International Review of Management and Marketing

ISSN: 2146-4405

available at http: www.econjournals.com

International Review of Management and Marketing, 2026, 16(6), 210-225.

Deciding Under Uncertainty: A Systematic Review and Integrated Theories–Contexts–Methods and Antecedents–Decisions–Outcomes Framework of Artificial Intelligence-Driven Decision-Making in Small and Medium-Sized Enterprises

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Received: 24 March 2026 **Accepted:** 12 July 2026 **DOI:** https://doi.org/10.32479/irmm.24320

ABSTRACT

Despite the transformative potential of artificial intelligence (AI) for organizational decision-making, significant knowledge gaps remain regarding how small and medium-sized enterprises (SMEs) leverage AI under volatile business conditions. This study systematically reviews AI-driven decision-making in SMEs operating under environmental uncertainty. Following the scientific procedures and rationales for systematic literature reviews (SPAR-4-SLR) protocol, we analyze 72 peer-reviewed articles (2018-2025) and develop an integrated theories–contexts–methods and antecedents–decisions–outcomes (TCM–ADO) framework. The findings show that manufacturing is the dominant research context and that Asia, especially China, accounts for 55% of studies, with quantitative cross-sectional surveys the prevailing methodology. AI adoption is shaped by technological, organizational, environmental, and leadership antecedents that influence strategic, operational, financial, and human–AI decision processes; the resulting outcomes span business performance, innovation, sustainability, and resilience. Notably, environmental uncertainty amplifies rather than diminishes AI benefits, positioning AI as an adaptive mechanism during turbulence rather than a barrier. The review contributes an integrated framework that connects how the phenomenon is studied with what is substantively known about it, and it offers a structured agenda for future work. For practitioners, the findings underscore the value of treating AI strategically, building complementary capabilities, and maintaining flexible organizational structures.

Keywords: Artificial Intelligence, Small and Medium-Sized Enterprises, Environmental Uncertainty, Artificial Intelligence-Driven Decision-Making
JEL Classifications: D81, L25, M15, O33

1. INTRODUCTION

The emergence of artificial intelligence (AI) has transformed how organizations operate, compete, and create value in an increasingly complex business landscape (Del Giudice et al., 2023; Qin et al., 2025). With its capacity to process large volumes of data, identify patterns, and generate predictive insights, AI has evolved from an experimental technology into a strategic asset for firms seeking competitive advantage (Gupta et al., 2023; Perifanis and Kitsios, 2023). Its integration into business processes has been particularly consequential for decision-making, enabling firms to respond more effectively to market shifts, customer demands, and operational challenges (Rodgers et al., 2024; Wong and Ngai, 2025). AI-driven decision-making is now recognized as a pivotal innovation that can fundamentally alter how firms process information, evaluate alternatives, and make strategic and operational choices (Aljarboa, 2024; Chen et al., 2022).

At the same time, the global business environment has experienced unprecedented volatility arising from the COVID-19 pandemic, supply chain crises, geopolitical conflict, and rapid technological change (Ho et al., 2022; Rashid et al., 2024; Alquraish, 2025). These disruptions have intensified "environmental uncertainty"—conditions of unpredictability, complexity, and dynamism in which decision-makers lack reliable information about external factors (Han et al., 2025; Kong and Du, 2025). Such uncertainty spans market volatility, technological turbulence, regulatory change, and competitive intensity, straining traditional decision-making approaches that struggle with the volume, velocity, and variety of relevant data (Žigienė et al., 2022; Benzidia et al., 2021). Firms have consequently turned to AI to improve information processing, reduce cognitive bias, and increase decision speed and accuracy under these conditions (Wang and Chen, 2025; Zhang and Wei, 2025).

SMEs occupy a particularly exposed position. Representing 90-95% of businesses worldwide and generating 60-70% of employment, they form the backbone of most economies (Badghish and Soomro, 2024; Schwaeke et al., 2025). However, compared with larger firms, they operate with constrained resources, limited technological infrastructure, and less specialized expertise, which can impede their ability to respond to turbulence (Qu and Kim, 2025; Perifanis and Kitsios, 2023). The literature increasingly recognizes that SMEs face distinct barriers in adopting advanced technologies, including financial constraints, knowledge gaps, and limited organizational readiness (Badghish and Soomro, 2024; Salinas-Navarro et al., 2024).

Prior research on AI in business has concentrated on large organizations with substantial resources and established digital infrastructure (Larbi-Siaw et al., 2022; Chen et al., 2022), examining how AI can strengthen supply chain resilience (Rashid et al., 2024; Kong and Du, 2025), improve customer relationship management (Roy et al., 2025), enable sustainable performance (Khan et al., 2024; Wang et al., 2025), and drive innovation (Corrales-Garay et al., 2024; Bahoo et al., 2023), as well as specific applications in accounting (Bin-Nashwan and Li, 2025), manufacturing (Peretz-Andersson et al., 2024), and entrepreneurship (Giuggioli and Pellegrini, 2023). Despite this growth, important gaps persist regarding how SMEs leverage AI for decision-making under uncertainty. First, although several studies examine AI adoption factors in SMEs (Badghish and Soomro, 2024; Schwaeke et al., 2025), how these firms actually implement and use AI within decision processes remains underexplored; Peretz-Andersson et al. (2024) characterize AI implementation in resource-constrained SMEs as a "dynamic, self-nurturing" journey whose mechanisms are not well understood. Second, the antecedents that enable or inhibit AI-driven decision-making in volatile settings are insufficiently specified (Bin-Nashwan and Li, 2025; Qu and Kim, 2025), and findings are at times contradictory—for example, Han et al. (2025) report that uncertainty can negatively moderate the link between innovation resources and AI orientation. Third, comprehensive frameworks linking AI-enhanced decisions to multidimensional outcomes are rare (Kong and Du, 2025; Wang and Chen, 2025; Khan et al., 2024). Fourth, theoretical treatments remain fragmented across the resource-based view (Vărzaru and Bocean, 2024), dynamic capabilities (Wong and Ngai, 2025), the technology–organization–environment framework (Badghish and Soomro, 2024), and information processing theory (Benzidia et al., 2021), with little integration. Finally, the field is methodologically narrow, dominated by cross-sectional designs (Qu and Kim, 2025; Wang and Chen, 2025) and small-sample qualitative work (Peretz-Andersson et al., 2024), with few longitudinal or mixed-method studies.

These gaps carry practical weight: as SMEs face mounting pressure to digitalize amid rising volatility, the absence of integrative frameworks and actionable evidence impedes effective AI adoption. To address them, this study employs the SPAR-4-SLR methodology (Paul et al., 2021) to assemble, arrange, and assess the literature, guided by three questions:

- RQ1 (How do we know?): What theories, contexts, and methods characterize research on AI-driven decision-making in SMEs under environmental uncertainty?
- RQ2 (What do we know?): What are the antecedents, decisions, and outcomes of AI-driven decision-making in SMEs under environmental uncertainty?
- RQ3 (Where should we be headed?): What research trajectories should be pursued to advance this literature?

The study makes four contributions. It develops an integrated TCM–ADO framework synthesizing the theories–contexts–methods (TCM) framework with the antecedents–decisions–outcomes (ADO) framework; it maps the dominant theoretical, contextual, and methodological paradigms and their emerging alternatives; it specifies the antecedents of AI adoption, the forms of AI-enhanced decision-making, and their multidimensional outcomes; and it advances a future research agenda spanning theoretical, contextual, methodological, and practical considerations. The remainder of the paper presents the methodology, reports the findings across the three research questions, and discusses the theoretical and practical implications, limitations, and conclusions.

