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Managing innovation performance in Industry 5.0: The role of environmental turbulence, dynamic capabilities, and AI acceptance

Bilal Afzal [a,c,*], Ana Beatriz Hernandez Lara [a], Anna Visvizi [b], Xiaoni Li [a]

[a] Department of Business Management, Universitat Rovira i Virgili, Facultat d'Economia i Empresa, Reus, Spain
[b] SGH Warsaw School of Economics, Warsaw, Poland
[c] EU Business School, Barcelona, Spain

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ABSTRACT

This paper examines how market and technological turbulence (MT, TT) influence AI-enabled inbound and outbound open innovation (IOI, OOI), their mediating effects on innovation performance (IP), and the moderating roles of effort expectancy (EE) and performance expectancy (PE) within the Industry 5.0 framework. A dual-method approach combining PLS-SEM and NCA was applied to survey data from 245 industry professionals collected between November 2024 and February 2025. Both IOI and OOI significantly enhance IP, with OOI emerging as the stronger predictor. MT positively influences both IOI and OOI, while TT affects only OOI. EE and PE moderate the turbulence–IOI relationship, and several mediation effects through open innovation are supported. The study extends Dynamic Capability Theory (DCT) and UTAUT by integrating AI-enabled open innovation into the Industry 5.0 paradigm, emphasizing the human factor in innovation management.

1. Introduction

Recent technological advances, particularly in artificial intelligence (AI), combined with growing societal demands for sustainability, resilience, and human-centered design, have given rise to the Industry 5.0 paradigm (Latino, 2025; Troisi et al., 2024). Unlike Industry 4.0, which primarily focuses on automation and efficiency, Industry 5.0 emphasizes human-centered innovation, sustainability, and resilience (Breque, 2021; Brückner et al., 2025). This evolution highlights the collaborative potential of human-AI interactions, where AI enhances efficiency and adaptability while promoting inclusion and ecological responsibility (Breque, 2021; Shahi and Sinha, 2021). Within this paradigm, AI-enabled open innovation (OI) and digital platforms play a central role in driving innovation performance (IP) and enterprise resilience (Ferràs et al., 2024; Herbst and Hausberg, 2024).

Despite growing interest, current research has yet to explain how firms can leverage AI-enabled open innovation to enhance innovation performance under the environmental dynamism characteristic of Industry 5.0 (Ferràs et al., 2024; Herbst and Hausberg, 2024). While open innovation is recognized as a dynamic capability, its effectiveness under market turbulence (MT) and technological turbulence (TT) remains unclear (Dutot et al., 2014; Hein-Pensel et al., 2023). Moreover, the influence of AI platforms has been insufficiently explored (Shi et al., 2025), especially regarding human factors such as perceived performance (Performance Expectancy,

* Corresponding author at: Department of Business Management, Universitat Rovira i Virgili, Facultat d'Economia i Empresa, Reus, Spain.
E-mail address: bilal.afzal@outlook.com (B. Afzal).

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PE) and ease of use (Effort Expectancy, EE). Although prior studies have addressed inbound open innovation (IOI) in contexts like Industry 4.0 (Fiorini et al., 2024; Wang and Quan, 2021), there is limited understanding of the combined effects of MT and TT on both inbound and outbound open innovation (OOI) and how expectancy-related perceptions shape these relationships.

To address this gap, this study investigates the following research questions:

RQ1. : How do market turbulence and technological turbulence influence inbound and outbound open innovation?

RQ2. : How do inbound and outbound open innovation mediate the relationship between environmental turbulence and innovation performance?

RQ3. : How do effort expectancy and performance expectancy, as human factors associated with AI platform use, moderate the impact of environmental turbulence on inbound open innovation?

Beyond its theoretical contributions, this study also offers practical significance by showing how expectations surrounding AI platforms influence open innovation outcomes. The findings provide actionable insights for firms aiming to strengthen IP through digital platforms, ICT infrastructures, and AI-driven tools particularly in turbulent and rapidly transforming environments.

2. Literature review and hypotheses development

2.1. Innovation performance

From “new combinations” (Schumpeter, 1934) to “systematic value creation” (Drucker, 1985a, 1985b), innovation has been recognized as a key driver of economic and industrial transformation. Building on this foundation, innovation performance; defined as an organization’s ability to generate and apply new ideas, depends on its capacity to adapt to disruptive change (Christensen, 1997) and is reinforced by organizational learning and trust (Ahmad et al., 2024). Extant literature underscores the complex and multidimensional nature of IP, shaped by internal capabilities, external networks, technological developments, and institutional environments (Ahmad et al., 2024; Freixanet et al., 2021). Among these, open innovation plays a particularly influential role. Firms that cultivate vertical and horizontal partnerships, especially with customers and suppliers, tend to see enhanced innovation outcomes (Christensen, 1997; Zeng et al., 2010).

Digital platforms and AI further enhance IP by fostering organizational agility, strategic alignment, and experimentation (Sarwar et al., 2024). Studies found that AI fosters green technology innovation, big data analytics enhances strategic agility in turbulent markets, and deep learning with IoT optimizes innovation processes (Alghamdi and Agag, 2023; Luo, 2022; Tian et al., 2023). Beyond technology, financial resources, university collaborations, and scientific networks advance interdisciplinary R&D, while dynamic capabilities; sensing, seizing, and transforming, enable firms to sustain innovation under uncertainty (Melnychuk and Schultz, 2025). Collectively, these insights highlight that digital transformation, open innovation networks, and dynamic capabilities jointly shape IP in Industry 5.0 contexts.

2.2. Inbound and outbound open innovation

Inbound open innovation (IOI) involves acquiring external knowledge and ideas to boost internal innovation (William Chesbrough et al. 2006). It is particularly advantageous in dynamic environments, enabling firms to adapt quickly to technrological changes (Sahoo et al., 2024). Research shows that high-tech firms facing technology turbulence often leverage external collaborations to improve innovation success (William Chesbrough et al. 2006). On the other hand, outbound open innovation (OOI) emphasizes the external commercialization of internally developed innovations through licensing and strategic partnerships (Chesbrough and Bogers, 2014; Masucci et al., 2020). OOI allows firms to create additional value by transferring knowledge beyond their boundaries, thereby enhancing competitiveness in turbulent markets (Dong, 2023). It is especially effective under certain conditions and in rapidly evolving technological landscapes, enabling firms to externalize surplus innovations and maintain market relevance (Boadu et al., 2023; Camerani et al., 2016).

2.3. Market and technology turbulence

MT refers to unpredictable shifts in consumer preferences and demand patterns, which create uncertainty for firms striving to maintain consistent innovation strategies (Boadu et al., 2022). To remain competitive, companies must adopt agile, customer-driven innovation models that incorporate real-time market insights (Lin et al., 2022). In this context, transformational leadership plays a crucial role in fostering a culture of continuous learning and adaptability, helping firms respond effectively to market volatility (Dong, 2023). In contrast, TT involves the rapid evolution of technologies that disrupt existing business models and reshape innovation processes (Lin et al., 2022; Zahoor and Adomako, 2023). High-tech firms, in particular, often face challenges in anticipating technological trends, prompting the need for strong adaptive capabilities and learning-oriented cultures (Sai et al., 2025). Research indicates that such firms frequently turn to IOI to access external knowledge, mitigate risk, and enhance responsiveness (Yong et al., 2019). However, when technological change becomes excessive or fragmented, it can hinder the integration of new knowledge and reduce innovation efficiency (Kamasak et al., 2016; Zahoor and Adomako, 2023). Firms with well-developed absorptive capacities and robust collaboration networks are better positioned to manage these challenges and sustain IP (Boadu et al., 2023).

2.4. Performance and effort expectancy of AI-human collaboration

The successful integration of AI in collaborative innovation environments depends on user's performance expectancy (PE) and effort expectancy (EE) within AI-human collaboration (Venkatesh et al. 2003). Within an Industry 5.0 paradigm, these constructs extend beyond traditional technology acceptance and reflect managerial perceptions of the feasibility and value of human–AI collaboration in innovation processes. Specifically, PE reflects the extent to which users expect AI to enhance efficiency, productivity, and innovation outcomes thereby linking technology adoption to innovation management. In open innovation contexts, AI contributes by generating data-driven insights and automating routine tasks, thereby augmenting human problem-solving in dynamic, turbulent environments (Ferràs et al., 2024). High PE is associated with efficient adoption of AI tools in R&D and knowledge creation, especially when AI is positioned as a complement to human expertise; rather than a replacement, thus avoiding mistrust and strategic misalignment (Benito et al., 2024).

Similarly, EE concerns the perceived cognitive and operational feasibility of interacting with AI systems, reflecting the human-centered dimension of Industry 5.0. Rather than merely ease of use, EE captures the extent to which AI tools can be integrated into existing innovation routines without excessive cognitive burden or workflow disruption. When AI tools are intuitive, require minimal adjustments, and integrate smoothly into existing workflows, they are more likely to be adopted and used effectively (Abdalla et al., 2024). Conversely, complex or disruptive implementations can lead to user resistance (Andersson et al., 2020). Organizations that prioritize usability, provide adequate training, and clearly communicate AI's role as a supportive partner can enhance both PE and EE, thereby enhancing the firm's ability to leverage AI-enabled open innovation under turbulence.

