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Generative Artificial Intelligence in Organizations

Strategic Decisions and Human Adaptations

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TIIVISTELMÄ

Tämä väitöskirja tarkastelee, miten tekoäly, erityisesti generatiivinen tekoäly, muokkaa organisaatioiden päätöksentekoa sekä ihmisten sopeutumista nykyaikaisissa työympäristöissä. Tutkimuksessa kehitetään monitasoinen viitekehys, joka yhdistää organisaatiotason tekoälyyn perustuvan päätöksenteon tuen yksilötason psykologisiin ja työuraan liittyviin seurauksiin ihmisen ja tekoälyn välisessä yhteistyössä. Väitöskirjan tavoitteena on selittää, miten tekoäly muuttaa päätöksentekoprosesseja ja työntekijöiden reaktioita teknologiaa hyödyntävissä organisaatioissa.

Väitöskirja nojaa kriittisen realismin paradigmaan ja abduktiiviseen tutkimuslogiikkaan, ja siinä hyödynnetään monimenetelmällistä tutkimusasetelmaa neljän toisiinsa kytkeytyvän osatutkimuksen kautta. Ensimmäinen osatutkimus raportoi systemaattisen kirjallisuuskatsauksen ihmisen ja tekoälyn välisestä vuorovaikutuksesta organisatorisessa päätöksenteossa sekä jäsentää tutkimuskenttää tekijät–ilmiö–seuraukset -viitekehyksen avulla. Toinen osatutkimus perustuu laadulliseen teema-analyysiin ja analysoi ammattilaisille suunnattuja podcast-aineistoja. Tulokset valottavat organisaatioiden siirtymää tekoälyn kokeiluista kohti strategisesti ja operatiivisesti integroitua käyttöä. Kolmas ja neljäs osatutkimus hyödyntävät kyselyaineistoihin perustuvaa rakenneyhtälömallinnusta ja tarkastelevat työntekijöiden ja tekoälyn välistä yhteistyötä erityisesti työhön sitoutumisen ja työuran kestävyyden näkökulmista.

Tulokset osoittavat, että tekoälyn organisatoriset vaikutukset eivät määräydy pelkästään teknisen suorituskyvyn perusteella, vaan sen mukaan, miten tekoälyjärjestelmät kytkeytyvät organisaation päätöksentekokäytäntöihin. Yksilötasolla tekoäly on positiivisesti yhteydessä työssä koettuun sitoutuneisuuteen. Kestävien työurien näkökulmasta tekoäly vaikuttaa uran kestävyyteen epäsuorasti sopeutumiskyvyn kautta, joka toimii keskeisenä mekanismina ihmisen ja tekoälyn yhteistyön ja urakehityksen välillä. Näitä vaikutuksia muovaavat edelleen kontekstuaaliset tekijät, kuten luottamus tekoälyyn, koettu helppokäyttöisyys ja koettu työsuhteen jatkuvuus.

Väitöskirja edistää tietämystä käsitteellistämällä tekoälyn sosioteknisenä toimijana organisatorisissa työn järjestelmissä. Se yhdistää strategiset, psykologiset ja työuraan liittyvät näkökulmat yhtenäiseksi selitykseksi tekoälyavusteisesta muutoksesta. Lisäksi tutkimus tarjoaa käytännön suosituksia organisaatioille, jotka pyrkivät hyödyntämään tekoälyä päätöksenteossa, työntekijöiden sitouttamisessa ja työurien kestävyyden tukemisessa.

Asiasanat: tekoäly, generatiivinen tekoäly, tekoälyvuorovaikutus, tekoäly-yhteistyö, päätöksenteko, kognitiivinen arviointi, työssä koettu sitoutuminen, uran sopeutumiskyky, uran kestävyys.

ABSTRACT

This dissertation examines how artificial intelligence (AI), particularly generative AI (GenAI), is reshaping organizational decision-making and human adaptation in contemporary work contexts. It develops a multi-level perspective linking organizational integration of AI-enabled decision support with individual-level psychological and career-related outcomes of human–AI collaboration. The overarching aim is to explain how GenAI transforms decision-making processes and employee responses within technology-enabled organizations.

Adopting a critical realist paradigm and an abductive research logic, the dissertation employs a mixed-methods design across four interrelated studies. The first study presents a systematic literature review of human–AI interaction in organizational decision-making, structured using an antecedents–phenomenon–consequences framework. The second study draws on qualitative thematic analysis of practitioner-oriented podcast data to explore how organizations move from experimentation with GenAI toward more integrated strategic and operational use, resulting in an actionable integration framework. The third and fourth studies apply survey-based structural equation modeling to examine employee responses to GenAI collaboration, focusing on work engagement and career sustainability, respectively.

Across the studies, the findings show that the organizational implications of AI and GenAI are shaped less by technological capability alone and more by how these systems are situated within organizational decision-making contexts and practices. At the individual level, GenAI collaboration is positively associated with work engagement, primarily through opportunity appraisals. In relation to sustainable careers, the results indicate that GenAI collaboration contributes indirectly through career adaptability, which functions as a key mechanism linking collaboration to longer-term career outcomes. The effects of GenAI collaboration are further shaped by contextual conditions such as trust in AI, perceived ease of use, and job insecurity.

The dissertation advances theory by reconceptualizing GenAI as a generative and interactive socio-technical collaborator that reshapes both decision-making processes and human adaptation across levels. By integrating strategic, psychological, and career perspectives, it provides a coherent account of AI-enabled transformation and offers actionable insights for organizations seeking to deploy GenAI in ways that support effective decision-making, employee engagement, and sustainable careers.

Keywords: artificial intelligence, generative AI, AI interaction, AI collaboration, decision-making, cognitive appraisal, work engagement, career adaptability, career sustainability.

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Abbreviations

AI	Artificial intelligence
GenAI	Generative artificial intelligence
LLMs	Large language models
APC	Antecedents-phenomenon-consequences
SEM	Structural equation modelling
CFA	Confirmatory factor analysis

Publications

[1] Zhe, Z., & Vartiainen, T. Human-AI in Decision-making: A systematic literature review and future direction. Presented at the Conference of International Association for Development of the Information Society 2025.

[2] Zhe, Z., & Vartiainen, T. (2025). From Potential to Practice: Harnessing Generative AI for Enhanced Decision-Making. European Academy of Management (EURAM) 2025 Proceedings. Published.

[3] Zhe, Z., (2025). Understanding Employee Responses to AI Collaboration: A Dual Appraisal Model of Work Engagement. European International Business Academy (EIBA) 2025 Proceedings. Published.

[4] Zhe, Z., & Vartiainen, T. Generative AI Collaboration and Sustainable Career: A Career Construction Perspective on Expatriates' Adaptability and Development. Presented at the conference of European International Business Academy (EIBA) 2025.

1 INTRODUCTION

1.1 Research background

Artificial intelligence (AI), and more recently generative AI (GenAI), has emerged as a transformative force reshaping organizational structures and work practices. Across industries, firms are increasingly embedding AI systems into decision-making processes in pursuit of enhanced efficiency, strategic intelligence, and competitive advantage (Al-Surmi et al., 2022; Coussement et al., 2024; Krakowski et al., 2023). At the same time, the rise of GenAI tools, capable of generating text, visuals, and solution alternatives, has introduced new dynamics into everyday work, particularly in knowledge-intensive domains. Unlike earlier forms of AI that primarily support prediction and optimization, GenAI enables the iterative generation of alternative solutions, thereby reshaping how decisions are formulated rather than merely evaluated. These developments are not only technological but also organizational and human, as they redefine how decisions are constructed and how work is experienced in digitally mediated environments (Benbya et al., 2021; Pachidi et al., 2021).

While the adoption of AI technologies holds considerable promise, their integration into organizations is far from straightforward. Strategic implementation requires rethinking decision configurations, human–AI collaboration models, and governance frameworks (Kolbjørnsrud, 2024; Papagiannidis et al., 2023; Shrestha et al., 2019). In this context, GenAI does not simply improve decision efficiency but transforms decision processes by expanding the range of possible alternatives and embedding a more interactive mode of collaboration between humans and intelligent systems. Organizations must therefore move beyond viewing AI as a support tool and instead consider how it becomes an integral part of decision formulation and execution.

Equally important are the human implications of these shifts. As AI becomes increasingly embedded in the workplace, employees are required to collaborate with intelligent systems, adapt to evolving task structures, and reassess their future career paths (Bankins et al., 2024; Jia et al., 2024). For some, GenAI may serve as an enabler of learning, autonomy, and growth (Chowdhury et al., 2024; Eapen et al., 2023). For others, it may generate concerns about deskilling, obsolescence, or loss of professional identity (Chowdhury & Wood, 2024; Demirci et al., 2025; Goto, 2021). These dynamics are particularly salient for knowledge workers and globally mobile professionals, who operate in complex and uncertain environments and must continuously adapt to technological change.

These developments collectively point to the need for an integrated perspective that captures both organizational and individual dimensions of AI-enable transformation. While existing research often examines these domains separately, this dissertation adopts a multi-level approach that links the organizational integration of AI-enabled decision processes with individual psychological and career-related outcomes of human–AI collaboration. By bringing together insights from strategic management, human–computer interaction, and career development research, it seeks to explain how GenAI reshapes both decision-making processes and human adaptation in contemporary work environments.

1.2 Research gap

While the organizational application of AI has received considerable scholarly attention, the literature remains fragmented across disciplinary silos and levels of analysis. Research in information systems, strategy, and operations has mainly highlighted AI's technological affordance, with attention to data-driven decision-making, resource allocation, and operational efficiency (Coussement et al., 2024; Li et al., 2021; Olan et al., 2022). Meanwhile, organizational behaviour and human resource studies have examined how AI influences individual work experiences, job design, and employee perceptions (Bankins et al., 2024; Rodgers et al., 2023). However, relatively few studies have sought to connect these perspectives into a coherent multi-level understanding of how AI, and particularly GenAI, simultaneously reshapes both organizational decision processes and individual adaptation.

At the strategic level, existing research has largely focused on predictive analytics and automation, offering limited insight into how GenAI, as a generative and interactive system, can be integrated into decision-making processes (Hillebrand et al., 2025). The emergence of GenAI challenges traditional notions of expertise and introduces a more interactive mode of engagement, enabling the iterative development of alternative solutions. Despite this shift, empirical studies examining how firms reconfigure their internal systems, structures, and workflows to integrate GenAI remain scarce. In particular, the mechanisms through which firms move from experimentation to embedding GenAI into core decision-making practices are not well understood. Consequently, the literature lacks actionable frameworks to guide firms in transitioning from experimentation to the strategic integration of GenAI within core decision-making processes.

At the individual level, the psychological and career-related implications of AI collaboration are still emerging. While concerns about job displacement and resistance have been widely discussed, less attention has been given to how employees interpret GenAI collaboration as part of their work experience (Lin et al., 2024). In particular, the cognitive and emotional mechanisms through which individuals evaluate AI collaboration, especially the interplay between opportunity and threat appraisals, remain insufficiently theorized and empirically examined. Moreover, long-term career implications are often overlooked, particularly in global work contexts where adaptability and sustainability are critical. How GenAI collaboration influences individuals' career adaptability and future-oriented development therefore remains underexplored.

Crucially, existing research rarely connects these organizational and individual perspectives. Studies tend to examine either strategic integration or human responses in isolation, overlooking the interdependencies between technological systems and human adaptation. This separation limits our ability to understand how GenAI is embedded within organizational decision processes while simultaneously shaping employee experiences and developmental trajectories. Together, these gaps point to the need for a multi-level, socio-technical perspective that explains how GenAI reshapes both decision-making processes and human adaptation in an integrated manner. Addressing this gap, the present dissertation develops a multi-level framework that links the organizational integration of GenAI-enabled decision processes with the psychological and career-related outcomes of human–AI collaboration.

1.3 Research questions and objectives

In response to the fragmented understanding of AI's organizational role and the underexplored human consequences of AI collaboration, this dissertation adopts a multi-level approach to investigate how AI, particularly GenAI, reconfigures strategic decision-making and shapes human adaptation in contemporary work settings. The research seeks to unpack the dual transformation within organizations: on the one hand, the strategic integration of AI to enhance decision-making; on the other, the psychological and developmental adjustments required of individuals who collaborate with and adapt to intelligent systems.

The overarching research question guiding this dissertation is:

How is AI, especially GenAI, reshaping strategic decision-making and human adaptation in organizations?

To address this broad inquiry, the dissertation pursues four interrelated research objectives, each explored through an individual study contributing to a unified research agenda:

(1) To map the conceptual landscape of Human–AI interaction in organizational decision-making.

The first objective identifies foundational themes, theoretical approaches, and future research avenues by systematically reviewing existing literature. This offers a structured synthesis of how AI has been conceptualized and studied in decision-making contexts, establishing a base for the dissertation's multi-level framework.

(2) To explore the strategic challenges and opportunities of integrating GenAI into organizational decision-making process.

The second objective investigates how firms are transitioning from viewing GenAI as a novel tool to embedding it within strategic and operational workflows. Drawing on real-world cases and practitioner narratives, it develops an empirically grounded framework for managing GenAI adoption and alignment.

(3) To examine employees' cognitive and emotional responses to AI collaboration in the workplace.

The third objective centers on the psychological mechanisms, particularly opportunity and threat appraisals, through which AI collaboration influences work engagement. It explains how employees interpret GenAI-enabled work and how these appraisals are shaped by contextual conditions such as perceived job insecurity and ease of use.

(4) To assess the impact of GenAI collaboration on long-term career adaptability and sustainability.

The fourth objective extends the analysis to future-oriented career outcomes, focusing on how GenAI affects expatriates' career adaptability and sustained development in global work environments. It highlights the moderating roles of trust in AI and perceived uncertainty in shaping these relationships.

Together, these objectives form an integrated research program that advances understanding of how GenAI transforms organizational systems and human experiences. Each paper provides a distinct perspective, including systematic, strategic, psychological, and developmental, while contributing to the overarching aim of theorizing AI’s role in the evolving workplace.

1.4 Positioning and contributions

This dissertation is situated at the intersection of digital transformation, organizational decision-making, and career development in the age of AI, with a particular focus on the growing role of GenAI. It brings together multi-disciplinary perspectives from strategic management, information systems, organizational behaviour, and career studies to develop an integrated understanding of how AI and GenAI technologies are reshaping the workplace. By investigating both firm-level strategy and individual-level adaptation, the dissertation responds to a growing call in the literature for multi-level theorization of AI’s impact in organizational settings.

While building on broader AI research, the dissertation specifically focuses on GenAI to explain how decision-making processes are reshaped rather than merely supported. Unlike earlier forms of AI that primarily assist prediction or optimization, GenAI enables the iterative generation of alternative solutions through human–AI interaction. This shifts decision-making from selecting among predefined options to constructing and exploring possible alternatives. As a result, GenAI alters not only decision outcomes but also the processes through which decisions are developed, positioning human–AI collaboration as an integral part of decision formulation.

At the firm level, the dissertation contributes to ongoing debates on how organizations move from experimentation to embedding AI and GenAI into core decision-making processes. Paper 1 systematically reinterprets the human–AI decision-making literature, identifying fragmented research streams and proposing a more integrated perspective on how decision processes are structured. Building on this foundation, Paper 2 develops an empirically grounded framework based on qualitative analysis of practitioner discourse, showing that GenAI adoption is not solely a technical challenge but a process of organizational design and governance. The resulting framework identifies key mechanisms, including collaboration design, user-centricity, rapid prototyping, and ethical governance, that enable firms to translate generative capabilities into decision-making practice.

At the individual level, the dissertation extends existing research on employee experience and sustainable careers in AI-mediated contexts. Paper 3 introduces a dual-appraisal framework, grounded in cognitive appraisal theory, to explain how employees interpret and respond to GenAI collaboration. It identifies opportunity and threat appraisals as coexisting mechanisms influencing work engagement, and highlights the role of contextual factors, such as job insecurity and perceived ease of use in shaping these appraisals. Paper 4 extends this perspective to longer-term outcomes by applying career construction theory to examine how GenAI collaboration influences expatriates' career adaptability and sustainability. The findings demonstrate that career adaptability functions as the central mechanism through which GenAI contributes to sustainable career development, particularly under conditions of uncertainty.

Methodologically, the dissertation adopts a multi-method approach that integrates systematic literature review, qualitative thematic analysis, and quantitative survey-based modelling. This combination enhances both the breadth and depth of the analysis and supports the development and validation of theoretical insights across levels.

Theoretically, the dissertation advances research by reconceptualizing GenAI as an interactive and generative socio-technical collaborator that reshapes both organizational decision-making processes and individual adaptation. Rather than viewing AI as a tool that augments predefined tasks, the dissertation highlights how GenAI participates in the construction of decisions through iterative human–AI interaction. By integrating strategic, psychological, and career perspectives, it offers a coherent explanation of AI-enabled transformation across organizational and individual domains.

In sum, the dissertation makes four core contributions:

(1) It maps and organizes the fragmented literature on Human–AI interaction in decision-making.

(2) It offers a strategic integration framework for GenAI adoption based on real-world organizational narratives.

(3) It introduces a dual-appraisal model to explain employee engagement in AI-mediated work.

(4) It reveals how GenAI collaboration fosters career adaptability and sustainability, especially for global talent.

These contributions offer an integrated, future-oriented perspective on how organizations and individuals can adapt to and operate effectively in AI-enabled environments.

1.5 Key concept definitions

To ensure conceptual clarity and consistency across the four dissertation papers, this section defines the core constructs used throughout the research. These definitions are grounded in relevant academic literature but also reflect the specific operationalizations adopted in each study.

- **AI**: AI refers to computational systems that perform tasks typically requiring human intelligence, including learning, reasoning, perception, and decision-making (Russell & Norvig, 1995). In organizational contexts, AI technologies are commonly used to support prediction, classification, and optimization tasks, enabling firms to enhance efficiency and generate data-driven insights. In this dissertation, AI is conceptualized not only as a technical capability but also as a socio-organizational phenomenon that reshapes decision systems and work practices.

- **GenAI**: GenAI is a subset of AI that leverages advanced machine learning models, particularly large language models (LLMs) and generative adversarial networks, to produce novel outputs such as text, images, designs, or code (Goodfellow et al., 2020; Radford et al., 2018). Unlike traditional AI systems that focus on prediction or classification, GenAI enables the generation of alternative solutions through iterative interaction (Storey et al., 2025). This generative capability allows AI to participate more directly in the construction of decision processes by expanding the range of possible options available to human actors. As a result, GenAI introduces new affordances and uncertainties for organizations and individuals, particularly in contexts requiring judgment, interpretation, and problem formulation.

- **Human–AI collaboration**: Human–AI collaboration refers to the interactive processes in which humans and AI systems work together to achieve shared goals, often by complementing each other's capabilities (Wilson & Daugherty, 2018). This collaboration can range from assistive and advisory roles to more integrated forms of joint problem-solving. In this dissertation, the concept captures how individuals engage with AI or GenAI systems as part of ongoing decision processes and task execution.

- **Strategic decision-making**: Strategic decision-making refers to processes through which organizations formulate and implement decisions that shape their long-term direction, structure, and performance (Eisenhardt & Zbaracki, 1992). In AI-enabled contexts, these processes increasingly involve hybrid forms of intelligence, where human judgment is combined with machine-generated inputs. This dissertation examines how GenAI influences not only the outcomes but also the processes through which strategic decisions are developed.

- **Work engagement**: Work engagement is a positive, fulfilling, work-related state of mind characterized by vigour, dedication, and absorption (Schaufeli et al., 2002). It is widely associated with motivation, performance, and well-being. Within AI-mediated environments, engagement is shaped not only by task characteristics but also by how employees appraise their interaction with intelligent systems—as an opportunity for growth or a threat to autonomy and competence.

- **Career adaptability**: Career adaptability is defined as a set of psychosocial resources that individuals use to cope with current and anticipated career-related tasks, transitions, and traumas (Savickas, 1997). It comprises four dimensions: concern (future orientation), control (self-discipline), curiosity (exploratory behaviour), and confidence (problem-solving efficacy). In the context of AI transformation, career adaptability is critical to helping individuals remain resilient and proactive in managing evolving roles and skill demands.

- **Career sustainability**: Career sustainability refers to the extent to which individuals can pursue a viable, meaningful, and enduring career path in the face of technological, organizational, and global change (De Vos et al., 2020). It reflects not just continuous employment, but the ability to grow, adapt, and find purpose over time. This dissertation examines how GenAI collaboration influences sustainability by shaping employees' psychological resources and adaptability trajectories, particularly among globally mobile workers like expatriates.

1.6 Structure of the dissertation

This dissertation is composed of four standalone but interrelated research papers, preceded by this comprehensive introductory chapter (Kappa) that integrates the overall research framework, positioning, and contributions. Together, these components offer a multi-level investigation into how AI, especially GenAI, is reshaping both strategic decision-making processes and individual career trajectories within organizations.

The structure is as follows:

- Chapter 1: Introduction: The current chapter sets the stage for the dissertation by outlining the research background, identifying key gaps in the literature, and presenting the research questions and objectives. It also positions the study within relevant academic fields, highlights its theoretical and practical contributions, defines core concepts, and explains the structure of the dissertation.

- Chapter 2: Theoretical background and conceptual integration: This chapter provides a synthesis of the theoretical frameworks and literatures that underpin the dissertation. It integrates insights from strategic management, information systems, cognitive psychology, and career development to offer a multi-level conceptual model of AI's impact in organizations. The chapter clarifies how each paper contributes to the overarching framework and advances knowledge in its respective domain.

- Chapter 3: Methodological approach: This chapter outlines the methodological choices across the four papers, highlighting their complementarity and rigor. It discusses the rationale for adopting a mixed-method research design, including systematic literature review, qualitative analysis of industry discourse, and two quantitative survey studies. It also addresses issues of validity, reliability, and ethical considerations.

- Chapter 4: Summary of dissertation papers: This chapter presents concise summaries of each of the four papers, detailing their aims, methods, key findings, and individual contributions. It illustrates how each paper addresses a different layer of the overarching research problem, ranging from systems-level mapping to employee engagement and long-term career development.

- Chapter 5: Discussion and conclusions: The final chapter synthesizes the findings of all four papers to articulate an integrated narrative on how AI and GenAI are transforming work and organizations. It revisits the research questions, discusses theoretical and managerial implications, and outlines limitations and future research directions. The chapter concludes by emphasizing the importance of developing strategic and human-centered capabilities for thriving in AI-augmented environments.

Each chapter builds on the previous to construct a coherent, multi-level perspective on how organizations and individuals can co-evolve with AI technologies. By weaving together insights from conceptual, qualitative, and quantitative inquiry, the dissertation offers a holistic account of AI's role in shaping the future of work.

2 THEORETICAL BACKGROUND AND CONCEPTUAL INTEGRATION

This dissertation is situated at the intersection of AI, strategic decision-making, and individual career development within organizations. It investigates how AI, particularly GenAI, is shaping both firm-level processes and individual-level experiences in contemporary work environments. The chapter begins by framing AI and GenAI as socio-technical systems, emphasizing their embeddedness in organizational and human contexts. It then introduces two complementary theoretical perspectives that guide the analysis: cognitive appraisal theory and career construction theory, which together illuminate individual responses to AI collaboration and long-term career development. These perspectives are integrated with a socio-technical view of AI to provide a coherent lens for understanding how AI-driven transformations unfold across organizational and individual domains. In the final section, the chapter synthesizes these perspectives into a coherent multi-level understanding of AI in organizations, setting the foundation for the empirical investigations that follow.

2.1 AI as a socio-technical transformation

The rapid diffusion of AI across sectors has initiated a paradigmatic shift in how organizations operate, innovate, and relate to human capital. While early discourse framed AI as a tool for task automation or analytical optimization, more recent scholarship emphasizes its role as a socio-technical force that reshapes not only processes and structures but also social dynamics, cultural logics, and normative expectations within organizations (Makarius et al., 2020; Orlikowski & Scott, 2008). This perspective invites a move away from purely technological determinism and toward a more integrated understanding of how AI is co-constituted through human intentions, institutional routines, and broader systems of meaning.

The socio-technical tradition in organization studies emphasizes the interdependence between social systems (e.g., people, roles, norms) and technical systems (e.g., tools, infrastructure). Applied to AI, this lens foregrounds the mutual shaping of human and machine agency, where technologies are not passive instruments but active participants in organizing (Leonardi, 2011). In the context of GenAI, this interaction becomes even more pronounced. In the context of GenAI, this interaction becomes more pronounced. Its ability to generate text, images, or code introduces new forms of collaboration, co-production, and uncertainty (Azer & Alexander, 2025), challenging traditional boundaries between users and tools, problem solvers and decision aids.

A socio-technical perspective also highlights the organizational embeddedness of AI. Technologies do not function in isolation; their effects are mediated by implementation practices, power structures, and institutional norms. As AI systems are introduced into workflows, they often trigger adaptations in job design, decision authority, and interdepartmental coordination (He et al., 2024; Shrestha et al., 2019). This makes the success of AI integration contingent not only on system performance but also on the ability of organizations to align technological affordances with human values and operational realities.

Building on this foundation, the dissertation examines how AI, especially GenAI, is enacted and experienced across two interrelated domains: strategic decision-making at the organizational level and psychological and career development at the individual level. This perspective reflects a central insight of socio-technical theory: organizational transformation involves not only adopting new technologies but also reconfiguring work practices, meaning systems, and adaptive responses (Willems & Hafermalz, 2021). GenAI is thus conceptualized as a catalyst that reshapes strategic logic, managerial practice, and individual sensemaking.

Understanding AI as a socio-technical transformation therefore allows for a more holistic analysis that accommodates complexity, emergence, and interdependence. It also supports the integration of multiple theoretical lenses across the dissertation, including socio-technical systems, cognitive appraisal theory, and career construction theory. By grounding the analysis in this framework, the dissertation avoids linear or overly functionalist accounts of AI adoption and instead attends to the interplay between technology, strategy, and human adaptation in shaping the future of work.

2.2 Strategic decision-making and GenAI

Strategic decision-making lies at the core of how organizations respond to complex and fast-changing environments, encompassing how firms gather information, evaluate alternatives, and allocate resources in pursuit of competitive advantage (Wu et al., 2017). Traditionally, this process has been conceptualized as a boundedly rational activity shaped by cognitive limitations, organizational routines, and institutional pressures (Simon, 1979; Eisenhardt & Zbaracki, 1992). However, the growing incorporation of AI, and especially GenAI, into strategic contexts is reshaping these established models by introducing new sources of information, patterns of inference, and modes of human–machine collaboration. In this sense, GenAI does not simply enhance decision-making efficiency but reshapes the process itself by expanding the space of alternatives and embedding iterative human–AI interaction into how decisions are constructed (Pachidi et al., 2021).

Human–AI collaboration in strategic decision-making can be understood as a cognitive and epistemic division of labour rather than a mere substitution of agents. GenAI broadens the option space by rapidly assembling dispersed facts, surfacing patterns, and proposing candidate alternatives or arguments. Human decision makers then scrutinize these proposals, inject contextual knowledge, weigh trade-offs, and retain accountability under uncertainty (Hao et al., 2024). The interaction is iterative: machine-generated outputs stimulate hypothesis formation and exploration, while human feedback refines questions and evaluative criteria (Glickman & Sharot, 2025). Effective collaboration depends on how organizations institutionalize these processes, including when AI-generated inputs are used, how they are evaluated, and what standards guide their adoption in strategic deliberation.

From a socio technical perspective, effective integration hinges less on acquiring advanced models than on embedding them where strategic choices are actually made. Integration entails articulating decision rights and handoffs between humans and systems, aligning interfaces and artifacts, such as prompts, drafts, and rationales, with the cognitive tasks of decision makers, and installing guardrails for provenance, explainability, and auditability (Cheong, 2024). These activities are inherently organizational. They rely on cross-functional coordination, shared vocabularies, and governance routines that manage risks such as hallucination, bias, and inappropriate generalization while maintaining flexibility and speed (Huang et al., 2025).

The integration of GenAI into strategy also raises epistemic and normative questions (Muzanenhamo & Power, 2024; Wamba et al., 2025). Epistemically, it shifts what counts as relevant evidence, how alternatives are surfaced, and how uncertainty is represented. Normatively, it affects whose voices gain influence when model outputs are persuasive, how dissent is expressed, and what constitutes a sufficient justification for consequential choices. As AI becomes woven into planning cycles and portfolio reviews, organizations must calibrate standards of justification, for example how human judgment engages with generated reasoning, establish legitimate forums for contestation, and align incentives so that careful review is valued alongside rapid drafting.