2. METHODOLOGY

This review adopts a domain-based, framework-driven approach (Paul and Criado, 2020; Paul et al., 2021) focused on AI-driven decision-making in SMEs under environmental uncertainty. Framework-based content analysis tends to be more impactful and transparent than narrative alternatives (Paul et al., 2021). Following the design used by Wolf (2023), we combine the TCM framework (Paul et al., 2017) with the ADO framework (Paul and Benito, 2018) to clarify both how the phenomenon has been studied and what is known about it, and to indicate where the field should head and how (Bhatia et al., 2021; Khatri and Duggal, 2022; Lim et al., 2021). To ensure a transparent and replicable selection process (Palmatier et al., 2018; Snyder, 2019), we applied the SPAR-4-SLR protocol (Paul et al., 2021), which proceeds through three stages—assembling, arranging, and assessing the literature—as summarized in Figure 1 (Basu et al., 2022; Hassan et al., 2022).

2.1. Assembling

The assembling stage identifies and acquires the literature. Acknowledging the topic's interdisciplinary nature, the review targets peer-reviewed journal articles in business, management, computer science, decision sciences, economics, econometrics,

Figure 1: The systematic literature review using the SPAR-4-SLR protocol

Assembling Phase

Identification
- **Domain:** AI-driven decision-making in SMEs under environmental uncertainty
- **Research Questions:**
  - RQ1 (How do we know?): What theories, contexts, and methods characterize research on AI-driven decision-making in SMEs under environmental uncertainty?
  - RQ2 (What do we know?): What are the antecedents, decisions, and outcomes of AI-driven decision-making in SMEs under environmental uncertainty?
  - RQ3 (Where should we be headed?): What research trajectories should be pursued to advance this literature?
- **Source Type:** Peer-reviewed journal articles to ensure academic rigor and quality
- **Source Quality:** Scopus databases, recognized for their comprehensive coverage and quality standards (Pranckutė, 2021)

Acquisition
- **Databases**: Scopus
- **Search Period:** Until December, 31, 2025, ensuring comprehensive coverage of available literature
- **Search Keywords:** ("artificial intelligence" OR "AI" OR "machine learning" OR "business analytics" OR "predictive analytics" OR "data-driven") AND ("decision making" OR "decision support" OR "decision speed" OR "decision accuracy" OR "strategic decision*") AND ("SME*" OR "small and medium enterprise*" OR "small business*" OR "medium-sized compan*") AND ("performance" OR "ROI" OR "return on investment" OR "market share" OR "business value" OR "competitive advantage") AND ("environmental uncertainty" OR "market volatility" OR "external factor*" OR "business environment")
- **Subject area:** Business, Management and Accounting, Computer Science, Decision Sciences, Economics, Econometrics and Finance
- **Document type:** Article and Review
- **Source type:** Journal
- **Language:** English
- **Search period:** 2018-2025
- **Initial Results:** 1,501 articles in the preliminary dataset

Arranging Phase

Organization
- **Organizing codes:** Theories, contexts (country, industry sector, customer journey stage), methods (research design, sample, data collection, data analysis), antecedents, decisions, outcomes
- **Organizing frameworks:** TCM-ADO framework

Purification
- Inclusion criteria: Article must address the AI-driven decision-making in SMEs under Environmental Uncertainty. Article must include at least one empirical study (quantitative or qualitative)
- Screening and selection:
  - Total number of articles after title and abstract screening: n = 184
  - Total number of articles after assessment for eligibility: n = 78
  - Total number of articles after cross-referencing: n = 72

Assessing Phase

Evaluation
- **Analysis method:** Descriptive analysis of theories, contexts, and methods; Qualitative inductive coding of antecedents, decisions, and outcomes relating to device-mediated customer behavior on the Internet

Reporting
- **Reporting convention:** Frameworks, tables, and words
- **Limitations:** Exclusion of potentially relevant papers (from conferences or non-business journals)
- **Support:** No funding received

and finance. To ensure quality, we searched only the Scopus database, given its comprehensive coverage and rigorous quality standards (Pranckūtė, 2021). A Boolean search string combined terms for AI (e.g., "artificial intelligence," "machine learning," "business analytics"), decision-making (e.g., "decision support," "strategic decision"), SME contexts (e.g., "small and medium enterprises," "small business"), performance (e.g., "ROI," "competitive advantage"), and environmental uncertainty (e.g., "market volatility," "external factors"). Results were limited to the relevant subject areas, to articles and reviews published in English-language journals, and to titles, abstracts, or keywords. Covering 2018-2025, the search returned an initial dataset of 1,501 articles. Scopus was chosen as the sole source for its broad multidisciplinary coverage and consistent indexing; we recognize, however, that relying on a single database may have omitted relevant work indexed elsewhere (e.g., Web of Science), and that incorporating performance- and uncertainty-oriented terms in the search string may have biased the corpus toward studies already framed around these constructs. These choices, together with the exclusion of conceptual and review articles, are revisited as limitations in Section 4.3.

2.2. Arranging

The arranging stage organizes and purifies the literature using the TCM–ADO framework (Paul et al., 2017; Paul and Benito, 2018). Organizing codes were developed for theories; contexts (country and industry sector); methods (research design, sample, data collection, and analysis); and antecedents, decisions, and outcomes related to AI in SME decision-making. Two purification criteria were applied: An article had to address AI-driven decision-making in SMEs under environmental uncertainty explicitly, and it had to report at least one empirical study (other reviews and conceptual works were excluded). Title-and-abstract screening reduced the 1,501 records to 184 potentially relevant articles; full-text eligibility assessment yielded 78; and cross-referencing produced a final corpus of 72 articles. To support transparency and replicability, records were screened against pre-specified inclusion and exclusion criteria at each stage—identification, title-and-abstract screening, full-text eligibility, and cross-referencing—with the number excluded and the principal reasons documented at each step. Coding into the TCM–ADO categories followed a written protocol: all articles were coded by the lead researcher and independently cross-checked by a second reviewer. Rather than computing a formal agreement statistic, coding discrepancies were discussed and reconciled to consensus. Ambiguous cases—for instance, constructs that could function as either antecedents or decision elements—were classified according to the construct's primary role in the source study, with any residual ambiguity resolved through discussion.

2.3. Assessing

The assessing stage evaluates and reports the corpus, both descriptively and thematically (Paul, et al., 2021). Descriptive information was extracted into a concept matrix (Webster and Watson, 2002), recording theories, methods, country, industry sector, and other contextual factors (Snyder, 2019). A descriptive analysis mapped the field's theoretical, geographic, and methodological landscape, while an inductive thematic coding process following Braun and Clarke (2006)—familiarization, initial coding, theme search, review, and definition—identified patterns in antecedents, decisions, and outcomes. The review acknowledges its scope limitations, notably the exclusion of conference proceedings and non-business journals. It reports that no external funding was received, ensuring transparency regarding potential conflicts of interest.

3. RESULTS

3.1. Publication and Outlet Trends

Research on AI-driven decision-making in SMEs under environmental uncertainty is recent and rapidly expanding. As Figure 2 shows, the field was essentially dormant in 2018, with a single article in 2019 and none in 2020. Activity rose modestly in 2021 (two articles) before accelerating sharply: nine articles in 2022, ten in 2023, peaking at 26 in 2024, and 24 in 2025. This trajectory—from obscurity to prominence in roughly 5 years—parallels the diffusion of AI in business and heightened awareness of environmental volatility, with early contributions such as Thamik and Wu (2022) and Sreenivasan et al. (2023) signaling the field's formation.

As Table 1 shows, the 72 articles are distributed across 46 journals, reflecting the topic's multidisciplinary character.

