Open Innovation and Sustainable Technology Development: The Moderating Role of AI Capability

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ABSTRACT:

Sustainable technology development has become a strategic priority for manufacturing firms undergoing digital transformation and facing increasing environmental pressures. Open innovation (OI), particularly inbound knowledge acquisition, plays a crucial role by enabling organizations to integrate diverse technological, scientific, market-based, and digitally mediated knowledge. However, the effectiveness of inbound OI depends on the firm's ability to absorb, analyse, and apply external information, a capability that is increasingly shaped by artificial intelligence (AI). This study investigates how four dimensions of inbound OI (external technology sourcing, university–industry collaboration, customer and market knowledge acquisition, and digital platform engagement) affect sustainable technology development in Saudi Arabian manufacturing firms, and whether AI capability strengthens these effects. Using data collected from 211 IT managers and IT experts and analysed through Smart PLS 4, the results show that all four inbound OI dimensions significantly enhance sustainable technology development. AI capability moderated the relationship between inbound OI and sustainability outcomes. These findings enrich OI theory by introducing a multidimensional conceptualization and highlight AI capability as a strategic enabler of environmental technological progress. The study offers actionable insights for managers and policymakers seeking to accelerate sustainable industrial transformation.

Keywords: Inbound open innovation, Sustainable technology development, Artificial intelligence, Manufacturing firms, Resource based view

1. Introduction

The accelerating pace of technological change and the growing demand for sustainable solutions have transformed the global manufacturing landscape (Al-Mutawa & Saeed Al Mubarak, 2024). Today, firms operate in an environment characterized by rapid digitalization, increasing ecological pressures, and heightened expectations for responsible innovation (Liputri & Gosal, 2024). In this context, open innovation (OI) has emerged as a strategic paradigm enabling organizations to access external knowledge sources, integrate diverse technological capabilities, and accelerate the development of

sustainable technologies (Bigliardi et al., 2022). Unlike closed, internally driven R&D models, OI allows firms to cross organizational boundaries, leverage distributed expertise, and co-create value through collaboration with external partners. Among the three OI modes (inbound, outbound, and coupled), inbound OI has become particularly critical for manufacturers seeking to build greener, more efficient, and future-ready technological systems (Lu et al., 2021; Tang et al., 2021).

Inbound OI refers to a firm's ability to acquire, integrate, and exploit external knowledge to enhance internal innovation activities. It includes several complementary practices such as external knowledge sourcing, technology scouting, crowdsourcing, supplier and customer involvement, research collaborations with universities, and participation in innovation networks (Petković & Radicic, 2025). These types of inbound OI activities provide firms with access to specialized expertise, advanced digital tools, new business models, and sustainability-oriented technologies that may not be available internally (Nduro & Duodu, 2025). For manufacturing companies, inbound OI enables the adoption of clean technologies, energy-efficient systems, circular production methods, and digital solutions that support sustainable operations (Fiorini et al., 2025). Recent studies have shown that firms actively engaged in inbound OI demonstrate faster innovation cycles, reduced development costs, and higher sustainability performance due to broader exposure to diverse environmental technologies and practices (Dorrego-Viera et al., 2025; Helm et al., 2025; Hosni et al., 2025).

Saudi Arabia provides a compelling setting for examining inbound OI and sustainable technology development. Amid Vision 2030, manufacturing firms are under increasing pressure to diversify the economy, adopt environmentally responsible technologies, and transition toward smart and sustainable production systems. The Saudi manufacturing sector is investing heavily in digital transformation, including automation, IoT integration, advanced analytics, and smart factories (Alquraish, 2025). Yet, sustainable technology development still faces persistent challenges, such as limited internal R&D capabilities, talent shortages, and varying levels of digital readiness (Al-Roubaie, 2025; Khan et al., 2025). Under these conditions, inbound OI becomes a strategic lever, allowing manufacturing firms to compensate for internal limitations by integrating external digital knowledge, global best practices, and environmentally oriented innovations sourced from research institutions, technology suppliers, international partners, and digital platforms (Petković & Radicic, 2025).

At the same time, AI is reshaping how firms search for, absorb, and exploit external knowledge for sustainable innovation (Al-Roubaie, 2025). AI enhances the ability to identify relevant technological opportunities, process complex environmental data, automate innovation routines, and optimize decision-making in R&D and sustainability projects (Alquraish, 2025). AI tools enable predictive analytics for energy management, advanced simulations for eco-efficient design, and intelligent monitoring for cleaner production (Mohammed Alarefi, 2024). AI also improves absorptive capacity by facilitating the integration and application of externally sourced knowledge, suggesting that AI capabilities may strengthen the relationship between inbound OI and sustainable technology development. However, empirical evidence on this moderating role remains limited, particularly in developing economies undergoing digital transformation (M Alarefi, 2023).

Despite the strategic importance of inbound OI for sustainability, prior research has disproportionately focused on general OI or on the performance effects of digitalization, with relatively few studies examining how specific inbound OI practices contribute to sustainable technology development within the manufacturing context (Di Rocco, 2025; Helm et al., 2025; Huynh et al., 2025). Even fewer studies have evaluated how advanced technologies, especially AI, shape or amplify these effects. Moreover, empirical evidence from the Gulf region, and Saudi Arabia in particular, remains scarce, despite the country's rapid technological modernization and increasing commitment to sustainable industrial development (Mohammed Alarefi, 2024).

To address these gaps, this study investigates the effect of inbound OI on sustainable technology development in Saudi Arabian manufacturing firms and assesses the moderating role of AI capabilities in this relationship. The study draws on data from IT experts and IT managers, uses purposive sampling, and applies Smart PLS to evaluate the proposed model. By focusing on the interplay between inbound OI types and AI-enabled capabilities, this research provides new insights into how firms can accelerate sustainability-oriented innovation through external knowledge integration and advanced digital technologies. The findings are expected to contribute to the literature on OI, digital transformation, and sustainable manufacturing while offering practical implications for firms and policymakers seeking to enhance the sustainability of the manufacturing sector under Saudi Vision 2030.

2. Literature Review

2.1 Inbound OI

Inbound OI has become a pivotal mechanism for firms seeking to strengthen their innovation capabilities by integrating knowledge that originates outside their organizational boundaries (Delshab et al., 2022). Traditional innovation models emphasized internal R&D as the primary driver of technological progress; however, contemporary manufacturing environments, characterized by rapid technological change, digital transformation, and sustainability pressures, require more porous, collaborative knowledge systems (Menne et al., 2022). As a result, inbound OI is increasingly conceptualized as a multifaceted construct, reflecting the diverse sources, channels, and types of external knowledge that firms must access to remain competitive (Liao et al., 2019). Rather than viewing inbound OI as a single activity, this study adopts a multidimensional perspective, identifying four distinct but complementary dimensions: external technology sourcing, university–industry and research collaboration, customer and market knowledge acquisition, and participation in digital platforms and crowdsourcing ecosystems (Naqshbandi & Tabche, 2018). These dimensions collectively provide a comprehensive representation of the strategic knowledge inflows necessary for sustainability-oriented technological development.

The first dimension, external technology sourcing, captures firms' engagement with external providers of technological solutions, including suppliers, engineering firms, digital tool vendors, and technology consultants (Hannu, 2025). This dimension is particularly relevant to manufacturing sectors where sustainability-oriented technological advancements often require specialized equipment and digital systems that firms cannot feasibly develop internally (Su et al., 2023). The rapid evolution of green technologies, clean production systems, and smart manufacturing tools reinforces the strategic importance of acquiring cutting-edge technological knowledge from external partners (Klueter et al., 2025).

