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AI-ENABLED LEADERSHIP AGILITY: A SYSTEMATIC REVIEW INTEGRATING TALENT MANAGEMENT, GREEN FINANCE, AND SUSTAINABLE BUSINESS

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Abstract

Purpose: This study examines the role of artificial intelligence (AI) in leadership agility and its integration with talent management, green-finance decision processes, and sustainable business outcomes.

Research Methodology: This study uses a PRISMA 2020-aligned systematic literature review. Peer-reviewed English-language journal articles published from 2013 to the final search date in 2026 were identified through Scopus and Web of Science, screened using predefined eligibility criteria, appraised using design-appropriate quality criteria, and synthesized through thematic coding.

Results: The synthesis identifies AI-enabled decision support as a potential enabler of leadership agility; talent intelligence as a workforce-adaptation capability; and AI-supported green-finance processes as mechanisms for ESG and climate-risk-informed decisions. Data quality, AI literacy, human oversight, governance, transparency, privacy protection, and credible ESG data emerge as key boundary conditions.

Limitations: The review is limited to English-language peer-reviewed articles and provides thematic synthesis rather than meta-analytic causal estimates.

Contribution: This study contributes to leadership, strategic management, human resource management, sustainable finance, and responsible-AI research by proposing an integrative framework linking AI infrastructure, leadership agility, talent intelligence, green-finance decisions, and multidimensional sustainable business outcomes.

Keywords: artificial intelligence, leadership agility, talent intelligence, green finance, systematic literature review, sustainable business



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1. INTRODUCTION

Artificial intelligence (AI) is increasingly embedded in organizational decision processes, from predictive analytics and workforce planning to environmental, social, and governance (ESG) analysis. Its organizational value, however, is not automatic. AI may improve the speed and breadth of information processing, yet its effects depend on how leaders interpret evidence, challenge recommendations, allocate accountability, and govern data-intensive practices. Research on human–AI symbiosis and organizational decision structures therefore cautions against treating AI as a substitute for leadership (Jarrahi, 2018; Raisch & Krakowski, 2021; Shrestha et al., 2019).

Three related streams have grown rapidly but are usually reviewed separately: AI-supported leadership and decision-making, AI in human resource management (HRM), and AI for sustainability and finance. The separation obscures a plausible organizational mechanism. Leaders need timely, contestable intelligence to sense and seize opportunities; talent systems determine whether appropriate skills and roles are available to act on those opportunities; and green-finance decisions translate environmental information into capital-allocation and risk-management choices. The present review addresses that fragmentation without making a regional claim that is not supported by a region-specific search and analysis.

The original submission used the labels “Eastern Asia” and “emerging economies,” although its search strategy, eligibility criteria, and extracted studies did not support those delimitations. This revised manuscript removes those claims. It also distinguishes a systematic-review dataset from supporting theory, books, methodological guidance, and practitioner reports. The review asks: (RQ1) What roles does AI play in enabling or constraining leadership agility? (RQ2) Through what mechanisms can AI-enabled talent intelligence connect leadership agility to organizational action? (RQ3) How is AI used in green-finance decision processes, and what sustainable-business outcomes and risks are reported?

The article contributes a transparent, testable conceptual synthesis rather than causal estimates. Its central argument is that leadership agility is an organizationally embedded, AI-augmented dynamic capability; talent intelligence is a complementary human-capital capability; and green finance is a strategic decision domain. Their relationship is conditional on responsible AI governance. The next sections develop this framing, document the reproducible review protocol, and present the synthesis and research agenda.

This positioning also avoids a common category error in interdisciplinary AI research. AI infrastructure is not equivalent to leadership; automated screening is not equivalent to talent management; and ESG data processing is not evidence of an environmental outcome. Each link must be understood as a contingent organizational mechanism. This distinction is important for research design because it specifies the relevant unit of analysis, makes the scope of the proposed constructs explicit, and prevents a conceptual review from implying untested statistical effects.