Importantly, the integration of GenAI is iterative and path dependent (Boussioux et al., 2024). Early implementation choices influence subsequent learning, adoption, and governance. Feedback mechanisms, such as post-implementation reviews and usage analytics, become essential for refining collaboration practices. Ultimately, what matters is not the adoption of a single powerful tool but the ongoing orchestration of socio-technical arrangements that combine human judgment, organizational routines, and AI capabilities to support strategic decision-making under uncertainty (Raisch & Krakowski, 2021).

2.3 Individual adaptation in human–AI collaboration: A cognitive appraisal perspective

As AI systems become increasingly embedded in everyday work routines, their influence extends beyond organizational strategy or operational efficiency to encompass transformations at the individual level (Bankins et al., 2024). One of the most profound shifts is how AI reconfigures the psychological experience of work. That is, how individuals perceive, interpret, and emotionally respond to their roles, tasks, and evolving workplace identities (Budhwar et al., 2023). The integration of AI, particularly GenAI, introduces new forms of interaction that influence how people engage with work and envision their future within organizations (Fügener et al., 2022). As tasks become increasingly co-executed with intelligent systems, employees may experience both empowerment and uncertainty. These reactions are not peripheral but central to how AI-enabled work is experienced and sustained in practice.

Against this backdrop, the locus of change has shifted from background decision support to ongoing human-AI collaboration embedded in daily tasks. Employees now engage with systems that generate content, provide feedback, and shape choices in real-time. This mode of interaction requires analytical attention to subjective sensemaking, since outcomes depend not only on what the system does but also on how individuals interpret its presence and adjust their engagement, learning, and well-being accordingly (Glikson & Woodlley, 2020).

Cognitive appraisal theory provides a useful lens for understanding these processes (Lazarus & Folkman, 1984). At its core, the theory posits that individuals' emotional and behavioral responses to novel situations are shaped not by the stimuli themselves, but by the meanings they ascribe to those stimuli. Applied to AI, this means that the same technology may elicit vastly different responses, ranging from enthusiasm to anxiety, depending on how it is appraised (He et al., 2024). In particular, two patterns are especially consequential. Opportunity appraisals reflect interpretations of AI as a pathway to growth, support, and improved performance. Threat appraisals capture interpretations of AI as undermining role boundaries, autonomy, or future security.

This dual-path framework is especially relevant in the context of GenAI, which blurs the lines between human and machine creativity. Unlike earlier forms of automation that replaced routine tasks, GenAI intervenes in more cognitive and identity-relevant domains, such as content creation, analysis, or client interaction. As a result, employees are likely to evaluate not just what the technology does, but what it means for their professional identity, development prospects, and long-term relevance (Cheng et al., 2023; Kong et al., 2024; Strich et al., 2021). Appraisal processes thus become a bridge between technological affordances and human outcomes.

Importantly, these responses do not arise in a vacuum. Empirical studies have demonstrated that they are shaped by contextual moderators, such as internal locus of control, AI knowledge, and GenAI expertise (Cheng et al., 2023; He et al., 2024; Nunes et al., 2025). These factors tilt whether AI is experienced as a resource or a risk. For example, employees with a stronger internal locus of control are more likely to view AI-related changes as challenges they can influence, rather than threats imposed upon them. Likewise, greater AI knowledge and hands-on GenAI expertise reduce ambiguity, making system outputs easier to interrogate and adapt, which can foster curiosity and skill growth. These dynamics highlight that human responses to AI depend on both individual psychological resources and the experiential conditions under which collaboration unfolds.

2.4 Career development in AI-enabled work: A career construction perspective

While AI has received significant attention for its impact on tasks, productivity, and organizational structures, its deeper implications for career development remain underexplored (Ekuma, 2024). As GenAI becomes more embedded in knowledge-intensive roles, it does not merely alter workflows. Indeed, it reshapes how individuals plan, adapt, and sustain their careers over time (Budhwar et al., 2023). In increasingly dynamic and technology-mediated environments, the notion of a stable, linear career is being replaced by one marked by continuous transitions, re-skilling, and identity negotiation. Understanding career development in such contexts requires attention to both individual agency and the enabling or constraining role of AI technologies.

Career Construction Theory (Savickas, 2005) provides a meaningful lens through which to examine these dynamics. At its core, the theory emphasizes how individuals construct their careers through the development of adaptive resources: concern (future orientation), control (agency), curiosity (exploratory behaviors), and confidence (self-efficacy). These resources enable people to respond proactively to change, craft meaningful career paths, and maintain a sense of coherence in the face of uncertainty. In AI-augmented work settings, career adaptability becomes particularly crucial as employees must continually reinterpret their value, relevance, and opportunities in light of evolving technological roles (Hessari et al., 2024).

Within this perspective, GenAI can operate as a career enabler. It expands access to information, supports rapid learning, and lowers barriers to engaging with complex tasks. By scaffolding experimentation and feedback, it can strengthen the very adaptability resources that sustain development over time (Borge et al., 2024; Jin et al., 2025).

The relationship between GenAI and career development is shaped by a range of contextual factors, such as perceived credibility of GenAI and task complexity (Li et al., 2025). When employees perceive GenAI as credible and reliable, they are more likely to integrate its outputs into their work, experiment with new functions, and view it as a developmental partner that enhances their expertise. Conversely, when credibility is low, individuals may disengage or rely solely on familiar routines, limiting opportunities for learning and adaptation. Task complexity further shapes these dynamics. In relatively simple or well-structured tasks, GenAI can streamline performance and free cognitive resources for career-related learning. In contrast, in complex or ambiguous tasks, collaboration with GenAI demands greater critical evaluation and problem-solving, which can strengthen adaptive capabilities but may also generate frustration if guidance or feedback is unclear (Wang et al., 2025).

Taken together, these factors shape whether GenAI is experienced as a catalyst for career growth or as a source of uncertainty and strain. Situating career adaptability within this broader socio-technical context provides a more nuanced understanding of career development. It shifts the focus from static notions of competence to ongoing processes of resilience, reflexivity, and agency in response to technological change. This perspective aligns with the aims of the dissertation, which examines how GenAI interacts with individual-level resources to support sustainable, future-oriented careers. In this view, career sustainability extends beyond employment continuity to encompass sustained growth, purpose, and psychological well-being in evolving work environments.

2.5 Toward a multi-level understanding of GenAI-enabled transformation in organizations

The preceding sections have illustrated that AI, and in particular, GenAI, functions not only as a technological innovation but as a multi-level transformative force that reshapes the way organizations make decisions and individuals navigate their careers. At the organizational level, AI challenges conventional approaches to strategic decision-making by introducing new capabilities for data synthesis, creative generation, and dynamic learning. At the individual level, it alters how employees appraise their roles, collaborate with machines, and plan their professional development. Yet despite this growing body of work across both levels, current research remains largely fragmented, with few integrative perspectives that bridge these levels of analysis.

To fully grasp the implications of AI and GenAI in organizational contexts, it is necessary to adopt a multi-level perspective that accounts for both macro-structural transformations and micro-psychological responses. This dissertation responds to that call by unifying conceptual and empirical insights that link the firm-level pursuit of strategic intelligence with the individual-level need for psychological adaptability and career sustainability. In doing so, it demonstrates that successful AI integration depends not only on technological infrastructure and strategic alignment, but also on the human capacity to engage with, interpret, and adapt to AI systems over time.

This multi-level view draws from and integrates complementary theoretical frameworks. Socio-technical systems theory situates AI as embedded in organizational structures, routines, and meanings, which directs attention to alignment between tools and contexts. Cognitive appraisal theory explains how people evaluate AI-mediated work through opportunity and threat interpretations, which then shape outcomes such as engagement, learning, and stress. Career construction theory identifies the adaptive resources that individuals mobilize to sustain coherent and future oriented career paths in technology rich environments. Considered together, these lenses enable a connected account of how system-level change and human adaptation co evolve.

This integrative approach also highlights that the relationship between firms and individuals in the AI era is mutually constitutive. Organizations that deploy AI without regard for employee experience may face resistance, disengagement, or talent loss. Conversely, individuals who feel supported and empowered by AI are more likely to contribute to innovation, learning, and long-term strategic goals. The future of AI in organizations, therefore, hinges on achieving alignment across levels, linking technological strategy with human development, and system-level intelligence with individual agency.

By weaving together these different strands, this dissertation contributes to a more holistic theory of AI in organizations. It not only advances scholarly debates about how AI alters work and strategy, but also provides practical insights into how organizations can design more inclusive, adaptive, and future-oriented pathways for AI implementation. Ultimately, it argues that sustainable value creation with AI requires equal attention to strategic decision processes and to the human conditions that enable people to thrive with intelligent technologies.

3 METHODOLOGY

This chapter provides an overarching discussion of the methodological framework that guides this dissertation. Rather than repeating the detailed methods presented in each individual paper, it synthesizes the philosophical foundations, research logic, and methodological choices that guide the dissertation as a coherent whole. The focus is on how different approaches, including systematic review, qualitative inquiry, and quantitative analysis, are combined to examine AI and GenAI across organizational and individual levels.

The chapter is structured around three key elements. It first introduces the critical realist paradigm that informs the study's ontological and epistemological assumptions. It then explains the abductive research logic adopted to iteratively link theory and empirical observations in developing context-sensitive explanations of AI-enabled decision-making and human adaptation. Finally, it outlines the mixed-method strategy, integrating conceptual synthesis, qualitative exploration, and quantitative testing, and summarizes the research design, data collection, and analytical procedures across the four studies to demonstrate overall methodological coherence and rigor.

3.1 Research paradigm

This dissertation adopts a critical realist paradigm, which provides a suitable ontological and epistemological foundation for examining the complex interplay between technological systems and human behaviour. Critical realism posits that reality exists independently of our perceptions but can only be known through socially constructed meanings and fallible interpretations (Bhaskar, 2013; Easton, 2010). This worldview is especially relevant to the study of AI and GenAI in organizational contexts, where both observable actions and latent mechanisms shape decision-making and employee experiences.

In contrast to positivist paradigms that focus solely on observable regularities, or constructivist paradigms that centre purely on subjective meanings, critical realism recognizes the stratified nature of reality, comprising the empirical (what is observed), the actual (what happens), and the real (the underlying mechanisms that produce events) (Wynn & Williams, 2012). This allows the research to move beyond surface-level description to examine how AI-enabled decision-making and human responses emerge from deeper socio-technical arrangements.

Throughout the dissertation, this paradigm supports a multi-level understanding of AI by enabling the investigation of both organizational phenomena (e.g., strategic decision-making enabled by GenAI) and individual psychological responses (e.g., appraisals of AI collaboration or career adaptability). It aligns well with the dissertation's central aim: to understand how AI acts as a socio-technical force that shapes strategic practices and human experiences in interconnected but distinct ways. The paradigm also accommodates methodological pluralism, allowing for both qualitative exploration and quantitative testing of theoretical propositions derived from abductive reasoning.

The adoption of a critical realist stance is particularly important given the emergent nature of the phenomenon under investigation. AI and GenAI are rapidly evolving technologies whose organizational impact is not fully understood, necessitating an approach that is both explanatory and exploratory. By embracing this paradigm, the dissertation acknowledges the partiality and situatedness of knowledge, while also striving for deeper theoretical insights into the conditions under which AI generates meaningful organizational and individual outcomes.

3.2 Research approach

This dissertation adopts an abductive research approach, which enables a flexible and iterative process of theory development grounded in both empirical observations and existing theoretical frameworks. Abduction is particularly suited to the study of emerging phenomena such as AI and GenAI, where existing theories provide only partial explanations (Dunne & Dougherty, 2016). Unlike purely inductive approaches that generate theory from data alone, or deductive approaches that test pre-defined hypotheses, abduction allows for a creative interplay between theory and data in the search for the most plausible explanations of complex phenomena (Dubois & Gadde, 2002; Janiszewski & Van Osselaer, 2022).

In this dissertation, abductive reasoning is applied across the four studies in distinct but connected ways. For example, in Paper 2, qualitative analysis of practitioner podcast data initially revealed a recurring tension between efficiency gains and uncertainty in GenAI adoption. This empirical pattern prompted a shift from viewing GenAI as purely an efficiency tool toward conceptualizing it as a socio-technical system requiring organizational alignment, which informed the development of the integration framework. Similarly, Papers 3 and 4 extend established theories, such as cognitive appraisal theory and career construction theory, by incorporating insights from GenAI-enabled work contexts, thereby refining theoretical mechanisms to account for new forms of human–AI collaboration. Abduction also guides the reinterpretation of existing literature in Paper 1, where prior findings are reorganized to identify patterns and gaps in human–AI decision-making research.

Across the dissertation, this iterative process allows theoretical constructs to be refined in light of empirical observations, while ensuring that explanations remain grounded in both data and established theory.

Importantly, the abductive approach also facilitates theoretical elaboration and contextualization, which are central goals of this dissertation. As AI technologies evolve, the meanings and implications of human–AI collaboration are not fixed but shaped by shifting social, technical, and organizational contexts (Bailey et al., 2022). Abductive reasoning enables the researcher to remain responsive to these contextual complexities and to propose models that are both empirically grounded and theoretically generative (Sætre & Van de Ven, 2021). This process is also aligned with the critical realist view of research as a layered investigation into underlying mechanisms that may not be directly observable but can be inferred through careful empirical and conceptual work (Mukumbang, 2023).

3.3 Research strategy

Research in social sciences generally employs three methodological orientations: qualitative, quantitative, and mixed-method. Each of these strategies offers distinct advantages and limitations depending on the nature of the research questions and epistemological assumptions. Qualitative research focuses on understanding meanings, interpretations, and underlying mechanisms through in-depth, contextual inquiry (Morgan & Smircich, 1980). It is particularly effective for theory-building, as it surfaces rich descriptions of organizational processes and uncovers subtle patterns often overlooked in structured data (Doz, 2011). In contrast, quantitative research, rooted in positivist epistemology, emphasizes the testing of relationships between predefined constructs using structured data and statistical analysis, providing a basis for generalizability and precision (Babbie, 2020).

While each tradition offers distinctive strengths, both carry inherent constraints that may limit inference when used in isolation. Against this backdrop, mixed-method research has emerged as a principled strategy for integrating breadth with depth. Defined as “the type of research in which a researcher or team of researchers combines elements of qualitative and quantitative research approaches for the broad purposes of breadth and depth of understanding and corroboration” (Johnson et al., 2007, p. 123), it provides a more holistic understanding of complex social phenomena. By integrating diverse data types and interpretive logics, mixed-method research enhances the credibility, depth, and applicability of findings (Clark & Creswell, 2007). This is particularly valuable when examining emerging phenomena such as AI and GenAI, where both socio-technical systems and human responses are evolving.

This dissertation adopts a mixed-method strategy, consistent with its critical realist paradigm and abductive research logic. Critical realism acknowledges the layered structure of reality and the existence of underlying mechanisms that may not be directly observable, thereby legitimizing the use of both empirical generalization and contextual explanation (Easton, 2010). Within this framework, an abductive approach (Dubois & Gadde, 2002) enables iterative movement between empirical data and theoretical development, which is essential for understanding how AI operates across organizational and individual levels.

Given the complexity of AI integration in organizational contexts, a single methodological lens would be insufficient to capture both its breadth and depth. Each of the four papers therefore adopts complementary methodological approaches. Paper 1 provides a systematic literature review that identifies theoretical and empirical gaps in AI-enabled decision-making and establishes the conceptual foundation for subsequent studies. Paper 2 employs a qualitative approach, using podcast-based content analysis to explore strategic challenges and opportunities in GenAI adoption. Papers 3 and 4 adopt survey-based quantitative designs to test the psychological and behavioural mechanisms through which GenAI influences work engagement and career sustainability.

This design follows an exploratory sequential mixed-methods approach (qualitative to quantitative) as articulated by Ivankova et al. (2006), in which initial qualitative and conceptual exploration informs subsequent quantitative testing. In this dissertation, insights from Papers 1 and 2 guided construct specification, item development, and model formulation for Papers 3 and 4, where survey instruments were validated and hypothesized relationships examined using larger samples. Sequencing the studies in this way strengthens content and construct validity, supports abductive refinement of theory, and enables both contextual depth and population-level inference.

3.4 Data collection and analysis

This dissertation employs a multi-method research design comprising a systematic literature review, qualitative inquiry, and two quantitative studies. Each paper addresses a specific dimension of the overarching research objective, namely understanding the organizational and individual implications of AI and GenAI integration. The combined use of secondary literature, qualitative data, and survey-based evidence reflects a deliberate strategy to ensure methodological rigor, contextual richness, and analytical robustness. The following sections outline the data collection and analysis procedures for each study.

Paper 1

Paper 1 is a systematic literature review that explores human–AI interaction in decision-making through a socio-technical lens. The review was conducted using a structured protocol to ensure transparency and replicability. The process involved four key steps.

Step 1: Review scope and inclusion criteria. The study focused on peer-reviewed journal and conference papers published after 2010 that examined human–AI interaction in organizational decision-making contexts. Articles were included if they met the following criteria: (1) they involved human users interacting with AI systems in decision-related settings; (2) they focused on workplace or organizational contexts; and (3) they offered theoretical, empirical, or conceptual insight into decision processes mediated by AI. Studies with a purely technical focus or outside organizational settings were excluded.

Step 2: Search and screening process. A systematic search was conducted in major databases including Scopus, Web of Science, and IEEE Xplore using keyword strings combining terms such as “artificial intelligence,” “decision-making,” “human–AI interaction,” and “organizational context.” This yielded an initial sample of 189 studies. After applying the inclusion criteria and screening titles, abstracts, and full texts, a final dataset of 77 relevant studies was selected for in-depth review.

Step 3: Coding and data extraction. A structured coding protocol was developed based on an antecedents–phenomenon–consequences (APC) framework. Each study was coded along several dimensions: (1) AI role and functionality (e.g., decision support, automation); (2) human interaction type (e.g., supervision, collaboration); (3) decision domain (e.g., HR, operations, finance); (4) theoretical grounding; and (5) reported outcomes. Coding was conducted independently by two researchers with discrepancies resolved in consultation with a third reviewer to ensure reliability.

Step 4: Data analysis and synthesis. Using NVivo software, qualitative thematic analysis was employed to identify emerging patterns. The findings were organized into six socio-technical dimensions, including people, goals, technology, processes, infrastructure, and culture, each containing several key elements (e.g., trust, explainability, complementarity). The analysis illuminated how human and technical factors jointly influence decision quality and organizational outcomes, and it laid the foundation for the empirical studies in subsequent papers.

Paper 2

Paper 2 employs a qualitative research design using podcast-based content analysis to investigate how organizations are integrating GenAI into decision-making processes. This approach allows the study to capture contemporary and practice-driven insights unavailable through conventional qualitative methods such as interviews or case studies.

The dataset comprises 51 podcast episodes focused on GenAI and its business applications, particularly in decision-intensive contexts. These episodes were sourced from reputable technology and management platforms and featured a diverse set of informants, including executives, innovation leaders, AI researchers, consultants, and policy experts. The inclusion criteria required that each podcast contain substantive discussion of GenAI deployment in real-world organizational settings, with particular attention to decision-making processes.

The data were analysed using a structured thematic analysis approach. First, all episodes were transcribed and subjected to open coding to identify recurring ideas, tensions, and action strategies. Through iterative categorization, the research team distilled the findings into key thematic clusters that captured both opportunities and challenges related to GenAI adoption. To ensure rigor and transparency, coding reliability was established through repeated team discussions and cross-checking of thematic interpretations.

The analysis revealed a dual narrative: while GenAI offers opportunities for knowledge acceleration and enhanced collaboration, organizations face challenges related to explainability, ethical governance, and implementation complexity. These insights informed the development of a seven-pillar framework outlining key mechanisms for strategic GenAI integration.

Paper 3

Paper 3 adopts a quantitative survey design to examine the psychological mechanisms through which AI collaboration influences employee work engagement, grounded in Cognitive Appraisal Theory.

Data were collected using Prolific, a widely used crowdsourcing platform that ensures data quality through pre-screened participant pools. A total of 395 valid responses were obtained from U.S.-based knowledge workers across sectors such as technology, education, marketing, and consulting. Eligibility screening ensured that all participants had hands-on experience using GenAI tools (e.g., ChatGPT, Jasper, GitHub Copilot) within their professional roles.

Survey instruments were adapted from established scales to capture human–GenAI collaboration, opportunity appraisal, threat appraisal, work engagement, job insecurity, and perceived ease of use. All items used seven-point Likert-type response options (1 = strongly disagree; 7 = strongly agree).

The data were analysed using structural equation modelling (SEM) in Mplus. First, confirmatory factor analysis was conducted to evaluate the reliability, convergent validity, and discriminant validity of all constructs. After ensuring good model fit, the full structural model was tested to examine hypothesized direct and indirect effects. Moderation effects were tested using interaction terms and simple slope analyses. Common method bias was assessed via the marker variable technique, and multicollinearity was ruled out through VIF diagnostics. The results provided empirical support for a dual-path appraisal model and established boundary conditions through moderator effects.

Paper 4

Paper 4 adopts a survey-based design to investigate the relationship between GenAI collaboration and career sustainability, with career adaptability as the mediating mechanism, grounded in career construction theory. The study uses the same dataset as Paper 3, focusing on a subsample of expatriate professionals to capture global career dynamics. Specifically, the data were filtered to include respondents with prior or current experience working in foreign countries and who regularly use GenAI tools in their job roles. This filtering ensured alignment with the study's focus on global career sustainability.

All constructs were measured using validated scales. Career adaptability was assessed using the Career Adapt-Abilities Scale, encompassing four dimensions: concern, control, curiosity, and confidence. Career sustainability captures perceptions of future employability, skill relevance, and career continuity. GenAI collaboration was measured using the same scale as in Paper 3. AI trust and job insecurity were included as moderators, using established scales validated in prior technology and career research. All constructs were measured using seven-point Likert-type response formats.

Data were analysed using structural equation modelling (SEM) in AMOS 26. Confirmatory factor analysis established the reliability and validity of all latent constructs. The hypothesized model was then tested for both mediation and moderation effects. Bootstrapping (5,000 samples) was used to estimate indirect effects and corresponding confidence intervals. Interaction terms were created to test the moderating influence of AI trust and job insecurity on the relationship between GenAI collaboration and career adaptability. The final model demonstrated good fit, and the findings provide robust empirical support for the proposed career adaptation mechanism in the context of AI-enabled global careers.

4 SUMMARY OF DISSERTATION PAPERS

This chapter outlines the key findings, theoretical contributions, and practical implications of the four papers that comprise this dissertation. Each paper addresses a distinct yet interconnected dimension of AI integration, spanning both organizational and individual levels of analysis. Collectively, the studies develop a multi-level perspective on how AI, particularly GenAI, reshapes strategic decision-making processes, employee experiences, and long-term career development.

Figure 1 presents an overview of the dissertation's research framework, illustrating how the overarching research objective and central research question are decomposed into four sub-questions, each corresponding to an individual paper. Specifically, Paper 1 examines the antecedents, interaction characteristics, and outcomes of human–AI decision-making through a systematic literature review, establishing the conceptual foundation of the dissertation. Paper 2 explores how organizations integrate GenAI into decision-making processes, identifying key challenges and strategic mechanisms through qualitative analysis. Paper 3 investigates employees' cognitive and emotional evaluations of GenAI collaboration and their implications for work engagement using a quantitative approach. Paper 4 extends this analysis to long-term outcomes by examining how GenAI collaboration influences expatriates' career adaptability and sustainability.

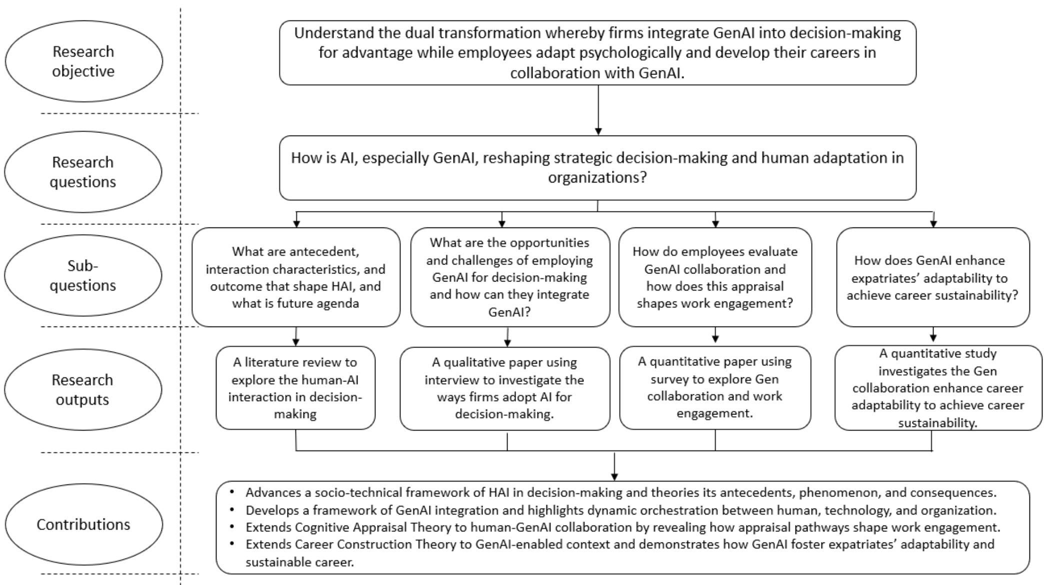

Figure 1. Overview of research framework and structure of the dissertation

4.1 Paper 1: Human–AI interaction in decision-making: A systematic literature review and future directions

The integration of AI into organizational decision-making is transforming how firms generate, process, and act on information. However, the effectiveness of AI is no longer determined solely by its computational capacity, but by how it interacts with human judgment in complex socio-technical systems. Despite a growing body of research on human–AI interaction, existing studies remain fragmented across disciplines such as psychology, information systems, and management, often focusing narrowly on isolated elements such as trust, transparency, or team composition. This fragmentation limits theoretical development and constrains practical guidance for organizations seeking to design effective human–AI decision systems.

To address this gap, this study conducts a systematic literature review (SLR) of 77 peer-reviewed articles published since 2012. Drawing on the antecedents–phenomenon–consequences (APC) framework, the review integrates diverse findings to identify (1) the antecedents that shape human–AI interaction (e.g., task uncertainty, human expertise, organizational norms), (2) the key characteristics of interaction (e.g., trust calibration, explainability, anthropomorphism, and structural models of collaboration), and (3) the outcomes of human–AI interaction for decision quality, efficiency, and ethical risk. The synthesis highlights two complementary research streams: psychological mechanisms that govern trust and reliance, and structural mechanisms that determine process complementarity between humans and AI.

The review makes three main contributions. Theoretically, it consolidates fragmented insights into a coherent framework that advances understanding of human–AI interaction as a socio-technical system. Conceptually, it positions the role of AI from a substitute for human decision-making to a complementary actor that enables alignment of human cognition and computational capabilities. Managerially, it offers actionable guidance for trust calibration, structural design, and governance, particularly in light of GenAI and its iterative, co-creative interaction models. Furthermore, by developing an integrative framework and outlining a future research agenda, this study advances cumulative knowledge on human–AI decision-making and provides a foundation for both scholarly inquiry and organizational practice.

4.2 Paper 2: From potential to practice: Harnessing generative AI for enhanced decision-making

This paper examines how organizations integrate GenAI into their decision-making processes, with the aim of identifying both the opportunities and challenges associated with its adoption. It addresses two key research questions: What are the core opportunities and challenges of using GenAI in organizational decision-making, and how can firms strategically integrate GenAI into decision processes? The objective is to move beyond technological hype and provide grounded insights into how GenAI can be operationalized for real-world decision support.

The study adopts a qualitative research design based on podcast-based content analysis. A total of 51 industry-focused podcast episodes were selected for their relevance to GenAI and business decision-making. These episodes, drawn from credible sources across the technology and management domains, feature discussions with executives, innovation leaders, AI researchers, consultants, and policy experts. The data were analyzed using thematic analysis to identify recurring patterns, tensions, and narratives related to GenAI adoption. This dataset provides real-time, practice-oriented insights into an evolving phenomenon, offering an alternative to conventional qualitative methods such as interviews or case studies.

The analysis reveals both opportunities and tensions in GenAI integration. On the one hand, GenAI enables rapid prototyping, accelerates knowledge discovery, and enhances human–AI collaboration. On the other hand, organizations face challenges related to hallucinations, limited explainability, ethical ambiguity, regulatory uncertainty, and internal resistance. Building on these insights, the paper develops an 8A strategic integration framework—aligning, assuring, adapting, accelerating, anchoring, amplifying, assembling, and anticipating—which provides a structured approach for managing GenAI adoption in decision-intensive contexts.