The second dimension involves collaboration with universities and research institutions (Gnekpe et al., 2023). Sustainability-oriented innovation frequently relies on scientific insights and long-term research capabilities that exceed what firms can maintain internally (Zhang, 2024). Academic institutions provide access to laboratories, scientific expertise, and specialized research networks that support the development of eco-materials, renewable energy technologies, and environmental data analytics (Liu et al., 2022). This dimension is theoretically justified by the increasing reliance on science-based innovation to meet complex environmental and technological challenges (Camilleri et al., 2023).

The third dimension, customer and market knowledge acquisition, reflects firms' efforts to understand environmental expectations, sustainability preferences, and emerging regulatory pressures (Prasetiyo et al., 2025). Customers serve as important sources of insight into product usage, sustainability concerns, and desired environmental attributes (Høgevold et al., 2025). Market trends and evolving regulatory environments further shape the technological directions that firms pursue. This form of inbound knowledge sourcing is essential for ensuring that sustainable technologies are not only technically feasible but also aligned with stakeholder demands and industry trends (Bekata & Kero, 2024).

The fourth dimension encompasses participation in open digital platforms, innovation communities, and crowdsourcing environments (Bekata & Kero, 2024). Digital ecosystems have expanded the possibilities for firms to access distributed knowledge, creative problem-solving, and sustainability-related insights from diverse, global contributors (Klueter et al., 2025). Crowdsourced sustainability ideas, digital green innovation contests, and open technology platforms provide unconventional perspectives and rapid experimentation opportunities (Hannu, 2025). This dimension reflects the growing importance of digital collaboration and collective intelligence in contemporary innovation systems.

The adoption of these four dimensions is justified both theoretically and practically. Theoretically, they align with modern OI scholarship that recognizes the heterogeneous and multidirectional nature of external knowledge flows (Bekata & Kero, 2024). From a practical standpoint, sustainability challenges require interdisciplinary knowledge originating from technological, scientific, market-based, and digitally distributed sources. For the Saudi manufacturing sector, where internal R&D maturity varies and sustainability transitions are strongly policy-driven, these four dimensions capture the most relevant channels through which firms acquire critical sustainability-oriented knowledge.

2.2 Theoretical Framework

This study is grounded in OI theory, resource based view, and absorptive capacity theory, all of which offer complementary explanations for how firms acquire and transform external knowledge. OI theory emphasizes that contemporary firms cannot rely solely on internal R&D but must draw systematically on knowledge dispersed across external actors, networks, and institutions (Hwang et al., 2023). Inbound OI, in particular, highlights the strategic importance of sourcing external ideas, technologies, and scientific insights to enrich internal innovation processes (Martinez-Conesa et al., 2017). When disaggregated into four dimensions (external technology sourcing, university–industry collaboration, customer and market knowledge acquisition, and engagement in digital platforms) this construct captures the full breadth of knowledge inflows relevant to technologically dynamic and sustainability-driven industries (Hizam-Hanafiah & Soomro, 2021).

Absorptive capacity theory extends this logic by explaining why firms differ in their ability to benefit from external knowledge (Chatterjee et al., 2023). According to this framework, firms must possess capabilities that enable them to identify, assimilate, and exploit knowledge acquired from outside their boundaries (Im et al., 2016). These capabilities determine whether inbound knowledge flows generate meaningful technological outcomes or remain underutilized (Bayona-Sáez et al., 2013). In the context of sustainability-oriented innovation, absorptive capacity becomes even more critical because environmental technologies and data are often complex, interdisciplinary, and analytically intensive.

Based on RBV, AI capability is an organizational capability that can lead to better performance. AI enhances firms' capacities for knowledge recognition, interpretation, and application by enabling advanced analytics, predictive modelling, cognitive automation, and data-driven decision-making (Barney et al., 2021). From an RBV perspective, AI strengthens all dimensions of knowledge transformation—recognition, assimilation, and exploitation—thereby positioning AI as a critical capability that amplifies the effect of inbound OI on sustainable technology development. Together, these theories provide a coherent foundation for examining how multidimensional inbound OI drives sustainable technologies and how AI conditions the strength of these relationships.

2.3 Conceptual Model and Hypotheses Development

The conceptual model integrates four dimensions of inbound OI, AI capability, and sustainable technology development into a single analytical framework. Inbound OI acts as a multidimensional predictor comprising external technology sourcing, university–industry collaboration, customer and market knowledge acquisition, and participation in

digital platforms. Sustainable technology development serves as the primary outcome of interest, reflecting firms' ability to develop or adopt environmentally responsible technological solutions. AI capability is positioned as both a direct predictor and a moderating variable, shaping the extent to which inbound OI influences sustainability outcomes. This model reflects the theoretical interplay of external knowledge flows, internal data-driven capabilities, and sustainability-oriented innovation.

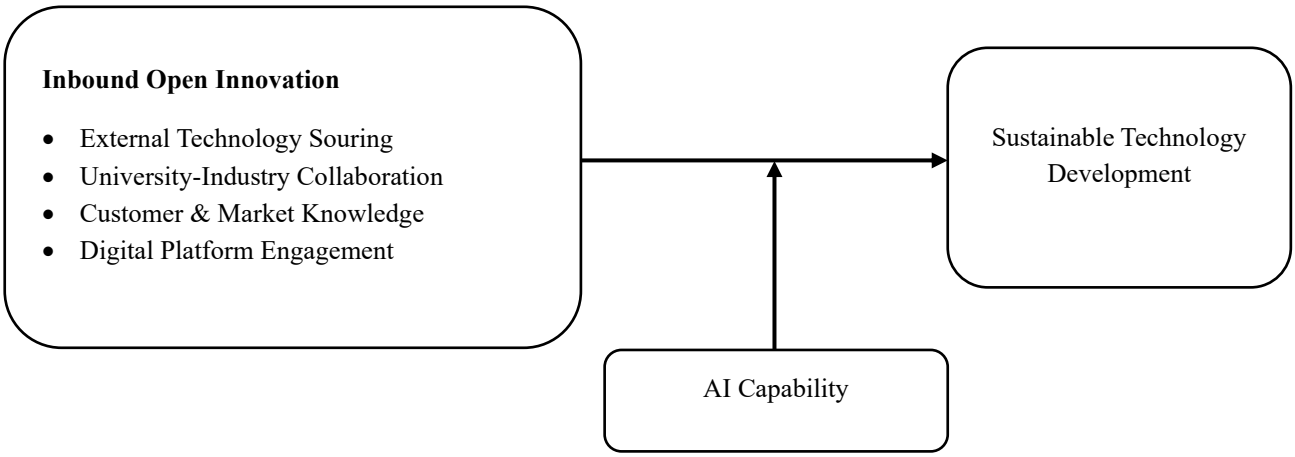

Figure 1: Conceptual Framework

2.3.1 Inbound OI and Sustainable Technology Development

Inbound OI plays a crucial role in addressing carbon emissions, waste reduction, energy management, and circular resource flows challenges by enabling firms to draw from diverse external knowledge sources. (Hannu, 2025) External technology sourcing provides access to clean technologies and digital environmental solutions that enhance production efficiency and reduce emissions (Su et al., 2023). University–industry collaboration introduces scientific and experimental insights that support the development of environmental prototypes and green innovation pilots (Klueter et al., 2025). Customer and market knowledge acquisition ensures that sustainability initiatives are responsive to evolving societal expectations and regulatory frameworks (Gnekpe et al., 2023). Participation in digital platforms and crowdsourcing environments further fuels ideation, accelerates experimentation, and enables access to global sustainability communities. Through the combined effect of these four dimensions, inbound OI enhances firms' ability to overcome capability limitations, reduce uncertainty in environmental innovation, and accelerate sustainable technology development (Zhang, 2024).