LITERATURE REVIEW AND PROPOSITION DEVELOPMENT

A. LITERATURE REVIEW

2.1 Theoretical framing and level of analysis

Dynamic capabilities theory provides the primary explanatory frame: organizations sense change, seize opportunities, and reconfigure resources in changing environments (Teece, 2007). AI can expand sensing and analytical capacity, but it does not itself decide strategic priorities. The human–AI augmentation perspective explains the complementarity: human judgment supplies contextual interpretation, value choices, and accountability, while AI can process and surface patterns at scale (Jarrahi, 2018; Raisch & Krakowski, 2021). Strategic human-capital reasoning positions workforce knowledge, skills, and deployment as resources through which decisions are enacted (Wright et al., 1994). Finally, the natural-resource-based view directs attention to environmental value creation and risk (Hart, 1995); institutional pressures explain why disclosure, accountability, and credibility requirements shape sustainable-finance practices (DiMaggio & Powell, 1983).

Table 1. Conceptual boundaries of the revised synthesis.

Concept	Level of analysis	Role in the framework	Boundary
AI infrastructure	Organizational	Data, models, interfaces, and governance enabling decision support	Not a leader or autonomous strategic actor
Leadership agility	Individual–organizational	Sensing, interpreting, deciding, and reconfiguring under change	Requires human accountability and discretion
Talent intelligence	Organizational	Integrated workforce information and decision processes	Not merely automated recruitment
Green-finance decision process	Organizational–market	Use of ESG/climate information in allocation, risk, and disclosure choices	Not synonymous with sustainable performance
Sustainable business outcomes	Organizational	Economic, environmental, social, and governance results	May include trade-offs and unintended effects

2.2 AI-enabled leadership agility

Leadership agility concerns the capacity to interpret changing conditions, make timely but accountable choices, and adjust resources and routines. AI-enabled dashboards, forecasting, and scenario tools can support these activities by widening the information base. Yet the literature on AI and management emphasizes an automation–augmentation paradox: automation may narrow human scrutiny if leaders defer to opaque outputs, whereas augmentation is valuable when humans can question, contextualize, and revise model-based recommendations (Raisch & Krakowski, 2021). Accordingly, the relevant relationship is conditional, not uniformly positive.

At the leader level, agility therefore involves more than faster decisions. It involves deciding which signals deserve attention, identifying when model outputs should be challenged, coordinating affected stakeholders, and reallocating resources when assumptions no longer hold. At the organizational level, these activities become repeatable only when decision rights,

data stewardship, and escalation procedures are embedded in routines. The review consequently treats AI-enabled decision support as an antecedent infrastructure and leadership agility as the capability through which information is translated into action.

2.3 Talent intelligence as a complementary capability

AI in HRM includes candidate screening, skills inference, workforce analytics, learning recommendations, and performance-support tools. These practices can integrate dispersed workforce information into talent intelligence, but the same systems can reproduce historical bias, intensify surveillance, and reduce employee voice (Brougham & Haar, 2018; Köchling & Wehner, 2020). Talent intelligence is therefore defined here as a governed organizational capability for using workforce data to support recruitment, development, mobility, and deployment decisions; it is not a validated measurement scale and it should not be represented by untested questionnaire indicators in a review article.

A capability view also clarifies why adopting an AI tool is insufficient. Talent intelligence requires common data definitions, documented data lineage, role-based access, opportunities for workers and managers to question outputs, and processes for correcting inaccurate records. Recruitment, performance support, learning, and mobility should not be treated as isolated applications because their combined use can amplify both organizational learning and adverse consequences. The relevant question is therefore not whether an organization uses AI in HRM, but whether it can govern the use of workforce information in a way that is fair, intelligible, and aligned with a legitimate developmental purpose.