2.5. Theoretical framework and hypotheses development

Understanding how firms respond to turbulence, adopt digital technologies, and integrate AI into their innovation processes calls for a multifaceted theoretical approach. To examine these dynamics, this study draws on Dynamic Capability Theory (DCT), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the principles of Innovation 5.0. Together, these perspectives inform a framework that conceptualizes how firms leverage open innovation, AI–human collaboration, and external knowledge ecosystems to drive IP in dynamic market environments (Afzal et al., 2024; Teece et al., 1997; Venkatesh et al. 2003).

In this study, environmental turbulence is conceptualized not as a direct determinant of innovation performance, but as a contextual trigger that necessitates the activation of dynamic capabilities. Specifically, inbound and outbound open innovation are theorized as operational manifestations of sensing, seizing, and transforming capabilities within Industry 5.0 ecosystems. Thus, rather than treating open innovation as a strategic posture, this study positions IOI and OOI as organizational capabilities that enable firms to reconfigure resources under turbulence.

In dynamic business environments, market and technological turbulence significantly shape firms' innovation strategies (Lin et al., 2022; Sai et al., 2025). According to DCT, firms must develop the ability to sense environmental shifts, seize emerging opportunities, and reconfigure resources to respond effectively to uncertainty (Teece et al., 1997). Such turbulence compels organizations to build adaptive capabilities and adopt open innovation practices that enhance responsiveness and sustain long-term IP (Kuo, 2024).

MT, driven by unpredictable consumer preferences, competitive intensity, and demand fluctuations, amplifies uncertainty and pressures firms to implement agile, customer-responsive innovation models (Boadu et al., 2022; Dong, 2023). Under high MT, firms face intensified sensing requirements, increasing reliance on IOI as a structured sensing capability that integrates dispersed market knowledge. Simultaneously, MT strengthens the need for seizing and transforming activities, positioning OOI as a capability for external commercialization and ecosystem reconfiguration. In such conditions, IOI enables firms to integrate real-time market insights for faster product development (Cui et al., 2022). Similarly, OOI allows firms to commercialize innovations externally, ensuring adaptability in volatile markets (Mustafa et al., 2023).

TT, marked by rapid innovation and evolving technologies, disrupts traditional innovation cycles, requiring continuous strategic adjustments (Boadu et al., 2023). Firms facing TT often engage in IOI to access emerging technologies and collaborate externally (Yong et al., 2019), and use OOI to share excess innovations and reduce R&D risks (Boadu et al., 2023). However, excessive TT may hinder knowledge integration, making strong dynamic capabilities and open innovation strategies essential (Kamasak et al., 2016). In this context, IOI functions as a sensing and absorptive capability for identifying technological shifts, while OOI reflects seizing and transforming processes that redeploy technological assets across digital ecosystems.

Based on these insights, we hypothesize:

H1a. : ***Market Turbulence (MT) has a positive effect on Inbound Open Innovation (IOI).***

H1b. : ***Market Turbulence (MT) has a positive effect on Outbound Open Innovation (OOI).***

H2a. : ***Technological Turbulence (TT) has a positive effect on Inbound Open Innovation (IOI).***

H2b. : ***Technological Turbulence (TT) has a positive effect on Outbound Open Innovation (OOI).***

IOI fosters external collaboration, reduces R&D cycle time, and promotes adaptability (Chabbouh and Boujelbène, 2021; Li and Hou, 2023)., while OOI through licensing and partnerships, enables firms to optimize resources and sustain competitive advantages in turbulent conditions (Dong, 2023). From a dynamic capability perspective, IOI and OOI are conceptualized as organizational routines that.

ensuring internal innovations translate into competitive advantages. By effectively sensing, seizing, and transforming knowledge

flows, firms enhance resilience and maintain long-term innovation performance (Cohen and Levinthal, 1990). From a dynamic capability perspective, IOI and OOI are conceptualized in this study as organizational-level capabilities that operationalize sensing, seizing, and transforming activities under environmental turbulence. IOI primarily structures knowledge inflows to enhance absorptive and sensing processes, whereas OOI structures knowledge outflows to enable opportunity exploitation and resource reconfiguration. Rather than representing specific technological tools, these constructs capture firm-level innovation routines that allow organizations to reconfigure resources in response to technological and market change. In this way, IOI and OOI act as strategic enablers linking environmental turbulence to innovation outcomes. Firms utilize IOI to transform technological advancements and market shifts into innovation success integrating external knowledge to improve internal processes (Chabbouh and Boujelbène, 2021). Likewise, OOI facilitates knowledge transfer, reducing risk exposure in uncertain environments, focusing on commercializing innovations through licensing or strategic alliances (Lin et al., 2022). These aspects enhance firms' ability to innovate amidst dynamic challenges (Martinez-Conesa et al., 2017). Therefore, we hypothesize that:

H3. : ***Inbound Open Innovation (IOI) positively influences Innovation Performance (IP)***.

H4. : ***Outbound Open Innovation (OOI) positively influences Innovation Performance (IP)***.

H5a. : ***Inbound Open Innovation (IOI) mediates the relationship between Technological Turbulence (TT) and Innovation Performance (IP)***.

H5b. : ***Inbound Open Innovation (IOI) mediates the relationship between Market Turbulence (MT) and Innovation Performance (IP)***.

H6a. : ***Outbound Open Innovation (OOI) mediates the relationship between Market Turbulence (MT) and Innovation Performance (IP)***.

H6b. : ***Outbound Open Innovation (OOI) mediates the relationship between Technological Turbulence (TT) and Innovation Performance (IP)***.

Building on the UTAUT framework (Venkatesh et al. 2003), the integration of AI into open innovation is further shaped by the moderating roles of PE and EE. These dimensions help explain how firms perceive and adopt AI-human collaboration in innovation processes. In contrast to traditional UTAUT applications focused on individual technology adoption, EE and PE are positioned here as organizationally embedded microfoundational cognitive conditions that shape how AI-enabled dynamic capabilities are enacted under environmental turbulence. That is, EE and PE do not constitute the capability itself, but condition how effectively IOI and OOI translate environmental turbulence into innovation performance. PE shapes how firms leverage AI in open innovation, particularly in decision-making, knowledge transfer, and market forecasting (Fasano et al., 2025; Ferràs et al., 2024). When PE is high, firms are more likely to invest in AI-enabled R&D and open innovation, using AI to manage uncertainty, increase adaptability, and boost efficiency (Bouteraa et al., 2024). Conversely, low PE can result in underutilization of AI tools, limiting innovation outcomes. EE, on the other hand, captures the perceived ease of integrating AI into innovation workflows (Abdalla et al., 2024). High EE reduces cognitive and operational resistance, enabling smoother AI adoption in areas such as inbound open innovation, knowledge acquisition, and strategic decision-making (Andersson et al., 2020). In contrast, when AI systems are seen as complex or disruptive, firms may hesitate to adopt them, dampening their innovation potential (Benito et al., 2024).

In the face of market and technological turbulence, PE and EE act as moderators, shaping how effectively AI supports open innovation. In this study, EE and PE are conceptualized as organizational-level microfoundational enablers that condition the effectiveness of AI-enabled dynamic capabilities (IOI and OOI) in translating environmental turbulence into innovation performance. High PE enhances firms' ability to exploit AI for innovation gains under uncertainty, while high EE facilitates adoption and collaboration,

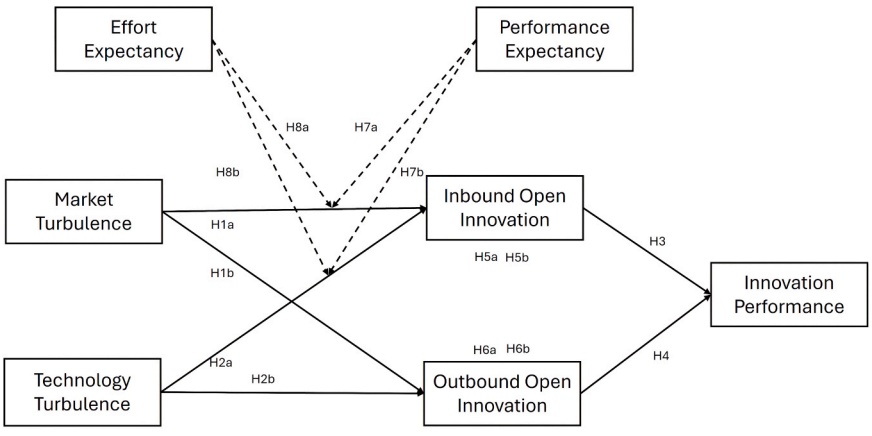


Fig. 1. Research model.
Source: Authors' own work

amplifying AI's strategic value in turbulent environments. Based on these insights, we propose the following hypotheses:

H7a. : ***Effort Expectancy (EE) of AI-Human collaboration moderates the relationship between Technological Turbulence (TT) and Inbound Open Innovation (IOI), such that higher EE strengthens this relationship.***

H7b. : ***Effort Expectancy (EE) of AI-Human collaboration moderates the relationship between Market Turbulence (MT) and Inbound Open Innovation (IOI), such that higher EE strengthens this relationship.***

H8a. : ***Performance Expectancy (PE) of AI-Human collaboration moderates the relationship between Technological Turbulence (TT) and Inbound Open Innovation (IOI), such that higher PE strengthens this relationship.***

H8b. : ***Performance Expectancy (PE) of AI-Human collaboration moderates the relationship between Market Turbulence (MT) and Inbound Open Innovation (IOI), such that higher PE strengthens this relationship.***

Fig. 1 presents the research model, illustrating how environmental turbulence influences IP through dynamic capabilities, with a focus on the strategic roles of open innovation and AI in competitive markets.