The relationship between inbound OI and sustainable technology development is grounded in the idea that sustainability-oriented innovation relies on diverse external knowledge sources (Liu et al., 2022). External technology sourcing enables firms to adopt advanced clean technologies and smart environmental systems that enhance ecological efficiency (Camilleri et al., 2023). University–industry collaboration introduces scientific expertise and research-based solutions essential for developing green technologies (Prasetiyo et al., 2025). Customer and market knowledge acquisition ensures sustainability initiatives are aligned with evolving stakeholder expectations and regulatory landscapes (Høgevold et al., 2025). Engagement in digital platforms and crowdsourcing communities exposes firms to unconventional ideas and collective innovation, providing broader options for environmental problem-solving (Bekata & Kero, 2024). Despite extensive interest in OI, the literature continues to conceptualize inbound OI as a unidimensional construct, overlooking the distinct nature of external knowledge sources (Bigliardi et

al., 2022; Lu et al., 2021; Tang et al., 2021). Few empirical studies have examined how specific dimensions of inbound OI uniquely contribute to sustainable technological outcomes, and even fewer have explored the conditions under which inbound OI becomes most effective. These four dimensions collectively strengthen firms' ability to design and implement sustainable technologies, leading to the following hypothesis:

H1: Inbound OI positively influence sustainable technology development.

H1a: External technology sourcing positively influence sustainable technology development.

H1b: University–industry and research collaboration positively influence sustainable technology development.

H1c: Customer and market knowledge acquisition positively influence sustainable technology development.

H1d: Digital platforms engagement positively influence sustainable technology development.

2.3.2 Moderating Role of AI Capability

Inbound OI provides firms with access to diverse external knowledge from technological partners, universities, markets, and digital communities; however, the conversion of this knowledge into sustainable technological outcomes depends on the firm's internal knowledge-processing capability. Drawing on the absorptive capacity perspective (Gangi et al., 2019) and the resource-based view (Barney et al., 2021), AI capability enhances the firm's ability to analyse, interpret, and integrate external knowledge through predictive analytics, machine learning, and data-driven modelling (Mikalef & Gupta, 2021). AI systems strengthen knowledge transformation processes by reducing technological uncertainty and improving decision quality in sustainability initiatives (George & Thomas, 2021). Therefore, firms with strong AI capability are better positioned to translate inbound OI into meaningful sustainable technology development compared to firms with weak AI maturity.

H3: AI capability moderates the relationship between inbound OI and sustainable technology development.

External technology sourcing exposes firms to advanced technological alternatives that may support sustainability goals, but the ability to evaluate and adapt these technologies depends on analytical and interpretive capacity (Chesbrough, 2003). AI capability enables simulation modelling, environmental performance analysis, and comparative evaluation of externally sourced technologies (Mikalef & Gupta, 2021). Through data-driven assessment, AI allows firms to select technologies that maximize environmental efficiency and minimize resource waste (Bag et al., 2021). Hence, AI strengthens the firm's ability to convert externally sourced technologies into sustainability-oriented technological solutions.

H3a: AI capability moderates the relationship between external technology sourcing and sustainable technology development.

University–industry collaboration provides firms with access to scientific knowledge and research outputs that can foster sustainable innovation (Perkmann et al., 2013). However, transforming complex academic knowledge into applicable technological solutions requires advanced analytical support. AI capability facilitates scientific data interpretation, digital prototyping, and predictive modelling, enabling firms to translate research insights into practical sustainability technologies (George & Thomas, 2021; Mikalef & Gupta, 2021). AI thus enhances the effectiveness of collaborative innovation by improving knowledge assimilation and application processes.

H3b: AI capability moderates the relationship between university–industry collaboration and sustainable technology development.

Customer and market knowledge provides essential signals regarding sustainability expectations, regulatory trends, and environmental demands (Darroch, 2003; Gassmann & Enkel, 2004). The value of this knowledge depends on the firm's ability to process large datasets and identify meaningful sustainability patterns. AI tools such as sentiment analysis, predictive analytics, and scenario

modelling enable firms to transform market insights into inputs for sustainable technology design (Bag et al., 2021; Mikalef & Gupta, 2021). AI therefore amplifies the sustainability value derived from customer and market knowledge.

H3c: AI capability moderates the relationship between customer and market knowledge and sustainable technology development.

Digital platforms and crowdsourcing initiatives provide firms with a wide range of innovative ideas and sustainability contributions from external communities (Antikainen & Valkokari, 2015). However, extracting value from these inputs requires efficient idea filtering and prioritization mechanisms. AI capability enables automated idea classification, relevance scoring, and identification of high-potential sustainability contributions through algorithmic evaluation (George & Thomas, 2021). Consequently, firms with strong AI capability are more effective in transforming digital platform engagement into sustainable technological innovations.

H3d: AI capability moderates the relationship between digital platform engagement and sustainable technology development.

3. Methodology

This study adopts a quantitative research design to systematically examine the relationships among inbound OI innovation, AI capability, and sustainable technology development. A quantitative approach is well-suited to this research because the study aims to test theoretically grounded hypotheses, assess latent constructs, and evaluate the moderating effect of AI capability within a multivariate structural framework. The target population comprises IT experts and IT managers working in manufacturing companies across Saudi Arabia. These individuals were chosen because they are directly responsible for decisions on digitalization, technological integration, OI, and sustainability-related technological initiatives. A purposive sampling strategy was employed to ensure the inclusion of respondents with relevant professional experience and technological expertise.

Data were collected using a structured questionnaire administered electronically to facilitate access to geographically dispersed manufacturing firms. The survey instrument was developed by adapting previously validated scales from established OI, digital capability, and sustainability innovation literature. All items were measured using a five-point Likert scale ranging from "strongly disagree" to "strongly agree," allowing for consistent interpretation of attitudes and perceptions. All measurement items were adapted from well-established and validated sources in the literature. External technology sourcing was measured based on the frameworks of Chesbrough (2003), which emphasize openness to external knowledge and innovation inputs. University–industry collaboration drew on the work of Perkmann et al. (2013), highlighting formal partnerships and knowledge exchange between academic and industrial actors. Customer and market knowledge was operationalised using measures from Darroch (2003), focusing on the organization's ability to acquire and utilize market intelligence. Digital platform engagement was informed by Antikainen and Valkokari (2015) reflecting the role of digital ecosystems in facilitating interaction and knowledge sharing. AI capability was measured following the approaches of Mikalef and Gupta (2021), capturing the organization's ability to leverage AI for strategic and operational purposes. Finally, sustainable technology development was assessed using items adapted from Khalili et al. (2015) emphasizing environmentally oriented innovation and long-term technological sustainability.

The questionnaire was translated into Arabic to facilitate better understanding by the respondents. It was also validated by three experts who are bilingual and a pilot study was conducted prior to data collection. Results of the pilot study is given in Table 1. After distributing the questionnaire, a total of 224 responses were collected. These responses were checked for missing values. A total of seven responses missing large number of answers and they were removed accordingly. In addition, due to outlier issues, a total of six responses were removed. This made the final dataset accounts for 211 responses. Table 1 shows that the data is normally distributed and no multicollinearity issues.