2.4 Green-finance decisions and sustainable business

AI can assist ESG data processing, climate-risk modelling, anomaly detection, and sustainability reporting. These uses may improve the timeliness and granularity of information available to financial decision makers (Nishant et al., 2020; Vinuesa et al., 2020). They do not, by themselves, establish environmental benefit. The decision process must be assessed against economic, environmental, social, and governance outcomes and against risks of incomplete data, model opacity, and greenwashing. This distinction prevents green finance from being treated as an automatic outcome of AI adoption. At the organizational level, AI capability is also associated with the capacity to mobilize data and skills for innovation and performance (Mikalef & Gupta, 2021).

This review uses the term green-finance decision process deliberately. It encompasses how organizations and financial institutions identify relevant sustainability information, evaluate uncertainty, allocate capital, manage climate-related risk, and disclose the basis of decisions. It does not assume that every investment labelled green is environmentally beneficial. Independent assurance, credible data provenance, and governance over model assumptions are therefore included as conditions of the proposed relationship.

The proposed framework should also be interpreted with attention to potential tensions among outcomes. A data-driven allocation decision can improve the efficiency of environmental-risk assessment while reducing the transparency available to affected stakeholders. A talent system can improve skills matching while increasing the visibility of employee behavior. A sustainability score can improve comparability across investments while

concealing context-specific trade-offs. These tensions are analytically important because sustainable business is not achieved by optimizing a single indicator; it requires organizations to make justified choices among economic, environmental, social, and governance considerations.

B. CONCEPTUAL PROPOSITION

Proposition 1. AI-enabled decision support is more likely to contribute to leadership agility when data quality, leaders' AI literacy, human oversight, and organizational AI governance are high.

Proposition 2. Talent intelligence is more likely to translate leadership agility into workforce adaptation when AI-enabled HRM systems are transparent, contestable, privacy-protective, and aligned with development rather than surveillance.

Proposition 3. AI-supported green-finance decision processes are more likely to contribute to sustainable business outcomes when ESG data are credible, environmental claims are independently governable, and financial optimization is assessed alongside environmental, social, and governance criteria.

Taken together, the propositions do not specify a simple linear technology-to-performance effect. The expected value of AI depends on the joint alignment of technical infrastructure, leadership practice, human-capital systems, financial decision routines, and governance. In empirical work, researchers may model leadership agility as a mediator between AI capability and the two downstream organizational routes; alternatively, talent intelligence and green-finance processes may be examined as parallel mediators. The appropriate design depends on the setting and should maintain a clear distinction between individual leadership perceptions, organizational capabilities, and observed sustainability outcomes.

METHOD

3.1 Review design and protocol transparency

This study follows PRISMA 2020 reporting guidance (Page et al., 2021) and management-review principles (Tranfield et al., 2003). A protocol was prepared before the updated search. The protocol was not preregistered; this is reported as a limitation. The resubmission must be accompanied by a machine-readable extraction dataset and a coding matrix. Supporting theoretical and methodological references are retained in the manuscript but are not counted as included studies.

3.2 Sources, search strings, and eligibility

Table 2. Reproducible search protocol. Bracketed fields must be completed from exported database records before submission.

Database	Field	Exact search string
Scopus	TITLE-ABS-KEY	("artificial intelligence" OR "machine learning" OR "generative AI") AND ("leadership agility" OR "agile leadership" OR "strategic leadership" OR "managerial decision making")

Database	Field	Exact search string
Web of Science	Topic	TS=((("artificial intelligence" OR "machine learning" OR "generative AI") AND ("leadership agility" OR "agile leadership" OR "strategic leadership" OR "managerial decision making"))
Scopus / Web of Science	TITLE-ABS-KEY / Topic	("artificial intelligence" OR "machine learning") AND ("talent management" OR "human resource management" OR "workforce analytics" OR "people analytics")
Scopus / Web of Science	TITLE-ABS-KEY / Topic	("artificial intelligence" OR "machine learning") AND ("green finance" OR "sustainable finance" OR ESG OR "climate risk")

Eligible studies are peer-reviewed journal articles in English published from 2013 to the date of the final search in 2026. They must address an AI application and at least one focal domain (leadership/decision-making, talent management/HRM, or green/sustainable finance) with a clear organizational implication. Editorials, books, reports, working papers, conference papers, duplicate records, and sources lacking retrievable bibliographic information are excluded from the SLR dataset. Such items may be cited only as background where appropriate.