Figure 2: Distribution of articles by year of publication

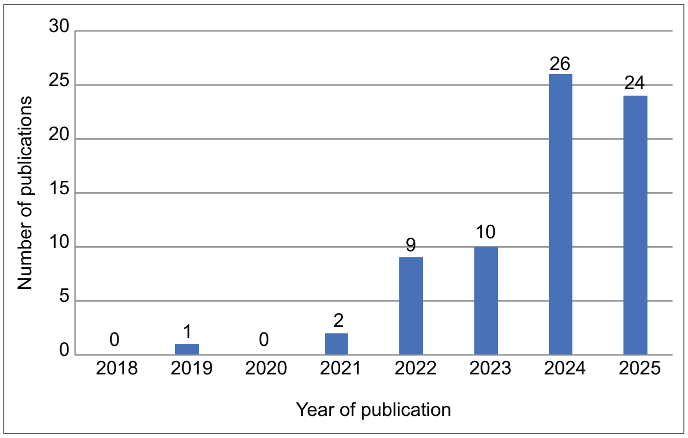


Table 1: Journals disseminating research on AI-driven decision-making in SMEs under environmental uncertainty

No.	Journal	No. of articles	Publisher
1	Sustainability (Switzerland)	10	MDPI
2	Technological forecasting and social change	8	Elsevier
3	Technology in society	5	Elsevier
4	IEEE transactions on engineering management	3	IEEE
5	Asia-Pacific journal of business administration	2	Emerald
6	Business strategy and the environment	2	Wiley
7	IEEE access	2	IEEE
8	International journal of production research	2	Taylor and Francis
9	Annals of operations research	1	Springer
10	Business process management journal	1	Emerald
11	Computers and industrial engineering	1	Elsevier
12	Computers in human behavior reports	1	Elsevier
13	Corporate social responsibility and environmental management	1	Wiley
14	Economics of innovation and new technology	1	Routledge
15	Emerging markets review	1	Elsevier
16	Expert systems	1	Blackwell
17	Human resource management review	1	Elsevier
18	Industrial management and data systems	1	Emerald
19	Information (Switzerland)	1	MDPI
20	Information discovery and delivery	1	Emerald
21	Information and management	1	Elsevier
22	International journal of entrepreneurial behavior and research	1	Emerald
23	International journal of financial studies	1	MDPI
24	International journal of information management	1	Elsevier
25	International journal of information management data insights	1	Elsevier
26	International journal of logistics management	1	Emerald
27	International journal of organizational analysis	1	Emerald
28	International journal of physical distribution and logistics management	1	Emerald

(Contd...)

Table 1: ***(Continued)***

No.	Journal	No. of articles	Publisher
29	International review of management and marketing	1	Econjournals
30	Journal of business research	1	Elsevier
31	Journal of business and industrial marketing	1	Emerald
32	Journal of computer information systems	1	Taylor & Francis
33	Journal of entrepreneurship in emerging economies	1	Emerald
34	Journal of global information technology management	1	Routledge
35	Journal of innovation and knowledge	1	Elsevier
36	Journal of manufacturing technology management	1	Emerald
37	Journal of open innovation: technology, market, and complexity	1	Elsevier
38	Journal of risk and financial management	1	MDPI
39	Journal of small business management	1	Taylor and Francis
40	Kybernetes	1	Emerald
41	Management decision	1	Emerald
42	Pacific Asia journal of the association for information systems	1	AIS
43	Proceedings of the IEEE	1	IEEE
44	Resources policy	1	Elsevier
45	Systems	1	MDPI
46	WSEAS transactions on business and economics	1	WSEAS

Article count orders outlets, then alphabetically. The distribution across 46 journals reflects the field's multidisciplinary nature

Sustainability (10 articles), technological forecasting and social change (8), and technology in society (5) are the principal outlets, with the remainder spread across broad-scope outlets such as the Proceedings of the IEEE and the international journal of information management, as well as more specialized publications. Elsevier, Emerald, and MDPI are the most active publishers.

3.2. Theoretical Foundations

The corpus rests on a diverse theoretical base, organized in Table 2 into six clusters. Resource- and capability-based theories dominate. The resource-based view (RBV) appears in 17 articles, consistent with the argument that unique internal resources confer competitive advantage, including through AI-enabled process optimization (Khan et al., 2024; Vărzaru and Bocean, 2024). Dynamic capabilities theory (DCT) follows in 15 articles, explaining how firms integrate, build, and reconfigure competencies in response to environmental change—for example, how AI adoption strengthens operational performance through dynamic capabilities (Wong and Ngai, 2025). Resource orchestration theory (four articles) and the natural resource-based view (three articles) extend this lens to the ways SMEs structure, bundle, and leverage AI resources (Peretz-Andersson et al., 2024; Wang et al., 2025).

Technology adoption theories form the second cluster. The technology–organization–environment (TOE) framework is the second most-used theory overall (10 articles), often combined with the technology acceptance model (TAM, five articles) to explain how perceived usefulness and competitive pressure shape adoption (Qu and Kim, 2025; Abaddi, 2025). The unified theory of acceptance and use of technology and the diffusion of innovations appear less frequently in the literature (Ahmad et al., 2024; Bin-Nashwan et al., 2025). Information and knowledge management theories—notably information processing theory (five articles)—explain how AI augments organizational information processing during disruption (Benzidia et al., 2021; Rashid et al., 2024), while organizational and institutional theories (institutional theory, stakeholder theory, and others) situate adoption within external pressures and dependencies (Rodríguez-Espíndola et al., 2022; Chotia et al., 2024). Human behavior and specialized theories—uncertainty reduction, self-actualization, socio-technical systems, and strategic HRM—complete the landscape (Abaddi, 2025; Wang et al., 2025; Wang and Chen, 2025; Yamin et al., 2024), underscoring the phenomenon's multifaceted nature.

3.3. Research Contexts

As Table 3 shows, research spans eighteen contexts with clear clustering. Manufacturing (11 articles) and technology adoption (10) dominate: studies examine how AI strengthens manufacturing resilience and reduces production uncertainty (Khan et al., 2024; Peretz-Andersson et al., 2024; Qu and Kim, 2025) and identify the barriers and enablers SMEs encounter when implementing AI (Badghish and Soomro, 2024; Schwaeke et al., 2025; Ahmad et al., 2024). Supply chain management (8) and digital transformation (7) form a second cluster, addressing AI-enabled resilience during disruption and AI-enabled transformation strategies (Rashid et al., 2024; Singh et al., 2025; Tian et al., 2024; Wong and Ngai, 2025; Perifanis and Kitsios, 2023).

Corporate performance (6) and financial services (5) reflect the field's business-impact orientation, linking AI adoption to financial performance and to AI-driven financial decision models in developing economies (Wang and Chen, 2025; Bin-Nashwan and Li, 2025; Nguyen et al., 2025). Sustainability (5) and innovation (5) capture forward-looking concerns, connecting AI to sustainability outcomes and innovation-driven revenues (Wang and Zhang, 2024; Vărzaru and Bocean, 2024). Contexts overlap substantially—manufacturing intersects with supply chain management (Rashid et al., 2024; Singh et al., 2025) and sustainability with green entrepreneurship (Wang and Zhang, 2024)—indicating a holistic treatment of the phenomenon. Risk management (5) and green entrepreneurship (4) represent emerging contexts (Rodríguez-Espíndola et al., 2022; Gupta et al., 2023).