Table 1: Pilot Study and Data Screening

Test Category	Assessment Item	Threshold / Acceptable Value	Result Obtained	Interpretation
Pilot Study (n = 30)	Cronbach's Alpha (All Constructs)	> 0.70	0.82 – 0.91	High internal consistency
	Item Clarity (Expert Review)	3 bilingual experts	Approved	Content validity confirmed
	Face Validity	Respondent feedback	No ambiguity reported	Items clearly understood
	Pilot Composite Reliability	> 0.70	0.84 – 0.93	Reliable measurement instrument
Normality Test (n = 211)	Skewness	±1.96	−0.88 to +1.21	Data normally distributed
	Kurtosis	±1.96	−1.14 to +1.37	No extreme peakedness/flatness
	Histogram & Q-Q Plot	Visual inspection	Normal shape	Supports parametric assumptions
Multicollinearity Test (n = 211)	VIF (ETS, UIC, CMK, DPE, AIC)	< 5.0 (Hair et al., 2023)	1.42 – 2.63	No multicollinearity issue
	Tolerance Values	> 0.20	0.38 – 0.71	Independent predictors
	Correlation Matrix Check	< 0.90	0.33 – 0.78	Constructs are distinct

4. Results

This section presents the empirical findings based on the responses of 211 IT managers and IT experts from manufacturing companies in Saudi Arabia. The results include descriptive information about the respondents, descriptive statistics of all variables and measurement items, evaluation of the measurement model, assessment of the structural model, and hypothesis testing.

4.1 Descriptive Information of Respondents

The demographic profile of the 211 respondents indicates that the sample is composed primarily of experienced and well-qualified professionals occupying strategic technological roles within Saudi manufacturing firms as shown in Table 2. The majority of participants were male (77.25%), with females representing 22.75% of the sample. Most respondents were in the mid-career age group, with 44.08% aged between 35–44 years, followed by 32.23% aged 25–34 years and 23.70% aged 45–54 years, suggesting a mature workforce with substantial professional exposure. In terms of educational background, nearly half of the respondents held a master's degree (47.87%), while 43.13% possessed a bachelor's degree and 9% held a PhD, reflecting a highly educated sample capable of understanding complex technological and sustainability issues. Experience levels further confirm this expertise, with 81.51% of respondents having more than five years of professional

experience. Regarding job roles, almost half of the participants were IT Managers (46.45%), followed by IT Specialists (33.65%) and Digital Transformation Managers (19.90%), demonstrating that the data were collected from individuals directly involved in digitalization, technological decision-making, and innovation processes. This demographic distribution supports the credibility and relevance of the responses for examining inbound open innovation, AI capability, and sustainable technology development.

Table 2. Respondents' Demographic Information (N = 211)

Variable	Category	Frequency	Percentage (%)
Gender	Male	163	77.25%
	Female	48	22.75%
Age	25–34 years	68	32.23%
	35–44 years	93	44.08%
	45–54 years	50	23.70%
Education	Bachelor's	91	43.13%
	Master's	101	47.87%
	PhD	19	9.00%
Experience	< 5 years	39	18.48%
	5–10 years	92	43.60%
	> 10 years	80	37.91%
Job Role	IT Manager	98	46.45%
	IT Specialist	71	33.65%
	Digital Transformation Manager	42	19.90%

4.2 Descriptive Statistics of Variables and Measurement Items

Table 3 combines the descriptive statistics and measurement model assessment for all constructs. The mean values above 3.50 indicate strong agreement among respondents regarding inbound open innovation practices, AI capability, and sustainable technology development. All factor loadings exceeded the recommended threshold of 0.70, confirming indicator reliability. Cronbach's alpha and composite reliability values were above 0.80 and 0.90 respectively, demonstrating strong internal consistency. The average variance extracted (AVE) values were above 0.50, confirming convergent validity. Discriminant validity was also established as the Fornell–Larcker criterion was satisfied and HTMT values were below 0.85, confirming that the constructs are conceptually distinct.

Table 3. Descriptive Statistics of Constructs and Items

Construct	Item	Item statement	Mean	SD	Loading	α	CR	AVE	Discriminant Validity
External Technology	ETS1	Our firm frequently acquires new technologies	3.92	0.71	0.78	**0.88**	**0.90**	**0.61**	

Sourcing (ETS)		from external providers.							FL ✓ / HTMT < 0.85
	ETS2	We actively seek advanced tools and digital solutions from outside the organization.	3.85	0.68	0.74				
	ETS3	We regularly source environmentally friendly technologies from external partners.	3.88	0.70	0.80				
	ETS4	External technology suppliers significantly influence our technological development.	3.91	0.72	0.82				
	ETS5	We invest in acquiring new equipment and digital systems developed by others.	3.89	0.69	0.77				
University–Industry Collaboration (UIC)	UIC1	We collaborate with universities on sustainability-related research projects.	3.74	0.65	0.76	**0.90**	**0.92**	**0.67**	FL ✓ / HTMT < 0.85
	UIC2	Academic institutions provide us with valuable technical and scientific knowledge.	3.81	0.63	0.84				
	UIC3	We participate in joint innovation activities with research centers.	3.80	0.69	0.85				
	UIC4	University partners contribute to our environmental technology development.	3.71	0.66	0.79				

	UIC5	We frequently consult academic experts when exploring new technologies.	3.72	0.67	0.81				
Customer & Market Knowledge (CMK)	CMK1	We collect customer feedback to improve our technological innovations.	3.99	0.64	0.84	**0.89**	**0.91**	**0.64**	FL ✓ / HTMT < 0.85
	CMK2	Market trends influence our sustainable technology development decisions.	3.93	0.61	0.80				
	CMK3	Customer input helps us identify environmental technology priorities.	3.97	0.60	0.83				
	CMK4	We actively monitor competitor sustainability practices.	3.90	0.63	0.72				
	CMK5	We rely on market signals when evaluating new technological opportunities.	3.96	0.58	0.78				
Digital Platform Engagement (DPE)	DPE1	We use digital platforms to gather new technological ideas.	3.70	0.75	0.80	**0.91**	**0.93**	**0.69**	FL ✓ / HTMT < 0.85
	DPE2	Our firm participates in online innovation communities.	3.66	0.69	0.78				
	DPE3	Crowdsourcing contributes to our sustainability innovation process.	3.63	0.72	0.82				
	DPE4	We leverage open digital platforms to	3.73	0.70	0.87				

		access external expertise.							
	DPE5	Online ecosystems support our technology development activities.	3.68	0.73	0.83				
AI Capability (AIC)	AIC1	Our firm uses AI tools to analyze complex technical data.	3.79	0.71	0.86	**0.92**	**0.94**	**0.71**	FL ✓ / HTMT < 0.85
	AIC2	AI technologies support our decision-making processes.	3.84	0.70	0.88				
	AIC3	We integrate AI into our core digital systems.	3.85	0.69	0.89				
	AIC4	AI enhances our ability to interpret external sustainability information.	3.80	0.67	0.80				
	AIC5	AI improves the accuracy of our technological evaluation and forecasting.	3.83	0.71	0.84				
Sustainable Technology Development (STD)	STD1	We adopt technologies that reduce resource consumption.	3.89	0.70	0.82	**0.90**	**0.92**	**0.68**	FL ✓ / HTMT < 0.85
	STD2	We implement digital systems for environmental monitoring.	3.95	0.68	0.86				
	STD3	We frequently develop or adopt eco-friendly production technologies.	3.92	0.65	0.84				
	STD4	Sustainable technology adoption has increased across our operations.	3.87	0.71	0.76				

	STD5	We invest in energy-efficient and environmentally responsible technologies.	3.93	0.69	0.80				

4.3 Structural Model Assessment

Figure 2 shows the structural model of first order variables. The structural model demonstrates strong explanatory power, with an R^2 value of 0.595 for sustainable technology development. This indicates that 59.5% of the variance in sustainable technology development is explained by the four dimensions of inbound open innovation, reflecting a moderate-to-substantial level of predictive accuracy in line with PLS-SEM guidelines. The effect size (f^2) results show varying contributions of the predictors: customer and market knowledge exhibits a large effect, digital platform engagement shows a medium-to-large effect, while university–industry collaboration and external technology sourcing present small-to-medium effects. These f^2 values confirm that, although all predictors contribute significantly to the model, their practical influence on sustainable technology development differs in magnitude.