3.3 Screening, quality assessment, and audit trail

Two reviewers should screen titles/abstracts and full texts independently; disagreements should be resolved through discussion and, if needed, a third reviewer. The final paper must report records by database, duplicates removed, exclusions at title/abstract screening, full-text exclusions with reasons, and included studies in a PRISMA 2020 flow diagram. The original count of 42 is withdrawn until every record is verified against its source metadata.

Each included article should be appraised with a design-appropriate checklist: MMAT for mixed empirical evidence, CASP/JBI items where applicable, and an explicit relevance appraisal for conceptual papers. For transparency, the dataset must report the tool used, item scores, decision threshold, assessor initials, and reconciliation notes. Citation counts and journal indexing may be recorded descriptively but must not substitute for methodological quality appraisal.

The study-level spreadsheet is the decisive audit artifact for this review. For every candidate record, the authors must preserve the database-export identifier, verify the bibliographic record against the publisher or DOI landing page, state the inclusion decision, and record the reason for exclusion where applicable. This procedure ensures that books, reports, working papers, editorials, duplicate records, and unverifiable entries remain background materials rather than being silently counted as included evidence.

3.4 Extraction and thematic synthesis

The extraction sheet should record full verified reference; DOI/URL; country/context; sector; sample and design; theory; AI technology; focal construct; relationship or mechanism; sustainability outcome; risks/limitations; quality score; and decision. Coding is deductive at the top level (AI infrastructure, leadership agility, talent intelligence, green-finance process, outcomes, governance) and inductive for mechanisms, boundary conditions, and risks. A codebook, coded excerpts, and a code-to-category-to-theme audit trail should be supplied as supplementary material. Thematic claims in the final manuscript must identify the number and

type of included studies supporting them rather than use unqualified phrases such as “most studies.”

The coding process should begin with a pilot subset of independently coded articles. Reviewers should compare interpretations, refine definitions and decision rules, and document changes in the codebook. The final coding matrix should retain both a short summary and a source excerpt or page reference for each coded mechanism. This record enables a reader to trace a thematic statement back to the included studies and to distinguish direct evidence from the review team’s higher-order interpretation. If one reviewer conducts the synthesis, this limitation must be stated and an audit by a second reviewer should be sought for a subset of records.

A transparent synthesis also requires separation of evidence types. Empirical studies, conceptual articles, review articles, and methodological papers can all inform an interdisciplinary conversation, but they do not provide the same kind of evidence. The extraction sheet should preserve this distinction and the discussion should avoid aggregating them as though they were equivalent observations. Reports and books may be useful for context, definitions, or practitioner relevance, but they must not be used to inflate the included-study count when the review protocol limits inclusion to peer-reviewed journal articles.

RESULTS AND DISCUSSION

A. RESULTS

The original submission did not provide a verifiable extraction dataset. Consequently, this revised narrative does not repeat the original study count, percentages, country distributions, or causal claims. Once the verified dataset is attached, this section must be completed from the extraction sheet and limited to traceable evidence. The required descriptive reporting is shown in Table 3; it is intentionally structured to prevent unsupported aggregation.

Table 3. Mandatory evidence map for the final results section.