3. Methodology

3.1. Sample and data collection

The data for this study were collected through an online survey (Google Forms) between November 2024 and February 2025, targeting industry professionals engaged in technological innovation, digital transformation, and AI adoption. The research adopted an international perspective, collecting data primarily from Europe (48.57%), with additional respondents from North America, East Asia, Latin America, South Asia, and Africa, providing insights that are most directly relevant to European contexts while offering exploratory evidence from other rapidly digitalizing regions (Dwivedi et al., 2021; ughin, 2019).

A purposive sampling approach combined with snowball sampling was utilized to gather participants (Palinkas et al., 2015). Initial seed participants were identified through professional networks, industry associations, and innovation-focused online groups,

Table 1
Sample characteristics.

Classification	Item	Frequency	Percentage
Age	18–24	18	7.35
	25–34	113	46.12
	35–44	76	31.02
	45–54	30	12.24
	55–64	6	2.45
	65 +	2	0.82
Job Title	Director (or equivalent)	29	11.84
	Senior Manager (or equivalent)	28	11.43
	Manager (or equivalent)	47	19.18
	Executive (or equivalent)	42	17.14
	Team Leader (or equivalent)	27	11.02
	Operative Employee (Operational Staff)	32	13.06
	Others	40	16.33
Total Experience	10–15 Years	57	23.27
	1–3 Years	43	17.55
	15 + Years	30	12.24
	3–5 Years	40	16.33
	5–10 years	62	25.31
	Less than 1 Year	13	5.31
Headquarters	Africa	2	0.82
	Asia	94	38.37
	Australia	2	0.82
	Europe	119	48.57
	North America	21	8.57
	South America	7	2.86
Education	Associate's Degree	7	2.86
	Bachelor's Degree	84	34.29
	Bachelors or Masters in Business Administration (BBA/MBA)	31	12.65
	High School Diploma	13	5.31
	Master's Degree	72	29.39
	PhD or Doctorate	38	15.51
AI Platform Usage	Expert	32	13.06
	Moderately familiar	73	29.80
	Not at all familiar	13	5.31
	Somewhat familiar	45	18.37
	Very familiar	82	33.47

targeting individuals with demonstrated experience in AI adoption and digital transformation initiatives. Selection criteria required that participants hold decision-making or managerial roles in innovation-related functions. To avoid geographic or organizational clustering, seed participants were intentionally drawn from multiple regions and firms operating in different sectors. This strategy was intended to reduce network homogeneity and enhance variation in organizational contexts. Subsequent referrals were encouraged across organizational and regional boundaries to minimize clustering within single firms or local networks (Etikan, 2016).

Sample size was determined using G*Power 3.1, based on six independent variables, a medium effect size ($f^2 = 0.15$), a significance level (α) of 0.05, and a power of 0.95 (Faul et al., 2009). This analysis suggested a minimum of 146 participants, but 245 valid responses were ultimately collected to improve model stability and robustness of parameter estimation (Hair et al. 2022). Given the study's theory-testing orientation, the sampling strategy was designed to capture experienced AI practitioners across diverse contexts rather than to generate population-representative estimates.

3.2. Demographic information of respondents

The study surveyed 245 respondents across various industries, with the majority aged 25–34 (46.12%). Most respondents are mid-career professionals, and the highest departmental representation is from Information Technology (24.08%) and Operations (21.22%). In terms of experience, 35.51% have 1–3 years in their current roles, while the largest total experience category is 5–10 years (25.31%). Respondents with over 10 years of experience tend to be more familiar with AI, whereas those with less experience are less familiar. Geographically, most respondents are based in Europe (48.57%). A majority have a Bachelor's (34.29%) or Master's degree (29.39%). In AI platform usage, 33.47% are very familiar with AI technologies, indicating a strong overall knowledge base. Table 1 presents a summary of the key demographic characteristics of the respondents in the sample.

3.3. Measures

This study employs a single-layer reflective measurement model using Composite Mode A, assuming high correlation and interchangeability among indicators (Hair et al. 2022). To ensure the validity of the constructs, measurement items were adapted from well-established sources in the literature. PE and EE each had four items assessing user's perceived benefits and ease of AI integration (Cimino et al., 2024). IOI and OOI were also measured with four items each reflecting knowledge acquisition and internal commercialization (Zahoor and Adomako, 2023). Turbulence was evaluated with six items for MT and five for TT, highlighting market and technological dynamics that affect innovation strategies (Zahoor and Adomako, 2023). IP was assessed measuring the successful

Table 2
Descriptive statistics.

	Mean	Median	Standard deviation	Excess kurtosis	Skewness	VIF	Factor Loading
EE1	4.845	5.000	1.171	1.376	−1.152	2.411	0.820
EE2	4.706	5.000	1.234	0.611	−0.974	3.298	0.905
EE3	4.702	5.000	1.238	0.531	−0.912	3.777	0.905
EE4	4.629	5.000	1.218	0.293	−0.869	3.300	0.874
IOI1	4.453	5.000	1.256	−0.039	−0.707	1.716	0.773
IOI2	4.384	5.000	1.268	−0.089	−0.631	1.724	0.768
IOI3	4.029	4.000	1.398	−0.600	−0.394	1.879	0.814
IOI4	3.788	4.000	1.513	−0.858	−0.276	1.698	0.749
IP1	4.090	4.000	1.331	−0.403	−0.396	2.448	0.845
IP2	4.249	4.000	1.245	−0.076	−0.520	2.976	0.880
IP3	4.122	4.000	1.229	−0.190	−0.527	2.566	0.856
IP4	4.008	4.000	1.337	−0.562	−0.458	2.523	0.851
IP5	4.037	4.000	1.269	−0.452	−0.419	2.352	0.839
MT1	4.237	4.000	1.307	−0.508	−0.402	2.358	0.805
MT2	4.371	5.000	1.238	−0.426	−0.502	2.134	0.754
MT3	4.331	4.000	1.209	−0.459	−0.379	1.831	0.781
MT4	4.314	4.000	1.273	−0.151	−0.535	2.068	0.808
MT5	4.216	4.000	1.290	−0.338	−0.559	1.764	0.753
MT6	4.653	5.000	1.271	−0.388	−0.731	1.559	0.710
OO1	3.457	4.000	1.635	−1.155	−0.101	1.569	0.753
OO2	3.910	4.000	1.501	−0.813	−0.327	1.901	0.816
OO3	4.412	5.000	1.375	−0.231	−0.697	2.034	0.844
OO4	4.433	5.000	1.331	−0.115	−0.674	1.855	0.828
PE1	4.882	5.000	1.290	1.398	−1.305	3.759	0.918
PE2	4.947	5.000	1.310	1.430	−1.393	3.866	0.919
PE3	4.841	5.000	1.253	0.891	−1.136	3.970	0.926
PE4	4.804	5.000	1.298	1.201	−1.232	3.398	0.911
TT1	4.457	5.000	1.359	−0.191	−0.694	2.203	0.850
TT2	4.653	5.000	1.211	0.317	−0.819	2.550	0.876
TT3	4.355	5.000	1.376	−0.286	−0.650	1.848	0.778
TT4	4.469	5.000	1.267	−0.072	−0.719	2.625	0.889
TT5	removed						

introduction of new offerings (Freixanet et al., 2021). Each construct was evaluated using a six-point Likert scale to minimize central tendency bias and enhance response variability. For most constructs, 1 represented "Strongly Disagree" and 6 represented "Strongly Agree," while IP was scaled from 1 = "Very Low" to 6 = "Very High" (Podsakoff et al., 2003). A pilot test was conducted with 17 industry professionals, including AI practitioners, R&D managers, and innovation strategists, to assess the clarity and relevance of the questionnaire items (Malhotra et al., 2006).

4. Results and discussion

4.1. Descriptive statistics and indicator reliability

SmartPLS 4 was employed (Hair et al., 2019). This approach is especially advantageous when the hypothesized model includes first-order reflective constructs (Hair et al. 2022; Joe, Sarstedt, 2011). Prior to hypothesis testing, we assessed key data assumptions by examining measures of central tendency (mean, median), dispersion (standard deviation), excess kurtosis, skewness, VIF and factor loadings, as detailed in Table 2 (Vinzi et al., 2010). During the measurement model assessment, item TT5 (“Technological developments in our industry tend to be relatively minor”) exhibited a factor loading below the recommended threshold of 0.40. As this item was reverse-coded and did not load consistently with the remaining TT indicators, it was removed prior to further analysis to improve construct reliability and convergent validity (Hair Joe et al. 2016; Saunders et al., 2023).