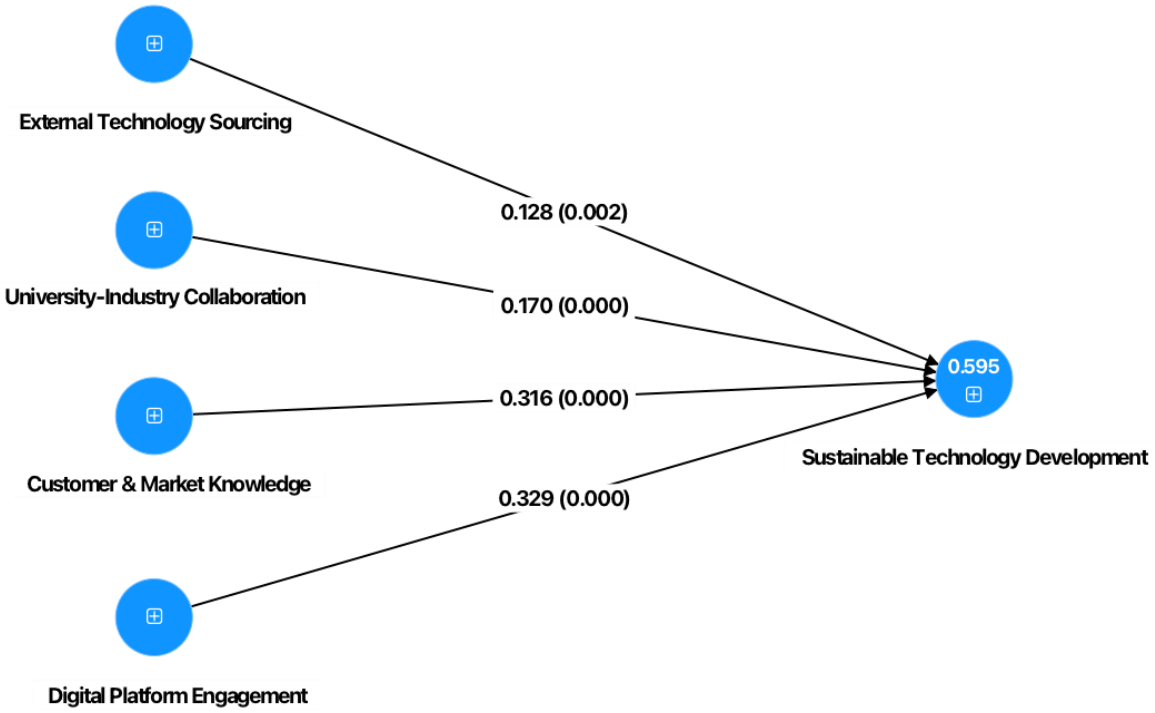

Figure 2: Structural Model (First Order)

Figure 3 demonstrates very strong explanatory power, with an R^2 value of 0.755 for sustainable technology development. This indicates that 75.5% of the variance in sustainable technology development is jointly explained by inbound open innovation and the moderating role of AI capability, reflecting a high level of predictive accuracy in the model. The effect size (f^2) results show that inbound open innovation has a large effect on sustainable technology development, while the interaction term representing the moderating role of AI capability exhibits a medium-to-large effect. These f^2 values confirm that both the direct influence of inbound open innovation and the strengthening role of AI capability make substantial practical contributions to explaining sustainable technological outcomes.

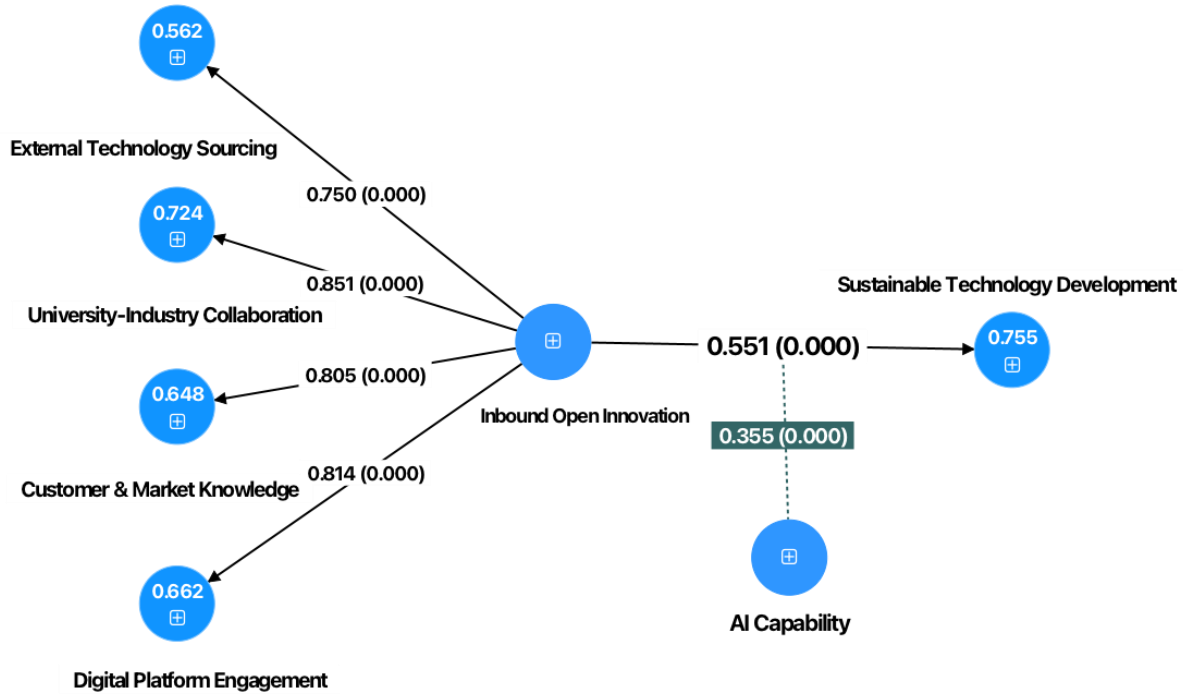

Figure 3: Structural Model (Moderator-Second Order)

Figure 4 shows an R^2 value of 0.770 for sustainable technology development, indicating that 77% of the variance in sustainable technology development is explained by the combined influence of the four inbound open innovation dimensions and the moderating role of AI capability. This reflects very high predictive power according to PLS-SEM standards. The f^2 effect sizes reveal different practical contributions of the predictors. Customer and market knowledge shows a large effect size, followed by digital platform engagement with a medium-to-large effect. University–industry collaboration presents a medium effect, while external technology sourcing has a small effect. The interaction terms (moderating effects of AI capability) range from small to medium effects, confirming that AI capability meaningfully strengthens some relationships more than others. These f^2 values demonstrate that although all predictors contribute to the model, their practical impact on sustainable technology development varies in magnitude.