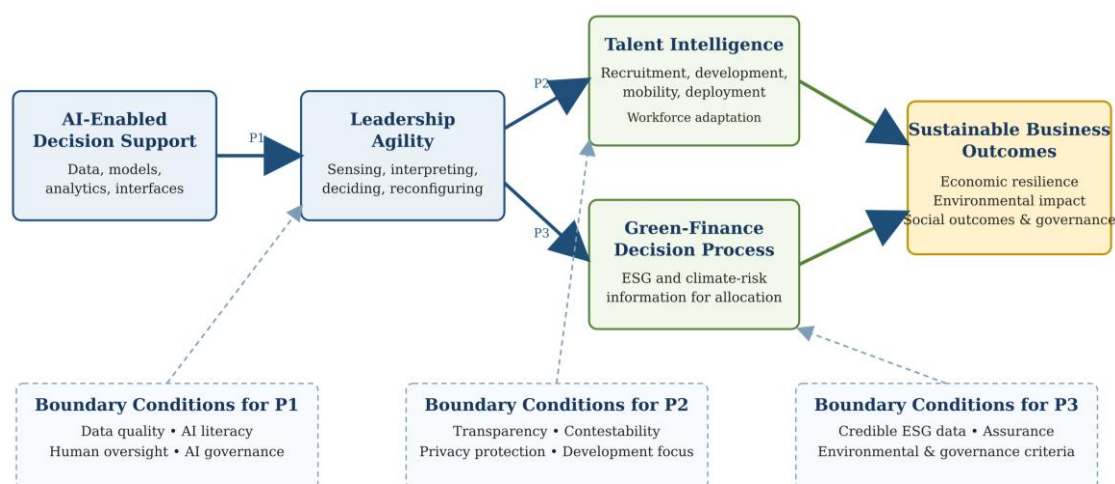
Required result	How it must be reported	Evidence source
Publication trend	Number of included studies by year; no inferred trend without counts	Verified dataset
Context and sector	Country/region and sector frequency; identify multi-country studies	Verified dataset
Methods and theory	Design and theory distribution; distinguish empirical, conceptual, and review articles	Verified dataset
AI and focal domains	Technology, organizational level, and focal relationship	Verified dataset + coding matrix
Outcomes and risks	Positive, negative, mixed, and null findings; bias, surveillance, explainability, data, and greenwashing risks	Verified dataset + coded excerpts

B. DISCUSSION

Integrative Synthesis

The framework in Figure 1 represents a conceptual synthesis to be tested, not a causal estimate. AI infrastructure provides data, analytical models, and interfaces. Under conditions of quality, literacy, oversight, and governance, it can augment leadership sensing, interpretation, and reconfiguration. Leadership agility then helps coordinate two organizational routes: talent intelligence, which supports workforce adaptation, and green-finance decision processes, which incorporate ESG and climate-risk evidence into allocation and disclosure choices. Sustainable business performance is multidimensional: economic resilience, environmental impact, social outcomes, and governance quality may improve, remain unchanged, or trade off.

The framework distinguishes the propositions and their conditions. Proposition 1 concerns the contribution of AI-enabled decision support to leadership agility; it is bounded by data quality, AI literacy, human oversight, and governance. Proposition 2 concerns the translation of leadership agility into talent intelligence; it is bounded by transparency, contestability, privacy, and a developmental rather than surveillance-oriented use of employee data. Proposition 3 concerns green-finance decisions; it is bounded by credible ESG data, assurance, and the explicit consideration of environmental and governance criteria. These boundaries make the model suitable for later empirical testing without overclaiming that they have already been confirmed by the review.



The framework also includes a cross-cutting risk pathway. Biased data or models may create discriminatory talent decisions; monitoring systems can undermine privacy and trust; opaque models can obscure accountability; and incomplete ESG data can enable greenwashing. These risks are not peripheral limitations. They are boundary conditions that determine whether AI is augmentation in service of responsible leadership or automation that weakens accountable decision making.

Responsible-AI governance should be understood as a set of organizational practices rather than a single policy statement. At minimum, it includes accountability for decisions,

documentation of model purpose and limitations, data-quality controls, meaningful human review for consequential decisions, mechanisms to detect and remedy unfair impact, and transparent communication to affected stakeholders. In financial and sustainability settings, governance also includes the ability to explain how ESG evidence informs a decision and to prevent sustainability claims from exceeding the underlying evidence. These safeguards make the model analytically balanced: AI may generate value, but it may also redistribute risk and responsibility in ways that require active oversight.