The paper makes important theoretical and practical contributions. Theoretically, the study enriches the decision-making literature by demonstrating how GenAI adoption is shaped by socio-organizational dynamics, and not merely algorithmic performance. It also extends methodological boundaries by demonstrating the value of podcast-based qualitative research as a tool for capturing emerging digital practices in real-time. Practically, it offers actionable guidance for organizations seeking to deploy GenAI effectively, grounded in practitioner discourse rather than purely technical optimism. The framework helps align technological capabilities with organizational goals, regulatory norms, and human values.

4.3 Paper 3: Understanding employee responses to AI collaboration: A dual appraisal model of work engagement

This paper investigates how employees psychologically respond to collaborating with GenAI in the workplace, particularly in relation to their levels of work engagement. As GenAI tools become increasingly embedded in professional tasks, understanding how such collaboration shapes employee experience has become critical. Drawing on cognitive appraisal theory, the paper proposes a dual-path model capturing both positive (opportunity) and negative (threat) evaluations that employees may form in response to GenAI. It investigates which appraisal pathways most strongly influence work engagement and the conditions under which these appraisals are amplified or attenuated.

The study employs a quantitative survey design, collecting data from 395 U.S.-based professionals with regular experience using GenAI tools in their work. Measures include GenAI collaboration, opportunity appraisals, threat appraisals, job insecurity, perceived ease of use, and work engagement. Structural equation modeling is used to test the hypothesized relationships, including mediation and moderation effects.

The findings support the dual-path appraisal model. GenAI collaboration significantly enhances opportunity appraisals, which in turn are strongly associated with higher work engagement. Although threat appraisals are negatively related to engagement, they are not directly driven by GenAI collaboration, suggesting that employees do not inherently perceive AI as threatening unless additional contextual stressors are present. Job insecurity amplifies both opportunity and threat appraisals, functioning as a cognitive sensitivity factor, whereas perceived ease of use attenuates these appraisals. Overall, the results show that engagement outcomes depend more on subjective interpretations than on the presence of AI technology alone.

The paper makes both theoretical and practical contributions. Theoretically, it develops a nuanced psychological framework that explains employee responses to GenAI by integrating cognitive appraisal theory into the study of AI-mediated work. The dual appraisal model advances prior research by demonstrating that AI collaboration is neither inherently motivating nor demotivating; rather, its effects depend on how individuals interpret the collaboration experience. Practically, the study provides actionable insights for managers and HR practitioners. To foster work engagement, organizations should design AI systems and workflows that enhance perceived opportunities while reducing uncertainty and fear.

4.4 Paper 4: Generative AI collaboration and sustainable careers: A career construction perspective on expatriates' adaptability and development

This paper examines how collaboration with GenAI influences the long-term career development of expatriates, a group often navigating uncertainty and complexity in global work environments. While prior research has primarily emphasized GenAI's role in enhancing productivity and task performance, this study shifts the focus toward its developmental implications for individual careers. Drawing on Career Construction Theory, the paper investigates how GenAI collaboration impacts career adaptability and how this adaptability, in turn, supports career sustainability.

The study employs a quantitative survey method, gathering responses from 361 expatriate professionals across diverse sectors who regularly use GenAI tools in their work. Measures include perceived GenAI collaboration, the four dimensions of career adaptability, and overall perceptions of career sustainability. Two moderators, AI trust and job insecurity, are also included to test boundary conditions. Structural equation modeling is used to assess direct, indirect, and moderated relationships, with appropriate control variables included for demographic and contextual factors.

The findings indicate that GenAI collaboration significantly enhances career adaptability, which in turn mediates its effect on career sustainability. Specifically, GenAI does not exert a direct effect on sustainability; rather, its impact operates through the strengthening of adaptive resources. All four adaptability dimensions (i.e., concern, control, curiosity, and confidence) are positively associated with GenAI collaboration. In addition, AI trust strengthens the positive effect of GenAI collaboration, while job insecurity intensifies the role of adaptability, suggesting that individuals facing greater uncertainty derive more benefit from developing adaptive capacities. Overall, the results highlight career adaptability as a key mechanism linking GenAI collaboration to sustainable career outcomes.

The paper makes both theoretical and practical contributions. Theoretically, it integrates career construction theory with emerging research on AI-mediated work, offering a psychological framework for understanding career development in the context of GenAI. It also extends the literature on career sustainability by demonstrating that digital transformation can function not only as a source of disruption but also as a driver of adaptive growth. Practically, the study provides insights for global talent management: organizations should design AI-enabled work systems that support reflection, learning, and the development of career confidence.

5 DISCUSSION AND CONCLUSION

5.1 Key integrated findings

Revisiting the central objective of this dissertation, the aim is to understand how AI, particularly GenAI, is integrated into contemporary organizational and individual contexts. Specifically, the dissertation examines how AI and GenAI reshape decision-making processes, influence human–AI collaboration, and transform employee experiences, including work engagement and career sustainability. To achieve this goal, one overarching research question and four research objectives guided the inquiry, each examined through a dedicated paper. This section synthesizes the key findings across the four studies to provide an integrated response to these objectives. Table 1 presents a consolidated summary of the findings.

Table 1. Summary of key findings

Main Research Question	Research Aims	Integrated Findings
How does the integration of AI, particularly GenAI, reshape organizational decision-making and individual career experiences in the workplace?	To map the conceptual landscape of Human–AI interaction in organizational decision-making	• AI's impact in decision-making depends on the quality of human– AI interaction within socio-technical systems, not raw computation. • The evidence organizes into three dimensions: antecedents (i.e., characteristics of task, team, and human), phenomenon (i.e., interaction characteristics), and outcomes (i.e., consequences at decision, individual, and organizational levels). • Effectiveness reflects two intertwined mechanisms, psychological mechanisms around trust and reliance and structural mechanisms around coordination and complementarity. • Human–AI interaction is conceptualized as complementary to human judgment, yielding an integrative framework with guidance for trust calibration, structural design, and governance in iterative, co-creative GenAI settings.
	To explore the strategic challenges and opportunities of integrating GenAI into organizational	• GenAI affords rapid prototyping, enhanced knowledge discovery, and improved human–AI collaboration within decision processes. • Adoption is constrained by hallucinations, limited explainability, ethical ambiguity, regulatory gaps, workflow misfit, and organizational resistance. • Effective integration hinges on socio-organizational orchestration rather than model

Main Research Question	Research Aims	Integrated Findings
	decision-making process	performance alone, aligning human judgment, routines, and governance with model affordances. • The 8A strategic integration framework offers practical guidance: aligning, assuring, adapting, accelerating, anchoring, amplifying, assembling, anticipating.
	To examine employees' cognitive and emotional responses to AI collaboration in the workplace	• GenAI collaboration relates to work engagement primarily through opportunity appraisals, not through threat appraisal. • Opportunity appraisal increases with perceived GenAI collaboration and positively predicts engagement. • Threat appraisal is negatively related to engagement but is not directly triggered by GenAI collaboration. It emerges under additional stressors. • Job insecurity amplifies both opportunity and threat appraisals, acting as a sensitivity factor, while perceived ease of use dampens both appraisals, reducing emotional volatility and stabilizing engagement outcomes. • Overall, the dual-path appraisal model explains when and how GenAI collaboration supports or undermines employee engagement.
	To assess the impact of GenAI collaboration on long-term career adaptability and sustainability	• GenAI collaboration boosts career adaptability (concern, control, curiosity, confidence). • Career adaptability fully mediates the link between GenAI collaboration and career sustainability. • AI trust strengthens the positive pathway whereby GenAI collaboration builds adaptability that, in turn, supports career sustainability. • Job insecurity heightens reliance on adaptability resources, making the pathway more pronounced under uncertainty. • GenAI collaboration scaffolds reflection, learning, and confidence, especially for expatriates in complex contexts.

Building on the consolidated findings, several overarching insights emerge across the four studies. To enhance clarity and generalizability beyond the specific empirical contexts, these insights are synthesized into a set of propositions. Together, they articulate how AI, and particularly GenAI, functions as a socio-technical actor that both shapes and is shaped by organizational decision-making, employee experiences, and career development. These propositions are grounded in the cumulative evidence of the four studies and are intended as theoretically informed claims to guide future research.

Proposition 1: AI should be conceptualized as a socio-technical actor rather than a stand-alone technical system.

Across the four studies, AI and GenAI are consistently observed not as isolated technical tools but as elements embedded within broader socio-technical arrangements. The systematic review (Study 1) demonstrates that outcomes attributed to AI in decision-making arise from its interaction with human actors, organizational routines, and institutional structures, rather than from model performance alone. The qualitative study (Study 2) further shows how GenAI tools are shaped through workflows, role expectations, and collaborative practices. The survey studies (Studies 3 and 4) reinforce this view by modeling AI use as relational and contextual, emphasizing interaction patterns, appraisals, and adaptability. Therefore, conceptualizing AI as a socio-technical actor foregrounds how its role is shaped by interactions among human actors, technical artefacts, and organizational arrangements. It draws attention to how AI systems participate in organizing processes, where they shape information flows, structure decision options, influence human judgments, and interact with employees' expectations, emotions, and developmental trajectories.

Proposition 2: The integration of GenAI into decision-making hinges on socio-organizational orchestration rather than model capability alone.

The studies converge on the idea that GenAI's technical capabilities are necessary but not sufficient for beneficial decision outcomes. The systematic review (Study 1) identifies organizational integration, governance, and capability-building as recurrent conditions under which AI contributes to decision quality and learning. Study 2 shows that GenAI supports decision-making only when embedded within aligned workflows, strategic priorities, and governance structures. Studies 3 and 4 further demonstrate that outcomes depend on employee perceptions, including trust, ease of use, and job insecurity, which reflect how GenAI is implemented and managed. These findings suggest that GenAI's value depends on socio-organizational orchestration, including strategic alignment, governance mechanisms, user-centered design, and shared norms of use. Organizational integration capabilities are therefore as critical as technological sophistication in determining GenAI's impact.

Proposition 3: Employees' opportunity appraisals are the primary psychological mechanism linking GenAI collaboration to work engagement.

This proposition is grounded in the survey study on GenAI collaboration and work engagement (Study 3). In that study, GenAI collaboration was theorised and measured as giving rise to two distinct appraisals. Specifically, employees could experience GenAI as a source of opportunities (e.g. productivity gains, learning, task enrichment) and/or as a potential threat (e.g. job displacement, heightened monitoring, loss of autonomy). Both opportunity and threat appraisals were specified as potential mediators between GenAI collaboration and work engagement.

The empirical findings indicate that only opportunity appraisals form a significant indirect pathway. GenAI collaboration is positively associated with opportunity appraisals, which in turn are positively related to work engagement. In contrast, the pathway through threat appraisals is not supported, as it does not reach statistical significance and does not explain variation in engagement in the tested models. These results suggest that the effects of GenAI collaboration on work engagement depend primarily on how employees interpret its developmental potential. Engagement increases when employees perceive GenAI as expanding opportunities for effectiveness, learning, and meaningful task involvement, rather than as a source of threat.

Proposition 4: Career adaptability is a key mechanism through which GenAI collaboration contributes to sustainable careers.

This proposition is derived from Study 4, which examines the relationship between GenAI collaboration and long-term career outcomes. Rather than assuming a direct effect, the study conceptualizes career adaptability, comprising concern, control, curiosity, and confidence, as an intermediate psychological resource. The empirical results indicate that GenAI collaboration is positively associated with these adaptability dimensions, which in turn are linked to indicators of career sustainability.

These findings suggest that the effects of GenAI collaboration on sustainable careers operate indirectly through the strengthening of adaptive resources. Working with GenAI is associated with greater future orientation, increased agency over career decisions, enhanced exploration of new roles and skills, and stronger confidence in managing change. These capabilities enable individuals to navigate evolving work environments more effectively. For expatriates and other professionals operating under conditions of uncertainty and complexity, such adaptive resources are particularly important for maintaining long-term employability and psychological sustainability. Proposition 4 therefore highlights that GenAI contributes to sustainable careers not through direct effects on outcomes, but by enhancing individuals’ capacity to adapt to changing career demands

Proposition 5: Contextual conditions, especially AI trust, ease of using AI, and job insecurity, shape how GenAI collaboration affects engagement and career sustainability.

The effects of GenAI collaboration depend on the conditions under which employees interact with the technology (Studies 3 and 4). In particular, AI trust, perceived ease of use, and job insecurity influence how GenAI collaboration is interpreted and whether it is experienced as a source of opportunity or threat. These contextual factors shape the strength and direction of the pathways through which collaboration influences work engagement and career adaptability. The findings indicate that GenAI collaboration does not produce uniform outcomes. Instead, its impact is contingent on employees' evaluative environment, which can amplify, moderate, or constrain how collaboration is experienced. As a result, the same GenAI interaction may lead to different engagement and career outcomes depending on the surrounding psychological and technological conditions. This proposition therefore highlights the inherently contingent nature of GenAI's effects.

Proposition 6: Organizational GenAI integration capabilities and individual adaptability resources are mutually reinforcing within AI-enabled socio-technical systems.

The four studies collectively reveal a multi-level linkage between organizational capabilities and individual resources in AI-enabled work systems. Studies 1 and 2 show that effective GenAI integration depends on organizational capabilities such as governance structures, ethical guidelines, supportive infrastructures, and coordinated implementation practices. Studies 3 and 4 further demonstrate that within such environments, employees are more likely to develop adaptability resources, engage in opportunity-focused appraisals, and experience GenAI collaboration as developmental rather than threatening. This relationship is not one-directional but mutually reinforcing: well-designed organizational integration fosters positive employee responses, while adaptive employees help sustain and extend the value of GenAI-enabled work systems. Organizational capabilities and individual resources are thus interdependent elements shaping how GenAI is embedded in work, engagement, and career sustainability.

To move beyond a study-by-study synthesis, Table 2 presents an integrative framework that conceptualizes GenAI as operating through a multi-level mechanism within AI-enabled work systems. At the organizational level, GenAI effectiveness depends on integration capabilities that align governance, workflows, and technological affordances. At the individual level, outcomes are shaped by employees' cognitive appraisal processes and the development of adaptive resources. Bridging these levels, human–AI interaction functions as a socio-technical process through which collaboration is enacted and experienced. Importantly, these levels are not independent but mutually reinforcing, such that organizational systems shape individual responses, while adaptive employees sustain and extend system effectiveness. These relationships are further conditioned by contextual factors, including AI trust, ease of use, and job insecurity.

Table 2. A multi-level mechanism of GenAI in AI-enabled work systems

Analytical Level	Key Mechanism	Key Elements (From Studies)	Contextual Conditions	Outcomes	Supporting Studies
Organizational level	GenAI integration capabilities	Governance structures; Ethical guidelines; Technical infrastructure; Implementation practices	Organizational readiness; implementation quality; Strategic alignment	Effective decision-making; Scalable human–AI collaboration	Study 1 & 2
Individual Level	Cognitive and behavioural adaptation	Opportunity–threat appraisal; Career adaptability; Self-directed learning	AI trust; Job insecurity; Ease of use	Work engagement; Career sustainability	Study 3 & 4
Interaction Level	Human–AI collaboration as a socio-technical process	Alignment between organizational systems and individual responses	Quality of human–AI interaction; Supportive work context	Quality of decisions; Meaningful collaboration experience	Integrated across all studies

5.2 Theoretical contributions

This dissertation makes several interrelated theoretical contributions to the literature on AI in organizations, human–AI collaboration, decision-making, and sustainable careers in technology-enabled work contexts. Drawing on multiple methodological approaches and grounded in a critical realist perspective, the four studies collectively advance a view of AI, particularly GenAI, as a socio-technical actor embedded within organizational and individual processes. Rather than treating AI as an isolated technological artefact, the dissertation conceptualizes its effects as emerging through a multi-level mechanism that links organizational structures, human–AI interaction processes, and individual adaptive responses. Table 3 summarizes the key contributions across literature streams.

Table 3. Summary of key theoretical contributions

Literature Stream	Theoretical Contributions
Human–AI interaction and decision-making	• Develops an integrative synthesis of human–AI interaction research through an antecedents–phenomenon–consequences (APC) framework. • Re-conceptualizes human–AI interaction as a socio-technical process combining psychological (e.g., trust, reliance) and structural (e.g., coordination, role allocation) mechanisms. • Advances a complementarity perspective, showing that decision quality emerges from alignment between human judgment and AI capabilities. • Identifies key contingencies and highlights the shift toward iterative, co-creative interaction in GenAI contexts.
GenAI adoption and integration	• Reframes GenAI adoption as a process of socio-organizational orchestration rather than purely technological implementation. • Develops the 8A framework as a mid-range model linking generative capabilities to organizational practices and governance. • Conceptualizes benefits–risk dualities (e.g., innovation vs. error propagation) as inherent tensions requiring simultaneous management.
Organizational behaviour and work engagement	• Extends Cognitive Appraisal Theory to AI-enabled work by modelling dual appraisal pathways (opportunity and threat). • Demonstrates that opportunity appraisal is the dominant mechanism linking GenAI collaboration to work engagement. • Identifies boundary conditions (e.g., job insecurity, ease of use) that shape appraisal processes and engagement outcomes. • Moves beyond technology acceptance models by emphasizing meaning-making and value interpretation.
Career adaptability and sustainable careers	• Extends Career Construction Theory to AI-mediated work contexts by positioning career adaptability as the central mediating mechanism. • Demonstrates how GenAI collaboration enables the development of adaptability resources (concern, control, curiosity, confidence). • Introduces AI trust and career-related uncertainty as key contextual moderators. • Reframes GenAI as a career-enabling condition in dynamic and boundaryless career environments.

Literature Stream	Theoretical Contributions
Socio-technical systems theory	• Conceptualizes GenAI as an embedded socio-technical actor shaping both organizational structures and individual agency. • Develops a multi-level mechanism linking organizational integration, human–AI interaction, and individual adaptation. • Highlights mutual reinforcement between organizational capabilities and employee adaptability. • Advances an integrative perspective centered on co-evolution, complementarity, and emergent agency in AI-enabled work.

First, this dissertation contributes to the literature on human–AI interaction and decision-making by offering a systematic and integrative synthesis of empirical research in this rapidly expanding domain. Prior research has often examined isolated dimensions such as cognitive bias, technology adoption, or organizational routines, limiting cumulative theorizing. By reviewing 77 peer-reviewed studies and organizing them through an antecedents–phenomenon–consequences (APC) framework, this dissertation integrates task, human, AI, team, and structural elements within a unified model. This contribution reframes human–AI interaction as a socio-technical process that simultaneously involves psychological mechanisms (e.g., trust, reliance, bias) and structural mechanisms (e.g., coordination, role allocation, and aggregation). Importantly, it shifts the dominant logic from substitution to complementarity, demonstrating that decision quality emerges from the alignment of human judgment and computational capabilities. Furthermore, by identifying underexplored contingencies, including contextual and temporal dynamics, the study highlights how GenAI transforms interaction from static, one-shot decision support into iterative, co-creative processes. This provides a cumulative foundation for future research on AI-enabled decision systems.

Second, this dissertation contributes to the literature on GenAI adoption and organizational integration by developing a grounded, practice-oriented understanding of how firms embed generative technologies into workflows. Moving beyond abstract or purely technical perspectives, the findings demonstrate that GenAI adoption is characterized by persistent tensions between opportunities and risks, which must be managed simultaneously rather than sequentially. Building on these insights, the dissertation introduces the 8A framework as a mid-range theoretical model that links observed challenges to actionable organizational responses. This framework specifies how organizations align, evaluate, adapt, and govern GenAI within complex and uncertain environments. In doing so, the contribution reframes adoption as a process of socio-organizational orchestration, where technological capabilities must be aligned with human judgment, routines, and governance structures. This extends existing decision-making and innovation literature by highlighting the organizational work required to translate generative capabilities into reliable and accountable practices.

Third, this dissertation contributes to the organizational behavior literature by extending Cognitive Appraisal Theory to the context of GenAI-enabled work. It develops a dual-pathway model in which employees simultaneously engage in opportunity and threat appraisals when interacting with AI systems, while demonstrating that opportunity appraisal serves as the primary mechanism linking GenAI collaboration to work engagement. This finding moves beyond dominant technology acceptance perspectives by showing that engagement is shaped not only by perceived usefulness or ease of use but by deeper processes of meaning-making and value interpretation. The study further identifies key boundary conditions, including job insecurity and perceived ease of use, which influence how these appraisals translate into engagement outcomes. By integrating cognitive, emotional, and contextual dimensions, this contribution offers a more nuanced understanding of employee responses to AI-enabled work environments.

Fourth, this dissertation contributes to the literature on career adaptability and sustainable careers by extending Career Construction Theory to AI-mediated work contexts. It demonstrates that career adaptability functions as the central mechanism through which GenAI collaboration supports long-term career sustainability, particularly in complex and dynamic environments such as expatriate work. Rather than assuming a direct effect of technology on career outcomes, the findings show how individuals convert digital affordances into adaptive resources across concern, control, curiosity, and confidence. The study also introduces AI trust and career-related uncertainty as critical contextual moderators, offering a more refined understanding of when GenAI acts as a career-enabling condition. This contribution is particularly relevant in the context of increasingly boundaryless and technology-intensive careers, where adaptability becomes central to sustained professional development.

Finally, and most importantly, this dissertation contributes to socio-technical systems theory by developing a multi-level conceptualization of GenAI as an embedded actor within organizational systems. Across the four studies, the findings collectively demonstrate that the effects of GenAI emerge through the interaction of three interrelated levels: organizational integration capabilities, human–AI interaction processes, and individual adaptive responses. At the organizational level, GenAI reshapes workflows, governance structures, and decision architectures. At the interaction level, it operates as a co-creative and iterative collaborator, mediating how humans engage with tasks and decisions. At the individual level, it influences cognitive appraisals, learning processes, and career development trajectories.

Crucially, these levels are not independent but mutually reinforcing. Organizational systems shape how individuals interpret and use AI, while adaptive individuals contribute to the effective functioning and evolution of these systems. By articulating this cross-level mechanism, the dissertation moves beyond binary framings of human versus machine and advances a more integrative perspective centered on co-evolution, complementarity, and emergent agency. In doing so, it provides a unifying theoretical scaffold that connects decision-making, employee experience, and career development within AI-enabled work systems, offering a foundation for future research on organizational transformation in the age of generative AI.

5.3 Managerial implications

This dissertation provides a range of managerial insights for organizational leaders, HR professionals, and policymakers seeking to integrate GenAI into decision-making processes and workforce strategies. Across four interconnected studies, the findings highlight that effective GenAI deployment depends not only on technological capability but on the alignment between organizational systems, human–AI interaction processes, and employee adaptation. The managerial implications therefore emphasize strategic alignment, implementation discipline, and human-centered integration. Table 4 summarizes the key recommendations.

Table 4. Summary of managerial implications

Managerial Focus	Recommendations
Strategic integration of AI	• Align GenAI initiatives with clearly defined organizational objectives rather than adopting technology opportunistically. • Prioritize explainability, ethical governance, and human–AI complementarity in system design. • Ensure workflow integration and user-centric design to embed GenAI into everyday decision processes.
Organizational implementation	• Treat GenAI adoption as a cross-functional transformation involving coordination across technical, operational, and managerial units. • Avoid over-automation by preserving human judgment in tasks requiring ethics, creativity, and contextual reasoning. • Establish continuous evaluation mechanisms (e.g., audits, feedback loops, interaction monitoring) to refine AI deployment.

Managerial Focus	Recommendations
Employee experience and engagement	• Manage both opportunity and threat perceptions associated with GenAI collaboration. • Design training and onboarding to build AI confidence and reduce uncertainty. • Position GenAI as a developmental partner to support learning, experimentation, and skill enhancement.
Career sustainability	• Frame GenAI as a long-term capability that supports career development rather than short-term efficiency gains. • Invest in developing career adaptability (concern, control, curiosity, confidence) through structured learning and mentoring. • Tailor support based on AI trust and perceived job insecurity to sustain engagement and long-term career outcomes.

At the strategic level, organizations should move beyond opportunistic or hype-driven adoption and instead align GenAI initiatives with clearly defined business objectives. Effective integration requires early attention to explainability, transparency, and ethical governance, ensuring that AI systems are not only technically viable but also organizationally accountable. The 8A integration framework developed in this dissertation (Paper 2) provides structured guidance for aligning GenAI capabilities with organizational needs. In addition, firms should prioritize workflow compatibility and user-centric design so that GenAI complements, rather than disrupts, existing decision processes.

At the implementation level, GenAI adoption should be treated as a cross-functional transformation rather than a standalone technological upgrade. Organizations should establish cross-disciplinary teams to pilot, evaluate, and scale AI initiatives, ensuring coordination between technical and managerial domains. Avoiding over-automation is critical. Managers should retain human involvement in tasks requiring ethical judgment, contextual interpretation, and creative problem-solving. Continuous evaluation mechanisms, including performance audits, explainability testing, and monitoring of human–AI interaction, are essential for refining deployment and maintaining system reliability over time.

From an employee experience perspective, the dissertation offers an evidence-based playbook for fostering work engagement in AI-mediated contexts. Engagement depends less on the mere presence of technology and more on how employees interpret collaboration with it. Implementation strategies should make opportunities salient by positioning AI as a developmental partner that expands creative thinking, accelerates analysis, and supports mastery. Communication that clarifies goals, limits, and boundaries reduces ambiguity, while hands-on experimentation and co-design increase ownership. Where job insecurity is salient, leaders should pair honest role narratives with visible pathways for reskilling and with recognition of early exemplars of high-quality human–AI work.

With regard to career sustainability, this dissertation suggests that AI can be a developmental enabler when coupled with the right organizational support. GenAI should be viewed as part of an evolving work ecosystem, where adaptability and continuous learning are crucial. Career adaptability resources including concern, control, curiosity, and confidence can be cultivated through training programs, mentoring, and reflective career planning. Organizations must also account for individual differences in perceived AI trust and career uncertainty. For instance, workers who trust AI are more likely to view it as a growth partner, while those experiencing uncertainty may require more personalized support to avoid disengagement or burnout. In global or boundaryless career contexts, these dynamics are amplified, making culturally sensitive and future-oriented interventions essential.

5.4 Limitations and future research directions

This dissertation advances understanding of AI integration in organizational decision making and career development. Nonetheless, several limitations delimit its scope and open avenues for future research.

Firstly, this dissertation focuses predominantly on the strategic and psychological dynamics of GenAI integration in decision-making and employee experiences, drawing primarily on survey and interview methods. Although the included studies provide conceptual and empirical clarity on how GenAI reshapes decision-making structures and work engagement, further research could explore these dynamics using alternative organizational lenses. For instance, how GenAI transforms team-level collaboration, power dynamics, and organizational politics remains underexplored. Future studies could examine the meso-level processes through which AI adoption is diffused across departments or teams, and how this affects organizational learning, hierarchy, and resistance. Additionally, as most of the studies take short-term view, there is a clear need for longitudinal research that captures the evolution of GenAI integration and its sustained impact on organizational culture and governance.

Secondly, while the dissertation advances our understanding of employee responses to AI, it focuses primarily on attitudinal and motivational outcomes, such as engagement, adaptability, and career orientation. However, the actual behavioral consequences of AI collaboration, such as changes in performance, retention, upskilling trajectories, or task innovation, deserve more attention. Future research should go beyond intention-based metrics and explore observable behavioral data (e.g., promotion trajectories, skill adoption curves, project outcomes) to assess how GenAI shapes workforce outcomes over time. It would also be valuable to explore latent tensions or ethical dilemmas employees face in GenAI-enabled workflows, particularly those related to surveillance, job displacement, and transparency in decision rights.

Third, while the dissertation incorporates key individual-level moderators such as AI trust and perceived career uncertainty, it does not fully capture the broader heterogeneity of employee experiences. Factors such as industry context, job role, cultural background, and prior exposure to AI are likely to shape how individuals interpret and respond to GenAI collaboration. Future research should adopt multi-level or configurational approaches to examine how these contextual conditions interact. For example, the impact of GenAI may differ substantially between frontline employees and managerial roles, or across industries with varying levels of automation intensity. Such approaches would help clarify when GenAI functions as a career-enabling versus career-constraining force.

Fourth, while the studies in this dissertation integrate theoretical perspectives such as Career Construction Theory and Appraisal Theory, future research could benefit from adopting alternative or complementary frameworks, including socio-materiality, institutional theory, or paradox theory. These perspectives could offer richer insights into how tensions between human agency and algorithmic structure are navigated, and how organizations reconcile efficiency logics with ethical or relational concerns. Additionally, future work should also examine the epistemic status of AI generated outputs, including perceptions of credibility, authority, and fairness, and trace how those perceptions shape organizational legitimacy and trust.