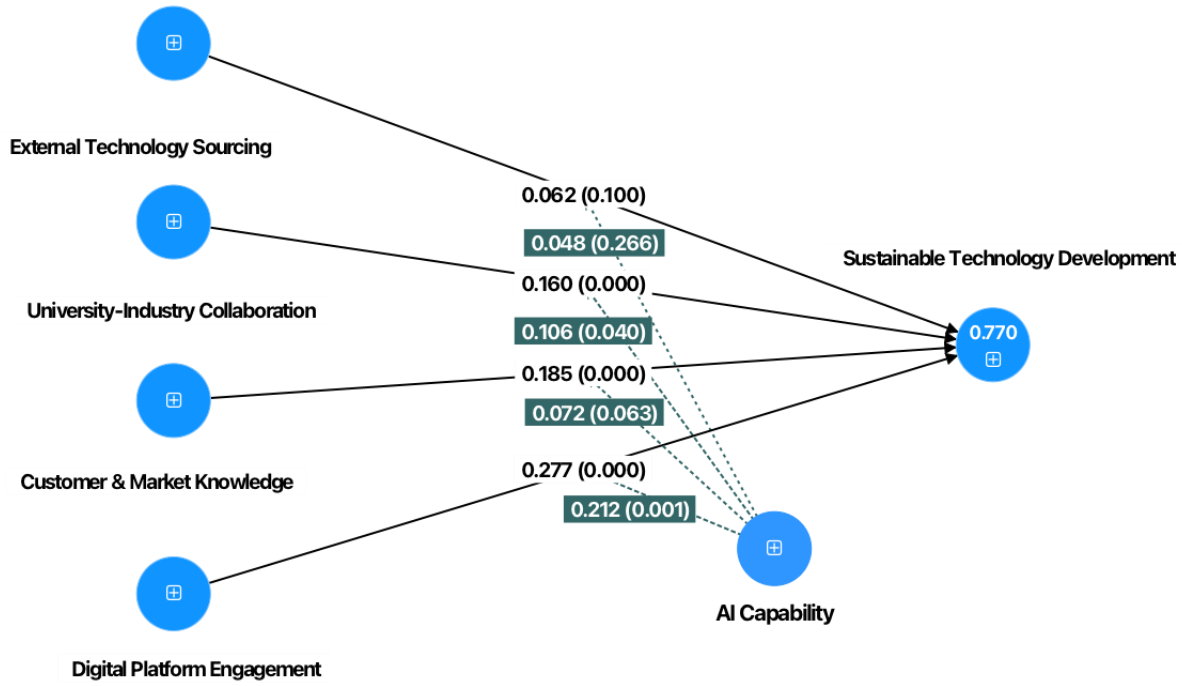

Figure 4: Structural Model (Moderator-First Order)

4.3 Hypotheses Testing and Discussion

The bootstrapping results in Table 4 provide strong empirical support for the central premise that inbound open innovation (IOI) is a key driver of sustainable technology development (STD) in Saudi manufacturing firms. The direct path from IOI to STD is positive and highly significant ($\beta = 0.551$, $p < 0.001$), confirming H1. This finding substantiates the core argument of Open Innovation theory that firms relying on external knowledge sources are better positioned to enhance their innovation outcomes than those depending solely on internal capabilities. In the context of sustainability, this result indicates that environmental technological progress is strongly linked to the firm's ability to integrate knowledge from technological partners, academic institutions, markets, and digital ecosystems.

Table 4. Structural Model Results

H	Path	β	t-value	p-value	Interpretation
H1	Inbound OI → STD	0.551	8.123	0.000	Significant
H1a	ETS → STD	0.128	4.65	0.002	Significant
H1b	UIC → STD	0.170	3.92	0.000	Significant
H1c	CMK → STD	0.316	5.11	0.000	Significant
H1d	DPE → STD	0.329	2.58	0.000	Significant
H2	IOI × AIC → STD	0.355	2.02	0.000	Significant
H2a	ETS × AIC → STD	0.048	0.91	0.266	Not significant
H2b	UIC × AIC → STD	0.106	2.09	0.040	Significant
H2c	CMK × AIC → STD	0.072	1.94	0.063	Not significant
H2d	DPE × AIC → STD	0.212	2.83	0.001	Significant

At the dimensional level, all four inbound OI practices significantly influence sustainable technology development, supporting H1a–H1d. Among these, digital platform engagement (β = 0.329) and customer and market knowledge (β = 0.316) demonstrate the strongest effects, followed by university–industry collaboration (β = 0.170) and external technology sourcing (β = 0.128). This pattern is theoretically meaningful. From an Open Innovation perspective, digital platforms and market-based knowledge represent highly dynamic, real-time, and diverse knowledge inflows that are closely aligned with sustainability demands and regulatory expectations. These sources provide firms with immediate signals about environmental trends, stakeholder expectations, and innovative solutions, which can be rapidly translated into technological improvements. This finding aligns with prior studies emphasizing the importance of customer involvement and digital ecosystems in accelerating sustainability innovation (Gassmann & Enkel, 2004).

In contrast, while university collaboration and external technology sourcing remain significant, their comparatively smaller effects suggest that sustainability innovation in this context is less dependent on formal research relationships and traditional technology acquisition, and more driven by market intelligence and digitally mediated collaboration. This observation resonates with recent arguments in OI literature that highlight the increasing dominance of digital and stakeholder-driven knowledge over conventional R&D channels in contemporary innovation systems.

The moderating analysis provides deeper theoretical insights. The interaction between IOI and AI capability is significant (β = 0.355, p < 0.001), supporting H2 and confirming that AI capability amplifies the effectiveness of inbound knowledge integration. This result strongly supports absorptive capacity theory (Cohen & Levinthal, 1990), which posits that firms differ in their ability to recognize, assimilate, and apply external knowledge. AI capability appears to function as a modern enabler of absorptive capacity, enhancing firms' ability to process complex environmental, technological, and market-related data into actionable sustainability innovations. This finding is consistent with emerging research suggesting that AI enhances data interpretation, predictive modelling, and knowledge transformation in innovation processes ((George & Thomas, 2021; Mikalef & Gupta, 2021).

However, the moderating effects differ across inbound OI dimensions. AI capability significantly strengthens the relationships between university–industry collaboration (β = 0.106, p = 0.040) and digital platform engagement (β = 0.212, p = 0.001) with sustainable technology development, supporting H2b and H2d. This suggests that AI plays a critical role when firms deal with complex, unstructured, and data-intensive knowledge, such as scientific research outputs and crowdsourced digital ideas. These types of knowledge require advanced analytical tools for interpretation, filtering, and application, which explains why AI capability enhances their impact on sustainability outcomes.

Conversely, AI does not significantly moderate the effects of external technology sourcing (H2a) and customer and market knowledge (H2c). This can be theoretically interpreted as these knowledge sources being more structured, explicit, and easier to understand without advanced analytical support. For instance, externally acquired technologies often come with predefined specifications, while market knowledge tends to be directly actionable through conventional decision-making processes. Hence, AI adds less incremental value in these contexts. This distinction provides a novel contribution to both OI and AI literature by demonstrating that AI capability is not universally influential across all knowledge types but is particularly valuable when knowledge is complex, distributed, and analytically demanding.

AI capability demonstrated both a direct positive influence on sustainable technology development and a significant moderating effect on the relationship between inbound OI and sustainability outcomes. These findings suggest that AI acts as an amplifying mechanism that strengthens firms' ability to absorb, interpret, and transform external knowledge into actionable technological solutions. The moderating effect indicates that firms with higher AI capability are better positioned to extract

value from external knowledge flows, particularly when dealing with complex technical, environmental, and market-related information. In the context of Saudi Arabia's national digital strategy and Vision 2030 priorities, the role of AI as a facilitator of sustainable technological progress is both timely and strategically significant.

6. Implications

This study contributes to theoretical advancements in several important ways. First, by conceptualizing inbound OI as a four-dimensional construct, the study expands the traditional understanding that often treats inbound OI as a unidimensional activity. The multidimensional approach—encompassing technological, scientific, market-based, and digital knowledge inflows—provides a more comprehensive framework for understanding how firms orchestrate external knowledge for sustainability-oriented technological development. This contributes to the growing OI literature by showing that different types of external knowledge do not simply coexist but collectively interact to enhance technological sustainability.