Table 4. AI-driven sustainable leadership ecosystem: mechanisms and conditions.

Element	Mechanism	Expected outcome	Key risk / boundary condition
AI infrastructure → leadership agility	Real-time forecasting, sensing, scenario analysis	More timely and informed adaptation	Data quality, AI literacy, human oversight, governance
Leadership agility → talent intelligence	Strategic prioritization of skills, development, and deployment	Workforce adaptability and employee development	Bias, surveillance, contestability, privacy
Leadership agility → green-finance process	Interpretation of ESG and climate-risk information in allocation choices	More credible sustainable investment and risk management	Model opacity, ESG-data quality, greenwashing
Integrated pathways → sustainable business	Alignment of technological, human, and financial decisions	Economic, environmental, social, and governance performance	Institutional constraints and outcome trade-offs

Theoretical and practical implications

The synthesis refines the theoretical contribution in three ways. First, it defines AI-augmented leadership agility as an organizationally embedded dynamic capability rather than a personal trait or a new standalone theory. Second, it identifies talent intelligence as a complementary capability through which leadership choices are operationalized. Third, it positions green finance as a strategic decision domain with sustainability outcomes that must be evaluated rather than assumed. This framing integrates dynamic capabilities, human-AI augmentation, strategic human capital, and sustainability perspectives without claiming that the present review proves causal effects.

For organizational leaders, the implication is to retain accountable human judgment in high-stakes decisions and to invest in AI literacy. For HR managers, the priority is transparent, contestable, and privacy-protective talent systems that support development instead of continuous surveillance. For financial institutions, the priority is traceable ESG and climate-risk inputs, model validation, and credible disclosure. For policymakers, the priority is interoperable standards for data quality, accountability, explainability, and anti-greenwashing enforcement.

Implementation should begin with a decision inventory rather than a technology purchase. Organizations can identify the decisions in which AI support is proposed, determine

their materiality for employees, customers, investors, or communities, and define the role that remains with accountable human decision makers. They should establish data-quality responsibilities, validate that model outputs are fit for the intended decision, and create escalation routes for contested or unexpected recommendations. This approach treats AI adoption as organizational change: successful use depends on leadership routines, employee capability, and stakeholder confidence as much as on technical accuracy.

For HR functions, a responsible implementation sequence includes communicating the purpose of data collection, minimizing unnecessary monitoring, conducting bias and impact assessments, providing meaningful review for consequential employment decisions, and using results to inform development rather than only selection or control. For financial functions, it includes documenting the origin and limitations of ESG data, testing model sensitivity, separating investment analysis from promotional claims, and ensuring that sustainability disclosures can be traced to underlying evidence. These practices turn the framework into a practical governance checklist without treating it as a universal prescription.

For research, the framework provides a disciplined agenda. Quantitative studies can test whether leadership agility mediates the relationship between AI capability and workforce or sustainability outcomes. Mixed-method studies can investigate how leaders contest algorithmic recommendations in practice. Comparative research can examine whether institutional rules, labor protections, data infrastructures, and sustainable-finance standards change the strength or direction of the proposed pathways. These designs should report negative and mixed outcomes alongside intended benefits.

Future research agenda

First, future empirical studies should disaggregate AI use by technology and decision context. Predictive analytics, machine-learning classification, natural-language processing, recommendation systems, and generative AI raise different forms of uncertainty and require different degrees of human review. Studies that combine all of these technologies in a single general measure risk obscuring the mechanism through which leadership agility develops. Researchers should therefore specify the technology, the decision it supports, the data on which it relies, the users who interpret its output, and the organizational consequence being assessed.

Second, outcome measurement should reflect the multidimensional nature of sustainable business. Economic outcomes may include resilience, operating efficiency, innovation, or risk-adjusted value; environmental outcomes may include emissions, resource use, or verified transition performance; social outcomes may include employee development, fairness, and stakeholder trust; and governance outcomes may include transparency, accountability, and compliance. A study should not infer all dimensions from a single perception-based measure. Where possible, perceptual measures should be complemented by archival indicators, sustainability disclosures, or independently verifiable performance records.