3.4. Geographic Distribution

The geographic distribution reveals pronounced regional concentration. As summarized in Table 4, Asia accounts for the majority of studies (55%), with China alone contributing 14 articles (23.3%) and notable work on China-specific implementation frameworks (Wang and Zhang, 2024; Bin-Nashwan and Li, 2025). Global or cross-national studies constitute the next-largest category (16.7%), offering comparative perspectives across economic settings (Perifanis and Kitsios, 2023; Ameye et al., 2024). Europe (15%) is more dispersed, with contributions from Italy and an EU policy analysis (Guida et al.,

Table 2: Theories in AI-driven decision-making research for SMEs under environmental uncertainty

Category	Theory	Founder (s)	Articles	Key references
Resource and capability-based	Resource-based view (RBV)	Barney (1991); Wernerfelt (1984)	17	Abdulmuhsin et al. (2025), Alquraish (2025), Bin-Nashwan and Li (2025), Bin-Nashwan et al. (2025), Di Vaio et al. (2022), Khan et al. (2024), Larbi-Siaw et al. (2022), Liu et al. (2024), Peretz-Andersson et al. (2024), Perifanis and Kitsios (2023), Qu and Kim (2025), Rashid et al. (2024), Salinas-Navarro et al. (2024), Vărzaru and Bocean (2024), Wang and Zhang (2024), Wang et al. (2025), Xavier et al. (2024)
	Dynamic capabilities theory (DCT)	Teece et al. (1997)	15	Aftab et al. (2025), Al-khatib et al. (2024), Barata et al. (2024), Chen et al. (2022), Chen et al. (2025), Kong and Du (2025), Khan et al. (2025), Liu et al. (2024), Nguyen et al. (2025), Rodríguez-Espíndola et al. (2022), Roy et al. (2025), Singh et al. (2025), Tian et al. (2024), Wang and Chen (2025), Wong and Ngai (2025)
	Resource orchestration theory	Sirmon et al. (2010)	4	Dey et al. (2024), Peretz-Andersson et al. (2024), Wang and Zhang (2024), Xavier et al. (2024)
	Natural resource-based view	Hart (1995)	3	Chang et al. (2023), Mukherjee et al. (2024), Wang et al. (2025)
	Knowledge-based view	Grant (1996)	2	Dey et al. (2024), Wang et al. (2025)
Technology adoption and acceptance	TOE framework	Tornatzky and Fleischer (1990)	10	Badghish and Soomro (2024), Bin-Nashwan and Li (2025), Bin-Nashwan et al. (2025), Chen et al. (2022), Mukherjee et al. (2024), Qu and Kim (2025), Rashid et al. (2024), Rodríguez-Espíndola et al. (2022), Schwaeke et al. (2025), Wong and Ngai (2025)
	Technology acceptance model (TAM)	Davis (1989)	5	Abaddi (2025), Alghizzawi et al. (2025), Bin-Nashwan et al. (2025), Del Giudice et al. (2023), Qu and Kim (2025)
	UTAUT	Venkatesh et al. (2003)	2	Ahmad et al. (2024), Sharma et al. (2024)
	Diffusion of innovations	Rogers (2003)	1	Bin-Nashwan et al. (2025)
Information and knowledge management	Information processing theory	Galbraith (1974); Tushman and Nadler (1978)	5	Benzidia et al. (2021), Chen et al. (2022), Guida et al. (2023), Liu et al. (2024), Rashid et al. (2024)
	Knowledge management theory	Darroch (2005); Nonaka (1994)	3	Abdulmuhsin et al. (2025), Qu and Kim (2025), Wang and Zhang (2024)
	Organizational information processing theory	Egelhoff (1991); Galbraith (1974)	3	Benzidia et al. (2021), Guida et al. (2023), Khan et al. (2025)
Organizational and institutional	Institutional theory	DiMaggio and Powell (1983); Meyer and Rowan (1977)	4	Di Vaio et al. (2022), Liu et al. (2024), Pai and Chandra (2022), Rodríguez-Espíndola et al. (2022)
	Stakeholder theory	Freeman (1984)	3	Chotia et al. (2024), Nguyen et al. (2025), Wang et al. (2025)
	Resource dependence theory	Pfeffer and Salancik (1978)	2	Bin-Nashwan and Li (2025), Bin-Nashwan et al. (2025)
	Other (ambidexterity, strategic choice, contingency, legitimacy, transaction cost)	Turner and Lee-Kelley (2012); Child (1972, 1997); Meyer and Scott (1983); Deephouse (2000); Williamson (1981)	1 each	Di Vaio et al. (2022), Han et al. (2025), Larbi-Siaw et al. (2022), Wang et al. (2025), Liu et al. (2024)
Human behavior and psychology	Self-actualization; uncertainty reduction; communication privacy management; cultural dimensions	Maslow (1943); Rogers (1963); Berger and Calabrese (1975); Petronio (2002); Hofstede (1980)	1 each	Wang et al. (2025), Abaddi (2025), Sharma et al. (2024)
Other specialized	Strategic HRM; socio-technical systems; relational leadership	Ferris et al. (1999); Huselid et al. (1997); McMahan et al. (1998); Wright (1998); Sony and Naik (2020); Sklaveniti (2016)	1 each	Yamin et al. (2024), Wang and Chen (2025), Divya et al. (2024)

Theories are grouped into six clusters; counts reflect the number of articles drawing on each theory

Table 3: Research contexts of AI-driven decision-making in smes under environmental uncertainty

Context	Articles	Key references
Manufacturing	11	Alquraish (2025), Dey et al. (2024), Khan et al. (2024), Khan et al. (2025), Peretz-Andersson et al. (2024), Perifanis and Kitsios (2023), Qu and Kim (2025), Rashid et al. (2024), Singh et al. (2025), Tian et al. (2024), Wang and Zhang (2024)
Technology adoption	10	Abaddi (2025), Ahmad et al. (2024), Ameye et al. (2024), Badghish and Soomro (2024), Chotia et al. (2024), Di Vaio et al. (2022), Han et al. (2025), Pai and Chandra (2022), Rodríguez-Espíndola et al. (2022), Schwaeke et al. (2025)
Supply chain management	8	Belhadi et al. (2022), Kong and Du (2025), Mukherjee et al. (2024), Rashid et al. (2024), Singh et al. (2025), Tian et al. (2024), Yamin et al. (2024), Žigienė et al. (2022)
Digital transformation	7	Ahmad et al. (2024), Al-khatib et al. (2024), Alquraish (2025), Di Vaio et al. (2022), Perifanis and Kitsios (2023), Rodgers et al. (2024), Wong and Ngai (2025)
Corporate performance	6	Ho et al. (2022), Wang and Chen (2025), Wang et al. (2025), Zhang et al. (2023), Zhang and Wei (2025)
E-commerce and retail	5	Aljarboa (2024), Barata et al. (2024), Chen et al. (2022), Roy et al. (2025), Sharma et al. (2024)
Financial services	5	Alnor (2024), Bin-Nashwan and Li (2025), Bin-Nashwan et al. (2025), Nguyen et al. (2025), Yi et al. (2023)
Innovation	5	Bahoo et al. (2023), Chen et al. (2025), Corrales-Garay et al. (2024), Giuggioli and Pellegrini (2023), Vărzaru and Bocean (2024)
Sustainability	5	Aftab et al. (2025), Benzidia et al. (2021), Khan et al. (2024), Larbi-Siaw et al. (2022), Wang and Zhang (2024)
Risk management	5	Nguyen et al. (2025), Quang Huy and Kien Phuc (2025), Rodríguez-Espíndola et al. (2022), Yamin et al. (2024), Žigienė et al. (2022)
Accounting and auditing	4	Bin-Nashwan and Li (2025), Bin-Nashwan et al. (2025), Muñoz-Izquierdo et al. (2019), Nguyen et al. (2025)
Green entrepreneurship	4	Chang et al. (2023), Chotia et al. (2024), Gupta et al. (2023), Wang and Zhang (2024)
Leadership and management	4	Aftab et al. (2025), Alawamleh et al. (2024), de Oliveira et al. (2021), Divya et al. (2024)
Organizational learning/ knowledge management	4	Abdulmuhsin et al. (2025), Del Giudice et al. (2023), Wang et al. (2025), Xavier et al. (2024)
Entrepreneurship	4	Giuggioli and Pellegrini (2023), Gupta et al. (2023), Salinas-Navarro et al. (2024), Xavier et al. (2024)
Human resource management	3	Del Giudice et al. (2023), Divya et al. (2024), Qin et al. (2025)
Sales and marketing	3	Alghizzawi et al. (2025), Li et al. (2024), Roy et al. (2025)
International business	2	Ameye et al. (2024), Liu et al. (2024)