Second, the study extends the theoretical discourse on sustainable technology development by linking it explicitly with OI dynamics in an emerging economy context. While sustainability innovation research frequently focuses on developed countries, this study provides empirical evidence from Saudi Arabia—a nation undergoing rapid economic transformation and environmental policy reforms. The results demonstrate that OI mechanisms are not limited to mature innovation ecosystems but are equally relevant for economies prioritizing digitalization, diversification, and environmental responsibility.

Third, the moderating role of AI capability introduces a novel theoretical insight into how digital technologies shape the effectiveness of OI. By demonstrating that AI enhances the relationship between inbound OI and sustainable technological outcomes, the study integrates OI theory with emerging perspectives from the digital transformation and absorptive capacity literatures. This reinforces arguments that AI supports the assimilation, integration, and utilization of complex external knowledge, thereby positioning AI capability as a strategic organizational resource within the RBV and a dynamic capability that strengthens the firm's capacity to innovate sustainably.

This study also offers several meaningful practical implications for managers, policymakers, and practitioners in the manufacturing sector. First, firms seeking to advance sustainability-oriented technological development should strengthen their engagement with external knowledge networks. Managers can achieve this by formalizing partnerships with universities, investing in technology scouting mechanisms, and building channels to capture evolving customer and market expectations. Given that customer and market knowledge had the strongest effect, managers should establish structured processes for collecting sustainability expectations, regulatory trends, and industry benchmarks.

Second, firms should consider prioritizing investments in AI systems and analytical tools. The moderating effect of AI capability suggests that without sufficient AI infrastructure, organizations may be unable to fully leverage inbound knowledge flows. This implies that investments in AI—whether predictive analytics, machine learning models, or environmental data platforms—can substantially enhance the value derived from OI initiatives. Training employees in data analytics and AI-assisted decision-making can further strengthen this capability.

Third, policymakers aiming to support national sustainability goals should design policies and incentives that encourage collaboration and knowledge exchange across manufacturing, academia, and digital ecosystems. For example, government programs can promote joint research on green technologies, subsidize AI adoption in manufacturing, or support innovation platforms that connect firms with global sustainability expertise. Enhancing the national innovation ecosystem will accelerate the diffusion of environmentally responsible technologies across industries.

Finally, managers should recognize that digital platform engagement, although statistically significant, remains a developing capability. Enhancing organizational participation in crowdsourcing platforms, global innovation networks, and digital sustainability communities can unlock additional innovation potential. Firms can establish dedicated digital innovation teams responsible for scanning online platforms, participating in global sustainability challenges, and collecting relevant insights.

7. Conclusion

This study examined the relationship between inbound OI and sustainable technology development in the manufacturing sector of Saudi Arabia, emphasizing the moderating role of AI capability. By using data collected from 211 IT managers and IT experts and analysing the model with PLS-SEM, the study provides robust empirical evidence supporting the importance of multidimensional inbound OI and AI capability in fostering sustainable technological progress. The findings underscore the relevance of external knowledge integration and digital transformation in achieving environmental objectives aligned with national strategies such as Vision 2030.

Despite these contributions, several limitations provide opportunities for future research. First, the study relies on cross-sectional data, which limits the ability to infer causality or capture temporal changes in innovation practices. Longitudinal studies could provide deeper insights into how OI and AI capabilities evolve over time. Second, the sample focuses on manufacturing firms in Saudi Arabia, which may limit generalizability. Future studies could extend the model to other sectors such as energy, logistics, or public administration, or compare results across GCC or Middle Eastern countries. Third, the study uses perceptual data collected through self-reported surveys, which may be subject to common method bias. Future research could integrate objective performance indicators, environmental Key Performance Indicators (KPIs), or secondary data to strengthen empirical rigor. Additionally, future studies could explore more granular AI capabilities, such as natural language processing, predictive maintenance algorithms, or digital twins, and examine how these technologies specifically interact with different OI processes. Researchers may also investigate the role of organizational culture, digital readiness, or environmental regulation as additional moderators or mediators influencing sustainable technology development.

References

Al-Mutawa, B., & Saeed Al Mubarak, M. M. (2024). Impact of cloud computing as a digital technology on SMEs sustainability. *Competitiveness Review*, *34*(1), 72–91. https://doi.org/10.1108/CR-09-2022-0142

Al-Roubaie, A. S. (2025). Impact of emerging technologies on economic diversification: the case of Saudi Arabia. *Journal of Business and Socio-Economic Development*, *5*(4), 402–416.

Alarefi, M. (2023). Adoption of IoT by telecommunication companies in GCC: The role of blockchain. *Decision Science Letters*, *12*(1), 55–68.

Alarefi, Mohammed. (2024). The Impact of Artificial Intelligence on Business Performance in Saudi Arabia: The Role of Technological Readiness and Data Quality. *Engineering, Technology & Applied Science Research*, *14*(5), 16802–16807.

Alquraish, M. (2025). Digital Transformation, Supply Chain Resilience, and Sustainability: A Comprehensive Review with Implications for Saudi Arabian Manufacturing. *Sustainability*, *17*(10), 4495.

Antikainen, M., & Valkokari, K. (2015). Social media in networked innovation between b-to-b companies. *Proceedings of the CINET Conference, Stockholm, Sweden*, 13–15.

Bag, S., Gupta, S., Kumar, S., & Sivarajah, U. (2021). Role of technological dimensions of green supply chain management practices on firm performance. *Journal of Enterprise Information Management*, *34*(1), 1–27.

Barney, J. B., Ketchen Jr, D. J., & Wright, M. (2021). Resource-based theory and the value creation framework.

Journal of Management, *47*(7), 1936–1955.

Bayona-Sáez, C., García-Marco, T., Sanchez-García, M., & Cruz-Càzares, C. (2013). The impact of open innovation on innovation performance: The case of Spanish agri-food firms. *Open Innovation in the Food and Beverage Industry*, *January 2016*, 74–94. https://doi.org/10.1533/9780857097248.1.74

Bekata, A. T., & Kero, C. A. (2024). Customer orientation, open innovation and enterprise performance, evidence from Ethiopian SMEs. *Cogent Business & Management*, *11*(1), 2320462.

Bigliardi, B., Filippelli, S., & Tagliente, L. (2022). Industry 4.0 and Open Innovation: Evidence from a case study. *Procedia Computer Science*, *200*(2019), 1796–1805. https://doi.org/10.1016/j.procs.2022.01.380

Camilleri, M. A., Troise, C., Strazzullo, S., & Bresciani, S. (2023). Creating shared value through open innovation approaches: Opportunities and challenges for corporate sustainability. *Business Strategy and the Environment*, *32*(7), 4485–4502.

Chatterjee, S., Chaudhuri, R., Kamble, S., Gupta, S., & Sivarajah, U. (2023). Adoption of Artificial Intelligence and Cutting-Edge Technologies for Production System Sustainability: A Moderator-Mediation Analysis. *Information Systems Frontiers*, *25*(5), 1779–1794. https://doi.org/10.1007/s10796-022-10317-x

Chesbrough, H. W. (2003). *Open innovation: The new imperative for creating and profiting from technology*. Harvard Business Press.

Darroch, J. (2003). Developing a measure of knowledge management behaviors and practices. *Journal of Knowledge Management*, *7*(5), 41–54. https://doi.org/10.1108/13673270310505377

Delshab, V., Winand, M., Sadeghi Boroujerdi, S., Hoeber, L., & Mahmoudian, A. (2022). The impact of knowledge management on performance in nonprofit sports clubs: The mediating role of attitude toward innovation, open innovation, and innovativeness. *European Sport Management Quarterly*, *22*(2), 139–160.