Third, longitudinal and multi-level designs are especially valuable. AI investments often affect organizational routines gradually, while workforce effects can occur at individual, team, and organizational levels simultaneously. A longitudinal design can distinguish immediate decision-support benefits from later reconfiguration and sustainability outcomes. Multi-source data can reduce common-method bias by combining leader assessments, HR-system data,

financial data, and external sustainability indicators. Qualitative process studies can add insight into how decision makers reconcile conflicting economic, social, and environmental signals.

Finally, comparisons across institutional settings should proceed only after a context-specific protocol is designed. If researchers seek to examine East Asia, emerging economies, or another region, the search strategy and extraction sheet must explicitly identify the countries, institutional variables, and inclusion criteria that justify that comparison. Context should not be added as a narrative label after a global search. Such a design would make it possible to investigate how regulations, financial-market maturity, digital infrastructure, cultural norms, and labor protections condition the proposed ecosystem.

CONCLUSION

This study contributes to the literature by offering an integrative perspective on how artificial intelligence can enhance leadership agility, optimize talent management, and drive sustainable finance innovation. By synthesizing these domains into a unified framework, this research provides both theoretical and practical insights into achieving sustainable business outcomes in the digital era. The findings underscore the importance of viewing AI not merely as a technological tool, but as a strategic capability that shapes organizational adaptability and long-term sustainability.

The findings demonstrate that AI significantly enhances leadership agility by enabling real-time, data-driven, and predictive decision-making. More importantly, this study reveals a conceptual shift in which leadership agility is no longer solely a human-centered capability but emerges as an AI-augmented dynamic capability, co-created through the interaction between human judgment and intelligent systems.

In the domain of human resource management, AI transforms traditional practices into integrated talent intelligence systems that support strategic workforce alignment and organizational adaptability. These systems enable organizations to move beyond administrative HR functions toward data-driven talent optimization that directly contributes to leadership effectiveness.

Furthermore, in the context of sustainability, AI plays a transformative role in green finance by embedding environmental considerations into financial decision-making processes. Rather than functioning as a supporting analytical tool, AI acts as a core driver of sustainable finance innovation, enabling organizations to align economic performance with environmental responsibility.

The central contribution of this study lies in the development of an AI-Driven Sustainable Leadership Ecosystem, which integrates leadership agility, talent intelligence, and green finance into a unified framework. This ecosystem perspective highlights that sustainable business outcomes are not achieved through isolated initiatives, but through the dynamic interaction of technological, human, and financial capabilities.

Overall, this study advances the literature by offering a holistic and theoretically grounded perspective on how AI can be leveraged to achieve both organizational performance and sustainability objectives in an increasingly complex business environment.

Despite its contributions, this study has several limitations that provide opportunities for future research. First, the study is based on a systematic literature review and does not include empirical validation of the proposed framework. Future research is encouraged to test the relationships identified in this study using quantitative methods such as structural equation modeling (SEM) or partial least squares (PLS).

Second, the analysis is limited to English-language publications, which may exclude relevant insights from non-English literature. Future studies could adopt a more global perspective by incorporating diverse sources.

Third, given the rapid evolution of AI technologies, the findings of this study represent a snapshot of a continuously evolving field. Future research should explore emerging developments, such as generative AI and autonomous decision systems, and their implications for leadership and sustainability.

Finally, further research is needed to examine the ethical and social implications of AI adoption, particularly in relation to trust, accountability, and organizational culture. Understanding these dimensions will be critical for ensuring the responsible and sustainable use of AI in business contexts.

DECLARATION ON THE USE OF AI-ASSISTED TECHNOLOGIES

The authors used AI-assisted language support only for language refinement and document organization. The authors independently verified and remain fully responsible for the accuracy, integrity, originality, references, tables, and analytical content of the manuscript.

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