4.2. Measurement model assessment

Table 3 shows that all constructs demonstrate strong reliability and validity. Cronbach’s Alpha (0.780–0.938) and composite reliability values exceed recommended thresholds, with PE highest. AVE values are all above 0.50, confirming convergent validity (Hair Joe et al. 2016).

The Heterotrait-Monotrait (HTMT) ratio, given in Table 4, was used to assess discriminant validity, with most values below the recommended 0.85/0.90 threshold (Henseler et al., 2015, 2016). One concern arises between OOI and IP, with an HTMT of 0.890, indicating possible overlap (Henseler et al., 2016). In contrast, lower HTMT values (e.g., PE–OOI = 0.419; TT–PE = 0.508) confirm distinctiveness. The Fornell–Larcker Criterion (Fornell and Larcker, 1981) supported these results: $\sqrt{\text{AVE}}$ values exceeded correlations for most constructs, though IP–OOI showed a close margin (correlation = 0.773 vs. $\sqrt{\text{AVE}}$: IP = 0.854, OOI = 0.811). Overall, both tests confirm acceptable discriminant validity, allowing us to retain all constructs.

Discriminant validity was assessed using both the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT). The square root of AVE for Innovation Performance (0.773) exceeded its correlations with other constructs, supporting discriminant validity based on the Fornell–Larcker criterion. Although the HTMT value between Outbound Open Innovation and Innovation Performance (0.890) indicates a strong association, this is theoretically expected given the capability–performance relationship central to the model and does not imply construct redundancy, particularly in the absence of overlapping item wordings (Fornell and Larcker, 1981; Henseler et al., 2016).

4.3. Model fit, explanatory and predictive power of the model

Model fit indices (Table 5) confirm an acceptable and robust structural model (Hair et al. 2022)(Hair et al. 2022). SRMR values (0.064 saturated; 0.080 estimated) fall within acceptable thresholds, while d_ULS and d_G support consistency between empirical and theoretical matrices. Chi-square results align with expectations given sample size, and NFI values (0.759 saturated; 0.752 estimated), though slightly below some benchmarks, remain satisfactory for complex innovation models. Overall, the model demonstrates structural soundness and validity (Hair et al. 2022).

Explanatory power (Table 6) was assessed using R^2, adjusted R^2, and Q^2_predict. IP shows the strongest explanatory capacity (R^2 = 0.609), followed by OOI (R^2 = 0.501) and IOI (R^2 = 0.415). Predictive relevance is also confirmed, with IP (Q^2_predict = 0.45) and OOI (0.48) demonstrating strong predictive capability, and IOI (0.35) within acceptable limits. Overall, the model exhibits solid explanatory and predictive strength, particularly for IP and Open Innovation, underscoring its robustness and applicability.

Table 3
Reliability, Validity and Collinearity.

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
EE	0.899	0.905	0.930	0.769
IOI	0.780	0.782	0.858	0.603
IP	0.907	0.908	0.931	0.730
MT	0.862	0.865	0.897	0.592
OOI	0.826	0.832	0.885	0.658
PE	0.938	0.939	0.956	0.844
TT	0.871	0.883	0.912	0.722

Table 4
HTMT and FLC.

	EE	IOI	IP	MT	OOI	PE	TT	EE	IOI	IP	MT	OOI	PE	TT
EE								0.877						
IOI	0.686							0.577	0.776					
IP	0.463	0.533						0.419	0.449	0.854				
MT	0.594	0.613	0.763					0.525	0.504	0.677	0.769			
OOI	0.511	0.567	0.890	0.802				0.447	0.456	0.773	0.684	0.811		
PE	0.889	0.578	0.432	0.533	0.419			0.814	0.495	0.398	0.480	0.376	0.919	
TT	0.551	0.523	0.588	0.734	0.663	0.508		0.491	0.434	0.529	0.634	0.573	0.465	0.850

Table 5
Model fit index.

	Saturated model	Estimated model
SRMR	0.064	0.080
d_ULS	2.165	3.409
d_G	0.679	0.713
Chi-square	944.780	974.960
NFI	0.759	0.752

Table 6
Explanatory and predictive power.

	R-square	R-square adjusted	Q^2predict
IOI	0.415	0.395	0.35
IP	0.609	0.606	0.45
OOI	0.501	0.496	0.48

4.4. Structural model assessment and hypothesis testing

The structural model was assessed using bootstrapping with 5000 subsamples (Hair et al., 2021)(Hair et al., 2021). Tables 7 and 8 explain the findings in detail. The direct effects entailed in **RQ1** indicate varying statistical significance. MT has a significant impact on both IOI ($\beta = 0.244$, $p = 0.001$) and OOI ($\beta = 0.536$, $p < 0.001$), thus supporting H1a and H1b. TT significantly affects OOI ($\beta = 0.234$, $p = 0.001$, $f^2 = 0.066$), confirming H2b, but does not significantly influence IOI ($\beta = 0.075$, $p = 0.196$, $f^2 = 0.005$), not supporting H2a. IP is significantly affected by both IOI ($\beta = 0.122$, $p = 0.004$, $f^2 = 0.03$) and OOI ($\beta = 0.717$, $p < 0.001$, $f^2 = 1.041$), supporting H3 and H4. The mediation effects entailed in **RQ2** showed that IOI partially mediates the relationship between MT and IP ($\beta = 0.03$, $p = 0.038$), supporting H5b, while not mediating TT and IP ($\beta = 0.009$, $p = 0.219$), leading to the rejection of H5a (Zhao et al., 2010). Conversely, OOI fully mediates the effect of MT on IP ($\beta = 0.384$, $p < 0.001$), supporting H6a, and also mediates TT's effect on IP ($\beta = 0.168$, $p = 0.001$), confirming H6b. Lastly, the moderating effects entailed in **RQ3** of EE and PE were assessed (Henseler and Fassott, 2010). EE significantly moderates the relationship between TT and IOI ($\beta = 0.257$, $p = 0.015$), supporting H7a, and negatively moderates the MT and IOI relationship ($\beta = -0.27$, $p = 0.012$), the direction of the effect was negative, contrary to the originally hypothesized positive moderation. Therefore, H7b is not supported and must be rejected. For PE, the moderation effect was significant for MT -> IOI ($\beta = 0.208$, $p = 0.017$), supporting H8b, but not for TT -> IOI ($\beta = -0.11$, $p = 0.103$), leading to the rejection of H8a.

Table 7
Path coefficient analysis.

	Relationship	β	M	SD	T	LLCI	ULCI	P values	Hypothesis
H1a	MT -> IOI	0.244	0.252	0.08	3.227	0.125	0.376	0.001	Accepted
H1b	MT -> OOI	0.536	0.536	0.06	8.577	0.431	0.637	0.000	Accepted
H2a	TT -> IOI	0.075	0.074	0.09	0.854	−0.07	0.214	0.196	Rejected
H2b	TT -> OOI	0.234	0.237	0.07	3.159	0.114	0.357	0.001	Accepted
H3	IOI -> IP	0.122	0.123	0.05	2.653	0.048	0.201	0.004	Accepted
H4	OOI -> IP	0.717	0.718	0.04	19.26	0.654	0.776	0.000	Accepted
H5a	TT -> IOI -> IP	0.009	0.009	0.01	0.777	−0.01	0.032	0.219	Rejected
H5b	MT -> IOI -> IP	0.03	0.032	0.02	1.78	0.009	0.063	0.038	Accepted
H6a	MT -> OOI -> IP	0.384	0.385	0.05	7.234	0.301	0.475	0.000	Accepted
H6b	TT -> OOI -> IP	0.168	0.17	0.05	3.225	0.078	0.249	0.001	Accepted
H7a	EE x TT -> IOI	0.257	0.259	0.12	2.165	0.068	0.461	0.015	Accepted
H7b	EE x MT -> IOI	−0.27	−0.25	0.12	2.255	−0.44	−0.06	0.012	Rjected
H8a	PE x TT -> IOI	−0.11	−0.12	0.09	1.267	−0.27	0.015	0.103	Rejected
H8b	PE x MT -> IOI	0.208	0.204	0.1	2.126	0.042	0.367	0.017	Accepted

Table 8
Effect size.

	Relationship	F Square
H1a	MT -> IOI	0.053
H1b	MT -> OOI	0.344
H2a	TT -> IOI	0.005
H2b	TT -> OOI	0.066
H3	IOI -> IP	0.03
H4	OOI -> IP	1.041

Table 8 presents the effect sizes (f^2), which align with the hypothesis testing results. Based on previous benchmarks (Cohen, 1988), MT shows a small effect on IOI ($f^2 = 0.053$) and a large effect on OOI ($f^2 = 0.344$), consistent with their significant paths ($\beta = 0.244$; $\beta = 0.536$). TT shows a negligible effect on IOI ($f^2 = 0.005$) and a small effect on OOI ($f^2 = 0.066$), matching its weak or non-significant paths. IOI modestly contributes to IP ($f^2 = 0.03$; $\beta = 0.122$, $p = 0.004$), while OOI exerts a very large effect ($f^2 = 1.041$; $\beta = 0.717$, $p < 0.001$), highlighting its central role. Overall, effect sizes confirm the dominant influence of MT and OOI on IP.