Finally, the dissertation focuses primarily on knowledge-intensive and digitally mature environments in Western contexts. This leaves open questions about how AI is adopted and experienced in non-Western or low-resource settings, where infrastructural, regulatory, or cultural differences may significantly shape AI's role. For instance, how does GenAI influence informal labor markets or precarious gig workers in emerging economies? How do national data policies, AI literacy, and trust in institutions influence GenAI implementation and reception across borders? Comparative or cross-cultural research would help broaden the generalizability of current insights and offer a more inclusive understanding of AI’s global impact. By addressing these questions, future research can build on the insights of this dissertation to create a more holistic, inclusive, and actionable understanding of how AI technologies transform the world of work.

REFERENCE

Al-Surmi, A., Bashiri, M., & Koliousis, I. (2022). AI based decision making: combining strategies to improve operational performance. *International Journal of Production Research*, *60*(14), 4464-4486.

Amankwah-Amoah, J., Abdalla, S., Mogaji, E., Elbanna, A., & Dwivedi, Y. K. (2024). The impending disruption of creative industries by generative AI: Opportunities, challenges, and research agenda. *International Journal of Information Management*, *79*, 102759.

Azer, J., & Alexander, M. (2025). Human-machine engagement (HME): conceptualization, typology of forms, antecedents, and consequences. *Journal of Service Research, 28*(1), 112-130.

Babbie, E. R. (2020). *The practice of social research*. Cengage Au.

Bailey, D. E., Faraj, S., Hinds, P. J., Leonardi, P. M., & von Krogh, G. (2022). We are all theorists of technology now: A relational perspective on emerging technology and organizing. *Organization Science*, *33*(1), 1-18.

Bankins, S., Ocampo, A. C., Marrone, M., Restubog, S. L. D., & Woo, S. E. (2024). A multilevel review of artificial intelligence in organizations: Implications for organizational behavior research and practice. *Journal of Organizational Behavior*, *45*(2), 159-182.

Benbya, H., Pachidi, S., & Jarvenpaa, S. L. (2021). Special Issue Editorial: Artificial Intelligence in Organizations: Implications for Information Systems Research. *Journal of the Association for Information Systems*, *22*(2), 281-303.

Bengio, Y., Hinton, G., Yao, A., Song, D., Abbeel, P., Darrell, T., ... & Mindermann, S. (2024). Managing extreme AI risks amid rapid progress. *Science*, *384*(6698), 842-845.

Boussioux, L., Lane, J. N., Zhang, M., Jacimovic, V., & Lakhani, K. R. (2024). The crowdless future? Generative AI and creative problem-solving. *Organization Science*, *35*(5), 1589-1607.

Borge, M., Smith, B. K., & Aldemir, T. (2024). Using generative AI as a simulation to support higher-order thinking. *International Journal of Computer-Supported Collaborative Learning*, *19*(4), 479-532.

Budhwar, P., Chowdhury, S., Wood, G., Aguinis, H., Bamber, G. J., Beltran, J. R., Boselie, P., Lee Cooke, F., Decker, S., & DeNisi, A. (2023). Human resource management in the age of generative artificial intelligence: Perspectives and research directions on ChatGPT. *Human Resource Management Journal*, *33*(3), 606–659.

Cheng, B., Lin, H., & Kong, Y. (2023). Challenge or hindrance? How and when organizational artificial intelligence adoption influences employee job crafting.

Journal of Business Research, *164*, 113987.

Cheong, B. C. (2024). Transparency and accountability in AI systems: safeguarding wellbeing in the age of algorithmic decision-making. *Frontiers in Human Dynamics*, *6*, 1421273.

Choudhury, A., & Chaudhry, Z. (2024). Large language models and user trust: consequence of self-referential learning loop and the deskilling of health care professionals. *Journal of Medical Internet Research*, *26*(2), e56764.

Chowdhury, S., Budhwar, P., & Wood, G. (2024). Generative artificial intelligence in business: towards a strategic human resource management framework. *British Journal of Management*, *35*(4), 1680-1691.

Clark, V. L. P., & Creswell, J. W. (2008). *The mixed methods reader*. Sage.

Coussement, K., Abedin, M. Z., Kraus, M., Maldonado, S., & Topuz, K. (2024). Explainable AI for enhanced decision-making. *Decision Support Systems*, *184*, 114276.

Demirci, O., Hannane, J., & Zhu, X. (2025). Who is AI replacing? The impact of generative AI on online freelancing platforms. *Management Science*, *71*(10), 8097-8108.

De Vos, A., Van der Heijden, B. I., & Akkermans, J. (2020). Sustainable careers: Towards a conceptual model. *Journal of Vocational Behavior*, *117*, 103196.

Doz, Y. (2011). Qualitative research for international business. *Journal of International Business Studies*, *42*(5), 582-590.

Dubois, A., & Gadde, L. E. (2002). Systematic combining: an abductive approach to case research. *Journal of Business Research*, *55*(7), 553-560.

Dunne, D. D., & Dougherty, D. (2016). Abductive reasoning: How innovators navigate in the labyrinth of complex product innovation. *Organization Studies*, *37*(2), 131-159.

Dwivedi, Y. K., Pandey, N., Currie, W., & Micu, A. (2024). Leveraging ChatGPT and other generative artificial intelligence (AI)-based applications in the hospitality and tourism industry: practices, challenges and research agenda. *International Journal of Contemporary Hospitality Management*, *36*(1), 1-12.

Eapen, T., Finkenstadt, D. J., Folk, J., & Venkataswamy, L. (2023). How generative AI can augment human creativity. *Harvard Business Review*, *101*(4), 56-64.

Easton, G. (2010). Critical realism in case study research. *Industrial Marketing Management*, *39*(1), 118-128.

Eisenhardt, K. M., & Zbaracki, M. J. (1992). Strategic decision making. *Strategic Management Journal*, *13*(S2), 17-37.

Ekuma, K. (2024). Artificial intelligence and automation in human resource development: A systematic review. *Human Resource Development Review*, *23*(2), 199- 229.

Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2022). Artificial intelligence and business value: A literature review. *Information Systems Frontiers*, *24*(5), 1709- 1734.

Fosso Wamba, S., Guthrie, C., Queiroz, M. M., & Minner, S. (2024). ChatGPT and generative artificial intelligence: an exploratory study of key benefits and challenges in operations and supply chain management. *International Journal of Production Research*, *62*(16), 5676-5696.

Fügener, A., Grahl, J., Gupta, A., & Ketter, W. (2022). Cognitive challenges in human–artificial intelligence collaboration: Investigating the path toward productive delegation. *Information Systems Research*, *33*(2), 678-696.

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals*, *14*(2), 627-660.

Glickman, M., & Sharot, T. (2025). How human–AI feedback loops alter human perceptual, emotional and social judgements. *Nature Human Behaviour*, *9*(2), 345-359.

Goodfellow, I. J., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., ... & Bengio, Y. (2014). Generative adversarial nets. *Communications of the ACM, 63*(11), 139-144.

Goto, M. (2021). Collective professional role identity in the age of artificial intelligence. *Journal of Professions and Organization*, *8*(1), 86-107.

Hao, X., Demir, E., & Eyers, D. (2024). Exploring collaborative decision-making: A quasi-experimental study of human and Generative AI interaction. *Technology in Society*, *78*, 102662.

He, C., Teng, R., & Song, J. (2024). Linking employees' challenge-hindrance appraisals toward AI to service performance: the influences of job crafting, job insecurity and AI knowledge. *International Journal of Contemporary Hospitality Management*, *36*(3), 975-994.

Hessari, H., Bai, A., & Daneshmandi, F. (2024). Generative AI: boosting adaptability and reducing workplace overload. *Journal of Computer Information Systems*, 1-14.

Hillebrand, L., Raisch, S., & Schad, J. (2025). Managing with artificial intelligence: An integrative framework. *Academy of Management Annals*, *19*(1), 343-375.

Huang, L., Yu, W., Ma, W., Zhong, W., Feng, Z., Wang, H., ... & Liu, T. (2025). A survey on hallucination in large language models: Principles, taxonomy, challenges, and open questions. *ACM Transactions on Information Systems*, *43*(2), 1-55.

Ivankova, N. V., Creswell, J. W., & Stick, S. L. (2006). Using mixed-methods sequential explanatory design: From theory to practice. *Field methods*, *18*(1), 3-20.

Janiszewski, C., & Van Osselaer, S. M. (2022). Abductive theory construction. *Journal of Consumer Psychology*, *32*(1), 175-193.

Jia, N., Luo, X., Fang, Z., & Liao, C. (2024). When and how artificial intelligence augments employee creativity. *Academy of Management Journal*, *67*(1), 5-32.

Jin, F., Lin, C. H., & Lai, C. (2025). Modeling AI-assisted writing: How self-regulated learning influences writing outcomes. *Computers in Human Behavior*, *165*, 108538.

Johnson, R. B., Onwuegbuzie, A. J., & Turner, L. A. (2007). Toward a definition of mixed methods research. *Journal of Mixed Methods Research*, *1*(2), 112-133.

Krakowski, S., Luger, J., & Raisch, S. (2023). Artificial intelligence and the changing sources of competitive advantage. *Strategic Management Journal*, *44*(6), 1425-1452.

Kumar, A., Shankar, A., Hollebeek, L. D., Behl, A., & Lim, W. M. (2025). Generative artificial intelligence (GenAI) revolution: A deep dive into GenAI adoption. *Journal of Business Research*, *189*, 115160.

Kolbjørnsrud, V. (2024). Designing the Intelligent Organization: six principles for Human-AI collaboration. *California Management Review*, *66*(2), 44-64.

Kong, H., Jiang, X., Zhou, X., Baum, T., Li, J., & Yu, J. (2024). Influence of artificial intelligence (AI) perception on career resilience and informal learning. *Tourism Review*, *79*(1), 219-233.

Lazarus, R. S., & Folkman, S. (1984). *Stress, appraisal, and coping*. Springer publishing company.

Leonardi, P. M. (2011). When flexible routines meet flexible technologies: Affordance, constraint, and the imbrication of human and material agencies. *MIS Quarterly*, *35*(1), 147- 167.

Li, G., Li, N., & Sethi, S. P. (2021). Does CSR reduce idiosyncratic risk? Roles of operational efficiency and AI innovation. *Production and Operations Management*, *30*(7), 2027-2045.

Li, J. M., Wu, H. Y., Zhang, R. X., & Wu, T. J. (2025). How employee-generative AI collaboration affects employees work and family outcomes? The relationship instrumentality perspective. *The International Journal of Human Resource Management*, *36*(8), 1431-1457.

Lin, H., Tian, J., & Cheng, B. (2024). Facilitation or hindrance: The contingent effect of organizational artificial intelligence adoption on proactive career behavior. *Computers in Human Behavior*, *152*, 108092

Liu-Thompkins, Y., Okazaki, S., & Li, H. (2022). Artificial empathy in marketing interactions: Bridging the human-AI gap in affective and social customer experience. *Journal of the Academy of Marketing Science*, *50*(6), 1198-1218.

Makarius, E. E., Mukherjee, D., Fox, J. D., & Fox, A. K. (2020). Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization. *Journal of Business Research*, *120*, 262-273.

Morgan, G., & Smircich, L. (1980). The case for qualitative research. *Academy of Management Review*, *5*(4), 491-500.

Mukumbang, F. C. (2023). Retroductive theorizing: a contribution of critical realism to mixed methods research. *Journal of Mixed Methods Research*, *17*(1), 93-114.

Muzanenhamo, P., & Power, S. B. (2024). ChatGPT and accounting in African contexts: Amplifying epistemic injustice. *Critical Perspectives on Accounting*, *99*, 102735.

Nunes, J. R., Rita, P., Pinto, D. C., Gonzalez-Jimenez, H., Akdim, K., & Wagner, R. L. (2025). Moral appraisals of generative AI: How mindset framing shapes moral judgments, emotional appraisals and privacy behavior. *International Journal of Information Management*, *84*, 102940.

Olan, F., Arakpogun, E. O., Suklan, J., Nakpodia, F., Damij, N., & Jayawickrama, U. (2022). Artificial intelligence and knowledge sharing: Contributing factors to organizational performance. *Journal of Business Research, 145*, 605-615.

Orlikowski, W. J., & Scott, S. V. (2008). 10 sociomateriality: challenging the separation of technology, work and organization. *Academy of Management Annals*, *2*(1), 433-474.

Pachidi, S., Berends, H., Faraj, S., & Huysman, M. (2021). Make way for the algorithms: Symbolic actions and change in a regime of knowing. *Organization Science*, *32*(1), 18- 41.

Papagiannidis, E., Enholm, I. M., Dremel, C., Mikalef, P., & Krogstie, J. (2023). Toward AI governance: Identifying best practices and potential barriers and outcomes. *Information Systems Frontiers*, *25*(1), 123-141.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879-903.

Radford, A., Narasimhan, K., Salimans, T., & Sutskever, I. (2018). Improving language understanding by generative pre-training. Available at: https://www.mikecaptain.com/resources/pdf/GPT-1.pdf.

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review*, *46*(1), 192-210.

Rodgers, W., Murray, J. M., Stefanidis, A., Degbey, W. Y., & Tarba, S. Y. (2023). An artificial intelligence algorithmic approach to ethical decision-making in human resource management processes. *Human Resource Management review*, *33*(1), 100925.

Russell, S., & Norvig, P. (1995). *Artificial intelligence: A modern approach*. Prentice Hall.

Savickas, M. L. (2005). The theory and practice of career construction. *Career development and counseling: Putting theory and research to work* (pp. 42-70), John Wiley & Sons.

Savickas, M. L. (1997). Career adaptability: An integrative construct for life-span, life-space theory. *The Career Development Quarterly*, *45*(3), 247-259.

Schaufeli, W. B., Salanova, M., González-Romá, V., & Bakker, A. B. (2002). The measurement of engagement and burnout: A two sample confirmatory factor analytic approach. *Journal of Happiness Studies*, *3*(1), 71-92.

Shrestha, Y. R., Ben-Menahem, S. M., & Von Krogh, G. (2019). Organizational decision- making structures in the age of artificial intelligence. *California Management Review*, *61*(4), 66-83.

Simon, H. A. (1979). Rational decision making in business organizations. *The American Economic Review*, *69*(4), 493-513.

Storey, V. C., Yue, W. T., Zhao, J. L., & Lukyanenko, R. (2025). Generative artificial intelligence: Evolving technology, growing societal impact, and opportunities for information systems research. *Information Systems Frontiers*, *27*(5), 2081-2102.

Strich, F., Mayer, A. S., & Fiedler, M. (2021). What do I do in a world of artificial intelligence? Investigating the impact of substitutive decision-making AI systems on employees' professional role identity. *Journal of the Association for Information Systems*, *22*(2), 304-324.

Sætre, A. S., & Van de Ven, A. (2021). Generating theory by abduction. *Academy of Management Review*, *46*(4), 684-701.

Wang, R., Zhang, Z., Zhao, W., Li, S. B., & Pan, Y. (2025). Exploring the relationship between generative AI usage and employee creativity: a dual-pathway mediation model. *European Journal of Innovation Management*, 1-25.

Wamba, S. F., Queiroz, M. M., Randhawa, K., & Gupta, G. (2025). Generative artificial intelligence and the challenges to adding value ethically. *Technovation*, *144*, 103235.

Willems, T., & Hafermalz, E. (2021). Distributed seeing: Algorithms and the reconfiguration of the workplace, a case of 'automated' trading. *Information and Organization*, *31*(4), 100376.

Wu, K. J., Tseng, M. L., Chiu, A. S., & Lim, M. K. (2017). Achieving competitive advantage through supply chain agility under uncertainty: A novel multi-criteria decision- making structure. *International Journal of Production Economics*, *190*, 96-107.

Wilson, H. J., & Daugherty, P. R. (2018). Collaborative intelligence: Humans and AI are joining forces. *Harvard Business Review*, *96*(4), 114-123.

Wynn Jr, D., & Williams, C. K. (2012). Principles for conducting critical realist case study research in information systems. *MIS quarterly*, *36*(3), 787-810.

PAPER 1

Human-AI interaction in decision-making: A systematic literature review and future direction

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Abstract

Artificial intelligence (AI) is increasingly embedded in organizational decision-making, yet effective outcomes depend not only on technological performance but also on the quality of human–AI interaction (HAI). Existing research is fragmented across disciplines, offering limited integration of psychological, technological, and organizational perspectives. This study conducts a systematic literature review of 77 peer-reviewed articles to synthesize knowledge on HAI in decision-making. Guided by an Antecedents–Phenomenon–Consequences framework, the review identifies the antecedents that shape HAI, the interaction characteristics that define how humans and AI collaborate, and the consequences for decision outcomes at individual, team, and organizational levels. The review advances theory by consolidating fragmented insights into a socio-technical framework. The study provides managerial implications for designing effective HAI systems and concludes with a research agenda to guide future inquiry into the evolving dynamics of human–AI decision-making.

Keywords: Artificial intelligence, human-AI interaction, decision-making, systematic literature review

1. INTRODUCTION

Artificial intelligence (AI) has rapidly become a defining force in contemporary organizations, where its integration is no longer considered optional but rather a strategic necessity. Firms that successfully implement AI are able to optimize efficiency, enhance productivity, and strengthen their competitive positioning (Weill & Woerner, 2018). Recent industry evidence suggests that organizations adopting AI achieve not only cost savings but also substantial gains in decision quality and speed (Al-Surmi et al., 2022). In financial services, AI-driven fraud detection and risk assessment models have reduced fraudulent activities by more than 20 percent (Ryman-Tubb et al., 2018), while in human resource management, AI systems increasingly support recruitment, training personalization, and performance monitoring (Marr, 2018; Guenole & Feinzig, 2018; Kellogg et al., 2020). These developments illustrate that AI has moved beyond being an experimental technology to becoming a pervasive decision-support instrument across organizational functions.

While the value of AI is clear, its adoption for decision-making introduces new complexities. Decision-making has traditionally been regarded as a distinctly human domain, shaped by cognitive reasoning, intuition, and experiential learning (Gigerenzer, 2007). Humans are skilled at interpreting ambiguous information and navigating uncertainty, yet they are also constrained by limited information-processing capacity and prone to systematic biases such as confirmation bias or anchoring. Conversely, AI excels at processing large-scale data and identifying patterns with consistency and accuracy, but it often struggles in contexts requiring judgment, tacit knowledge, or ethical reasoning (Shrestha et al., 2019). Moreover, AI is not immune to errors, such as biases embedded in training data or algorithmic design, which can produce unfair or unintended outcomes, as widely reported in cases of algorithmic hiring (Lambrecht & Tucker, 2019). These complementary strengths and weaknesses of humans and AI highlight the necessity of investigating how both can be integrated effectively to support organizational decision-making.

An emerging body of research points to the potential of human–AI interaction (HAI) to generate superior decision outcomes compared with either humans or AI acting in isolation. When humans and AI systems collaborate, they are able to combine tacit insights and contextual judgment with the computational power of advanced algorithms. For example, Steiner et al. (2018) show that AI-assisted pathologists demonstrate higher accuracy and efficiency in diagnostic tasks than either pathologists or algorithms working alone. Similarly, Fügener et al. (2022) demonstrate that hybrid teams composed of humans and AI surpass individual performance in image classification. These studies suggest that decision-making effectiveness increasingly depends not only on technological performance or human expertise but also on the quality of the interaction between the two. Accordingly, the focus of scholarship has shifted from evaluating AI as a stand-alone tool to examining HAI as a socio-technical system, in which human cognition, organizational processes, and technological design are deeply intertwined (Burton et al., 2020; Jain et al., 2023; Krakowski et al., 2023; Metcalf et al., 2019; Steyvers & Kumar, 2024).

Despite these advances, current research remains fragmented and often narrowly focused on isolated elements such as algorithmic transparency, user trust, or team composition. While these individual studies provide valuable insights, they rarely account for the broader interplay of factors that shape decision outcomes at both micro (individual and team) and macro (organizational) levels (Brougham & Haar, 2018). As a result, the literature lacks a comprehensive framework capable of explaining when and why HAI leads to enhanced decision performance and under what conditions it may instead produce inefficiencies, biases, or ethical concerns. This fragmentation constrains both theoretical development and practical guidance for managers seeking to design effective human–AI decision systems.

This paper addresses these gaps by conducting a systematic review of existing studies on HAI in organizational decision-making. The review is guided by two central research questions: (1) What are the antecedents, interaction characteristics, and outcomes that shape the dynamics and effectiveness of HAI in decision-making? (2) What directions should future research take to advance both theory and practice in this domain? To answer these questions, we integrate prior work into a holistic Antecedents–Phenomenon–Consequences (APC) framework that captures the multi-level drivers, interaction mechanisms, and outcomes of HAI in decision-making. This framework provides a structured basis for analyzing fragmented findings across psychology, information systems, and management, while also enabling the development of an agenda that emphasizes complementarity between human and AI contributions.

This review makes three main contributions. First, it consolidates a fragmented body of research by systematically integrating insights from diverse disciplines into a coherent framework, thereby enabling cumulative knowledge development in HAI and decision-making. Second, it advances theory by extending existing perspectives, such as technology adoption models and socio-technical systems theory, through the APC framework, which links antecedents, interaction characteristics, and outcomes into a unified model. Third, it generates practical insights for managers by identifying key mechanisms that enable complementarity between human cognition and AI capabilities, while also highlighting governance challenges in ensuring responsible adoption. Together, these contributions enhance scholarly understanding and offer actionable guidance for organizations navigating the complexities of AI-enabled decision-making.

The remainder of the paper is organized as follows. Section 2 reviews the background literature on AI, decision-making, and HAI. Section 3 outlines the systematic review methodology. Section 4 presents the findings structured through the APC framework. Section 5 discusses the implications for theory and practice, while Section 6 proposes an agenda for future research.

2. THEORETICAL BACKGROUND

2.1 Artificial intelligence

AI is a dynamic and evolving field, reflecting the broader trajectory of computational technologies over the past seven decades. From the early experiments in symbolic AI and rule-based systems to the rise of machine learning and, more recently, large-scale deep learning models, AI has continually expanded its scope and capabilities (Glikson & Woolley, 2020; Raj & Seamans, 2019). This progression illustrates not only technological advancement but also a shifting conceptualization of AI, from pre-programmed automation to adaptive systems capable of learning from data, generating content, and interacting with humans in increasingly natural ways.

Although definitions of AI vary, they generally converge on the notion of machines performing tasks that would normally require human intelligence, such as learning, reasoning, and problem-solving (Nilsson, 2005). Early definitions emphasized computational logic and symbolic representation, whereas contemporary accounts highlight systems that learn from experience and adapt their outputs based on feedback (Lu et al., 2018; Sjödin et al., 2021). For the purpose of this review, AI is defined as the ability of computer-based systems to perform cognitive functions, including pattern recognition, prediction, and decision-making, with varying degrees of autonomy (Glikson & Woolley, 2020). This definition accommodates both narrow, domain-specific applications (e.g., fraud detection or credit scoring) and more complex forms of AI, such as generative models that can interact iteratively with human users.

The functions of AI span a wide spectrum, ranging from data analysis and prediction to content creation and autonomous decision-making. Table 1 summarizes the principal functions identified in prior research, reflecting the breadth of AI applications that underpin contemporary organizational practices. These functions are critical for understanding how AI contributes to decision-making processes and for situating the review within the wider technological landscape.

Table 1. Summary of principal functions of AI

Research	Principal functions of AI highlighted	Applications
Varian (2014)	Prediction	Economics & policy analysis (forecasting demand, risk, and uncertainty)
Jordan & Mitchell (2015)	Classification/regression, density estimation, reinforcement learning	Computer vision, speech recognition, robotics, recommendation systems
Makarius et al. (2020)	Task automation, augmentation, sensing, decision support	Human resource management, workplace collaboration, job redesign
Kopalle et al. (2022)	Prediction, content personalization, optimization, conversational agents	Marketing (pricing, retail assortment, chatbots, customer engagement)
Metaxiotis et al. (2003)	Process automation, analytics, orchestration	Enterprise-level applications: ERP, CRM, finance, cross-functional decision orchestration

2.2 AI in decision-making

AI's role in decision-making has evolved alongside advances in computational power and algorithmic design. Early AI systems relied on symbolic, rule-based approaches in which outcomes were determined by predefined human-programmed logic (Nilsson, 2005). While these systems offered transparency and predictability, their rigidity constrained applicability in dynamic or ambiguous environments. The advent of machine learning, and particularly deep learning, transformed AI's role by enabling systems to learn patterns from large datasets, adapt to novel conditions, and generate probabilistic predictions without explicit instructions (LeCun et al., 2015). This transition greatly expanded the scope of AI in decision contexts, extending from operational optimization to complex strategic planning.

Across organizational domains, AI-driven decision systems now support diverse activities. In finance, algorithms analyze market dynamics and consumer behavior to detect fraud, assess credit risk, and inform investment strategies with accuracy levels surpassing traditional methods (Choi et al., 2019). In healthcare, AI assists medical professionals by interpreting complex diagnostic images and electronic health records, thereby supporting more timely and accurate clinical decisions (Liang et al., 2019). In supply chain and operations management, predictive models enhance resource allocation, demand forecasting, and risk management, enabling firms to respond with agility to environmental uncertainty (Pournader et al., 2021). These applications demonstrate AI's capacity to integrate massive datasets and generate insights that extend far beyond human analytical capacity, thereby reinforcing its transformative impact on decision-making processes.

Despite these successes, integrating AI into organizational decision-making is far from straightforward. The adoption of AI is frequently accompanied by challenges such as algorithmic opacity, which undermines transparency and raises concerns about accountability (Vayena et al., 2018). Ethical issues related to bias, fairness, and privacy further complicate its deployment, particularly in sensitive domains like hiring or credit assessment (Maddox et al., 2019; Mahmud et al., 2022). Moreover, trust remains a central barrier. Research shows that individuals often resist algorithmic advice, which is termed algorithm aversion (Dietvorst et al., 2015). Even when algorithms outperform humans, reluctance to rely on them persists, particularly when errors are observed. From a managerial standpoint, gaps in expertise regarding how to configure effective human–AI collaboration exacerbate these challenges, as decision-making frequently requires not only technological reliability but also organizational alignment and user acceptance (Kellogg et al., 2020; Khairat et al., 2018).

2.3 Human–AI interaction in decision-making

While AI systems have demonstrated transformative potential in decision-making, their effectiveness cannot be understood by focusing solely on algorithmic performance. Decision outcomes increasingly depend on the interaction between human judgment and AI capabilities, positioning HAI as a distinct domain of inquiry. Building on traditions of human–computer and human–robot interaction, HAI research emphasizes that decision-making is a socio-technical process in which human cognition, organizational context, and algorithmic design jointly shape outcomes (Glikson & Woolley, 2020).

Core issues in this literature include trust, reliance, explainability, and accountability. Trust calibration has been particularly emphasized. Insufficient trust can lead to the underuse of capable systems, while excessive trust risks overreliance and exposure to algorithmic errors (Naiseh et al., 2023). Explainability is closely tied to these dynamics, as transparent and interpretable systems can enhance user understanding, foster appropriate reliance, and strengthen accountability (Adadi & Berrada, 2018). These concerns extend beyond dyadic settings, where, at the group level, collective interaction with AI introduces coordination challenges and raises questions of responsibility, legitimacy, and bias amplification (Wu et al., 2022).

Despite growing scholarly attention, the literature remains fragmented across disciplines such as information systems, psychology, management, and computer science. Studies variously foreground psychological mechanisms (e.g., algorithm aversion), processual considerations (e.g., task allocation), or structural aspects (e.g., collaboration models), but seldom integrate these perspectives. Moreover, the proliferation of complex models, particularly deep neural networks, has heightened the "black box" problem, making it difficult for users to assess the rationale behind outputs (Iyer et al., 2018). While explainable AI (XAI) seeks to address this challenge, its organizational implications for trust calibration and decision-making effectiveness remain underexplored. These insights underline the need for an integrative framework that integrates psychological, technological, and organizational dimensions of HAI, which is necessary to capture the full range of factors influencing how humans and AI collaborate in decision-making and to provide clearer guidance for both theory and practice.

3. METHOD

We employed a systematic literature review (SLR) methodology, widely recognized for its rigor and replicability in synthesizing knowledge across fragmented domains (Tranfield et al., 2003). An SLR is particularly suited to emerging and multidisciplinary topics such as HAI in decision-making, as it enables the integration of diverse findings, the accumulation of insights, and the structured identification of research gaps. Following established guidelines (Madan & Ashok, 2023; Snyder, 2019), the review proceeded through three interrelated stages: identification, screening, and qualitative synthesis. Each stage followed a transparent and replicable procedure, as illustrated in Figure 1.