Many studies span multiple contexts; counts therefore exceed 72

Table 4: Geographic distribution of research on AI-driven decision-making in SMEs under environmental uncertainty

Country	Articles	Region	Key references
China	14	Asia	Bin-Nashwan and Li (2025), Bin-Nashwan et al. (2025), Chang et al. (2023), Chen et al. (2025), Kong and Du (2025), Li et al. (2024), Qu and Kim (2025), Tian et al. (2024), Wang and Chen (2025), Wang and Zhang (2024), Wang et al. (2025), Wong and Ngai (2025), Zhang and Wei (2025), Zhang et al. (2023)
Global/cross-national	10	—	Ameye et al. (2024), Bahoo et al. (2023), Belhadi et al. (2022), Chen et al. (2022), Giuggioli and Pellegrini (2023), Gupta et al. (2023), Han et al. (2025), Pai and Chandra (2022), Perifanis and Kitsios (2023), Qin et al. (2025)
Saudi Arabia	5	Middle East	Aljarboa (2024), Alquraish (2025), Badghish and Soomro (2024), Khan et al. (2025), Yamin et al. (2024)
India	5	Asia	Chotia et al. (2024), Divya et al. (2024), Mukherjee et al. (2024), Roy et al. (2025), Sreenivasan et al. (2023)
Vietnam	3	Asia	Dey et al. (2024), Nguyen et al. (2025), Quang Huy and Kien Phuc (2025)
Pakistan	3	Asia	Alghizzawi et al. (2025), Khan et al. (2024), Khan et al. (2025)
USA	3	North America	Chen et al. (2025), Rashid et al. (2024), Rodgers et al. (2024)
Italy	2	Europe	Aftab et al. (2025), Guida et al. (2023)
Jordan	2	Middle East	Abaddi (2025), Alawamleh et al. (2024)
Others (1 each)	—	Various	Sweden (Peretz-Andersson et al., 2024), Malaysia (Xavier et al., 2024), United Kingdom (Rodríguez-Espíndola et al., 2022), Brazil (de Oliveira et al., 2021), Iraq (Abdulmuhsin et al., 2025), EU (Vărzaru and Bocean, 2024), Portugal (Barata et al., 2024), Germany (Schwaeke et al., 2025), Spain (Muñoz-Izquierdo et al., 2019), Fiji (Sharma et al., 2024), Ghana (Larbi-Siaw et al., 2022), France (Benzidia et al., 2021), Lithuania (Žigienė et al., 2022)

Regional shares: Asia 55.0%; Global/cross-national 16.7%; Europe 15.0%; Middle East 11.7%; North America 5.0%; Africa 3.3%; South America 1.7%; Oceania 0.0%

2023; Aftab et al., 2025; Vărzaru and Bocean, 2024), while the Middle East (11.7%) is anchored by Saudi Arabia (Badghish and Soomro, 2024; Alquraish, 2025).

North America (5%) is represented mainly by U.S. work on AI-enabled supply chain resilience (Rashid et al., 2024), whereas Africa (3.3%), South America (1.7%), and Oceania (0%) are markedly underrepresented (Larbi-Siaw et al., 2022; de Oliveira et al., 2021). This concentration suggests that current understanding is shaped primarily by Asian, and especially Chinese, business environments, raising questions about generalizability across institutional, infrastructural, and cultural contexts.

3.5. Research Methods

Table 5 summarizes the methodological profile. Quantitative cross-sectional surveys dominate (21 articles), followed by systematic literature reviews (7) and bibliometric analyses (4); qualitative (3) and multiple-case (2) designs are comparatively scarce, as is mixed-method research (3), leaving "how" and "why" questions underexplored. Data collection mirrors this orientation: survey questionnaires (19) and database searches (11) lead, while semistructured interviews (5) and expert panels (2) are limited. Samples concentrate on manufacturing firms (9) and senior executives (7), with a striking geographic emphasis on Asian contexts (19), which constrains generalizability to Western settings.

Analytically, the field is firmly quantitative. Structural equation modeling (15 articles) and partial least squares SEM (12) predominate, reflecting an emphasis on modeling complex relationships among AI adoption, organizational factors, and performance, including mediation and moderation. Regression (6) and thematic or content analysis (5) follow, while machine-learning techniques (3) and specialized methods such as fuzzy or multi-criteria decision-making, total interpretive structural modeling, and MICMAC analysis (2 each) represent methodological innovations suited to decision-making under uncertainty.

3.6. Antecedents of AI-Driven Decision-Making

Table 6 organizes the antecedents of AI-driven decision-making into technological, organizational, environmental, data-related, strategic, psychological, and resource categories. Among technological factors, relative advantage, compatibility, perceived usefulness, ease of use, and AI autonomy shape adoption, with effects especially pronounced in resource-constrained SMEs (Badghish and Soomro, 2024; Wong and Ngai, 2025; Bin-Nashwan and Li, 2025; Abaddi, 2025). Organizational factors—readiness, top-management support, digital culture, innovation climate, leadership capabilities, firm size, and absorptive capacity—collectively determine implementation capacity; organizational readiness emerges as the strongest predictor of successful implementation, and innovation climate moderates the link between organizational factors and adoption (Wong and Ngai, 2025; Bin-Nashwan and Li, 2025; Dey et al., 2024; Han et al., 2025; Schwaeke et al., 2025; Qu and Kim, 2025).

Environmental factors operate as both context and driver: market volatility, technological turbulence, competitive pressure, government support, and vendor ecosystems heighten the urgency and reduce the perceived risk of adoption (Kong and Du, 2025; Bin-Nashwan and Li, 2025; Qu and Kim, 2025). Data-related factors—data quality, governance, and big-data analytical capabilities—are increasingly recognized as foundational to AI success (Chen et al., 2022; Bin-Nashwan et al., 2025; Aftab et al., 2025). Strategic factors such as strategic flexibility, technological opportunism, and green business strategies (Khan et al., 2024; Chen et al., 2025; Chotia et al., 2024), psychological factors such as risk perception, trust, and the not-invented-here syndrome (Abaddi, 2025; Del Giudice et al., 2023; Han et al., 2025), and resource factors such as financial resources, internal innovation resources, and collaborative networks (Schwaeke et al., 2025; Han et al., 2025) complete the multidimensional picture.