Figs. 2, 3 4 and 5 shows, simple slope analysis revealed differing influence patterns for EE and PE on innovation adoption across varying market and technological conditions.

The results provide valuable insights into the dynamics of open innovation under external turbulence. MT exhibits a stronger influence on innovation processes than TT, particularly through OOI. Moreover, EE and PE moderate these relationships in nuanced ways, indicating the role of human factors in technology adoption. However, while these findings highlight important relationships, they also suggest that traditional regression-based methods may not fully capture the necessary conditions required for high levels of IP. Therefore, we decided to apply NCA aiming to determine whether certain levels of MT and TT, as well as IOI and OOI, act as necessary conditions for achieving superior IP. This will help refine our theoretical contributions by distinguishing between enabling factors and truly indispensable drivers of innovation success.

4.5. Necessary condition analysis (NCA)

NCA was applied to identify the key Latent Variables (LVs) that constrain high levels of IP (Fig. 6). Unlike traditional regression, which examines variables that increase the likelihood or sufficiency of an outcome, NCA adopts necessity logic to determine whether specific conditions must be present at minimum levels for a desired outcome to be possible. This approach is theoretically appropriate, as it aligns with our aim to identify factors that constrain high performance if absent, rather than those that guarantee high performance if present.

The effect size results (Table 9) indicate the degree to which each LV constrains the attainment of high IP, but do not imply causality. For example, MT ($d = 0.323$) has the most significant necessity effect, suggesting it is a key precondition for achieving high IP. OOI ($d = 0.215$) is also vital, while PE ($d = 0.167$) and TT ($d = 0.163$) play moderate roles. EE ($d = 0.154$) and IOI ($d = 0.110$) have smaller effects, suggesting they are less critical as a necessity condition.

This bottleneck analysis (Table 10) specifies the minimum levels of each LV required to achieve different levels of IP (from 0% to 100%). For instance, to reach 50% IP, firms need MT $\geq$ 2.803, OOI $\geq$ 1.581, and TT $\geq$ 1.879. These thresholds increase at higher IP levels. At 80% IP, MT must be $\geq$ 3.985, OOI $\geq$ 3.15, and TT $\geq$ 2.468, emphasizing their growing importance. Additionally, EE and PE become constraints at the 90% and 100% IP levels highlighting their rising necessity as firms strive for excellence.

Figs. 7–12 present NCA XY plots for each LV-IP relationship. These charts visually map the ceiling line, (i.e., the necessity threshold) below which a given level of IP cannot be achieved unless the LV meets the minimum condition. A steeper ceiling line (e.g., for MT or OOI) reflects a stronger necessity constraint, while a flatter line (e.g., for IOI) suggests a weaker constraint.

Permutation tests (Table 11) confirm the statistical significance of necessity effects. The p-values indicate that MT, OOI, PE, TT, and

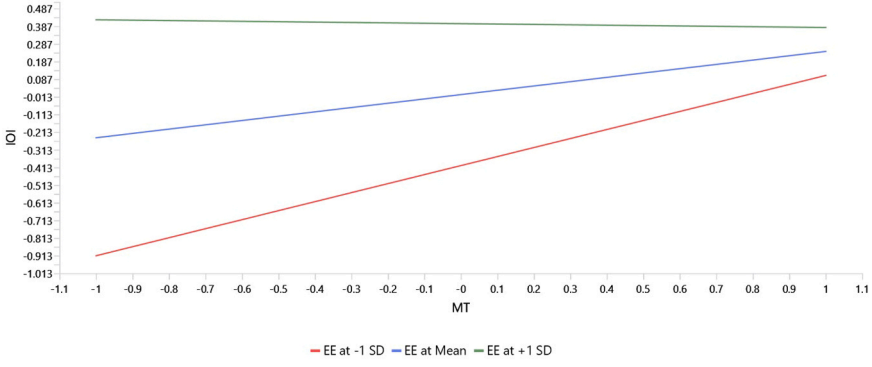


Fig. 2. Moderating Effect of EE on the Relationship between MT and IOI.

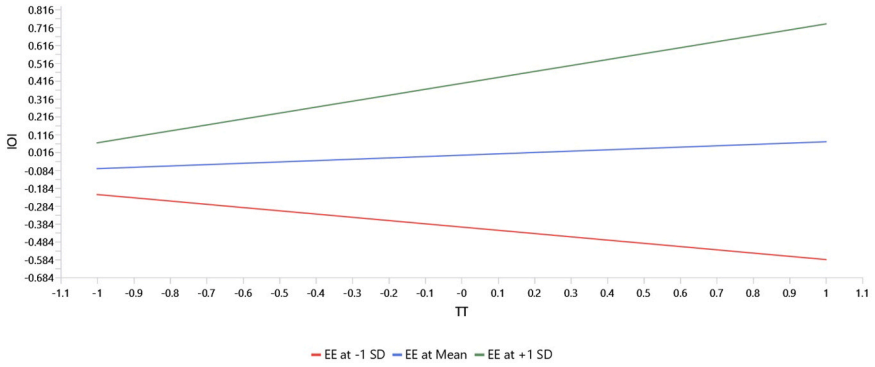


Fig. 3. Moderating Effect of EE on the Relationship between TT and IOI.

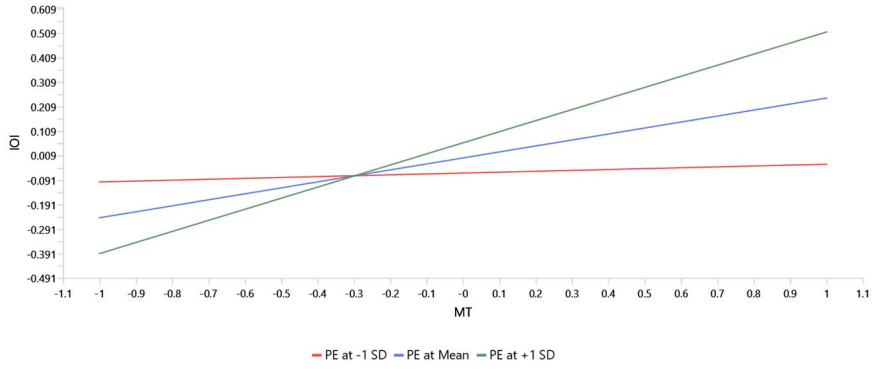


Fig. 4. Moderating Effect of PE on the Relationship between MT and IOI.

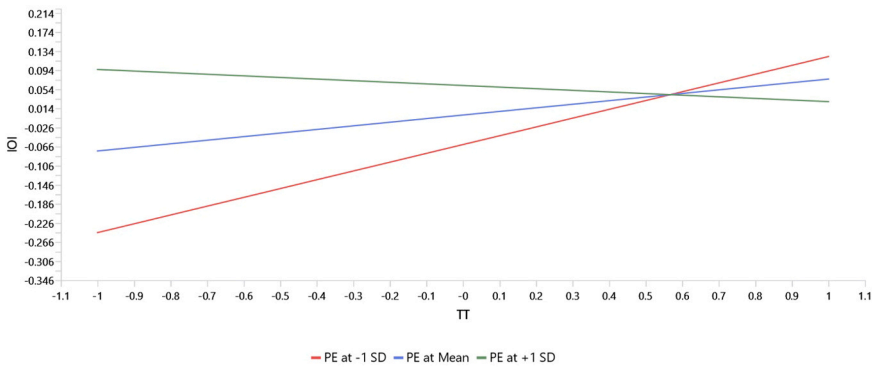


Fig. 5. Moderating Effect of PE on the Relationship between TT and IOI.

EE are significantly necessary for higher IP ($p \leq 0.004$), while IOI is marginally significant ($p = 0.050$).

Overall, MT and OOI emerge as the most critical necessary conditions for achieving IP across all levels. As IP levels increase, other conditions such as EE, TT, and PE become more prominent bottlenecks. Importantly, we interpret these results as identifying necessary constraints rather than implying direct causality.

4.6. Discussion

Our findings confirm that MT significantly drives both IOI ($\beta = 0.244$, $p = 0.001$) and OOI ($\beta = 0.536$, $p < 0.001$), with a stronger effect on OOI **(RQ1)**. These results endorse that MT activates organizational sensing and transforming mechanisms rather than individual adoption behaviors. It also enhances customer integration in open innovation (Schweitzer et al., 2011) and triggers open innovation-driven business model transformation (Albats et al., 2023). However, contrasting evidence suggests contextual variations (Luo et al., 2024). Significantly, the stronger predictive effect of OOI under turbulence indicates that external collaboration serves as

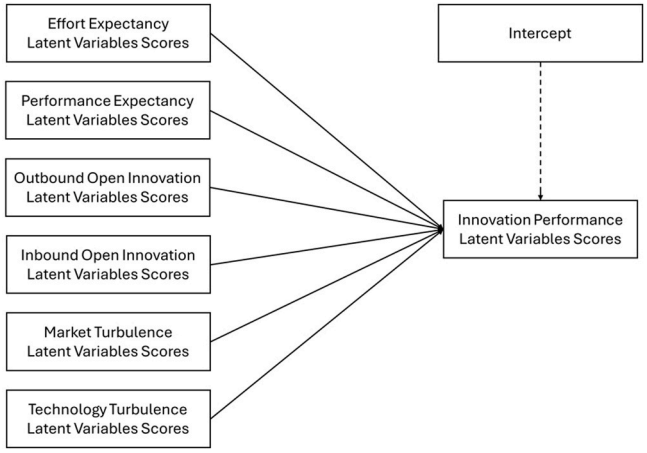


Fig. 6. NCA analysis.