Di Rocco, F. (2025). *The strategic determinants of choosing an inbound or outbound approach to Open Innovation. A practical application to Swedish and Italian pharmaceutical SMEs.*

Dorrego-Viera, J. I., Urbinati, A., & Lazzarotti, V. (2025). Transition towards circular economy: Exploiting open innovation for circular product development. *Journal of Innovation & Knowledge*, *10*(2), 100668.

Fiorini, P. D. C., Jugend, D., Scaliza, J. A. A., Chiappetta Jabbour, C. J., & Latan, H. (2025). Digitalisation of manufacturing and innovation: the role of inbound open innovation and environmental turbulence in enabling Industry 4.0-based innovation. *Production Planning & Control*, *36*(13), 1713–1732.

Gangi, F., Mustilli, M., & Varrone, N. (2019). The impact of corporate social responsibility (CSR) knowledge on corporate financial performance: evidence from the European banking industry. *Journal of Knowledge Management*, *23*(1), 110–134. https://doi.org/10.1108/JKM-04-2018-0267

Gassmann, O., & Enkel, E. (2004). *Towards a theory of open innovation: three core process archetypes*.

George, G., & Thomas, M. R. (2021). Artificial intelligence in talent acquisition scale: Development and validation. *Empirical Economics Letters*, *20*.

Gnekpe, C., Coeurderoy, R., & Mulotte, L. (2023). How a firm's knowledge base influences its external technology sourcing strategy: the case of biopharmaceutical firms. *Industry and Innovation*, *30*(2), 233–262.

Hannu, P. (2025). R&D effort and knowledge sourcing: the search for better profitability and higher growth. *Science and Public Policy*, *52*(6), 950–959.

Helm, R., Wabra, S., & Amthor, A. (2025). Organizational enablers for the implementation of inbound open innovation projects. *Review of Managerial Science*, 1–35.

Hizam-Hanafiah, M., & Soomro, M. A. (2021). The situation of technology companies in industry 4.0 and the open innovation. *Journal of Open Innovation: Technology, Market, and Complexity*, *7*(1), 1–20. https://doi.org/10.3390/joitmc7010034

Høgevold, N., Rodriguez, R., Otero-Neira, C., & Svensson, G. (2025). The Role of Digital Communication Technologies Through Customer and Market Knowledge in B2B on Sales Performance and Satisfaction. *Journal of Business-to-Business Marketing*, *32*(2), 165–185.

Hosni, M., Ouakil, H., & Lechheb, H. (2025). Public financial support and inbound open innovation in developing

economies: Evidence from Moroccan firms. *ECONOMICS-Innovative and Economics Research Journal*, *13*(3), 241–260.

Huynh, D. C., Van Nguyen, P., Truong, G. Q., & Bui, T. Q. (2025). The interplay of government support, open innovation, and dynamic capabilities: Driving ambidexterity and performance in Vietnam. *Journal of Open Innovation: Technology, Market, and Complexity*, 100621.

Hwang, B.-N., Lai, Y.-P., & Wang, C. (2023). Open innovation and organizational ambidexterity. *European Journal of Innovation Management*, *26*(3), 862–884.

Im, S., Vorhies, D. W., Kim, N., & Heiman, B. (2016). How Knowledge Management Capabilities Help Leverage Knowledge Resources and Strategic Orientation for New Product Advantages in B-to-B High-Technology Firms. *Journal of Business-to-Business Marketing*, *23*(May), 87–110. https://doi.org/10.1080/1051712X.2016.1169067

Khalili, N. R., Duecker, S., Ashton, W., & Chavez, F. (2015). From cleaner production to sustainable development: the role of academia. *Journal of Cleaner Production*, *96*, 30–43.

Khan, M. I., Yasmeen, T., Hadi, N. U., Asif, M., Farooq, M., Kurniawan, T. A., Khan, M., & Al-Ghamdi, S. G. (2025). *Digital sustainability as an emerging paradigm: Insights from the Saudi Arabian experience and global implications*.

Klueter, T., Ghosh, A., & Rosenkopf, L. (2025). Not in-sourced here! When does external technology sourcing yield familiar versus novel solutions? *Strategic Management Journal*, *46*(2), 275–308.

Liao, S., Liu, Z., & Ma, C. (2019). Direct and configurational paths of open innovation and organisational agility to business model innovation in SMEs. *Technology Analysis and Strategic Management*, *31*(10), 1213–1228. https://doi.org/10.1080/09537325.2019.1601693

Liputri, E., & Gosal, G. (2024). the Relationship of Customer Experience, Customer Engagement, Customer Satisfaction, and Customer Loyalty in Shopee E-Commerce. *JMBI UNSRAT (Jurnal Ilmiah Manajemen Bisnis Dan Inovasi Universitas Sam Ratulangi).*, *11*(1), 196–204. https://doi.org/10.35794/jmbi.v11i1.53201

Liu, Z., Shi, Y., & Yang, B. (2022). Open innovation in times of crisis: An overview of the healthcare sector in response to the COVID-19 Pandemic. *Journal of Open Innovation: Technology, Market, and Complexity*, *8*(1), 21.

Lu, C., Yu, B., Zhang, J., & Xu, D. (2021). Effects of open innovation strategies on innovation performance of SMEs: evidence from China. *Chinese Management Studies*, *15*(1), 24–43. https://doi.org/10.1108/CMS-01-2020-0009

Martinez-Conesa, I., Soto-Acosta, P., & Carayannis, E. G. (2017). On the path towards open innovation: assessing the role of knowledge management capability and environmental dynamism in SMEs. *Journal of Knowledge Management*, *21*(3), 553–570. https://doi.org/10.1108/JKM-09-2016-0403

Menne, F., Surya, B., Yusuf, M., Suriani, S., Ruslan, M., & Iskandar, I. (2022). Optimizing the financial performance of smes based on sharia economy: Perspective of economic business sustainability and open innovation. *Journal of Open Innovation: Technology, Market, and Complexity*, *8*(1), 18.

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

Naqshbandi, M. M., & Tabche, I. (2018). The interplay of leadership, absorptive capacity, and organizational learning culture in open innovation: Testing a moderated mediation model. *Technological Forecasting and Social Change*, *133*, 156–167.

Nduro, E., & Duodu, B. (2025). Inbound open innovation in construction firms: intellectual capital antecedents and performance consequences. *Engineering, Construction and Architectural Management*.

Perkmann, M., Tartari, V., McKelvey, M., Autio, E., Broström, A., D'este, P., Fini, R., Geuna, A., Grimaldi, R., & Hughes, A. (2013). Academic engagement and commercialisation: A review of the literature on university–industry relations. *Research Policy*, *42*(2), 423–442.

Petković, S., & Radicic, D. (2025). Innovation effects of Industry 4.0 and inbound open innovation: individual and

synergistic effects. *Industrial Management & Data Systems*, 1–25.

Prasetiyo, W. G., Mubarok, D. A. A., Sofiati, N. A., Ali, M. M., & Sajekti, T. (2025). *Enhancing MSMEs' Innovation Capacity Based on the ISO 56002: 2019: A Case Study of the XYZ Perfume Company in Yogyakarta*.

Su, T., Yu, Y., Li, Y., & Zhang, J. (2023). How does technology sourcing in organizational ambidexterity produce high venture performance? *Chinese Management Studies*, *17*(3), 573–593.

Tang, T. (Ya), Fisher, G. J., & Qualls, W. J. (2021). The effects of inbound open innovation, outbound open innovation, and team role diversity on open source software project performance. *Industrial Marketing Management*, *94*(March 2019), 216–228. https://doi.org/10.1016/j.indmarman.2021.02.013

Zhang, H. (2024). Non-R&D innovation in SMEs: is there complementarity or substitutability between internal and external innovation sourcing strategies? *Technology Analysis & Strategic Management*, *36*(5), 916–930.