3.7. AI-Driven Decision-Making Patterns

Table 7 identifies eight recurring decision-making patterns. The most frequent is the technology adoption decision process (12+ articles), a sequential evaluation of technological, organizational, and environmental factors; Bin-Nashwan and Li (2025) show that competitive pressure, vendor ecosystems, top-management support, relative advantage, and AI readiness drive adoption, while government support has limited effect and innovation climate acts as a moderator. The resource orchestration process (7-8 articles) describes how SMEs structure, bundle, and leverage AI resources in a dynamic, "self-nurturing" manner rather than a single step (Peretz-Andersson et al., 2024), and the investment

Table 5: Research methods in AI-driven decision-making research for SMEs under environmental uncertainty

Research design	Articles	Data collection	Articles
Quantitative cross-sectional survey	21	Survey questionnaire	19
Systematic literature review	7	Literature review/database search	11
Bibliometric analysis	4	Secondary data (reports, databases)	6
Mixed methods	3	Semi-structured interviews	5
Qualitative case study	3	Online survey via digital platforms	5
Panel data analysis	3	Document analysis	2
Conceptual framework development	3	Expert panel	2
Multiple/exploratory case study	2-2	Purposive/snowball sampling	2
Data analysis method		Sample characteristics	
Structural equation modeling (SEM)	15	Manufacturing firms/SMEs	9
Partial least squares SEM (PLS-SEM)	12	Senior executives/top management	7
Regression analysis	6	Academic publications/articles	7
Thematic/content analysis	5	Multiple industries	6
Bibliometric network analysis	4	Accounting/auditing professionals	3
Machine learning/AI techniques	3	Technology/digital firms	3
Fuzzy/multi-criteria; TISM; MICMAC; CB-SEM	2 each	Supply chain/logistics; listed firms	3 each

Some articles employ multiple methods, so totals may exceed 72. Sub-headers organize the design, data-collection, analysis, and sample dimensions

Table 6: Antecedents of AI-driven decision-making in SMEs under environmental uncertainty

Category	Representative antecedents	Exemplary studies
Technological	Relative advantage; compatibility; perceived usefulness; perceived ease of use; AI autonomy	Badghish and Soomro (2024); Wong and Ngai (2025); Bin-Nashwan and Li (2025); Abaddi (2025)
Organizational	Organizational readiness; top-management support; digital culture; innovation climate; leadership capabilities; firm size; human capital; absorptive capacity	Wong and Ngai (2025); Bin-Nashwan and Li (2025); Han et al. (2025); Dey et al. (2024); Schwaeke et al. (2025); Qu and Kim (2025)
Environmental	Environmental uncertainty; competitive pressure; market uncertainty; government support; vendor ecosystem	Kong and Du (2025); Bin-Nashwan and Li (2025); Qu and Kim (2025)
Data-related	Data quality; data governance; big-data analytical capabilities	Chen et al. (2022); Bin-Nashwan et al. (2025); Aftab et al. (2025)
Strategic	Strategic flexibility; technological opportunism; green business strategies; industry dynamism	Khan et al. (2024); Chen et al. (2025); Chotia et al. (2024); Alawamleh et al. (2024)
Psychological	Risk perception; trust in AI; not-invented-here syndrome	Abaddi (2025); Del Giudice et al. (2023); Han et al. (2025)
Resource	Financial resources; internal innovation resources; collaborative innovation networks	Schwaeke et al. (2025); Han et al. (2025)

Antecedents are grouped into seven categories; representative constructs and exemplary studies are listed for each

Table 7: AI-driven decision-making patterns in SMEs under environmental uncertainty

Category	Decision process pattern	Frequency	Exemplary study
Strategic adoption and implementation	Technology adoption decision process	High (12+)	Bin-Nashwan and Li (2025)
	Resource orchestration process	Medium (7-8)	Peretz-Andersson et al. (2024)
	Investment efficiency decision process	Low (3-4)	Wang and Chen (2025)
Operational resilience and risk management	Risk management decision process	Medium (6-7)	Žigienė et al. (2022)
	Supply chain process integration	Medium (7-8)	Belhadi et al. (2022)
	Strategic orientation alignment process	Low–Med (4-5)	Kong and Du (2025)
Organizational capability and knowledge management	Dynamic capability building process	Med–High (10+)	Zhang and Wei (2025)
	Knowledge management decision process	Medium (6-7)	Wang and Zhang (2024)
Customer-focused and ethical	AI-enabled value proposition process	Low (3-4)	Li et al. (2024)
	Ethical and responsible AI decision process	Low (3-4)	Alawamleh et al. (2024)

Frequency denotes the approximate number of articles exhibiting each pattern

efficiency process (3-4 articles) uses AI to improve capital allocation by reducing over- and under-investment (Wang and Chen, 2025).

Operational patterns include the risk management process (6-7 articles), an evolutionary transition from analytics to AI in supply chain risk (Žigienė et al., 2022); supply chain process integration (7-8 articles), in which distinct AI techniques support reengineering, collaboration, agility, and a risk-management culture (Belhadi et al., 2022); and strategic orientation alignment (4-5 articles), where AI amplifies the resilience benefits of aligning market and technological orientation (Kong and Du, 2025). Capability-oriented patterns include the dynamic capability building process (10+ articles), through which AI enhances sensing, seizing, and reconfiguring (Zhang and Wei, 2025), and the knowledge management decision process (6-7 articles), in which generative AI strengthens knowledge acquisition and green innovation (Wang and Zhang, 2024). Customer-focused and ethical processes (3-4 articles each) round out the typology, addressing AI-enabled value propositions and the balance between efficiency and responsible use (Li et al., 2024; Alawamleh et al., 2024).

3.8. Research Outcomes

Table 8 organizes outcomes into the following categories: business performance, innovation and knowledge management, resilience and risk management, sustainability and stakeholder management, and resource management. Operational performance is the most-studied outcome (11 articles); AI strengthens dynamic capabilities, with effects most pronounced under high competitive pressure (Wong and Ngai, 2025). Financial performance benefits (6 articles) include greater resilience and faster recovery during

Table 8: Research outcomes of AI-driven decision-making in SMEs under environmental uncertainty

Category	Outcome	Articles	Exemplary study
Business performance	Operational performance	11	Wong and Ngai (2025)
	Market performance	7	Li et al. (2024)
	Financial performance	6	Ho et al. (2022)
	Investment efficiency	3	Wang and Chen (2025)
Innovation and knowledge management	Innovation performance	8	Qu and Kim (2025)
	Knowledge management	3	Wang and Zhang (2024)
	Process optimization	3	Khan et al. (2024)
Resilience and risk management	Supply chain resilience	9	Rashid et al. (2024)
	Strategic flexibility	5	Kong and Du (2025)
	Risk management	3	Nguyen et al. (2025)
	Decision agility	3	Roy et al. (2025)
Sustainability and stakeholder management	Environmental performance	7	Wang et al. (2025)
	Customer engagement	2	Sharma et al. (2024)
	Self-actualization	1	Wang et al. (2025)
Resource management	Resource orchestration	5	Peretz-Andersson et al. (2024)

Counts denote the number of articles reporting each outcome market shocks such as COVID-19 (Ho et al., 2022), while market performance (7) improves through AI-enabled customer value propositions, whose effects vary with environmental heterogeneity (Li et al., 2024). Investment efficiency gains (3) are stronger in non-state-owned firms and high-uncertainty environments (Wang and Chen, 2025).

In the innovation domain, AI adoption advances open innovation through absorptive capacity, with market uncertainty acting as both a driver and a context (Qu and Kim, 2025), and generative AI enhances green knowledge processes and process optimization, moderated by organizational flexibility (Wang and Zhang, 2024; Khan et al., 2024). Resilience outcomes are prominent: supply chain resilience (9 articles) improves through adaptive capabilities, visibility, and risk prediction (Rashid et al., 2024), and AI strengthens enterprise risk management, strategic flexibility, and decision agility (Nguyen et al., 2025; Kong and Du, 2025; Roy et al., 2025). Sustainability outcomes (7 articles) include improved environmental performance, especially in competitive industries (Wang et al., 2025), and resource orchestration (5) enables SMEs to create value despite constraints (Peretz-Andersson et al., 2024). A consistent and counterintuitive pattern emerges: environmental uncertainty amplifies rather than diminishes AI benefits, positioning AI as a strategic response to turbulence rather than a tool best suited to stable conditions.