Table 9
NCA effect sizes based on CE-FDH estimation.

LV scores	CE-FDH
EE	0.154
IOI	0.110
MT	0.323
OOI	0.215
PE	0.167
TT	0.163

Table 10
Bottleneck analysis– minimum LV scores required at Each IP level.

	IP	EE	IOI	MT	OOI	PE	TT
0.00%	1	NN	NN	NN	NN	NN	NN
10.00%	1.5	NN	NN	1.503	NN	NN	NN
20.00%	2	NN	NN	1.503	NN	NN	NN
30.00%	2.5	NN	1.38	1.503	NN	NN	NN
40.00%	3	NN	1.38	1.503	1.581	NN	NN
50.00%	3.5	1.249	1.38	2.803	1.581	NN	1.879
60.00%	4	1.249	1.38	2.803	1.581	NN	2.353
70.00%	4.5	1.249	1.38	3.285	3.15	NN	2.468
80.00%	5	2.47	2.48	3.985	3.15	3	2.468
90.00%	5.5	4.502	2.48	4.52	4.59	4.747	2.894
100.00%	6	4.502	2.48	4.52	4.59	5.501	2.894

an adaptive mechanism in volatile environments. In dynamic capability terms, MT triggers seizing and transforming routines more intensively than sensing alone. Digital transformation accelerates this process by enabling coordinated experimentation, rapid validation, and distributed knowledge recombination. In digitally integrated ecosystems, firms can commercialize unused knowledge, license technologies, and co-develop solutions more efficiently, converting turbulence into a collaborative opportunity (Wang and Zhang, 2025a). This explains why OOI is particularly effective in Industry 5.0 contexts, where sustainability, digitalization, and AI-enabled collaboration converge, positioning outbound innovation as a driver of systemic, network-level innovation rather than mere knowledge commercialization.

Our results show a significant positive effect of TT on OOI ($\beta = 0.234$, $p = 0.001$), indicating that firms externalize knowledge to respond to rapid technological change. This suggests that technological turbulence stimulates transforming mechanisms that leverage external knowledge rather than inbound absorption mechanisms. This supports prior evidence that TT strengthens the link between partner heterogeneity and innovation performance (Huang et al., 2018) and enhances the effect of absorptive capacity on radical innovation (Lin et al., 2015) reinforcing its role in promoting external knowledge-sharing strategies. However, our results indicate that TT does not significantly influence IOI ($\beta = 0.075$, $p = 0.196$, H2a rejected). This suggests that TT primarily encourages firms to externalize knowledge rather than strengthen inbound mechanisms.

The relatively strong association between OOI and IP, reflected in both the structural paths and the HTMT statistic, reinforces the view of outbound innovation as a core dynamic capability rather than a peripheral practice. From a theoretical perspective, such

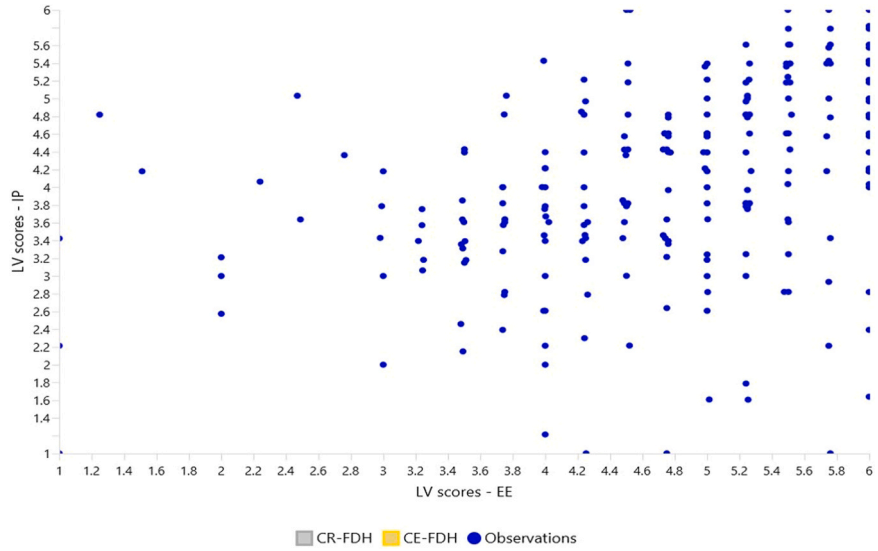


Fig. 7. NCA Ceiling Line Chart for Effort Expectancy (Latent Variable Scores).

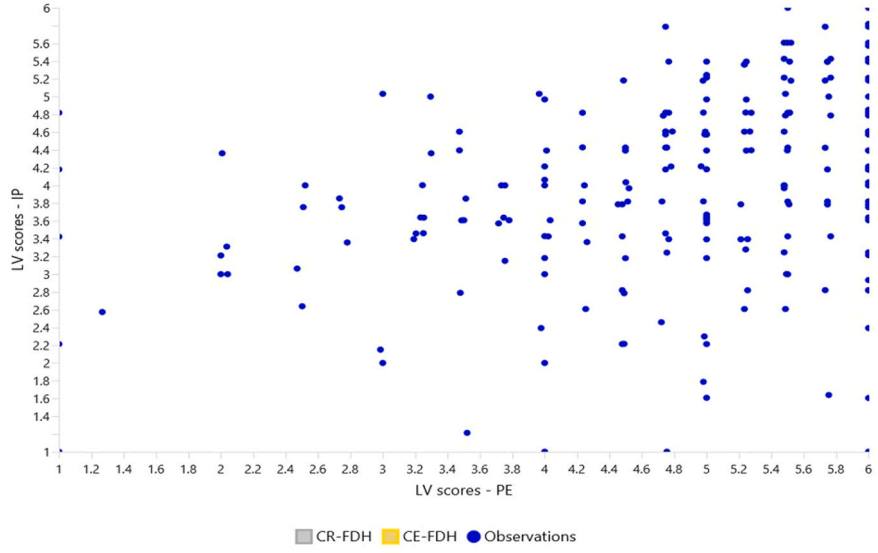


Fig. 8. NCA ceiling line chart for perfromance expectancy (Latent Variable Scores).

proximity is consistent with Industry 5.0 contexts, where value creation increasingly depends on the effective externalization and orchestration of firm knowledge.

Both IOI ($\beta = 0.122$, $p = 0.004$) and OOI ($\beta = 0.717$, $p < 0.001$) significantly enhance IP, with OOI being the dominant driver **(RQ2)**. This supports the dynamic capabilities framework, which emphasizes a firm's ability to integrate, build, and reconfigure internal and external competencies to achieve superior performance in dynamic environments. From a digital integration perspective, outbound collaboration is increasingly embedded within digitally connected and AI-supported coordination mechanisms. These systems enable real-time information sharing, joint innovation initiatives, and cross-boundary learning. As demonstrated by Wang and Zhang (2024), digitally integrated cooperation structures enhance both innovation performance and sustainability outcomes. Thus, in Industry 5.0 ecosystems, OOI operates through digitally mediated inter-organizational integration that strengthens not only innovation outputs but also green and ESG-aligned value creation.

Importantly, the NCA results complement these linear findings by clarifying which factors function as bottlenecks. While PLS-SEM shows that OOI is the strongest predictor of IP, NCA demonstrates that OOI ($d = 0.215$) is also a necessary condition, meaning that high innovation performance cannot be achieved unless minimum levels of outbound openness are secured. In contrast, IOI, although a significant predictor, shows a much smaller necessity effect ($d = 0.110$) and only marginal significance, indicating that inbound openness enhances performance but is less likely to act as a binding constraint. For engineering managers, this distinction implies that

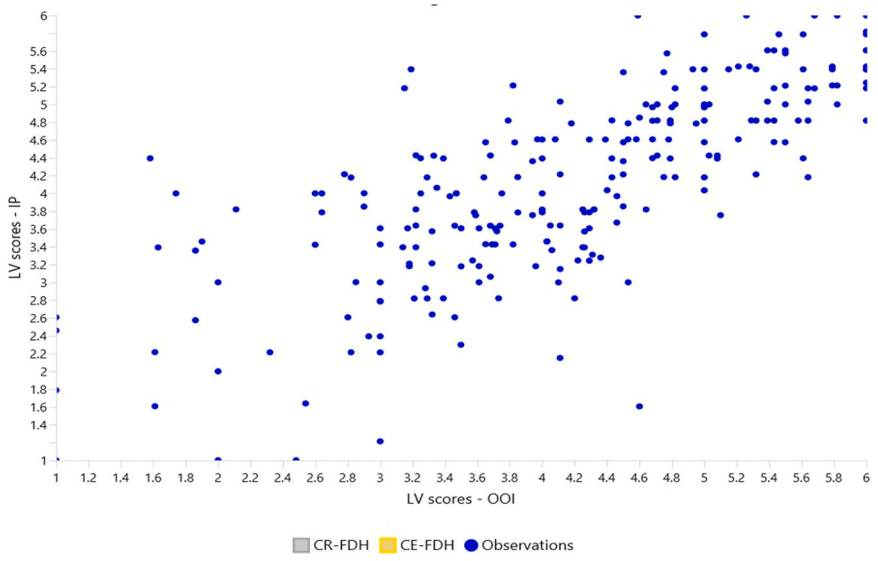


Fig. 9. NCA ceiling line chart for outbound open innovation (Latent Variable Scores).

