued)

	(1)	(2)
Oneling product × Automation AI strategy		−0.0430 (0.4055)
Oneling product × Augmentation AI strategy		−0.4310 (0.2870)
Oneling product × Dual automation-augmentation AI strategy		−0.1322 (0.3047)
Size (ln employees)	0.1351 (0.4561)	0.0986 (0.4658)
Age (ln years)	−0.1868 (0.1805)	−0.2099 (0.1827)
Propensity scores as covariates	Yes	Yes
Industry effects	Yes	Yes
Regional effects	Yes	Yes
Intercept	−0.0410 (1.4990)	0.0029 (1.5331)
F test	3.24***	3.12***
Adjusted R2	0.0670	0.0706
Mean VIF	4.04	9.38
Cases (product lines)	667	667

Robust standard errors clustered by manufacturer are shown in parentheses. For the regional effects Andalusia is the reference territory, while a dummy including products in NACE sectors 14–18 and 29 is the omitted industry category. In the table, specification (1) reports the results of the full model in Table 4. *, **, *** = significant at 10 %, 5 %, and 1 %, respectively.

Appendix 3. Regression results for the subsamples of oneling and non-oneling products

	Oneling products	Non-oneling products
Automation AI strategy	−0.2869 (0.2628)	−0.3947 (0.4785)
Augmentation AI strategy	0.1853 (0.1538)	−0.3257 (0.3039)
Dual automation-augmentation AI strategy	0.4666** (0.1857)	0.3760* (0.2169)
Size (ln employees)	0.2464 (0.7206)	1.2165 (1.1583)
Age (ln years)	0.0313 (0.2584)	−0.3390 (0.4000)
Propensity scores as covariates	Yes	Yes
Industry effects	Yes	Yes
Regional effects	Yes	Yes
Intercept	−0.0266 (2.2575)	−3.5585 (4.2017)
F test	2.77***	2.12***
Adjusted R2	0.0938	0.2647
Mean VIF	4.35	4.35
Cases (product lines)	443	188

Robust standard errors clustered by manufacturer are shown in parentheses. For the regional effects Andalusia is the reference territory, while a dummy including products in NACE sectors 14–18 and 29 is the omitted industry category. *, **, *** = significant at 10 %, 5 %, and 1 %, respectively.

Data availability

Data will be made available on request.

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