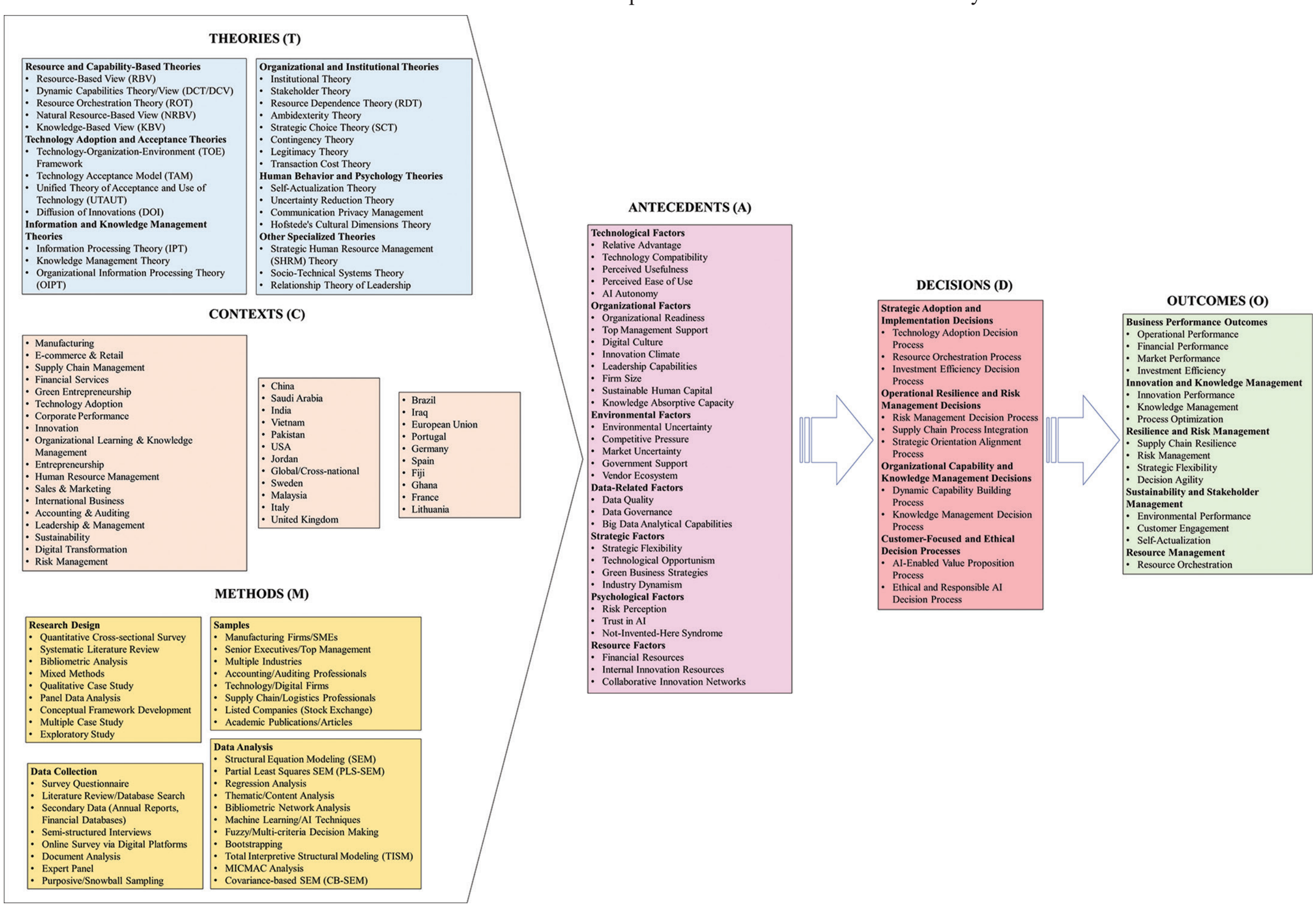
3.9. An Integrated TCM–ADO Framework

Synthesizing the preceding analyses yields an integrated TCM–ADO framework, presented in Figure 3. On the TCM side, predominantly resource- and capability-based theories (RBV, DCT) and technology adoption frameworks (TOE, TAM) inform research conducted largely in manufacturing, supply chain, and technology adoption contexts, and examined chiefly through quantitative methods. On the ADO side, technological, organizational, environmental, and resource antecedents shape strategic, operational, financial, and human–AI decision processes, which in turn generate multidimensional outcomes spanning operational and financial performance, innovation, resilience, sustainability, and resource orchestration. The framework's central insight is that AI adoption in SMEs is less a discrete technological event than a dynamic process of capability development whose value is heightened—not eroded—by environmental uncertainty. By linking how the phenomenon is studied (TCM) with what is substantively known about it (ADO), the framework addresses the fragmentation of prior work and provides a foundation for theory development and a structured research agenda.

3.10. A Future Research Agenda

Drawing on the TCM–ADO synthesis, several trajectories emerge. Theoretically, future work should extend dynamic

Figure 3: Integrated theories–contexts–methods and antecedents–decisions–outcomes framework for artificial intelligence-driven decision-making in small and medium-sized enterprises under environmental uncertainty



capabilities theory to specify how AI capabilities translate into sensing, seizing, and reconfiguring capabilities under turbulence (Peretz-Andersson et al., 2024; Tian et al., 2024), and integrate resource orchestration theory with knowledge management to clarify how resource-constrained SMEs structure, bundle, and leverage AI resources (Xavier et al., 2024; Wang and Zhang, 2024). The TOE framework remains foundational but warrants industry-specific elaboration—for example, how market uncertainty shapes open innovation in particular sectors (Badghish and Soomro, 2024; Bin-Nashwan and Li, 2025; Qu and Kim, 2025)—and information processing theory should be advanced to explain how AI augments processing capacity as environmental complexity rises (Benzidia et al., 2021; Chen et al., 2022; Guida et al., 2023).

Contextually, the field needs research on resource-constrained, SME-specific implementation; cross-industry comparison of manufacturing, services, and retail (Tian et al., 2024; Khan et al., 2024); emerging-economy settings where institutional support is pivotal (Abaddi, 2025; Ahmad et al., 2024; Bin-Nashwan and Li, 2025); crisis-response decision-making when uncertainty peaks (Ho et al., 2022; Singh et al., 2025; Kong and Du, 2025); and the influence of cultural and regulatory environments on adoption and governance (Alquraish, 2025; Sharma et al., 2024). Methodologically, the dominance of cross-sectional surveys points to a need for mixed-method designs (Singh et al., 2025), longitudinal studies that establish causality and capture learning effects (Tian et al., 2024), advanced and configurational quantitative techniques (Belhadi et al., 2022; Larbi-Siaw et al., 2022; Rodgers et al., 2024), comparative case studies (Salinas-Navarro et al., 2024), and validated AI-specific measurement scales (Han et al., 2025; Chen et al., 2025; Wang and Chen, 2025).

Along the ADO dimension, antecedent-focused research should examine how AI compatibility with legacy systems and dimensions of technological readiness affect integration in low-resource firms (Qu and Kim, 2025; Peretz-Andersson et al., 2024), how distinct forms of market uncertainty and government support condition adoption (Kong and Du, 2025; Wang and Zhang, 2024), and which leadership styles and forms of top-management support most effectively drive adoption (Alghizzawi et al., 2025; Han et al., 2025). Decision-focused research should investigate AI-enhanced strategic decision-making and the exploration–exploitation balance (Perifanis and Kitsios, 2023), operational and real-time decisions in supply chains (Al-khatib et al., 2024; Singh et al., 2025), financial decisions including investment efficiency and reporting accuracy (Wang and Chen, 2025; Bin-Nashwan et al., 2025), and human–AI collaboration models and the allocation of decision rights (Alawamleh et al., 2024; Del Giudice et al., 2023). Outcome-focused research should identify which performance metrics improve most and at what adoption maturity (Zhang et al., 2023), how AI enables product, process, and business-model innovation (Vărzaru and Bocean, 2024; Corrales-Garay et al., 2024), how AI advances environmental and triple-bottom-line performance (Wang et al., 2025; Abdulmuhsin et al., 2025), and how AI capabilities build resilience and business continuity under different disruptions (Khan et al., 2025; Alquraish, 2025). To sharpen these directions, illustrative research questions for each dimension include: (Theories) How do AI capabilities translate into the sensing, seizing, and reconfiguring micro-foundations of dynamic capabilities in resource-constrained SMEs under turbulence? (Contexts) How does AI-driven decision-making differ across manufacturing, service, and retail SMEs in emerging versus developed economies? (Methods) Which longitudinal and mixed-method designs can establish the causal and learning effects that cross-sectional surveys cannot capture? (Antecedents) Which configurations of technological readiness, market uncertainty, and top-management support most strongly enable AI adoption in low-resource SMEs? (Decisions) How should decision rights be allocated between managers and AI systems across strategic, operational, and financial decisions? (Outcomes) At what adoption maturity, and through which mechanisms, does AI most improve SME resilience and triple-bottom-line performance under different types of disruption?