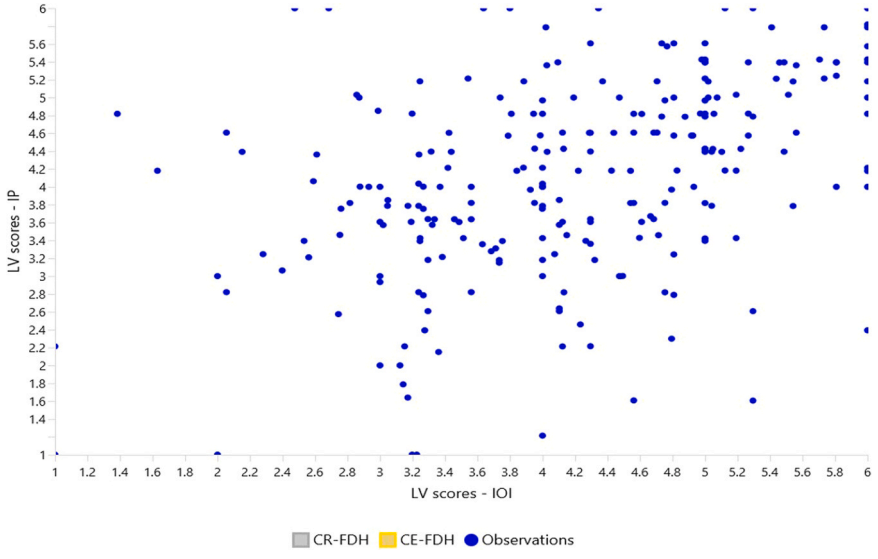


Fig. 10. NCA ceiling line chart for inbound open innovation (Latent Variable Scores).

establishing effective outbound collaboration channels is a prerequisite for high innovation performance, whereas inbound acquisition mechanisms, though beneficial, operate more as performance enhancers than structural bottlenecks.

Further, IOI and OOI drive IP through organizational capabilities like absorptive capacity and learning culture, with OOI often having a more pronounced effect due to its role in leveraging external knowledge networks (Zhang et al., 2024). Research found that both IOI and OOI enhance IP, particularly when mediated by digital platform capabilities, reinforcing the role of dynamic capabilities in orchestrating external knowledge flows(Wang et al., 2023). Additionally, the mediating role of dynamic capabilities in linking IOI to IP has also been proven in prior studies, further supporting our findings(Chabbouh and Boujelbene, 2023)(Chabbouh and Boujelbene, 2023). However, certain forms of OOI, such as spin-along activities, may not directly enhance IP due to reduced structural holes in innovation networks, indicating that the effectiveness of OOI may depend on network configurations (Meng et al., 2022). Taken together, these findings reinforce the view that innovation managers must not only invest in open innovation activities but also align them with contextual factors such as network design and absorptive capacity.

Our findings, grounded in the UTAUT framework (Venkatesh et al, 2003) and the Sextuple Helix Model highlight the human factor in open innovation **(RQ3)**. EE positively moderates the relationship between technological turbulence (TT) and IOI ($\beta = 0.257$, $p = 0.015$). This suggests that when employees perceive AI as intuitive and supportive, firms can more easily adopt IOI under technological disruption. This aligns with Abdalla et al. 2024 who reported that EE as a key predictor of adopting data-driven innovations

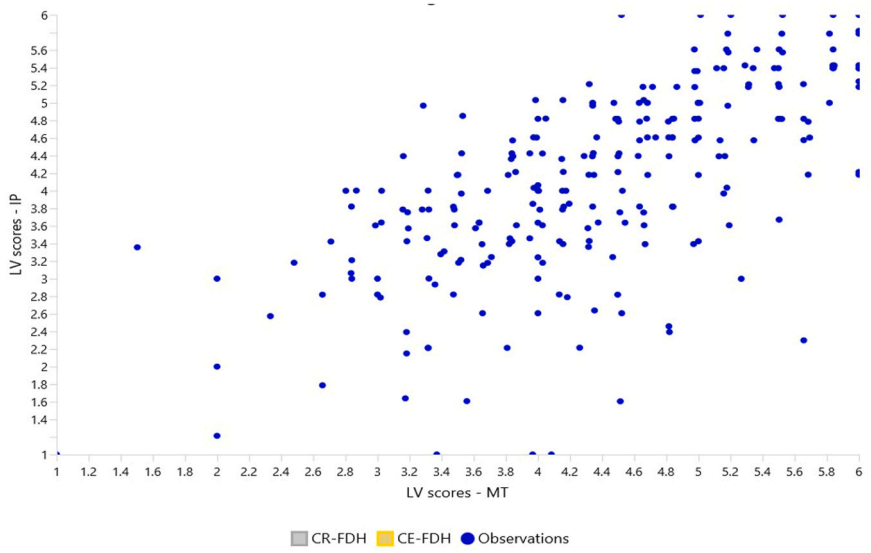


Fig. 11. NCA ceiling line chart for market turbulence (Latent Variable Scores).

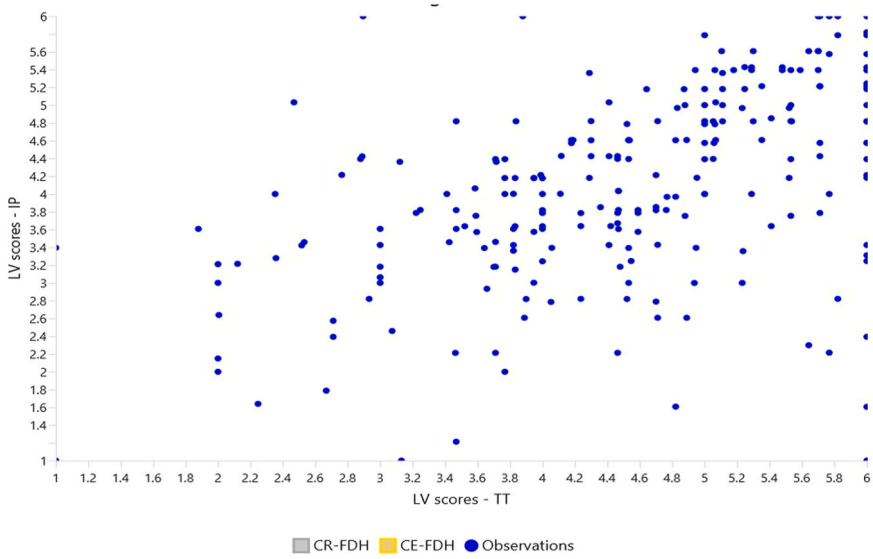


Fig. 12. NCA ceiling line chart for technology turbulence (Latent Variable Scores).

Table 11
Permutation test results for necessity effects.

	Original effect size	95.0%	Permutation p value
LV scores - EE	0.154	0.116	0.004
LV scores - IOI	0.110	0.110	0.050
LV scores - MT	0.323	0.155	0.000
LV scores - OOI	0.215	0.071	0.000
LV scores - PE	0.167	0.099	0.000
LV scores - TT	0.163	0.110	0.001

emphasizing the role of perceived ease of use in technology integration (Abdalla et al., 2024). Similarly, PE, reflecting users' expected benefits of AI, positively moderates the relationship between MT and IOI ($\beta = 0.208$, $p = 0.017$), indicating that firms are more likely to adopt AI-enabled IOI when tangible benefits are clear. Benito et al., 2024 found PE to significantly drive the acceptance of e-learning platforms (Benito et al., 2024). However, AI adoption in Industry 5.0 contexts is not driven solely by individual perceptions of

usefulness or ease. Strategic orientation, particularly proactive sustainability strategy, may shape how firms leverage AI under turbulence. Recent research shows that proactive sustainability strategies strengthen the relationship between AI-enabled adaptive supply chains and innovation capabilities (Wang and Zhang, 2025a). This suggests that PE and EE may reflect not only user-level acceptance but also broader strategic alignment with ESG and sustainability objectives.

Conversely, contrary to **H7b**, EE negatively moderates the MT-IOI relationship (Bouteraa et al., 2024)($\beta = -0.270$, $p = 0.012$), suggesting that high MT increases perceived effort in adopting AI-enabled IOI, potentially due to resource constraints or complexity in dynamic markets. While UTAUT generally predicts a positive role for perceived ease of use, this finding suggests an important boundary condition under high turbulence. Dynamic capability theory posits that rapidly changing markets require intensive experimentation, rapid recombination of knowledge, and deep analytical processing. In such contexts, AI systems perceived as "easy to use" may signal standardization or limited analytical depth rather than adaptive sophistication. Firms facing extreme market shifts may therefore prioritize more advanced, customized, and effort-intensive AI-enabled processes to manage uncertainty effectively. Consequently, when MT is high, an emphasis on ease of use may inadvertently weaken firms' engagement in IOI by reducing exploratory intensity and strategic adaptation. This interpretation positions EE not simply as a facilitator, but as a context-dependent cognitive condition whose effectiveness varies with environmental complexity.