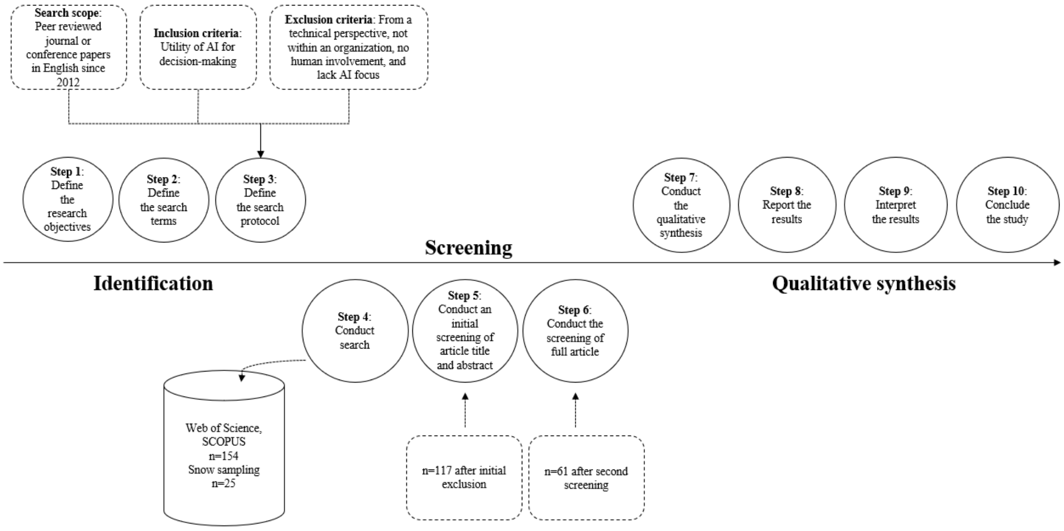

Figure 1. SLR procedures

3.1 Identification

The first stage involved clarifying the review objectives and developing guiding questions. Consistent with the recommendations of Sekaran and Bougie (2016), our objectives were threefold: (1) to map the contexts in which HAI in decision-making has been examined and identify the characteristics that influence decision outcomes; (2) to evaluate the theoretical perspectives and methodological approaches employed across studies; and (3) to critically assess limitations in the existing literature and propose avenues for future research. These objectives ensured that the review was both comprehensive in scope and directed toward advancing cumulative understanding of HAI.

A systematic search protocol was then developed. Searches were conducted in Scopus and Web of Science, two multidisciplinary databases that ensure broad coverage of high-quality journals in management, information systems, psychology, and computer science. To capture relevant studies, we employed the Boolean search string:

(“machine learning” OR “AI” OR “artificial intelligence”) AND (“HAI” OR “human-AI” OR “human-AI interaction”) AND (“decision-making” OR “make decision” OR “algorithmic decision-making”)

The string was refined through preliminary scoping and expert consultation to balance sensitivity and specificity. To ensure contemporaneity, only peer-reviewed journal articles and conference proceedings published in English from 2012 onward were included. Exclusion criteria ruled out studies that (a) did not address human perspectives, (b) were not situated in organizational or decision-making contexts, or (c) treated AI solely as an automation tool without explicit consideration of interaction.

3.2 Screening

Following the initial database search, the screening process was conducted to ensure that only the most relevant and methodologically robust studies were retained. The database search yielded 154 articles. To broaden coverage and minimize the risk of omitting influential studies, we also employed snowball sampling, examining the reference lists of the initially identified articles. This supplementary search added 25 studies. After removing duplicates, a total of 189 unique articles were retained for further review.

Screening proceeded in two stages. First, titles and abstracts were reviewed to assess alignment with the review scope. Studies were excluded if they focused solely on technical algorithm development, automation without human involvement, or applications unrelated to decision-making. This step reduced the pool to 117 articles considered suitable for full-text examination.

In the second stage, full-text screening was undertaken to confirm relevance and evaluate conceptual and methodological contributions. Particular attention was paid to whether studies explicitly addressed decision-making processes involving both humans and AI, and whether they provided substantive insights into psychological mechanisms or structural and processual dynamics. Articles lacking conceptual depth, methodological rigor, or explicit relevance to human–AI decision-making were excluded.

Through this rigorous and iterative process, 77 studies were selected for qualitative synthesis. These articles formed the empirical and conceptual foundation for the subsequent thematic analysis, ensuring that the review captured the most relevant and reliable contributions to the field.

3.3 Qualitative synthesis and analysis

The final stage of the review involved synthesizing the selected studies through a structured qualitative analysis. To ensure consistency and transparency, each article was coded using a comprehensive template that captured publication details, methodological design, theoretical framing, and substantive findings. This cataloguing process not only provided a systematic overview of the literature but also allowed for the identification of temporal, disciplinary, and methodological patterns. Recording information on publication year, outlet, research design, geographic focus, and author affiliations further supported the interpretation of emerging trends across contexts.

Building on this foundation, a thematic analysis was undertaken to distill the essential characteristics of HAI in decision-making. To guide this process, we drew on the APC framework (Pisani et al., 2017; Sousa et al., 2021), which organized findings along three dimensions: (1) antecedents, capturing the drivers of AI adoption in decision-making (e.g., efficiency pressures, demand for predictive accuracy); (2) the phenomenon, representing attributes of HAI such as cognitive biases, system features, and task complexity; and (3) consequences, encompassing both positive outcomes (e.g., improved decision quality, productivity gains) and potential downsides (e.g., overreliance, ethical risks). This structured approach facilitated the identification of recurring patterns as well as important divergences across studies.

Finally, practical implications and future research directions were systematically extracted from the reviewed studies. This step ensured that the synthesis not only consolidated academic knowledge but also highlighted recurrent managerial challenges, such as calibrating trust in AI systems, aligning human skills with technological capabilities, and embedding AI ethically into decision-making structures. Taken together, this stage of analysis provided the conceptual and empirical basis for the model and agenda advanced in the subsequent sections.

4. RESULTS

The findings are presented using the APC framework. Antecedents capture the contextual factors that shape HAI in decision-making, the phenomenon refers to the characteristics of the interaction itself, and consequences denote the outcomes observed. The following subsections reflect these dimensions, synthesizing key themes from the reviewed studies.

4.1 Antecedents: drivers and contextual factors

Task characteristics

Task features shape how humans and AI can productively combine their capabilities. Across the reviewed studies, uncertainty and complexity emerge as the most pervasive descriptors with consistent implications for HAI effectiveness. Uncertainty refers to insufficiency, ambiguity, or variability in available information during the decision process (Daft & Lengel, 1986). It is amplified when decision makers have limited prior experience with AI or when technologies and data sources are novel (Liu, 2021). Complexity arises both from the external environment (e.g., dynamic conditions, volatility) and from AI systems themselves, which increasingly integrate vast datasets and intricate functions (Snowden & Boone, 2007; Bossaerts & Murawski, 2017). The interaction of environmental and technological complexity amplifies decision-making challenges and highlights the importance of effective human–AI collaboration (Lee & Cha, 2023).

Team characteristics

HAI frequently occurs within team-based contexts, and the reviewed literature highlights the importance of distinguishing between dyadic and group arrangements. Dyadic structures, comprising one human and one AI system, are comparatively straightforward, with clear lines of communication and decision responsibility (Zhao et al., 2022). In these settings, reliance patterns are easier to calibrate, and accountability remains transparent. By contrast, group settings, where multiple humans and sometimes multiple AI systems collaborate, introduce added complexity. Research shows that groups may benefit from pooling diverse judgments and algorithmic outputs, but coordination challenges, responsibility diffusion, and inconsistent reliance on AI can offset these advantages (Wu et al., 2022).

Effective team-level HAI depends on team attributes (e.g., diversity, expertise distribution, role clarity) and team processes (e.g., information sharing, conflict resolution, decision protocols). Studies show that well-designed team processes mitigate over-reliance on algorithmic advice and reduce susceptibility to collective biases (Buçinca et al., 2021). Conversely, poor role specification can create confusion about when and how to engage with AI recommendations, leading to performance losses.

Human characteristics

The literature consistently emphasizes human attributes as pivotal to the effectiveness of HAI. Two domains dominate: cognitive characteristics (domain knowledge, biases) and psychological characteristics (trust, perceived controllability).

Domain knowledge enhances human capacity to scrutinize AI outputs and detect potential errors. Studies demonstrate that users with higher expertise are less prone to blind reliance and more capable of calibrating their trust in AI systems (Schaffer et al., 2019; Dikmen & Burns, 2022). Conversely, when domain knowledge is absent, individuals often default to AI advice without sufficient scrutiny (Wang et al., 2022).

Cognitive biases also shape interaction. Confirmation bias leads users to accept AI advice that aligns with prior beliefs while disregarding alternatives (Alon-Barkat & Busuioc, 2023). Anchoring bias results in excessive reliance on initial information, such as the first AI recommendation, even when better alternatives exist (Vaccaro & Waldo, 2019). Automation bias fosters over-trust in AI systems, creating a tendency to accept algorithmic outputs as accurate even in the face of errors (Jones-Jang & Park, 2022).

Trust emerges as the most central factor. Defined as the expectation that an agent will act in one's interests under uncertainty (Lee & See, 2004), trust in AI is dynamic and contingent. It is influenced by factors such as system transparency, prior user experiences, and observed performance (Asan et al., 2020). Importantly, trust is not static but develops, erodes, and repairs over time (Lewis et al., 2018). Studies emphasize that both under-trust (disuse of capable systems) and over-trust (misuse of fallible systems) reduce decision quality (Glikson & Woodlley, 2020).

Finally, perceived controllability shapes willingness to engage with AI. Users demonstrate greater acceptance when they retain authority to override AI outputs or when delegation rules are transparent (Dietvorst et al., 2018). Conversely, when humans feel excluded from the decision process, they are less likely to adopt AI recommendations, even when these improve accuracy (Ning et al., 2021).

4.2 Phenomenon: characteristics of human–AI interaction

HAI characteristics

The reviewed literature consistently emphasizes three system features that shape HAI in decision-making: performance (accuracy and reliability), explainability and transparency, and anthropomorphism. These attributes determine not only whether AI systems can generate technically robust outputs but also whether humans perceive them as trustworthy, understandable, and suitable partners in decision-making.

Performance (accuracy and reliability). Accuracy and consistency are the most fundamental performance measures of AI systems. However, studies show that user reliance is highly sensitive to variability in performance. Even when AI generally outperforms humans, visible errors significantly reduce reliance, a phenomenon often linked to algorithm aversion (Turel & Kalhan, 2023). This highlights that consistent accuracy, rather than occasional peaks of high performance, is critical for sustained collaboration (Cabitza et al., 2020; Zhang et al., 2023).

Explainability and transparency. As algorithms, particularly deep learning models, grow in complexity, their decision logic becomes increasingly opaque (Iyer et al., 2018). XAI has emerged as a response, offering both global explanations of overall model behavior and local justifications for specific outputs (Adadi & Berrada, 2018; Angelov et al., 2021). Empirical evidence demonstrates that effective explanations enhance user comprehension, support trust calibration, and reduce decision times (Lim et al., 2009). Closely related is uncertainty communication, where systems disclose confidence levels or error margins. Such transparency helps users form more informed judgments and reduces automation bias by discouraging blind reliance (Kupfer et al., 2023).

Anthropomorphism. Assigning human-like qualities to AI—through appearance, communication style, empathy, or linguistic cues—also influences user perceptions. Studies consistently find that anthropomorphic features increase trust, perceived warmth, and willingness to collaborate (Waytz et al., 2010; De Visser et al., 2017; Yuan & Dennis, 2019). However, the effect is double-edged: users may over-rely on systems that appear human-like but lack sufficient capability (; Qiu et al., 2020). In general, anthropomorphic design enhances engagement and coordination, but its benefits depend on alignment between perceived social presence and actual technical performance (Choi et al., 2019; de Kervenoaelet al., 2020; Zhu & Chang, 2020).

HAI structures

The reviewed studies identify three prevalent structures of human–AI collaboration, each defined by the direction of information flow and the distribution of decision authority. These structures illustrate alternative ways in which humans and AI contribute to decision processes and how responsibility is shared.

The first structure is AI-human collaboration. In this structure, algorithms generate recommendations that humans validate and finalize. The AI typically functions as a screening or filtering mechanism, narrowing the set of viable options and thereby accelerating decision-making. Such applications are common in recruitment, project evaluation, and risk management, where AI reduces informational overload but humans retain ultimate accountability (Shrestha et al., 2019; Black & van Esch, 2020).

Another structure is human-AI collaboration. Here, human pre-structure the decision space by generating a limited set of alternatives. The AI system then evaluates and ranks these options through large-scale analysis. This approach suits contexts where human domain expertise is strong, but the combinatorial evaluation of alternatives exceeds human cognitive capacity (Logg et al., 2019). For example, in professional sports team selection or clinical monitoring tasks.

The last one is the aggregated structure, where humans and AI produce independent judgments which are subsequently combined through mechanisms such as voting or averaging. This model leverages complementary error structures: human intuition and contextual reasoning counterbalance algorithmic limitations, while AI reduces bias and enhances consistency. Aggregated approaches are particularly valued in investment and strategic decisions, where auditability and collective validation are essential (Burridge, 2017).

4.3 Consequences: outcomes of HAI in decision-making

The synthesis reveals that HAI in decision-making produces a complex set of outcomes. These consequences extend beyond technical performance to include human attitudes and organizational implications, reflecting both the benefits and risks of integrating AI into decision processes.

Decision outcomes. At the task level, evidence suggests that human–AI collaboration often enhances decision quality and efficiency. In domains such as healthcare diagnostics and financial forecasting, joint human–AI efforts consistently outperform either humans or AI operating alone, demonstrating complementarity between human intuition and algorithmic precision (Steiner et al., 2018; Fügener et al., 2022). At the same time, inappropriate reliance can reduce accuracy: under-trust leads to disuse of capable systems, while over-trust results in vulnerability to algorithmic errors or biased outputs (Jones-Jang & Park, 2023). These findings underline that decision quality depends not only on system capability but also on the calibration of human reliance.

Human outcomes. Beyond task performance, HAI influences individual cognition, behavior, and perceptions. Studies highlight that effective interaction can increase user confidence, reduce cognitive load, and improve decision satisfaction. Conversely, exposure to algorithmic errors can trigger algorithm aversion, eroding trust even when overall accuracy remains high (Burton et al., 2020). Psychological consequences also include shifts in responsibility perception: when AI is involved, humans may feel either relieved of cognitive burden or, conversely, more anxious about accountability for outcomes (Elahi et al., 2021; Li & Huang, 2020). These dynamics illustrate that human outcomes hinge on both system design and organizational context.

Organizational outcomes. At the broader level, HAI affects organizational performance, legitimacy, and governance. Positive consequences include enhanced strategic agility, more effective resource allocation, and the ability to respond to uncertainty with data-driven insights (Chua et al., 2023). However, risks also emerge:

opacity and bias in AI systems can undermine stakeholder trust, while unclear responsibility structures complicate accountability (Vayena et al., 2018; Maddox et al., 2019). Organizations thus face a dual challenge: capturing the efficiency and innovation benefits of HAI while ensuring ethical alignment, transparency, and accountability.

5. DISCUSSION

5.1 Finding discussions

This review synthesizes the fragmented literature on HAI in decision-making through the APC framework. By organizing prior research along these three dimensions, our findings highlight not only the determinants of effective HAI but also the conditions under which its benefits or risks manifest. To consolidate these insights, Figure 2 presents an integrative framework of HAI in decision-making. It depicts how antecedent factors shape the characteristics of the phenomenon, which in turn condition the consequences observed at decision, human, and organizational levels. Importantly, the figure highlights two complementary pathways: a psychological pathway and a structural pathway, emphasizing psychological mechanisms such as trust and reliance, and a hard route, focusing on structural and processual mechanisms such as task allocation and collaboration models.

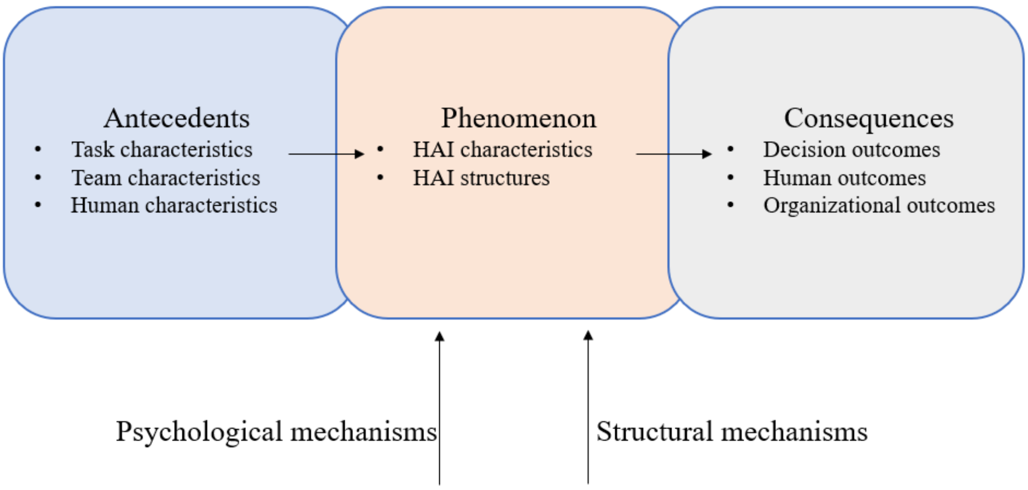

Figure 2. APC framework with two mechanisms

Antecedents: the conditions shaping HAI. Task, team, and human factors emerge as critical drivers of how HAI unfolds. Uncertainty and complexity intensify the need for algorithmic support but simultaneously elevate the risks of misalignment between human and machine capabilities. Similarly, team context determines whether collaboration remains streamlined (dyadic) or becomes entangled in coordination and accountability challenges (group-based). At the individual level, domain knowledge, cognitive biases, and trust calibration strongly condition reliance patterns. These antecedent factors illustrate that HAI is never neutral; it is always situated in specific cognitive, social, and organizational contexts that shape how algorithms are received and used.

Phenomenon: the dynamics of interaction. The findings reveal that AI characteristics (performance, explainability, anthropomorphism) and interaction structures (sequential vs. aggregated) jointly determine the quality of human–AI collaboration. High accuracy is necessary but insufficient without transparency and uncertainty communication that allow users to make sense of algorithmic outputs. Anthropomorphic design further influences perceptions of competence and warmth, although these effects are contingent on alignment with actual system capabilities. Similarly, the three identified interaction structures reflect different balances of human authority and algorithmic input: sequential models preserve human primacy but risk under- or over-reliance, while aggregated models maximize complementarities but raise governance questions. These dynamics underscore that the "phenomenon" of HAI is as much about interaction design as it is about technological capability.

Consequences: dual outcomes of HAI. The review highlights both positive and negative consequences of HAI across decision, human, and organizational levels. At the decision level, joint systems often outperform either humans or AI alone, but miscalibrated reliance leads to error amplification. At the human level, HAI can reduce cognitive burden and improve decision satisfaction, yet it also fosters algorithm aversion or over-reliance depending on error visibility. At the organizational level, HAI can enhance strategic agility and efficiency but also raises persistent challenges of accountability, fairness, and legitimacy. These findings demonstrate that the consequences of HAI are contingent, not deterministic: they depend on how antecedent factors and interaction structures are configured.

The findings suggest that the effectiveness of HAI in decision-making depends on the alignment of antecedents (task, team, human conditions) with phenomenon (AI features and interaction structures), which then shape the consequences. One way of synthesizing this complexity is through the distinction between psychological and structural themes. The psychological theme emphasizes the psychological mechanisms through which humans perceive, evaluate, and rely on AI-generated advice. Studies in this stream focus on trust calibration, cognitive biases, and mental models, showing that user attitudes toward AI are highly sensitive to factors such as task type, observed system errors, and explanatory cues (Castelo et al., 2019; Kelly et al., 2023). Trust emerges as the cornerstone: both under-trust and over-trust impair performance, and trust evolves dynamically across cycles of building, violation, and repair (Lewis et al., 2018). This theme therefore explains why and when humans choose to accept or reject AI input, highlighting the psychological contingencies of effective interaction.

The structural theme focuses on structural and process mechanisms that enable human and AI strengths to complement one another. This includes the design of collaboration structures (e.g., AI-human, human-AI, or aggregation), the allocation of decision authority, and adaptability through mutual learning. Research shows that alignment between human and AI contributions, which are supported by role clarity, override mechanisms, and iterative feedback loops,yields superior decision outcomes (Shrestha et al., 2019; Holzinger et al., 2019; Liu et al., 2019). The structural theme thus explains how to organize collaboration so that human intuition and algorithmic analysis function synergistically rather than at cross purposes.

5.2 Theoretical contributions

This review makes several important contributions to the theoretical understanding of HAI in decision-making.

First, the review consolidates a fragmented field by building an integrative framework across disciplinary boundaries. Prior studies on HAI have been distributed across psychology, information systems, and management, each emphasizing a specific dimension—cognitive biases in psychology, technology adoption in information systems, or organizational routines in management research. This fragmentation has limited cumulative theoretical progress. By systematically reviewing 77 studies and synthesizing them through the APC lens, this study brings together task, human, AI, team, and structural dimensions into a single coherent framework. This integration contributes theoretically by positioning HAI as a socio-technical phenomenon that spans individual cognition, technological features, and organizational arrangements, thereby moving the field beyond isolated findings toward a cumulative knowledge base.

Second, the review advances the conceptualization of decision-making by introducing the distinction between the soft and hard routes. Existing theories such as the Technology Acceptance Model and socio-technical systems theory illuminate partial aspects of HAI but fail to provide a holistic framework. The psychological–structural pathways distinction bridges this gap by linking psychological processes (e.g., trust, reliance, biases) with structural and processual mechanisms (e.g., collaboration structures, role allocation, aggregation). This dual framework explains not only why humans vary in their acceptance of AI advice but also how organizations can design interactions that realize complementarity. As such, it extends and integrates prior theoretical perspectives rather than substituting them.

Third, the review redefines the role of AI in organizational decision-making from a substitution model to one of complementarity. Earlier research frequently framed AI as either replacing human judgment or serving as a passive support tool. Our findings highlight that effective decision-making arises not from substitution but from the alignment of human cognitive strengths with AI's computational capabilities. This conceptual shift resonates with emerging theories of augmented intelligence and human–machine teaming, but provides empirical grounding by showing how alignment is contingent on both psychological and structural factors. By emphasizing complementarity, this review contributes to a growing literature that views AI as a co-actor in socio-technical systems rather than merely a tool.

Finally, this synthesis extends the theoretical agenda by highlighting underexplored contingencies and boundary conditions. The review identifies cultural, contextual, and temporal factors that condition both two mechanisms. For instance, trust calibration may follow different trajectories across cultural contexts that vary in uncertainty avoidance, while structural mechanisms may need to adapt to institutional differences in governance or regulation. Moreover, the rise of GenAI fundamentally alters the interaction paradigm by shifting from one-shot advice to iterative, co-creative exchanges. These insights push theory toward a more dynamic, context-sensitive understanding of human–AI decision-making, opening new avenues for theoretical development.

5.3 Managerial implications

This review also offers several managerial implications for organizations seeking to design and implement effective human–AI decision-making systems.

First, managers must actively manage trust calibration. Trust in AI systems is neither automatic nor stable; it evolves dynamically as users observe system performance and interact over time. Under-trust can lead to costly disuse of capable systems, while over-trust creates risks of blind reliance on flawed outputs. To mitigate these risks, organizations should provide mechanisms for transparency (e.g., explainable outputs, confidence levels), maintain opportunities for human oversight, and establish feedback loops that allow users to recalibrate trust as system performance changes. Investing in training programs that build both domain knowledge and AI literacy will further enable employees to engage critically with AI recommendations rather than defer uncritically.

Second, organizations should intentionally design structural arrangements that facilitate complementarity between human and AI contributions. Ad hoc or unstructured use of AI often leads to confusion, resistance, or accountability gaps. Instead, managers should explicitly allocate roles, specifying when AI is responsible for generating alternatives, when humans should evaluate or refine options, and when aggregation mechanisms are most appropriate. Escalation protocols and override rights are also essential to maintain human agency, thereby reducing resistance to adoption. Furthermore, ensemble approaches that combine human and AI judgments can leverage complementary error structures, improving both accuracy and accountability. Such intentional structuring embeds HAI within workflows, turning abstract technological potential into practical organizational value.

Third, managers must address team-level dynamics in group decision-making contexts. When AI is introduced into teams, issues of coordination, accountability, and conflict management become amplified. Without explicit process scaffolds, teams may either amplify individual biases or diffuse responsibility across human and non-human actors. To avoid these pitfalls, managers should implement protocols that document decision rationales, assign explicit roles for engaging with AI outputs, and create structured opportunities for deliberation. Doing so transforms potential confusion into richer deliberation and ensures that algorithmic inputs are critically assessed rather than passively accepted.

Finally, organizations must adapt to the evolving nature of AI technologies, particularly with the rise of GenAI. Unlike traditional decision-support systems, GenAI enables iterative, conversational interactions that shift trust formation from outcome evaluation to process engagement. This creates opportunities for enhancing creativity, knowledge sharing, and co-design, but also introduces new risks such as dependency, over-reliance, and ethical concerns about content generation. Proactive governance frameworks—covering accountability, data integrity, fairness, and ethical use—are essential to guide responsible deployment. Firms that establish such frameworks early will be better positioned to harness the creative and operational benefits of GenAI while safeguarding against reputational and regulatory risks.

6. FUTURE DIRECTIONS

This review highlights both the achievements and persistent gaps in understanding HAI in decision-making. While research has advanced considerably, insights remain fragmented across psychology, information systems, and management, with limited integration of individual, technological, and organizational perspectives. Building on our APC framework (Figure 2), we outline a multi-level agenda for future inquiry organized around six thematic areas: task, team, human, AI, interaction structures, and governance. Table 2 provides illustrative research questions to guide future work.

Table 2. Illustrative research questions for future studies on HAI in decision-making

Theme	Illustrative Research Questions
Task	• How do different types of tasks (diagnostic vs. creative vs. strategic) moderate trust and reliance on AI? • In what ways do time pressure and task urgency shape patterns of human–AI collaboration? • How does task complexity interact with AI explainability to influence decision quality?
Team	• How do group attributes (e.g., expertise diversity, hierarchy) shape reliance on AI in collective decision-making? • Does AI mitigate or exacerbate group biases in committees and cross-functional teams? • What coordination mechanisms are most effective for integrating multiple humans and AI agents in team-based contexts?
Human	• How do cultural, organizational, or personal values condition trust in AI advice? • How do knowledge asymmetries between domain expertise and AI literacy affect adoption and reliance patterns? • To what extent do demographic factors (e.g., age, professional identity) influence algorithm aversion or acceptance?
AI	• Beyond accuracy and explainability, how can we evaluate AI's capacity to enhance creativity and co-production? • How do users perceive and adapt to multi-model AI ecosystems where several specialized models operate simultaneously? • What role does uncertainty communication (e.g., confidence intervals, error margins) play in calibrating trust?
Structures	• How do unidirectional versus bidirectional (iterative) interaction structures affect reliance and trust trajectories? • What protocols help balance efficiency with oversight in iterative co-creation settings enabled by GenAI? • How does the distribution of decision authority across AI and humans affect accountability and legitimacy?
Governance	• What governance frameworks ensure fairness, transparency, and accountability in AI-enabled decisions across industries? • How can organizational policies align AI use with societal values and ethical standards? • What regulatory approaches are most effective for safeguarding against risks of algorithmic bias or over-reliance?

One promising direction concerns the nature of tasks. Existing studies have concentrated on diagnostic and classification activities, overlooking the growing diversity of AI applications in creative content generation, strategic forecasting, and crisis management. These emerging contexts involve multi-modal inputs, real-time constraints, and fluid decision boundaries, which differ significantly from traditional tasks. Future work should therefore build typologies that differentiate contexts where AI primarily reduces uncertainty, enhances exploration, or supports rapid decisions under pressure. Such typologies will clarify how task characteristics moderate trust, reliance, and complementarity.

Another gap lies at the team level. Much of the HAI literature examines dyadic human–AI settings, while many organizational decisions are made in groups where multiple humans and AI systems interact simultaneously. These contexts introduce dynamics of responsibility diffusion, conflict management, and consensus formation that cannot be reduced to dyadic reliance models. Research should explore how team attributes, such as diversity, hierarchy, and expertise distribution, interact with processes of information sharing and escalation rules to shape HAI effectiveness. This line of inquiry will help determine whether AI amplifies or mitigates group biases and how accountability can be preserved in collective decision-making.