4. DISCUSSION

This review analyzed 72 peer-reviewed articles to map AI-driven decision-making in SMEs under environmental uncertainty. Regarding RQ1, resource-based theories (RBV, DCT) and technology adoption frameworks (TOE, TAM) dominate the theoretical landscape; manufacturing is the primary context; Asia, especially China, accounts for 55% of studies; and quantitative cross-sectional surveys prevail, with limited qualitative and longitudinal work. Regarding RQ2, technological, organizational, environmental, and leadership antecedents shape strategic, operational, financial, and human–AI decision processes that yield outcomes across performance, innovation, sustainability, and resilience—and, contrary to conventional assumptions, environmental uncertainty amplifies rather than diminishes AI benefits. Regarding RQ3, the principal gaps are geographic imbalance, the scarcity of longitudinal and mixed-methods designs, the limited treatment of ethics, and a thin understanding of human–AI collaboration.

Three patterns merit emphasis. First, AI is increasingly conceptualized not as a discrete technological tool but as a strategic capability enhancing organizational adaptability, consistent with the prevalence of resource- and capability-based theories. Second, the amplifying effect of uncertainty is robust across studies (Kong and Du, 2025; Zhang and Wei, 2025; Ho et al., 2022): uncertain environments raise the value of AI's information-processing capacity (Benzidia et al., 2021), intensify competitive incentives to adopt (Bin-Nashwan and Li, 2025), and reward effective resource orchestration under constraint (Peretz-Andersson et al., 2024). Third, implementation follows a non-linear, "self-nurturing" path (Peretz-Andersson et al., 2024) rather than a simple stage model, underscoring the centrality of ongoing capability development.

The findings extend prior work in several ways while also surfacing tensions. They build on research linking AI to sustainable entrepreneurship and performance (Gupta et al., 2023; Bin-Nashwan and Li, 2025), yet they contradict Han et al.'s (2025) conclusion that uncertainty negatively moderates the innovation-resources–AI-orientation link, instead indicating that uncertainty can strengthen AI's effect on performance and resilience (Kong and Du, 2025; Zhang and Wei, 2025). The role of government support is likewise context-dependent—significant for Chinese MSMEs (Qu and Kim, 2025) but limited elsewhere (Bin-Nashwan and Li, 2025)—and Zhang et al. (2023) report an inverted-U relationship between IT capability and performance, implying diminishing returns to excessive AI integration (Wang and Chen, 2025). These contradictions point to genuinely contingent, non-linear relationships that warrant more nuanced investigation.

4.1. Theoretical Implications

The review offers five theoretical contributions. It extends resource orchestration theory by showing how SMEs structure, bundle, and leverage AI resources to create value under uncertainty, reframing AI implementation as capability development rather than mere adoption (Peretz-Andersson et al., 2024). It refines dynamic capabilities theory by identifying AI-enabled sensing, seizing, and reconfiguring mechanisms whose value rises with competitive pressure (Wong and Ngai, 2025). It integrates technology adoption frameworks (TOE, TAM) with strategic management theories to capture both adoption decisions and their strategic consequences (Qu and Kim, 2025). It advances information processing theory by explaining how AI augments processing capacity during disruption (Benzidia et al., 2021; Rashid et al., 2024). Finally, the integrated TCM–ADO framework is itself a contribution, connecting theoretical foundations, contexts, and methods with antecedents, decisions, and outcomes, and thereby addressing the fragmentation of prior research.

4.2. Practical Implications

For SME managers, the findings translate into actionable guidance. AI should be treated as a strategic initiative aligned with organizational goals and backed by top management rather than as a standalone tool (Bin-Nashwan and Li, 2025), and it should be accompanied by complementary capabilities developed through deliberate resource orchestration (Peretz-Andersson et al., 2024). Building a data-driven culture and sound data governance strengthens AI-enabled knowledge management and innovation (Wang and Zhang, 2024). Given resource constraints, SMEs should prioritize AI in the decision areas of highest strategic impact (Schwaeke et al., 2025), cultivate flexible and adaptable structures that magnify AI benefits (Khan et al., 2024), and draw on vendor ecosystems and government support to offset limited internal capabilities (Badghish and Soomro, 2024). Because uncertainty amplifies AI's value, turbulent periods are precisely when targeted AI investment can yield the greatest returns.

4.3. Limitations and Future Research

Several limitations qualify these conclusions. The focus on peer-reviewed, English-language journal articles may have excluded relevant conference proceedings, books, non-English-language literature, and practitioner literature, potentially reinforcing the observed geographic imbalance. The rapid evolution of AI means some recent developments may not yet be captured in published work, and the synthesis of reported findings—rather than a meta-analysis of effect sizes—precludes quantifying cross-study relationships or fully detecting publication bias toward positive, self-reported results. The review also relied on a single database (Scopus) and a search string weighted toward performance- and uncertainty-related terms, which may have under-represented studies indexed elsewhere or framed in other vocabularies; it excluded conceptual and review articles that may carry influential theoretical contributions; it applied no formal quality-appraisal instrument to the included studies; and the coding of theories, antecedents, decisions, and outcomes involved interpretive judgment that, despite the use of a protocol, retains a degree of subjectivity. The TCM–ADO framework, while integrative, necessarily simplifies nuanced contingencies and feedback loops. Future research should therefore prioritize geographically diverse and cross-cultural samples; longitudinal and mixed-method designs that establish causality; explicit study of human–AI collaboration and the ethical dimensions of AI use in SMEs that often lack formal governance; and investigation of how distinct types of uncertainty—market volatility, technological turbulence, and regulatory change—condition the AI–performance relationship, helping to reconcile the contradictory moderation findings reported above.

5. CONCLUSION

This systematic review of 72 articles develops an integrated TCM–ADO framework that clarifies the theories, contexts, methods, antecedents, decisions, and outcomes characterizing AI-driven decision-making in SMEs under environmental uncertainty. AI adoption is shaped by multiple antecedents across the technological, organizational, environmental, and leadership domains and, contrary to conventional assumptions, environmental uncertainty amplifies rather than diminishes the benefits of AI—positioning the technology as an adaptive mechanism during turbulence. The evolution of AI from a technological innovation to a strategic capability enables decision patterns spanning strategic adoption, operational resilience, capability building, and customer-focused processes, which translate into multidimensional gains in performance, innovation, sustainability, and resilience. Important gaps remain, including the geographic concentration of evidence in Asia, the predominance of cross-sectional designs, and the limited attention to ethics and to potential negative consequences. By synthesizing fragmented findings into a coherent framework, the review establishes a foundation for understanding how SMEs can effectively leverage AI under uncertainty and identifies a structured agenda for advancing both research and practice.

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