Accordingly, EE and PE are treated as shared cognitive orientations within the organization that influence the deployment and effectiveness of dynamic capabilities, rather than as individual or purely cultural perceptions. Organizational digital culture shapes how employees interpret AI tools, allocate resources, and integrate digital solutions into innovation routines. Previous studies demonstrate that organizational digital culture moderates the relationship between integration mechanisms and performance outcomes (Wang and Zhang, 2025b). This organizational-level perspective elevates the interpretation of EE beyond individual cognition to strategic digital readiness.

The NCA findings further refine this interpretation. While EE and PE function as moderators in the PLS-SEM model, NCA shows that they become necessary conditions only at higher IP thresholds, particularly at 90% and 100% performance levels. This indicates that AI-related human factors may not be critical for moderate innovation outcomes but become binding constraints when firms aim for excellence. Practically, this means that engineering managers must first secure minimum levels of market alignment and outbound openness, and subsequently strengthen AI-related competencies and user acceptance to reach top-tier innovation performance.

NCA provides further insights into the minimum conditions (Zhou et al., 2024) required for firms to achieve high IP in AI-enabled ecosystems. At 80% IP levels, AI-powered ICT platforms emerge as essential, reinforcing the Sextuple Helix Model, which expands traditional innovation ecosystems to include Media, ICT platforms, and AI-driven collaboration mechanisms. At 100% IP levels, AI-driven automation tools and high PE become indispensable, suggesting that innovation managers must prioritize AI adoption, digital literacy, and platform-based co-creation to unlock full innovation potential.

5. Theoretical contributions and practical implications

5.1. Theoretical insights

This study makes a significant theoretical contribution by integrating dynamic capability theory to provide a novel innovation management lens that highlights how AI-driven platforms enable knowledge flows, collaboration, and adaptive decision-making in turbulent environments (Karstegl et al., 2025; Teece et al., 1997; Venkatesh et al. 2003). By bridging these frameworks, the research highlights how AI-driven platforms facilitate knowledge flows, collaboration, and adaptive decision-making within dynamic market environments. Traditional DCT focuses on human decision-making and resource reconfiguration. Our results highlight AI as an enabler that augments managerial decision-making and supports continuous reconfiguration of innovation management.

This study, further, contributes theoretically by positioning IOI and OOI explicitly as sensing, seizing, and transforming mechanisms at the organizational level within DCT. Environmental turbulence activates these capability configurations, with outbound openness functioning as the dominant transforming mechanism.

Additionally, the study enriches the UTAUT by identifying the moderating effects of user's perception of EE and PE on firms' innovation strategies as microfoundational cognitive conditions (Venkatesh et al. 2003). The findings indicate that firms' willingness to adopt AI-driven platforms is shaped by user's perceived ease of use and operational benefits. These findings contribute to the broader discourse on technology acceptance in innovation ecosystems, particularly in AI-enabled environments (Bouteraa et al., 2024).

Finally, this research advances the ongoing debate on AI-human collaboration by emphasizing that AI does not replace human intelligence but rather augments cognitive and creative capacities (Breque, 2021). Innovation 5.0 advocates for a balanced integration of AI and human expertise, positioning AI as a facilitator rather than a substitute for human creativity. This study supports this perspective by demonstrating that AI-driven platforms enhance firms' ability to co-create and innovate, offering theoretical insights into how managers can strategically integrate AI into innovation management.

5.2. Practical and managerial contributions

The findings offer targeted implications for R&D managers, CTOs, and engineering leaders responsible for innovation portfolios in Industry 5.0 environments.

First, the strong effect of MT on OOI suggests that CTOs should institutionalize outbound commercialization mechanisms rather than treating open innovation as ad hoc collaboration. Engineering leaders should formalize technology scouting, co-development agreements, API-based platform integration, and spin-off strategies.

Under high market turbulence, a useful heuristic is: when customer needs shift rapidly, increase outbound knowledge flows and ecosystem experimentation. This allows engineering teams to test prototypes externally, accelerate validation cycles, and reduce time-to-commercialization risk.

Second, with respect to Technological Turbulence, engineering managers should differentiate between capability development at the technical layer and at the strategic application layer. The results indicate that open innovation mediates environmental turbulence and innovation performance, meaning that technology alone is insufficient without effective knowledge integration. Therefore, R&D leaders should not limit training to tool-specific mechanics. While improving technical proficiency increases Effort Expectancy by lowering operational friction, the greater leverage comes from increasing Performance Expectancy. Engineering training programs should focus on how AI tools enhance market sensing, predictive modeling, simulation accuracy, and portfolio decision-making. In turbulent technological environments, the decision rule becomes: prioritize strategic AI literacy over narrow technical tutorials.

Third, because EE and PE condition inbound responsiveness, engineering leaders must actively manage organizational AI readiness, integrating modular systems, workflow compatibility, and measurable pilot demonstrations. Observable performance gains increase organizational confidence and strengthen sensing capabilities under turbulence.

Fourth, portfolio governance in Industry 5.0 contexts should dynamically rebalance exploration and transformation activities toward resilience and human centricity. Engineering leaders should allocate innovation budgets across exploratory partnerships, AI-enabled experimentation, and incremental internal improvements. A practical heuristic is to dynamically rebalance the portfolio in response to turbulence signals: increase external collaboration intensity when market turbulence rises, and increase internal capability upgrading when technological turbulence accelerates.

Overall, the study suggests that engineering and technology managers must treat AI-enabled open innovation not as an IT investment but as an architectural redesign of the innovation system. The competitive advantage in Industry 5.0 emerges from aligning AI infrastructure, human cognitive readiness, and ecosystem integration within R&D strategy.

6. Conclusion, limitations and future research

This study demonstrates the transformative role of AI-powered digital platforms in driving IP within the Innovation 5.0 ecosystem. Using PLS-SEM and NCA, it shows that both inbound and OOI enhance IP, with OOI emerging as the stronger driver under conditions of market and technological turbulence. The moderating effects of PE and effort expectancy highlight the critical influence of human perceptions, underscoring that usability, training, and communication are as important as technological investment.

Theoretically, the research extends Dynamic Capability Theory and UTAUT by embedding them within the Innovation 5.0 and Sextuple Helix perspectives, emphasizing how AI augments, rather than replaces, human intelligence in turbulent environments. Practically, it offers managers actionable guidance: leverage AI-driven collaboration platforms, foster digital literacy, reduce perceived effort, and emphasize the tangible benefits of AI to strengthen innovation capacity and resilience.

This study has limitations, including its cross-sectional design, reliance on self-reported data, and limited attention to regulatory and ethical considerations. Future research should adopt longitudinal designs, expand across industries and countries, and address ethical issues such as data privacy and responsible AI use. Exploring complementary technologies (e.g., blockchain, digital twins, decentralized AI) may further enrich our understanding of open innovation in Industry 5.0.

Although Outbound Open Innovation and Innovation Performance were measured in the same survey, the constructs were operationalized using distinct, non-overlapping items, with performance assessed over a retrospective three-year period to introduce temporal separation. Procedural remedies (e.g., anonymity assurance and clear construct separation) were applied to reduce response bias. Statistically, full collinearity VIFs and discriminant validity tests (Fornell–Larcker and HTMT) suggest that common method bias is unlikely to materially affect the results.

Nevertheless, the cross-sectional and single-source design limits causal inference. Reverse causality and omitted variable bias cannot be fully ruled out, and future research should employ longitudinal or multi-source designs to better address potential endogeneity.

This study employed a purposive sampling approach combined with snowball sampling, which, although appropriate for reaching experienced AI and innovation professionals, limits the ability to make population-level inferences. While efforts were made to ensure geographic and sectoral diversity in the initial seed selection, the non-probability nature of the sampling design may introduce network-based bias and uneven regional representation. Therefore, the findings should be interpreted as evidence of structural relationships within an international professional sample rather than as representative estimates of the global population of high-technology firms. Future research may employ probability-based or stratified sampling designs to further validate and extend the generalizability of these results.

The unexpected negative moderation of EE under high market turbulence also suggests important boundary conditions for applying UTAUT constructs at the organizational level. While EE typically enhances technology adoption, its role in highly turbulent and complex environments may differ. Future research should further examine whether perceived ease of AI integration constrains exploratory capability development under extreme market volatility, ideally using longitudinal or multi-context designs.

CRediT authorship contribution statement

Bilal Afzal: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ana Beatriz Hernandez Lara:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **Anna Visvizi:** Writing – review & editing, Supervision, Resources, Project administration,

Investigation, Conceptualization. **Xiaoni Li:** Writing – review & editing, Supervision.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.jengtecman.2026.101987.

Data availability

Data will be made available on request.

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