The human side of HAI warrants deeper study at two levels: organizational and individual, and future work should treat AI, particularly GenAI, as a co-actor, examining strategy as the design of participation rules that govern how people and AI share proposal, critique, justification, and veto in everyday decisions across these intertwined levels. At the organizational level, research can investigate how the division of cognitive labour, understood as choices between augmentation and automation, the redistribution of voice, discretion, and accountability within teams, and the establishment of norms and routines such as rationale logging, dissent rituals, and reflective debriefs after use, contribute to granting legitimacy to AI-assisted inputs across cultural and institutional contexts. For small and medium-sized enterprises, capability building can be approached as socialization through communities of practice, peer coaching, and reflective dialogue, while governance can be understood as everyday practice involving uncertainty talk, auditable narratives, and graded override rights. Strategy in this sense can be framed as a portfolio of decision situations that specifies who contributes what, when, and according to which justificatory standards. At the individual level, research should theorize heterogeneity in culture, role, identity, and knowledge asymmetries between domain expertise and AI literacy through psychological lenses such as cognitive appraisal focusing on opportunity versus threat, job demands and resources, self-determination, conservation of resources, social identity, and attribution. Outcomes should be broadened beyond adoption to include work engagement, learning, creativity, voice, psychological safety, well-being, career adaptability, employability, and career sustainability, thereby providing a more granular account of how diverse users collaborate with, contest, and incorporate AI in practice.

Interaction structures also merit closer scrutiny. Earlier studies often framed HAI as unidirectional, where humans either provide inputs for AI analysis or evaluate outputs generated by AI. With the rise of GenAI, interactions increasingly involve iterative, bidirectional exchanges that complicate authority, oversight, and accountability. Future work should investigate how such structures alter reliance trajectories, trust calibration, and decision quality, as well as the organizational protocols that can balance efficiency with safeguards in iterative exchanges.

Finally, governance emerges as a critical but underdeveloped domain. Research has concentrated on micro-level trust and meso-level design but paid less attention to how AI systems are embedded within broader institutional and societal contexts. Yet, AI-enabled decisions often carry ethical, legal, and reputational stakes that demand robust governance frameworks. Future work should investigate evaluation criteria tailored to specific domains, explore cross-sector regulatory safeguards, and examine how decision outcomes can be aligned with societal values. A governance-oriented perspective will be crucial to ensure that HAI contributes not only to organizational performance but also to responsible and sustainable decision-making.

REFERENCE

Adadi, A., & Berrada, M. (2018). Peeking inside the black-box: a survey on explainable artificial intelligence (XAI). *IEEE Access*, *6*, 52138-52160.

Alon-Barkat, S., & Busuioc, M. (2023). Human–AI interactions in public sector decision making: "automation bias" and "selective adherence" to algorithmic advice. *Journal of Public Administration Research and Theory*, *33*(1), 153-169.

Al-Surmi, A., Bashiri, M., & Koliousis, I. (2022). AI based decision making: combining strategies to improve operational performance. *International Journal of Production Research*, *60*(14), 4464-4486.

Angelov, P. P., Soares, E. A., Jiang, R., Arnold, N. I., & Atkinson, P. M. (2021). Explainable artificial intelligence: an analytical review. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *11*(5), e1424.

Asan, O., Bayrak, A. E., & Choudhury, A. (2020). Artificial intelligence and human trust in healthcare: focus on clinicians. *Journal of medical Internet research*, *22*(6), e15154.

Black, J. S., & van Esch, P. (2020). AI-enabled recruiting: What is it and how should a manager use it? *Business Horizons*, *63*(2), 215-226.

Bossaerts, P., & Murawski, C. (2017). Computational complexity and human decision- making. *Trends in Cognitive Sciences*, *21*(12), 917-929.

Brougham, D., & Haar, J. (2018). Smart technology, artificial intelligence, robotics, and algorithms (STARA): Employees' perceptions of our future workplace. *Journal of Management & Organization*, *24*(2), 239-257.

Buçinca, Z., Malaya, M. B., & Gajos, K. Z. (2021). To trust or to think: cognitive forcing functions can reduce overreliance on AI in AI-assisted decision-making. *Proceedings of the ACM on Human-computer Interaction*, *5*(CSCW1), 1-21.

Burridge, N. (2017). *Artificial intelligence gets a seat in the boardroom: Hong Kong venture capitalist sees AI running Asian companies within 5 years*. Nikkei Asian Review.

Burton, J. W., Stein, M. K., & Jensen, T. B. (2020). A systematic review of algorithm aversion in augmented decision making. *Journal of Behavioral Decision Making*, *33*(2), 220-239.

Cabitza, F., Campagner, A., & Balsano, C. (2020). Bridging the "last mile" gap between AI implementation and operation:"data awareness" that matters. *Annals of translational medicine*, *8*(7), 501.

Castelo, N., Bos, M. W., & Lehmann, D. R. (2019). Task-dependent algorithm aversion. *Journal of Marketing Research*, *56*(5), 809-825.

Choi, S., Liu, S. Q., & Mattila, A. S. (2019). "How may I help you?" Says a robot: examining language styles in the service encounter. *International Journal of Hospitality Management*, *82*, 32-38.

Chua, A. Y., Pal, A., & Banerjee, S. (2023). AI-enabled investment advice: Will users buy it? *Computers in Human Behavior*, *138*, 107481.

Daft, R. L., & Lengel, R. H. (1986). Organizational information requirements, media richness and structural design. *Management Science*, *32*(5), 554-571.

De Kervenoael, R., Hasan, R., Schwob, A., & Goh, E. (2020). Leveraging human-robot interaction in hospitality services: Incorporating the role of perceived value, empathy, and information sharing into visitors' intentions to use social robots. *Tourism Management*, *78*, 104042.

De Visser, E. J., Monfort, S. S., Goodyear, K., Lu, L., O'Hara, M., Lee, M. R., . . . Krueger, F. (2017). A little anthropomorphism goes a long way: Effects of oxytocin on trust, compliance, and team performance with automated agents. *Human factors*, *59*(1), 116-133.

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2018). Overcoming algorithm aversion: People will use imperfect algorithms if they can (even slightly) modify them. *Management Science*, *64*(3), 1155-1170.

Dikmen, M., & Burns, C. (2020). Abstraction hierarchy based explainable artificial intelligence. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *64*(1), 319-323.

Elahi, H., Castiglione, A., Wang, G., & Geman, O. (2021). A human-centered artificial intelligence approach for privacy protection of elderly App users in smart cities. *Neurocomputing*, *444*, 189-202.

Fügener, A., Grahl, J., Gupta, A., & Ketter, W. (2022). Cognitive challenges in human– artificial intelligence collaboration: Investigating the path toward productive delegation. *Information Systems Research*, *33*(2), 678-696.

Gigerenzer, G. (2007). *Gut feelings: The intelligence of the unconscious*. Penguin.

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals*, *14*(2), 627-660.

Guenole, N., & Feinzig, S. (2018). *The business case for AI in HR: With insights and tips on getting started*. IBM Publishing.

Holzinger, A., Plass, M., Kickmeier-Rust, M., Holzinger, K., Crişan, G. C., Pintea, C. M., & Palade, V. (2019). Interactive machine learning: experimental evidence for the human in the algorithmic loop: A case study on Ant Colony Optimization. *Applied Intelligence*, *49*(7), 2401-2414.

Iyer, R., Li, Y., Li, H., Lewis, M., Sundar, R., & Sycara, K. (2018). Transparency and explanation in deep reinforcement learning neural networks. *In Proceedings of the 2018 AAAI/ACM Conference on AI, Ethics, and Society* (pp. 144-150).

Jain, R., Garg, N., & Khera, S. N. (2023). Effective human–AI work design for collaborative decision-making. *Kybernetes*, *52*(11), 5017-5040.

Jones-Jang, S. M., & Park, Y. J. (2022). How do people react to AI failure? Automation bias, algorithmic aversion, and perceived controllability. *Journal of Computer- Mediated Communication*, *28*(1), 1-8.

Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science*, *349*(6245), 255-260.

Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at Work: The New Contested Terrain of Control. *Academy of Management Annals*, *14*(1), 366-410.

Kelly, M., Kumar, A., Smyth, P., & Steyvers, M. (2023). Capturing Humans' Mental Models of AI: An Item Response Theory Approach. In *Proceedings of the 2023 ACM conference on fairness, accountability, and transparency* (pp. 1723-1734).

Khairat, S., Marc, D., Crosby, W., & Al Sanousi, A. (2018). Reasons for physicians not adopting clinical decision support systems: critical analysis. *JMIR medical informatics*, *6*(2), e8912.

Kopalle, P. K., Gangwar, M., Kaplan, A., Ramachandran, D., Reinartz, W., & Rindfleisch, (2022). Examining artificial intelligence (AI) technologies in marketing via a global lens: Current trends and future research opportunities. *International Journal of Research in Marketing*, *39*(2), 522-540.

Krakowski, S., Luger, J., & Raisch, S. (2023). Artificial intelligence and the changing sources of competitive advantage. *Strategic Management Journal*, *44*(6), 1425-1452.

Kupfer, C., Prassl, R., Fleiß, J., Malin, C., Thalmann, S., & Kubicek, B. (2023). Check the box! How to deal with automation bias in AI-based personnel selection. *Frontiers in Psychology*, *14*, 1118723.

Lambrecht, A., & Tucker, C. (2019). Algorithmic bias? An empirical study of apparent gender-based discrimination in the display of STEM career ads. *Management Science*, *65*(7), 2966-2981.

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*(7553), 436-444.

Lee, C., & Cha, K. (2023). FAT-CAT—Explainability and augmentation for an AI system: A case study on AI recruitment-system adoption. *International Journal of Human-Computer Studies*, *171*, 102976.

Lee, J. D., & See, K. A. (2004). Trust in automation: Designing for appropriate reliance. *Human Factors*, *46*(1), 50-80.

Lewis, M., Sycara, K., & Walker, P. (2018). *The role of trust in human-robot interaction.* Switzerland: Springer International Publishing AG.

Liang, H., Tsui, B. Y., Ni, H., Valentim, C. C., Baxter, S. L., Liu, G., ... & Xia, H. (2019). Evaluation and accurate diagnoses of pediatric diseases using artificial intelligence. *Nature Medicine*, *25*(3), 433-438.

Li, J., & Huang, J. S. (2020). Dimensions of artificial intelligence anxiety based on the integrated fear acquisition theory. *Technology in Society*, *63*, 101410.

Lim, B. Y., Dey, A. K., & Avrahami, D. (2009). Why and why not explanations improve the intelligibility of context-aware intelligent systems. In *Proceedings of the SIGCHI conference on human factors in computing systems* (pp. 2119-2128).

Liu, B. (2021). In AI we trust? Effects of agency locus and transparency on uncertainty reduction in human–AI interaction. *Journal of Computer-Mediated Communication*, *26*(6), 384-402.

Liu, Y., Zeng, Y., Chen, Y., Tang, J., & Pan, Y. (2019). Self-improving generative adversarial reinforcement learning. In *Proceedings of the 18th International Conference on Autonomous Agents and Multiagent Systems, AAMAS* (pp. 52-60).

Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes,* 151, 90-103.

Lu, H., Li, Y., Chen, M., Kim, H., & Serikawa, S. (2018). Brain intelligence: go beyond artificial intelligence. *Mobile Networks and Applications, 23*(2), 368-375.

Madan, R., & Ashok, M. (2023). AI adoption and diffusion in public administration: A systematic literature review and future research agenda. *Government Information Quarterly, 40*(1), 101774.

Maddox, T. M., Rumsfeld, J. S., & Payne, P. R. (2019). Questions for artificial intelligence in health care. *Jama*, *321*(1), 31-32.

Mahmud, H., Islam, A. N., Ahmed, S. I., & Smolander, K. (2022). What influences algorithmic decision-making? A systematic literature review on algorithm aversion. *Technological Forecasting and Social Change*, *175*, 121390.

Makarius, E. E., Mukherjee, D., Fox, J. D., & Fox, A. K. (2020). Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization. *Journal of Business Research*, *120*, 262-273.

Marr, B. (2018). *Data-driven HR: How to use analytics and metrics to drive performance*. Kogan Page Publishers.

Metaxiotis, K. S., Psarras, J. E., & Ergazakis, K. A. (2003). Production scheduling in ERP systems: an AI-based approach to face the gap. *Business Process Management Journal*, *9*(2), 221-247.

Metcalf, L., Askay, D. A., & Rosenberg, L. B. (2019). Keeping humans in the loop: Pooling knowledge through artificial swarm intelligence to improve business decision making. *California Management Review*, *61*(4), 84-109.

Naiseh, M., Al-Thani, D., Jiang, N., & Ali, R. (2023). How the different explanation classes impact trust calibration: The case of clinical decision support systems. *International Journal of Human-Computer Studies*, *169*, 102941.

Nilsson, N. J. (2005). Human-level artificial intelligence? Be serious!. *AI magazine*, *26*(4), 68-75.

Ning, H., Yin, R., Ullah, A., & Shi, F. (2021). A survey on hybrid human-artificial intelligence for autonomous driving. *Ieee Transactions on Intelligent Transportation Systems*, *23*(7), 6011-6026.

Pisani, N., Kourula, A., Kolk, A., & Meijer, R. (2017). How global is international CSR research? Insights and recommendations from a systematic review. *Journal of World Business*, *52*(5), 591-614.

Pournader, M., Ghaderi, H., Hassanzadegan, A., & Fahimnia, B. (2021). Artificial intelligence applications in supply chain management. *International Journal of Production Economics*, *241*, 108250.

Qiu, H., Li, M., Shu, B., & Bai, B. (2020). Enhancing hospitality experience with service robots: The mediating role of rapport building. *Journal of Hospitality Marketing & Management*, *29*(3), 247-268.

Raj, M., & Seamans, R. (2019). Primer on artificial intelligence and robotics. *Journal of Organization Design*, *8*(11), 1-14.

Ryman-Tubb, N. F., Krause, P., & Garn, W. (2018). How Artificial Intelligence and machine learning research impacts payment card fraud detection: A survey and industry benchmark. *Engineering Applications of Artificial Intelligence*, *76*, 130-157.

Schaffer, J., O'Donovan, J., Michaelis, J., Raglin, A., & Höllerer, T. (2019). *I can do better than your AI: expertise and explanations*. In *Proceedings of the 24th international conference on intelligent user interfaces* (pp. 240-251).

Sekaran, U., & Bougie, R. (2016*). Research methods for business: A skill building approach*. John Wiley & Sons.

Shrestha, Y. R., Ben-Menahem, S. M., & von Krogh, G. (2019). Organizational Decision- Making Structures in the Age of Artificial Intelligence. *California Management Review*, *61*(4), 66-83.

Sjödin, D., Parida, V., Palmié, M., & Wincent, J. (2021). How AI capabilities enable business model innovation: Scaling AI through co-evolutionary processes and feedback loops. *Journal of Business Research*, *134*, 574-587.

Snowden, D. J., & Boone, M. E. (2007). A leader's framework for decision making. *Harvard Business Review*, *85*(11), 68.

Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research*, *104*, 333-339.

Sousa, C. M., He, X., Lengler, J., & Tang, L. (2021). Foreign market re-entry: A review and future research directions. *Journal of International Management*, *27*(2), 100848.

Steiner, D. F., MacDonald, R., Liu, Y., Truszkowski, P., Hipp, J. D., Gammage, C., . . . Stumpe, M. C. (2018). Impact of deep learning assistance on the histopathologic review of lymph nodes for metastatic breast cancer. *The American Journal of Surgical Pathology*, *42*(12), 1636-1646.

Steyvers, M., & Kumar, A. (2024). Three challenges for AI-assisted decision-making. *Perspectives on Psychological Science*, *19*(5), 722-734.

Turel, O., & Kalhan, S. (2023). Prejudiced against the machine? Implicit associations and the transience of algorithm aversion. *MIS Quarterly*, *47*(4), 1369-1394.

Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a methodology for developing evidence-informed management knowledge by means of systematic review. *British Journal of Management*, *14*(3), 207-222.

Vaccaro, M., & Waldo, J. (2019). The effects of mixing machine learning and human judgment. *Communications of the ACM*, *62*(11), 104-110.

Van Der Waa, J., Nieuwburg, E., Cremers, A., & Neerincx, M. (2021). Evaluating XAI: A comparison of rule-based and example-based explanations. *Artificial Intelligence*, *291*, 103404.

Varian, H. R. (2014). Big Data: New Tricks for Econometrics. *The Journal of Economic Perspectives*, *28*(2), 3-27.

Vayena, E., Blasimme, A., & Cohen, I. G. (2018). Machine learning in medicine: addressing ethical challenges. *PLoS medicine*, *15*(11), e1002689.

Wang, X., Lu, Z., & Yin, M. (2022). Will You Accept the AI Recommendation? Predicting Human Behavior in AI-Assisted Decision Making. In *Proceedings of the ACM web conference 2022* (pp. 1697-1708).

Waytz, A., Morewedge, C. K., Epley, N., Monteleone, G., Gao, J.-H., & Cacioppo, J. T. (2010). Making sense by making sentient: effectance motivation increases anthropomorphism. *Journal of Personality and Social Psychology*, *99*(3), 410-435.

Weill, P., & Woerner, S. L. (2018). Is Your Company Ready for a Digital Future? *MIT Sloan Management Review*, *59*(2), 21-25.

Wu, Y., Kim, K. J., & Mou, Y. (2022). Minority social influence and moral decision- making in human–AI interaction: The effects of identity and specialization cues. *New media & society*, *26*(10), 5619-5637.

Yuan, L., & Dennis, A. R. (2019). Acting like humans? Anthropomorphism and consumer's willingness to pay in electronic commerce. *Journal of Management Information Systems*, *36*(2), 450-477.

Zhang, A., Walker, O., Nguyen, K., Dai, J., Chen, A., & Lee, M. K. (2023). Deliberating with AI: Improving Decision-Making for the Future through Participatory AI Design and Stakeholder Deliberation. *Proceedings of the ACM on Human-Computer Interaction, 7*(CSCW1), 1-32.

Zhao, M., Simmons, R., & Admoni, H. (2022). The role of adaptation in collective human–AI teaming. *Topics in Cognitive Science*, *17*(2), 291-323.

Zhu, D. H., & Chang, Y. P. (2020). Robot with humanoid hands cooks food better? Effect of robotic chef anthropomorphism on food quality prediction. *International Journal of Contemporary Hospitality Management*, *32*(3), 1367-1383.

APPENDIX: CODING PROTOCOL FOR SYSTEMATIC LITERATURE REVIEW

The following coding protocol was used to systematically extract, categorize, and analyze information from the 61 studies included in the review. This protocol ensures transparency and replicability of the synthesis process.

Category	**Description**	**Examples / Values Coded**
Bibliographic details	Basic information on the article	Author(s); Year; Journal / Conference; Country / Region
Study type	Classification of research design and contribution	Conceptual; Empirical–quantitative; Empirical–qualitative; Mixed-method; Review
Methodological approach	Research design and techniques employed	Experiment; Survey; Case study; Simulation; Text / content analysis; Multi-method
Context / Domain	Empirical or application domain	Healthcare; Finance; HR/Workforce; Marketing; Operations/Supply chain; Cross-domain
Theoretical lens	Explicit theory applied (if any)	TAM; Socio-technical systems; Algorithm aversion; Trust theory; None
Human characteristics	Human factors influencing decision-making	Cognitive biases; Domain expertise; Intuition; Trust; Reliance
AI characteristics	Attributes of the AI system studied	Transparency; Explainability; Accuracy; Adaptability; Autonomy level
Task characteristics	Nature and complexity of the decision-making task	Structured vs. unstructured; High vs. low uncertainty; Individual vs. group decision-making
Outcomes (Consequences)	Reported effects of HAI on decision-making performance	Accuracy; Efficiency; Speed; Fairness; Ethical concerns; Overreliance risks
Practical implications	Recommendations or lessons for managers / practitioners	Trust calibration; System design; Human–AI complementarity; Ethical safeguards
Future research	Suggestions explicitly noted by authors	Calls for longitudinal data; Cross-cultural studies; Strategic decision-making contexts

PAPER 2

Generative AI in business decision-making: challenges, opportunities, and a strategic integration framework

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Abstract

Generative AI (GenAI) is rapidly becoming a strategic tool for enhancing business decision-making. Yet many organizations struggle to translate its potential into practical outcomes. This study draws on insights from 51 expert interviews to explore the core challenges and opportunities that firms face when integrating GenAI into their operations. We identify five major barriers, ranging from ethical concerns to lack of trust, and five key opportunities, such as improved personalization and productivity. To help managers act on these insights, we introduce a seven-step framework that guides the effective implementation of GenAI, emphasizing ethical safeguards, user-centered design, and agile experimentation. This article provides actionable strategies for executives aiming to harness GenAI while minimizing risks, ensuring alignment with organizational goals, and unlocking long-term value.

Keywords: Artificial intelligence, human-AI interaction, decision-making, systematic literature review

1. INTRODUCTION

Generative AI (GenAI) has rapidly emerged as a game-changing technology, producing innovative outputs across domains such as text, image, audio, and more (Susarla et al., 2023). Unlike traditional AI systems that rely on predetermined outputs, GenAI stands out for its ability to create, simulate scenarios, and uncover patterns in complex data, making it a valuable tool for decision-making in modern businesses (Hao et al., 2024). Its applications span industries, from streamlining operations and driving innovation to delivering highly personalized user experiences. As organizations adapt to a data-driven world, GenAI provides avenues for creativity, operational improvement, and strategic insights, solidifying its role as a key driver of technological advancement (Doshi et al., 2025; Epstein et al., 2023; Wamba et al., 2023).

For large organizations, decision-making often involves navigating vast datasets, incorporating real-time insights, and developing adaptive strategies. GenAI enables firms to go beyond traditional data analysis by enabling firms to simulate scenarios, optimize processes, and anticipate trends using both current and historical data. By incorporating GenAI into decision-making, firms can unlock new levels of efficiency and accuracy, which are crucial for maintaining a competitive edge in dynamic markets (Khan et al., 2024). However, the integration of GenAI into decision-making processes is not without its challenges. Firms must navigate technological constraints, ethical concerns, and operational hurdles that come with adopting advanced AI systems (Park, 2024; Yan et al., 2024). At the same time, GenAI presents numerous opportunities, from enabling personalized customer experiences to expanding into new markets (Cillo & Rubera, 2025; Mogaji et al., 2024). Understanding these challenges and opportunities is essential for firms looking to harness the full potential of GenAI.

Although a growing body of literature examines AI adoption in firms, relatively few studies focus specifically on the unique implications of GenAI for decision-making (Hao et al., 2024). The distinctive nature of GenAI, its capacity for creativity, adaptability, and dynamic interaction, remains underexplored in empirical research (Baabdullah, 2024). GenAI introduces novel challenges, such as managing model hallucinations and balancing creative freedom with control (Epstein et al., 2023; Kankanhalli, 2024), which are less prevalent in other forms of AI. Furthermore, while strategic frameworks for AI adoption have been discussed extensively in the literature, there is a noticeable lack of targeted strategies that address the specific needs and complexities associated with GenAI (Budhwar et al., 2023). This study aims to bridge this gap by offering a comprehensive analysis of the challenges and opportunities GenAI presents for firms and proposing strategic approaches to optimize its integration for enhanced decision-making. Specifically, the study addresses the following research questions:

- What are the challenges and opportunities that firms encounter when integrating GenAI into their decision-making processes?

- How can firms strategically integrate GenAI in decision-making?

By addressing these questions, this study makes several theoretical contributions. First, it deepens understanding of how GenAI, as a distinct technological innovation, reshapes decision-making processes. Second, it highlights the unique challenges and opportunities GenAI presents to firms, such as fostering user trust, and navigating ethical and operational complexities. Third, the study provides insights into the strategic approaches firms can adopt to effectively integrate GenAI into their decision-making processes. By addressing these critical dimensions, this study not only advances the academic discourse on GenAI adoption but also offers actionable recommendations to guide firms in harnessing its transformative potential in this rapidly evolving landscape.

2. LITERATURE REVIEW

2.1 GenAI and its adoption in business contexts

GenAI, a subset of AI, has emerged as a powerful tool in reshaping business operations, decision-making, and value creation. Unlike traditional AI systems, which primarily analyze data or automate predefined tasks, GenAI produces novel and original content, such as text, images, and audio, using advanced models like Generative Adversarial Networks and transformer-based architectures (Kusiak, 2020; Liang et al., 2024). These technological advancements have positioned GenAI as a transformative enabler across various industries, particularly in enhancing creativity, innovation, and personalization.

The transformative potential of GenAI lies in its capacity to fundamentally disrupt traditional business paradigms, offering new avenues for innovation, operational efficiency, and strategic agility (Hendriksen, 2023; Talaei-Khoei et al., 2024). By generating unique, contextually relevant outputs, GenAI empowers organizations to rethink their approach to product design, customer engagement, and decision-making (Akhtar et al., 2024; Fakfare et al., 2025; Hao et al., 2024). For example, its ability to produce real-time predictive insights allows firms to anticipate market trends and consumer behaviors with unprecedented accuracy, enabling more informed and timely decision-making. Furthermore, GenAI enhances creative problem-solving by automating ideation processes, thereby reducing time to market for innovative solutions (Boussioux et al., 2024). Beyond these operational benefits, GenAI has the potential to create entirely new revenue streams by enabling businesses to monetize AI-generated content and personalized services (Wessel et al., 2025).

The adoption of GenAI is evident in diverse sectors such as marketing, tourism, healthcare, and education. Marketing firms, for example, leverage AI to create tailored campaigns that resonate with individual consumer preferences, while the hospitality industry employs tools like ChatGPT to provide customized customer experiences, aligning services more closely with dynamic consumer needs (Fakfare et al., 2025; Kshetri et al., 2024). Similarly, in education, GenAI has transformed the delivery of learning by personalizing content to suit diverse learner profiles and improving accessibility through adaptive technologies (Yan et al., 2024). Despite the breadth of its applications, much of the existing literature remains focused on conceptual explorations and theoretical frameworks, offering limited empirical evidence on how firms integrate GenAI into their operations and adapt to the challenges it presents (Baabdullah, 2024).

2.2 GenAI, business strategy, and decision-making

The integration of GenAI into business strategy and decision-making marks a significant shift in how organizations approach strategy, innovation, and resource management (Chowdhury et al., 2024). GenAI goes beyond automating processes or generating insights; it introduces creative capabilities that enhance firms' capacity to make informed, forward-looking decisions. For instance, firms use GenAI to simulate complex scenarios, forecast market trends, and optimize decision-making processes, providing a strategic advantage in volatile and uncertain environments (Hao et al., 2024). This shift underscores the growing role of AI not merely as a tool for incremental improvement but as a strategic enabler capable of redefining industries and unlocking untapped opportunities.

A critical advantage of GenAI in business strategy lies in its ability to support complex, large-scale decision-making required for strategic planning and organizational transformation. For example, firms leverage GenAI to model various organizational designs and forecast the potential outcomes of restructuring initiatives, helping leaders make informed choices about workforce management and resource deployment (Budhwar et al., 2023). In operations, GenAI aids in scenario analysis for supply chain optimization, enabling firms to plan for contingencies such as geopolitical disruptions or resource shortages (Fosso et al., 2024). Additionally, the technology facilitates mergers and acquisitions by providing data-driven insights into potential synergies and risk factors, allowing firms to make more calculated decisions during complex strategic transactions (Chiarello et al., 2024). These applications enable organizations to align their strategic goals with operational realities, ensuring coherence across all levels of management.

GenAI also enhances decision-making by empowering leaders to adopt evidence-based approaches to addressing multifaceted business challenges. By automating labor-intensive data processing and generating actionable insights, GenAI allows senior management to focus on high-priority strategic imperatives, such as scaling operations or entering new markets (Jackson et al., 2024). In talent management, for instance, GenAI provides predictive insights into workforce trends, enabling firms to anticipate skill gaps and design training programs aligned with future needs (Yan et al., 2024). Similarly, in crisis management, GenAI supports the rapid development of adaptive strategies to mitigate risks and ensure business continuity (Fosso et al., 2024). Beyond operational benefits, GenAI fosters collaboration among leadership teams by synthesizing complex data into clear, actionable recommendations, aligning diverse stakeholders around shared objectives and ensuring that decision-making is both strategic and inclusive (Hao et al., 2024).

2.3 Challenges and opportunities in GenAI adoption

The adoption of GenAI offers a plethora of opportunities for businesses, enabling them to redefine operational efficiency, resource optimization, and innovation. GenAI has proven transformative in industries such as construction, where it enhances risk management and forecasting accuracy, and finance, where it supports predictive analytics and personalized customer interactions (Dwivedi et al., 2024; Kalia, 2023). By leveraging AI-driven insights, firms can streamline complex processes, reduce costs, and improve decision-making. Furthermore, GenAI empowers businesses to unlock new revenue streams, such as AI-generated products and services, positioning them as leaders in increasingly competitive markets (Hermann & Puntoni, 2024). These capabilities demonstrate GenAI’s potential to disrupt conventional business practices, fostering agility and resilience in dynamic environments.

However, GenAI adoption also brings significant challenges, particularly in ethical, technical, and regulatory domains. Ethical concerns regarding data privacy, algorithmic bias, and transparency remain at the forefront of scholarly discussions (Ning et al., 2024). For instance, biases in AI models can perpetuate inequalities, especially in sectors where fairness is critical, such as financial services and human resource management. Additionally, the absence of standardized governance frameworks exacerbates challenges around compliance, accountability, and trust, making it difficult for organizations to navigate the complexities of GenAI integration (Yan et al., 2024). These ethical dilemmas underscore the importance of developing robust governance mechanisms to ensure that GenAI adoption aligns with societal values and organizational ethics.

Beyond ethical concerns, firms face technical and organizational challenges in GenAI adoption. The implementation of AI systems often requires significant investments in talent, infrastructure, and training, which many firms struggle to secure (Norbäck & Persson, 2024). Resistance to change within organizations, driven by fear of job displacement or a lack of understanding, further complicates the integration process (Budhwar et al., 2023). Additionally, GenAI systems are prone to technical issues such as hallucinations and unpredictability, which can undermine their reliability (Shore et al., 2024). Overcoming these barriers requires fostering a culture of innovation and adaptability, where employees are equipped with the skills to collaborate with AI systems effectively.

3. METHODOLOGY

3.1 Research design

This study adopts a qualitative research design to explore the challenges, opportunities, and strategic approaches firms face in integrating GenAI into their decision-making processes. Qualitative methods are particularly well-suited for this study, given the nascent and rapidly evolving nature of GenAI technology. By focusing on insights from industry leaders, technical experts, and AI practitioners, this research seeks to understand both the practical and theoretical implications of AI adoption in a variety of business contexts.

3.2 Data collection

Data for this study was collected from a total of 51 podcast episodes based on sample collection approach employed by Fisher et al., (2020) and Haefner (2023), each featuring interviews with experts, executives, and practitioners in the field of AI and technology. Different from traditional interviews or written reports, podcast discussions often provide a candid look into industry trends, challenges, and strategies, as speakers engage in open dialogue. Given that GenAI is a fast-evolving field, the insights from these podcasts offer timely, relevant information that is essential for understanding current trends and practices. Additionally, the podcast format allows for insights that are not confined to the formalities of structured interviews, thus offering a richer, more detailed view of the subject. The diverse range of industries represented in the podcast data, from AI data infrastructure and gaming to journalism and media production, enhances the generalizability of the findings. This cross-sectional approach ensures that the study captures both industry-specific challenges and broader trends that apply across sectors.

3.3 Data analysis and coding process

Data analysis followed a systematic coding process, guided by the Gioia method (Gioia et al., 2013), which is widely used for structuring qualitative data. Each podcast episode was transcribed and subjected to a rigorous coding process to identify key concepts, patterns, and themes. Initially, first-order concepts were developed by categorizing quotes and statements that related to specific challenges, opportunities, or strategies for AI integration. These concepts were then grouped into second-order themes that represented broader categories of findings, and finally, aggregate dimensions were formed to encapsulate overarching insights. This iterative and transparent nature of the Gioia method makes it particularly effective for capturing the complexity of qualitative data and grounding theoretical insights in empirical findings (Gioia et al., 2013). To enhance the rigor and transparency of our analysis, we utilized NVivo software for coding, analyzing, and synthesizing the data (Jackson & Bazeley, 2019).

More specifically, we began with open coding, guided by our research objectives and the data gathered through interviews (Corbin & Strauss, 1990). This phase involved identifying specific terms, phrases, and concepts expressed by participants, adhering closely to their language and perspectives to ground our analysis in empirical reality. For instance, respondents frequently highlighted challenges such as "managing LLM debugging loops" and "balancing memory and compute," which formed the initial first-order codes. Next, we grouped first-order codes into broader, more abstract second-order themes based on emerging patterns and theoretical underpinnings. These themes, such as "model and algorithm complexity" and "scaling and efficiency of AI models," reflect researcher interpretation informed by both empirical data and existing literature. During this phase, we iteratively refined the codes and themes through comparison with prior studies and theoretical frameworks. Finally, we synthesized the second-order themes into higher-level aggregate dimensions that encapsulate the overarching insights from the data. For example, themes such as "infrastructure and hardware limitations" and "market and competitive dynamics" were aggregated into the dimension "technological and operational constraints."

Figure 1 illustrates the coding process. This hierarchical structure ensures transparency in the progression from raw data to theoretical insights. Table 1 provides representative examples of the coding structure, demonstrating how specific participant quotes were systematically analyzed and integrated into the final coding scheme.

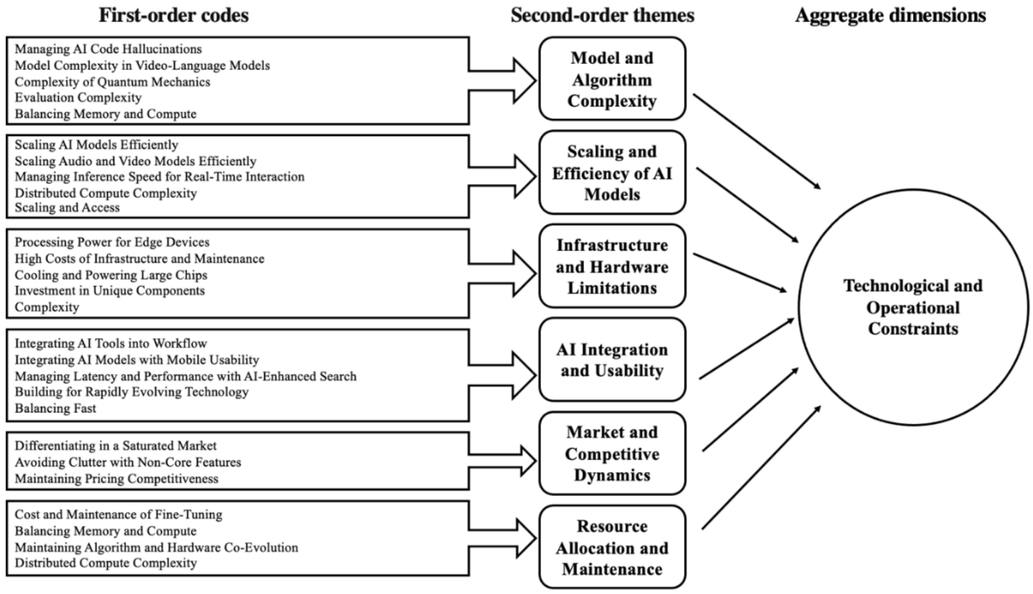

Figure 1. Coding process

Table 1. Representative examples from podcast interviews

Challenges	Representative quotes
Technical and operational barriers	“Real-time translation... is always going to have somewhat of a lag.” “Keeping any two datasets or databases in sync is hard”
User trust and experience	“We want to make sure it’s still telling a coherent story, even if different each time.” “The chatbot needs to understand... what do you want, can I handle it or not, and if I can’t, pass it to an agent” “People must trust that AI makes decisions for their benefit, not some third-party interest.”
Ethical and regulatory concerns	“We really wanted the category of these devices to have a privacy-first mandate to make this a mainstream socially acceptable device.” “We put a lot of effort into building a pipeline... to verify the output against the source material”
Market and competitive pressures	“Open-source AI can help democratize faster... anyone can build a product around it without a central provider.” “If you want to be early, you have to intercept the technology rather than wait for it.”

Responsible innovation and social impact	"We cut half of the app before launch... it's easy to build features but hard to make them work at a high standard." "We cut half of the app before launch... it's easy to build features but hard to make them work at a high standard."
Opportunities	Representative quotes
Enhanced personalization and user engagement	"You can upload a CSV file and ask questions... redefining interaction with data." "Personalization... a product that knows you extremely deeply... optimizes learning specifically for you." "Richly interactive experiences... more like realistic conversational Partners for language learning."
Expansion into new markets	"We're exploring how to make a business model that correlates with the usage of the content" "We're live in over 20 countries now and want to double that by the end of the year"
Empowering creativity and content creation	"Instead of writing prices right descriptions, now we're going to have ChatGPT write them" "Our goal is to make it so anyone, even without coding knowledge, can create a game"
Improved efficiency and productivity	"I can knock out quick prototypes... I can try more ideas in a day than before." "We approximate in a way... which provides maybe more than 30% savings in terms of flops."
Advancements in security, privacy, and safety	"GenAI is actually a huge step forward in terms of responsible AI or safety... We're able to turn that into interloop testing." "We actually use it to produce a lot more synthetic data to augment our safety models."

4. FINDING

4.1 Challenges in integrating GenAI for decision-making

Integrating GenAI into decision-making processes presents multifaceted challenges that organizations must address for effective implementation. These challenges can be grouped into five overarching categories: technical and operational barriers, user trust and experience, ethical and regulatory concerns, ethical and regulatory concerns, market and competitive pressures, and responsible innovation and social impact.

Technical and operational barriers. Organizations integrating GenAI face numerous technical and operational challenges, encompassing model complexity, scalability, and infrastructure limitations. Advanced AI models, such as large language models (LLMs) and video-language systems, require sophisticated debugging to address issues like code hallucinations and balancing memory usage with computational demands. These models are also prone to errors in highly specialized domains, such as quantum mechanics, necessitating continuous evaluation and fine-tuning. Scaling these models efficiently for diverse applications, such as real-time audio or video processing, demands high inference speeds and distributed computing capabilities. However, maintaining performance across edge devices and real-time interactions imposes further constraints on processing power and infrastructure. The costs of maintaining this infrastructure represent significant financial and operational burdens, particularly for smaller firms. Moreover, integrating AI tools into workflows is challenging due to compatibility issues with existing systems and the fast pace of AI innovation, which necessitates constant updates. For instance, balancing iterative improvements with system stability remains a critical hurdle. Collectively, these barriers underscore the importance of a strategic, well-resourced approach to deploying GenAI within organizational frameworks.

User trust and experience. Fostering user trust is critical for GenAI adoption. Users often hold inflated expectations about AI's capabilities, which can lead to mistrust when the technology produces errors or does not meet high expectations. Bridging this gap requires transparent communication about AI's strengths and limitations, along with user education to align technological readiness with consumer preparedness. Moreover, balancing innovation with usability is a key challenge; introducing multi-model integrations or advanced features without overwhelming users demands careful design. Striking this balance ensures that AI systems remain accessible while delivering powerful capabilities. Another crucial aspect is maintaining engagement and retention. AI developers must design systems that sustain long-term interest by offering economic value and ensuring compatibility with users' existing workflows. Personalization plays a significant role here, as tools that efficiently capture preferences and allow user control foster trust and loyalty. Maintaining human-centric values, such as ethical design and narrative coherence, is equally vital to ensure that users feel confident in the AI's role within decision-making processes.

Ethics, privacy, security, and risk management. The responsible adoption of GenAI hinges on navigating a complex landscape of ethical, privacy, security, and risk management challenges. Data privacy stands out as a critical concern, as AI models require extensive datasets that must comply with stringent regulations like GDPR. Ensuring robust safeguards against data breaches, unauthorized data extraction, and training biases is essential to maintain trust. Security vulnerabilities, including adversarial attacks, model theft, and manipulation through prompt injection, further complicate implementation and demand proactive countermeasures such as adversarial training and continuous monitoring. Equally significant is the challenge of mitigating biases inherent in AI systems, which, if left unaddressed, can perpetuate unfair outcomes in predictive algorithms or emotional recognition tools. Additionally, the evolving regulatory landscape creates uncertainty, requiring firms to balance compliance with innovation to avoid ethical lapses while maintaining competitive advantage. Explainable AI serves as a key tool to enhance transparency and accountability, particularly in high-stakes environments like healthcare or finance. Lastly, safeguarding content integrity in AI outputs, preventing hallucinations and ensuring narrative coherence, requires rigorous oversight mechanisms, including human-in-the-loop systems, to guarantee outputs are ethical, accurate, and aligned with organizational goals.

Market and competitive pressures. GenAI adoption is heavily influenced by competitive dynamics and market uncertainties, presenting firms with a series of significant challenges. Companies must contend with the dominance of established AI incumbents, whose market control exacerbates pricing pressures and limits visibility for newer entrants. Overcoming distribution barriers, such as gaining traction on search platforms and differentiating offerings, demands substantial resources and innovative strategies. Additionally, infrastructure costs skyrocket with rapid user growth, further compounded by the need to tailor solutions for diverse global markets. Firms also face increasing user fatigue with subscription-based AI models, which threatens retention and necessitates constant value delivery. Moreover, the automation of traditional software development roles by GenAI disrupts industry norms, introducing uncertainty about workforce structures and skill demands. These challenges underscore the necessity for organizations to remain agile and adaptable, navigating evolving competitive landscapes while striving to maintain relevance and operational viability.

Responsible innovation and social impact. GenAI raises significant challenges regarding responsible innovation and its societal implications. One pressing issue is ensuring fairness and inclusivity, as biases in AI systems can result in representational disparities and reinforce existing inequalities. Addressing these biases requires continuous audits and the inclusion of diverse datasets, particularly when deploying AI across culturally varied regions. Furthermore, the rapid pace of AI advancements often exacerbates public concerns about transparency and accountability, leading to heightened criticism and skepticism. The difficulty of aligning AI applications with ethical standards while managing the cost-efficiency of models further complicates their deployment. Organizations must also grapple with the potential risks associated with unintended consequences of AI outputs, such as hallucinations or harmful recommendations, particularly in high-stakes applications like healthcare. These challenges underscore the need for balancing innovation with the mitigation of social risks, as GenAI reshapes societal norms and expectations.

4.2 Opportunities for leveraging GenAI in decision-making

The integration of GenAI into organizational decision-making offers transformative opportunities across various domains. These opportunities can be categorized into enhanced personalization and user engagement, expansion into new markets, empowering creativity and content creation, improved efficiency and productivity, and advancements in security, privacy, and safety.

Enhanced personalization and user engagement. GenAI enables organizations to provide tailored and immersive user experiences, fostering deeper engagement and satisfaction. In education, AI-driven tools facilitate personalized learning at scale, catering to diverse student needs through interactive and adaptive platforms. In the media and entertainment sectors, GenAI supports hyper-personalized content creation, such as customizable game interactions and dynamic storytelling, enriching user experiences. Similarly, in design and visualization, AI-powered tools enable hyper-efficient personalization, enhancing creativity while meeting specific user preferences. These innovations redefine user engagement, positioning GenAI as a critical enabler of customer loyalty and satisfaction.

Expansion into new markets. GenAI's adaptability allows organizations to explore new market opportunities and address unmet needs across sectors. In healthcare, diagnostic AI tools enhance accessibility and personalization, empowering providers to deliver improved patient care. Similarly, AI applications in education and enterprise solutions revolutionize content accessibility, enabling global reach. E-commerce platforms leverage GenAI to expand consumer engagement and streamline operations, positioning organizations to capitalize on emerging trends in dynamic markets. These expansions open doors to previously underserved demographics and support organizations in diversifying their offerings.

Empowering creativity and content creation. GenAI democratizes the creative process, offering tools that cater to users with varying levels of expertise. In industries such as music, video production, and design, AI platforms enable creators to produce high-quality, personalized outputs efficiently. Features like multimodal editing and cross-platform integration streamline workflows and lower entry barriers for aspiring creators. These advancements not only foster innovation but also broaden access to creative tools, allowing users to explore novel formats and ideas. Organizations leveraging these capabilities can maintain a competitive edge by consistently delivering innovative, engaging content.

Improved efficiency and productivity. GenAI significantly enhances operational efficiency by automating routine tasks and optimizing workflows. In finance, AI streamlines processes like expense tracking and forecasting, enabling professionals to focus on strategic initiatives. Enhanced collaboration tools, such as cross-device memory and cognitive meeting support, facilitate seamless communication and productivity in hybrid work environments. Additionally, real-time data processing and monitoring capabilities enable faster, more informed decision-making, ensuring organizations remain agile and competitive in fast-paced industries. These productivity improvements translate to tangible benefits in cost savings and resource allocation.

Advancements in security, privacy, and safety. GenAI strengthens organizational safeguards by addressing critical concerns in security, privacy, and safety. Privacy-compliant AI solutions, such as differential privacy techniques, protect sensitive data while ensuring regulatory adherence. AI-driven innovations in safety, including synthetic data for testing and predictive analytics, reduce risks in high-stakes applications like transportation and healthcare. Furthermore, robust security measures, such as enhanced content analytics and real-world AI standards, mitigate vulnerabilities and build trust among stakeholders. These advancements position GenAI as a tool for not only operational efficiency but also ethical and secure organizational practices.

4.3 Strategic framework for GenAI integration

To translate the potential of GenAI into practice, we propose the 8A Framework for GenAI integration, a structured, practitioner-informed model that guides firms through the full implementation journey. First, firms must Align their GenAI initiatives with overarching business objectives to ensure strategic coherence and value delivery. Second, they should Assure ethical integrity and privacy protection by establishing clear governance frameworks and compliance mechanisms. Next, organizations must Adapt AI tools through iterative, user-centered development, ensuring contextual relevance and usability.

With validated insights, firms can Accelerate innovation via rapid prototyping and experimentation, followed by efforts to Anchor GenAI into core systems and workflows for operational continuity. To drive competitive advantage, firms should Amplify their solutions through specialization and high-impact customization. Once internal readiness is achieved, firms can Assemble broader collaborative ecosystems to support scalable deployment, cross-sector engagement, and shared learning. Finally, organizations must Anticipate evolving risks and regulatory shifts by developing proactive monitoring and policy adaptation strategies.
This eight-step framework equips decision-makers with a comprehensive roadmap for high-impact, responsible, and scalable integration of GenAI into business processes. Figure 2 presents a visual representation of this roadmap.

Figure 2. The 8A Framework: A Strategic Roadmap for Generative AI Integration

Step 1: Align GenAI with Business Objectives

To successfully integrate GenAI, firms must first ensure that their initiatives align with overarching business objectives. This alignment provides a strategic foundation, ensuring that AI efforts are purpose-driven rather than technology-led. GenAI should be mapped to specific use cases that contribute to organizational goals, such as improving decision-making speed, personalizing customer experiences, or enhancing product innovation. This strategic clarity enables resource prioritization and fosters cross-functional buy-in, laying the groundwork for scalable implementation.

Step 2: Assure Ethical and Privacy Safeguards

Ethical and privacy considerations must be at the core of GenAI implementation. Establishing transparent privacy policies and ethical guidelines is essential to gain user trust and ensure compliance with evolving regulations like GDPR. Firms can achieve this by collaborating with legal and ethical experts to build customizable privacy solutions tailored to diverse cultural and legal contexts. For example, leveraging feedback from global datasets helps refine AI applications to meet ethical benchmarks across different markets. In addition, adopting frameworks for transparent consent and ethical data use ensures that AI practices align with stakeholder expectations while minimizing reputational risks. These standards are critical not only for compliance but also for creating AI systems that are accountable and trustworthy.

Step 3: Adapt Through User-Driven Iterative Design

A user-focused iterative development process ensures that GenAI applications remain relevant and adaptive to changing demands. Incremental innovation, driven by continuous user feedback, allows firms to fine-tune their offerings while addressing emerging market needs. For instance, adaptive feedback systems can optimize product features based on real-time user inputs, making AI tools more intuitive and effective. Localization efforts further enhance usability by tailoring AI outputs to regional preferences and languages, demonstrating cultural sensitivity. This iterative approach promotes a cycle of improvement that not only satisfies user needs but also strengthens customer loyalty.

Step 4: Accelerate Innovation via Rapid Prototyping

Rapid prototyping enables firms to remain agile in fast-paced, competitive environments. By leveraging GenAI for experimental development, firms can test new features, such as voice-activated tools or hyper-personalized models, in controlled environments. This approach allows organizations to identify high-impact solutions while minimizing costs associated with large-scale implementation. Furthermore, rapid experimentation fosters a culture of innovation, empowering firms to explore uncharted markets and adapt to emerging trends. Prototyping also reduces the risk of costly failures by enabling early-stage testing and refinement.

Step 5: Anchor GenAI into Existing Systems

Seamless integration of GenAI into existing workflows and platforms is vital for operational efficiency. Multi-platform compatibility ensures that AI systems can be deployed without disrupting established processes. For example, developing scalable workflows with cross-device memory capabilities allows teams to work seamlessly across environments, increasing productivity. Adaptive designs that integrate with existing databases reduce the friction of AI adoption, enabling organizations to achieve a smoother transition. These integration efforts not only optimize operations but also enhance user satisfaction, as systems appear cohesive and intuitive.

Step 6: Amplify Differentiation Through Specialization

In an increasingly competitive market, differentiation is key. Firms must focus on domain-specific AI solutions tailored to unique industry needs. By developing specialized AI teams and leveraging pre-trained models, organizations can create cost-effective tools that address specific pain points. For instance, firms in the healthcare sector might prioritize AI features for advanced diagnostics, while retail companies focus on hyper-personalized shopping experiences. Differentiation strategies that emphasize utility and customer impact enable firms to stand out and build a loyal user base.

Step 7: Assemble Collaborative Ecosystems

As organizations move beyond pilot deployments of GenAI, assembling a robust collaborative ecosystem becomes essential for sustained innovation and scalability. Strategic partnerships with academic institutions, regulatory bodies, ethical advisors, and industry peers allow firms to broaden capabilities, access frontier knowledge, and build trust within the broader AI community. University collaborations, for example, provide cutting-edge research inputs and co-develop frameworks for responsible AI governance. Industry forums and open-source alliances create shared spaces to test standards, improve interoperability, and crowdsource solutions to common technical challenges. Additionally, cross-disciplinary collaboration across ethics, engineering, law, and user experience disciplines ensures that AI systems meet both technical performance goals and societal expectations. By assembling such ecosystems, firms can accelerate GenAI adoption responsibly while positioning themselves as credible leaders in shaping the future of intelligent technologies.

Step 8: Anticipate Risks and Regulatory Shifts

Navigating the evolving regulatory landscape requires proactive engagement with policymakers and robust risk management protocols. Firms must proactively engage with regulators to stay ahead of policy changes while advocating for balanced regulations that encourage innovation. Robust risk detection mechanisms, such as layered hallucination filters and adversarial testing, help prevent ethical or operational failures. Moreover, establishing real-world security standards builds trust among stakeholders, ensuring that AI systems remain reliable and safe in critical applications. These efforts position firms as responsible leaders in the GenAI space, fostering long-term success.

5. DISCUSSION AND CONTRIBUTIONS

This study set out to examine how firms integrate GenAI into decision-making and to identify the strategies they employ to cope with its dual potential. Drawing on insights from 51 industry experts, the analysis highlights that adoption is far from straightforward. On the one hand, organizations see significant opportunities in areas such as personalization, efficiency, creativity, and compliance support. On the other hand, they encounter considerable challenges, including infrastructure and resource demands, privacy and ethical concerns, competitive pressures, and cultural resistance. Importantly, these findings reveal that challenges and opportunities are not separate domains but interconnected dualities: the very features that make GenAI valuable also generate risks that can undermine adoption.

Building on this evidence, the study developed the 8A Framework, a structured roadmap that captures how firms cope with the complexities of GenAI integration. The framework emphasizes that adoption is not a one-off technical project but an ongoing organizational process. Firms must align GenAI initiatives with strategy, assure ethical and privacy safeguards, adapt iteratively with user feedback, accelerate through rapid prototyping, anchor tools into workflows, amplify adoption through differentiation, assemble collaborative ecosystems, and anticipate regulatory and ethical developments. Taken together, these practices represent a systematic approach to balancing the bright and dark sides of GenAI, moving from experimentation to responsible scaling.

5.1 Theoretical contributions

This study advances the literature on GenAI in three important ways. First, it provides one of the earliest empirically grounded mappings of the challenges and opportunities of GenAI adoption in decision-making. Whereas prior research has largely remained conceptual, this study identifies concrete categories of barriers and opportunities that organizations encounter in practice.

Second, the findings demonstrate that challenges and opportunities are not independent phenomena but intertwined dualities. For example, personalization simultaneously offers enhanced user engagement and creates heightened privacy risks, while accelerated prototyping can both speed innovation and propagate errors. By revealing these tensions, the study enriches theoretical understanding by showing that GenAI adoption must be conceptualized as a process of managing trade-offs rather than simply pursuing benefits or avoiding risks.

Third, the study contributes by introducing the 8A Framework, which synthesizes coping strategies into a structured roadmap. Unlike abstract models of digital transformation, the 8A Framework specifies actionable yet generalizable practices that link the identification of challenges and opportunities with organizational responses. This provides scholars with a mid-level theorization of how firms navigate the unique properties of GenAI, including its generativity, unpredictability, and ethical ambiguity, when embedding it into business processes.

5.2 Managerial contributions

The study also makes important contributions to managerial practice by offering executives a structured roadmap for GenAI adoption. The 8A Framework highlights that successful integration begins with strategic alignment, ensuring initiatives serve business objectives rather than remaining isolated pilots. Ethical and privacy assurance emerges as another essential condition, as user trust and regulatory compliance are easily jeopardized without proactive safeguards.

The framework further emphasizes the value of adaptability and speed. Iterative development grounded in user feedback allows firms to tailor AI applications to specific contexts, while rapid prototyping enables efficient experimentation and refinement. Yet adoption cannot stop at experimentation: anchoring AI into existing workflows supports employee acceptance and operational continuity, while amplifying adoption through domain-specific applications helps organizations differentiate in competitive markets.

Finally, the framework underscores the importance of collaboration and foresight. Building ecosystems with regulators, academic partners, and industry peers not only broadens access to expertise but also strengthens legitimacy. At the same time, anticipating regulatory shifts and emerging risks ensures that firms remain resilient in a fast-changing environment. Collectively, these managerial insights provide leaders with a comprehensive and empirically grounded approach to unlocking the bright potential of GenAI while mitigating its darker risks.

5.3 Limitations and future research

While this study provides new insights into GenAI adoption, several limitations open avenues for further research. Methodologically, the reliance on podcasts as the primary data source, while offering rich and candid insights, may bias findings toward the perspectives of high-profile or vocal individuals in the AI domain. Future research should expand data sources to include interviews, surveys, or case studies from a broader range of organizations. Moreover, the exploratory and qualitative design limits the generalizability of the findings. Combining qualitative insights with quantitative approaches would allow validation and extension of the 8A Framework across industries, organizational sizes, and geographic regions.

A second limitation relates to the temporal scope of this study. The analysis captures perspectives at a single point in time, but does not explore how firms adapt their strategies as technologies and ecosystems evolve. Longitudinal studies would therefore be valuable for tracing the evolution of GenAI adoption, assessing how coping strategies change with regulatory developments, and evaluating whether expected benefits, such as improved decision-making and competitive differentiation, are sustained over time.

Third, while the 8A Framework is designed to be broadly applicable, its relevance may vary across industries, institutional environments, and cultural contexts. Comparative studies across sectors such as healthcare, finance, and creative industries, as well as cross-country analyses, could shed light on how contextual factors shape both opportunities and challenges.

Finally, this study primarily emphasizes the organizational perspective. Future research should investigate the customer-facing implications of GenAI adoption, including how AI-driven tools influence consumer trust, perceptions, and satisfaction. Comparative work between SMEs and large enterprises, or between technologically mature and less mature industries, would further enrich understanding of the broader applicability and impact of GenAI strategies.

6. CONCLUSION

This study examined how organizations navigate the integration of GenAI into decision-making, identifying both the opportunities it creates and the challenges it poses. By analyzing the perspectives of industry experts, the study demonstrated that adoption is shaped by dualities: the same features that enable personalization, creativity, and efficiency also give rise to risks related to privacy, bias, and disruption.

To address these complexities, the study introduced the 8A Framework, which synthesizes coping strategies into a structured roadmap for practice. The framework emphasizes that adoption is not a discrete technological project but a continuous organizational process requiring strategic alignment, ethical safeguards, iterative adaptation, and proactive governance. For theory, the study advances understanding by mapping challenges and opportunities, highlighting their dualities, and offering an empirically grounded framework that links them to coping practices. For practice, it equips managers with a comprehensive roadmap for realizing the bright potential of GenAI while mitigating its darker risks.

Ultimately, the findings position GenAI not merely as a technical tool but as a transformative force that reshapes organizational routines, competitive dynamics, and governance demands. By translating diverse practitioner experiences into an actionable framework, this study contributes to both scholarly debates and managerial practice, offering a pathway for firms to harness GenAI responsibly and effectively.

REFERENCE

Akhtar, P., Ghouri, A. M., Ashraf, A., Lim, J. J., Khan, N. R., & Ma, S. (2024). Smart product platforming powered by AI and Generative AI: Personalization for the circular economy. *International Journal of Production Economics*, *273*, 109283.

Baabdullah, A. M. (2024). Generative conversational AI agent for managerial practices: The role of IQ dimensions, novelty seeking and ethical concerns. *Technological Forecasting and Social Change*, *198*, 122951.

Boussioux, L., Lane, J. N., Zhang, M., Jacimovic, V., & Lakhani, K. R. (2024). The crowdless future? Generative AI and creative problem-solving. *Organization Science*, *35*(5), 1589–1607.

Budhwar, P., Chowdhury, S., Wood, G., Aguinis, H., Bamber, G. J., Beltran, J. R., Boselie, P., Lee Cooke, F., Decker, S., & DeNisi, A. (2023). Human resource management in the age of generative artificial intelligence: Perspectives and research directions on ChatGPT. *Human Resource Management Journal*, *33*(3), 606–659.

Chiarello, F., Giordano, V., Spada, I., Barandoni, S., & Fantoni, G. (2024). Future applications of generative large language models: A data-driven case study on ChatGPT. *Technovation*, *133*, 103002.

Chowdhury, S., Budhwar, P., & Wood, G. (2024). Generative artificial intelligence in business: towards a strategic human resource management framework. *British Journal of Management*, *35*(4), 1680-1691.

Cillo, P., & Rubera, G. (2025). Generative AI in innovation and marketing processes: A roadmap of research opportunities. *Journal of the Academy of Marketing Science*, *53*(3), 684-701.

Corbin, J. M., & Strauss, A. (1990). Grounded theory research: Procedures, canons, and evaluative criteria. *Qualitative Sociology*, *13*(1), 3–21.

Doshi, A. R., Bell, J. J., Mirzayev, E., & Vanneste, B. S. (2025). Generative artificial intelligence and evaluating strategic decisions. *Strategic Management Journal*, *46*(3), 583-610.

Dwivedi, Y. K., Pandey, N., Currie, W., & Micu, A. (2024). Leveraging ChatGPT and other generative artificial intelligence (AI)-based applications in the hospitality and tourism industry: practices, challenges and research agenda. *International Journal of Contemporary Hospitality Management*, *36*(1), 1–12.

Epstein, Z., Hertzmann, A., & Investigators of Human Creativity (2023). Art and the science of generative AI. *Science*, *380*(6650), 1110–1111.

Fakfare, P., Manosuthi, N., Lee, J.-S., Han, H., & Jin, M. (2025). Customer word-of-mouth for generative AI: Innovation and adoption in hospitality and tourism. *International Journal of Hospitality Management*, *126*, 104070.

Fisher, G., Stevenson, R., Neubert, E., Burnell, D., & Kuratko, D. F. (2020). Entrepreneurial hustle: Navigating uncertainty and enrolling venture stakeholders through urgent and unorthodox action. *Journal of Management Studies*, *57*(5), 1002– 1036.

Gioia, D. A., Corley, K. G., & Hamilton, A. L. (2013). Seeking qualitative rigor in inductive research: Notes on the Gioia methodology. *Organizational Research Methods*, *16*(1), 15–31.

Haefner, N., Parida, V., Gassmann, O., & Wincent, J. (2023). Implementing and scaling artificial intelligence: A review, framework, and research agenda. *Technological Forecasting and Social Change*, *197*, 122878.

Hao, X., Demir, E., & Eyers, D. (2024). Exploring collaborative decision-making: A quasi-experimental study of human and Generative AI interaction. *Technology in Society*, *78*, 102662.

Hendriksen, C. (2023). Artificial intelligence for supply chain management: Disruptive innovation or innovative disruption? *Journal of Supply Chain Management*, *59*(3), 65–76.

Hermann, E., & Puntoni, S. (2024). Artificial intelligence and consumer behavior: From predictive to generative AI. *Journal of Business Research*, 180, 114720.

Jackson, I., Ivanov, D., Dolgui, A., & Namdar, J. (2024). Generative artificial intelligence in supply chain and operations management: a capability-based framework for analysis and implementation. *International Journal of Production Research*, *62*(17). 6120-6145.

Jackson, K., & Bazeley, P. (2019). *Qualitative data analysis with NVivo*, Sage Publications.

Kalia, S. (2023). Potential Impact of Generative Artificial Intelligence (AI) on the Financial Industry. *International Journal on Cybernetics & Informatics*, *12*(6), 37-51.

Kankanhalli, A. (2024). Peer Review in the Age of Generative AI. *Journal of the Association for Information Systems*, *25*(1), 76–84.

Khan, S., Mehmood, S., & Khan, S. U. (2024). Navigating innovation in the age of AI: how generative AI and innovation influence organizational performance in the manufacturing sector. *Journal of Manufacturing Technology Management*, *36*(3), 597-620.

Kshetri, N., Dwivedi, Y. K., Davenport, T. H., & Panteli, N. (2024). Generative artificial intelligence in marketing: Applications, opportunities, challenges, and research agenda. *International Journal of Information Management*, *75*, 102716.

Kusiak, A. (2020). Convolutional and generative adversarial neural networks in manufacturing. *International Journal of Production Research*, *58*(5), 1594–1604.

Liang, C., Du, H., Sun, Y., Niyato, D., Kang, J., Zhao, D., & Imran, M. A. (2024). Generative AI-driven semantic communication networks: Architecture, technologies and applications. *IEEE Transactions on Cognitive Communications and Networking, 11*(1), 27-47.

Mogaji, E., Viglia, G., Srivastava, P., & Dwivedi, Y. K. (2024). Is it the end of the technology acceptance model in the era of generative artificial intelligence? *International Journal of Contemporary Hospitality Management*, *36*(10), 3324–3339.

Ning, Y., Teixayavong, S., Shang, Y., Savulescu, J., Nagaraj, V., Miao, D., Mertens, M., Ting, D. S. W., Ong, J. C. L., & Liu, M. (2024). Generative artificial intelligence and ethical considerations in health care: a scoping review and ethics checklist. *The Lancet Digital Health*, *6*(11), e848–e856.

Norbäck, P.-J., & Persson, L. (2024). Why generative AI can make creative destruction more creative but less destructive. *Small Business Economics*, *63*(1), 349–377.

Park, H. E. (2024). The double-edged sword of generative artificial intelligence in digitalization: An affordances and constraints perspective. *Psychology & Marketing*, *41*(11), 2924–2941.

Shore, A., Tiwari, M., Tandon, P., & Foropon, C. (2024). Building entrepreneurial resilience during crisis using generative AI: An empirical study on SMEs. *Technovation*, *135*, 103063.

Susarla, A., Gopal, R., Thatcher, J. B., & Sarker, S. (2023). The Janus Effect of Generative AI: Charting the Path for Responsible Conduct of Scholarly Activities in Information Systems. *Information Systems Research*, *34*(2), 399–408.

Talaei-Khoei, A., Yang, A. T., & Masialeti, M. (2024). How does incorporating ChatGPT within a firm reinforce agility-mediated performance? The moderating role of innovation infusion and firms' ethical identity. *Technovation*, *132*, 102975.

Wamba, S. F., Queiroz, M. M., Jabbour, C. J. C., & Shi, C. V. (2023). Are both generative AI and ChatGPT game changers for 21st-Century operations and supply chain excellence? *International Journal of Production Economics*, *265*, 109015.

Wessel, M., Adam, M., Benlian, A., & Thies, F. (2025). Generative AI and its transformative value for digital platforms. *Journal of Management Information Systems*, *42*(2), 346-369.

Yan, L., Greiff, S., Teuber, Z., & Gašević, D. (2024). Promises and challenges of generative artificial intelligence for human learning. *Nature Human Behaviour*, *8*(10), 1839–1850.

PAPER 3

Understanding employee responses to AI collaboration: A dual appraisal model of work engagement

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ABSTRACT

As generative AI (GenAI) becomes increasingly embedded in workplace processes, understanding its impact on employee engagement is vital. Drawing on cognitive appraisal theory, this study develops and tests a dual path model to examine how employees psychologically respond to AI collaboration. Using survey data from 395 US-based professionals engaged with GenAI at work, the study reveals that AI collaboration significantly enhances opportunity appraisals, which reflect perceptions of growth and support, and these appraisals predict higher work engagement. Although threat appraisals (e.g., fear of obsolescence) negatively impact engagement, they are not directly triggered by collaboration itself. The results also show that job insecurity intensifies both opportunity and threat appraisals, while perceived ease of use reduces the salience of both.

Keywords: Generative AI collaboration, cognitive appraisal, work engagement, job insecurity, ease of use

1. INTRODUCTION

The widespread adoption of generative artificial intelligence (GenAI) is rapidly transforming contemporary workplaces. GenAI is now embedded in core business functions, assisting with tasks such as content generation, coding, and decision-making (Dwivedi et al., 2023; Rai et al., 2019). According to a recent McKinsey Global Survey, 71% of organizations report regular use of GenAI in at least one business function (Singla et al., 2025). In response, firms are actively redesigning workflows, introducing governance mechanisms, and retraining employees to operate effectively in AI-integrated environments. This evolution marks a shift from human–technology interaction to AI collaboration, where employees and GenAI systems jointly execute tasks and influence outcomes. While this shift offers notable operational advantages, such as increased efficiency, scalability, and innovation (Doshi et al., 2025), it also introduces psychological and emotional complexity, such as role ambiguity, emotional dissonance, and identity threat (Xu et al., 2024). Employees must therefore adjust to evolving roles, redefine their contributions, and adapt to the presence of intelligent systems within their work. These changes raise important questions about how AI collaboration influences employee experiences, particularly in relation to motivation and engagement.

Although existing research has begun to examine the implications of AI integration for employee well-being and performance, findings remain mixed. Some studies highlight benefits such as reduced workload and greater task focus (Jia et al., 2024), while others report unintended consequences, including job insecurity, loneliness, and burnout (Hu et al., 2023; Tang et al., 2023). However, much of this work treats AI as either a technical artifact or a stressor, overlooking the interpretive processes that shape employee experiences. Recent scholarship calls for moving beyond surface-level assessments of technology use to examine how AI systems, particularly those with generative, co-creative capacities, affect employees' perceptions of agency, relevance, and psychological safety (Bonnefon et al., 2024; Sundar, 2020).

Furthermore, as AI systems increasingly assume roles that involve decision-making, creativity, and communication, employees are no longer just using tools. Instead, they are collaborating with agents perceived to possess autonomy and intelligence. This shift introduces ambiguity around human contribution, role identity, and control, prompting employees to make sense of what AI collaboration means for their work (Dwivedi et al., 2023). From a psychological standpoint, such novel collaborations require individuals to evaluate whether AI enhances or undermines their goals, values, and self-worth in the workplace. These evaluations are not merely cognitive but also emotional, shaping how employees respond to AI integration over time (Hai et al., 2025). This highlights the need for a theoretical approach that accounts for both cognitive evaluation and affective responses, offering explanatory power for divergent outcomes such as engagement, resistance, or withdrawal.

To address this gap, we propose cognitive appraisal theory (Lazarus, 1984) as a lens to examine employee responses to AI collaboration. We conceptualize AI collaboration as a work arrangement in which employees and GenAI systems engage in interdependent tasks to co-produce outputs and share responsibility for performance outcomes. These interactions introduce uncertainty around one's role, contribution, and control, prompting employees to evaluate what AI collaboration means for their work (Fügener et al., 2022). Unlike traditional models such as the Technology Acceptance Model, which often assume uniform responses to technology, appraisal theory recognizes that individuals interpret the same work conditions differently depending on their goals, resources, and concerns (He et al., 2024). In the case of AI collaboration, some employees may perceive GenAI as an opportunity, a source of growth, learning, and support, while others may feel threatened by job insecurity or loss of autonomy. Moreover, we consider how contextual factors shape these evaluations. Specifically, we examine perceived job insecurity and ease of use as moderators that influence whether AI is appraised as empowering or disruptive.

This study makes three key contributions to the literature on AI integration, organizational behavior, and employee psychology. First, it advances theoretical understanding by applying cognitive appraisal theory to the context of human–AI collaboration, shifting the analytical focus from passive technology adoption to active psychological meaning-making. Rather than treating AI as a neutral tool, we frame collaboration with GenAI as a psychologically charged work condition that prompts employees to assess its significance for their professional goals, sense of identity, and perceived value. These assessments take the form of dual appraisals, which function as interpretive filters that shape how AI integration influences work engagement.

Second, this study extends the appraisal model by incorporating contextual and individual factors that influence how employees evaluate AI collaboration. The model considers how job insecurity may heighten sensitivity to the implications of AI for one's role, and how ease of use may affect the cognitive and emotional salience of the technology. By accounting for these conditions, the framework offers a more detailed understanding of how workplace context and technology perceptions shape the appraisal process.

Third, the study finds that opportunity appraisal is the main pathway through which AI collaboration enhances engagement, while threat appraisal only has a direct negative effect. These findings deepen our understanding of how GenAI influences the employee–technology relationship, not just through tasks, but through how employees interpret its impact on their motivation and emotional experience at work.

The remainder of this article is structured as follows. The next section develops the theoretical background and conceptual model, followed by our hypotheses. We then describe the methodology and present the results of our structural equation modeling analysis. The final sections discuss the theoretical and managerial implications of our findings, and outline avenues for future research.

2. LITERATURE REVIEW AND HYPOTHESE DEVELOPMENT

2.1 AI collaboration in the workplace

The increasing integration of GenAI into organizational processes has prompted growing academic interest in how these technologies reshape the nature of work. GenAI refers to a class of machine learning models capable of producing novel content, including text, images, audio, and code, based on patterns learned from large datasets (Kusiak, 2020; Liang et al., 2024). Tools such as ChatGPT, GitHub Copilot, and DALL·E exemplify the widespread and rapidly evolving adoption of gen AI in practice. Unlike traditional AI systems, which primarily automate rule-based or analytical tasks, GenAI enables more creative, dynamic, and context-sensitive outputs, allowing for real-time content generation, personalization, and ideation (Akhtar et al., 2024; Boussioux et al., 2024). As a result, businesses across sectors, such as IT, manufacturing, public administration, and services, are deploying GenAI to transform decision-making, enhance efficiency, and support knowledge-intensive work (Talaei-Khoei et al., 2024; Wamba et al., 2023). In this evolving landscape, employees are no longer interacting with AI solely as users of automated tools, but increasingly as collaborators in joint tasks and decision-making processes (Seeber et al., 2020). This shift introduces new cognitive and emotional dynamics into organizational life, as intelligent systems begin to support, influence, or even substitute human contributions in domains traditionally reserved for human judgment and creativity.

Human–AI collaboration represents the synergistic relationship in which employees and AI systems work together to accomplish tasks, share responsibilities, and co-create value (Wilson & Daugherty, 2018; Sowa et al., 2021). This approach highlights a shift toward collaborative intelligence, where AI augments human capabilities, and humans provide contextual judgment, oversight, and ethical reasoning. From the employee's perspective, this collaboration involves actively engaging with AI tools that are increasingly embedded in daily workflows, influencing how decisions are made, tasks are performed, and goals are achieved (Chowdhury et al., 2024). This collaborative configuration is especially relevant in knowledge-intensive work and offer mutual benefits: organizations gain efficiency and innovation, while employees can enhance their job performance, learning, and well-being. As these collaborative forms become increasingly integrated in organizational workflows, they not only redefine task structures but also open new pathways for employee skill development, autonomy, and engagement. Table 1 summarizes recent empirical studies that have examined human–AI collaboration within organizational settings.

Table 1. Empirical studies about AI collaboration

Author	Independent variable	Dependent variable	Moderator	Mediator	Findings
Hai et al., (2025)	Employee–generative AI collaboration	Employee expediency	Digital job demands	Work alienation	Collaboration with generative AI heightens alienation, fostering employee expediency; Digital job demands buffer these effects.
Jia et al., (2024)	AI-human collaboration	Employee creativity	N/A	N/A	AI assistance enhances creativity and performance for high-skilled employees; effects are weaker or negative for low-skilled employees, indicating skill-biased augmentation.
Kong et al., (2023)	AI Trust	Career sustainability (well-being, productivity)	Protean career orientation	Employee–AI collaboration	AI trust promotes career sustainability through employee–AI collaboration; protean career orientation strengthens this link, enhancing well-being and productivity; proactive career behaviours support thriving in AI-integrated work.
Marvi et al., (2025)	AI mastery goal orientation	User engagement in AI collaboration	Paradox mindset	Opportunity appraisal	AI mastery goals enhance engagement through opportunity appraisal; the effect is stronger when employees have a high paradox mindset.
Sowa & Ciechanowski (2021)	Human–AI collaboration	Productivity	N/A	N/A	Knowledge work should prioritize human–AI collaboration over full automation to leverage complementary strengths.
Tang et al., (2023)	Interaction frequency with AI	Helping behavior, insomnia, alcohol consumption	Attachment anxiety	Need for affiliation, loneliness	Frequent AI interaction promotes helping behaviour via social affiliation; AI interaction and attachment anxiety increase loneliness, leading to insomnia and alcohol use; attachment anxiety amplifies both adaptive and maladaptive outcomes.
Vann et al., (2025)	Human–AI collaboration	Supply chain performance outcomes	Not specified	Responsible AI	Human–AI collaboration positively influences supply chain outcomes through the mediating role of responsible AI implementation.
Westphal et al., (2023)	Explanation presence	User compliance, user perceptions	N/A	Perceived task complexity, cognitive ability	Users prefer collaboration when retaining decision control; explanations enhance fairness perception and compliance with AI suggestions.
Wu et al., (2024)	Job insecurity from human–AI interaction	Creative performance, informal field-based learning, well-beling, psychological health	Workplace mindfulness	Tech-learning from human-AI interaction	Job insecurity induced by AI collaboration negatively affects work–life balance and job engagement; workplace mindfulness buffers these effects.
Wu et al., (2025)	Human–AI collaboration	Work engagement	Person-job fit	Basic needs QWL, Growth needs QWL	Human-AI collaboration positively affected work engagement by meeting employees' basic needs of quality of work life and growth needs of quality of work life. Person-job fit strengthened above relationship.
Yin et al., (2024)	AI awareness, Change-oriented leadership	Employee–AI collaboration	N/A	Approach motivation and avoidance motivation	AI awareness promotes employee–AI collaboration through motivational pathways; the effect is strengthened under change-oriented leadership.

Recent research on human–AI collaboration has revealed both promising and problematic outcomes for employees. On the one hand, studies have shown that working with AI systems can foster creativity, boundary spanning, agility, and career sustainability, particularly when AI is used to augment rather than replace human work (Jia et al., 2024; Kong et al., 2023). These benefits can enhance employees' ability to adapt, innovate, and thrive in AI-integrated environments. On the other hand, the literature also highlights the risks of AI collaboration, including increased work intensification, emotional strain, and feelings of alienation, which can negatively impact well-being and lead to disengagement or even unethical behaviors (Hai et al., 2025; Tang et al., 2023). While these findings have advanced our understanding of the outcomes associated with AI use, little is known about the psychological processes through which employees appraise and respond to AI collaboration at work. In particular, few studies have explored how AI collaboration may be perceived as either an opportunity or a threat, and how these appraisals shape employee work engagement. Given that engagement is a key predictor of both individual and organizational performance, it is essential to examine how employees cognitively interpret AI integration and how these interpretations affect their motivational states. This study addresses this critical gap by applying a dual appraisal model to investigate how employees' perceptions of AI collaboration influence their work engagement through opportunity and threat appraisals.

2.2 Cognitive appraisals of AI: opportunity and threat evaluations

Cognitive appraisal theory (Lazarus, 1984) provides a valuable lens for understanding how individuals evaluate and respond to environmental change. Originally developed in the context of psychological stress, the theory has since been widely applied in organizational settings to explain employee reactions to job demands, technological change, and organizational restructuring (Ashford, 1988). The core tenet of the theory is that individuals do not passively absorb external stimuli but instead engage in appraisal processes, which is actively interpreting whether a given situation poses an opportunity for gain or a threat of harm. These appraisals are shaped by personal goals, perceived control, and available coping resources, and they play a critical role in shaping emotional, motivational, and behavioural responses to change.

In the context of AI collaboration, appraisal theory offers a compelling framework to explain the psychological variability in employees' responses. Although AI systems are often introduced with the intent to enhance efficiency, quality, and decision-making, they also create ambiguity around task ownership, cognitive authority, and future role stability (Raisch & Krakowski, 2021). As such, employees may engage in two distinct types of appraisals when encountering AI in their workflow. The first is opportunity appraisal, in which AI is perceived as a source of personal or professional benefit that enables skill development, improves job performance, or enhances role significance. Opportunity appraisals are often linked to perceptions of learning, autonomy support, and alignment with future career goals (Tims et al., 2013). For example, an employee who uses AI to automate administrative tasks may feel empowered to focus on more meaningful or strategic work, reinforcing a sense of growth and contribution.

The second type is threat appraisal, in which AI is viewed as a potential source of loss or disruption. This appraisal is triggered when employees perceive that AI undermines their control over work processes, devalues their expertise, or introduces role insecurity (Faraj et al., 2018). Employees who experience high threat appraisal may worry that AI systems will make their skills obsolete, displace core job functions, or diminish their relevance in future organizational configurations. Such appraisals have been associated with anxiety, withdrawal, and resistance to technological change (Tarafdar et al., 2019). Importantly, opportunity and threat appraisals are not mutually exclusive; they can coexist in varying intensities and may be influenced by individual differences, task complexity, and organizational context.

Despite the theoretical relevance of cognitive appraisal processes, empirical investigations linking AI collaboration to dual appraisals in workplace settings remain limited. While earlier conceptual work has suggested that employees may experience ambivalence in response to AI's agency and autonomy (Seeber et al., 2020), only recently have studies begun to empirically explore how AI adoption triggers distinct psychological evaluations. For example, Lin et al. (2024) and Zang et al. (2024) demonstrate that organizational AI adoption can evoke both opportunity and hindrance appraisals, which in turn influence proactive career behaviors, job crafting, and performance. However, these studies largely examine appraisal as a mediating mechanism in response to broader organizational AI strategies, rather than AI collaboration embedded in individual workflows. Building on cognitive appraisal theory and this emerging body of work, we propose that collaborating with AI directly activates both opportunity- and threat-related evaluative processes. Employees are likely to assess whether AI enhances or disrupts their work, and these appraisals are shaped not only by the functional characteristics of the AI systems but also by employees' interpretive orientations and contextual perceptions. Accordingly, we hypothesize:

> ***H1a****:* AI collaboration is positively associated with opportunity appraisal.
> ***H1b****:* AI collaboration is positively associated with threat appraisal.

2.3 Opportunity and threat appraisals as predictors of work engagement

Work engagement has emerged as a central outcome in organizational behavior research, representing a positive, fulfilling state of mind characterized by vigor, dedication, and absorption in one's work (Bakker et al., 2008). High levels of engagement have been linked to improved job performance, creativity, organizational citizenship behaviors, and employee retention (Xanthopoulou et al., 2009). Importantly, engagement is not a static disposition but a context-sensitive psychological state that is shaped by how individuals perceive and evaluate their work environment. As such, engagement serves as a meaningful indicator of how employees internalize the impact of broader organizational changes, including the increasing presence of AI technologies in daily tasks.

Within the framework of cognitive appraisal theory, both opportunity and threat appraisals are theorized to influence emotional and motivational outcomes, albeit in opposite directions (Lazarus, 1984). Employees who perceive AI collaboration as an opportunity are likely to view the technology as enabling their development, enhancing the meaning of their work, and supporting performance excellence. These employees may experience increased energy, focus, and enthusiasm—hallmarks of engagement. Consistent with job crafting theory and the opportunity-hindrance stressor model (LePine et al., 2005; Tims et al., 2013), positive appraisals of work conditions tend to be associated with motivational gains and proactive behavior. Empirical research also shows that when technology is framed or experienced as enhancing one's capabilities, it fosters greater identification with work and higher levels of engagement (Salanova & Schaufeli, 2008).

In contrast, threat appraisals are expected to undermine work engagement. When AI is perceived as a source of role ambiguity, deskilling, or job insecurity, employees may experience anxiety, reduced commitment, and a weakened sense of purpose. Threats to autonomy and professional identity are particularly salient in contexts where AI systems influence or override human judgment, thereby diminishing employees' perceived value (Newman et al., 2020). Such negative appraisals often lead to psychological withdrawal and emotional exhaustion, factors inversely related to engagement. This is consistent with findings from stress and coping research, where threat-based interpretations of work demands are associated with strain and disengagement (Crawford et al., 2010).

While both appraisal pathways are conceptually distinct, they are not independent from the broader structure of AI collaboration. As employees interact with AI systems in their daily work, these collaborations activate appraisal processes that in turn shape engagement outcomes. We thus posit a mediational relationship, whereby opportunity and threat appraisals jointly explain how AI collaboration influences work engagement. Employees do not respond to AI in a vacuum; rather, their cognitive interpretation of what AI represents (i.e., support versus risk) determines the emotional and motivational consequences. Accordingly, we hypothesize:

> ***H2a****:* Opportunity appraisal is positively associated with work engagement.
> ***H2b****:* Threat appraisal is negatively associated with work engagement.
> ***H3a****:* Opportunity appraisal mediates the relationship between AI collaboration and work engagement.
> ***H3b****:* Threat appraisal mediates the relationship between AI collaboration and work engagement.

2.4 The moderating role of job insecurity and ease of use

While cognitive appraisal theory offers a robust lens for understanding how employees interpret AI collaboration, it also emphasizes that appraisals are shaped by broader contextual and individual differences (Lazarus, 1984). Rather than being formed in a vacuum, cognitive evaluations of AI are influenced by employees' existing psychological states, workplace experiences, and perceptions of the work environment. In line with this perspective, the present study introduces two theoretically grounded moderators, job insecurity and perceived ease of use, to examine how they condition the relationship between AI collaboration and the formation of opportunity and threat appraisals.

Job insecurity refers to an employee's perceived threat of losing their job or experiencing substantial disruptions in their future employment (Greenhalgh & Rosenblatt, 1984). Prior research has linked job insecurity to adverse outcomes such as anxiety, resistance to change, and lower well-being (Sverke et al., 2002). In the context of AI, the increasing integration of intelligent systems into everyday work can evoke concerns about redundancy and long-term role stability. This study conceptualizes job insecurity as an AI-triggered perception that employees who feel uncertain about their job future may become especially attentive to how AI affects their work. However, this insecurity may not solely generate avoidance. Rather, some employees may perceive AI collaboration as a potential opportunity to upskill, signal adaptability, and retain relevance. In such cases, job insecurity acts as a motivational force that strengthens opportunity appraisal. At the same time, feelings of job insecurity may heighten perceptions of risk and ambiguity, making employees more likely to interpret AI as a threat to their competence or standing. Thus, job insecurity may amplify both positive and negative appraisals of AI, depending on how employees construe their career prospects. Accordingly, we hypothesize:

> ***H4a**:* Job insecurity strengthens the positive relationship between AI collaboration and opportunity appraisal.
> ***H4b**:* Job insecurity strengthens the positive relationship between AI collaboration and threat appraisal.

In contrast, perceived ease of use captures the degree to which employees view AI systems as intuitive, transparent, and cognitively manageable (Venkatesh & Davis, 2000). As a core component of the Technology Acceptance Model, ease of use has traditionally been associated with increased technology acceptance and reduced resistance. From a cognitive appraisal perspective, ease of use can reduce cognitive strain and increase perceived control, thereby lowering the likelihood of threat appraisal. When employees find AI tools easy to navigate, they may feel less anxious or overwhelmed, thus dampening threat-related interpretations. However, this ease may also reduce the novelty or opportunity of the AI system, potentially weakening its perceived value as a development-enhancing or growth-enabling resource. In such cases, overly simplistic systems may dilute the sense of opportunity associated with AI collaboration, resulting in lower opportunity appraisal. Accordingly, we hypothesize:

***H5a**: Perceived ease of use weakens the positive relationship between AI collaboration and opportunity appraisal.*

***H5b**: Perceived ease of use weakens the positive relationship between AI collaboration and threat appraisal.*

This study proposes a cognitive appraisal-based model to examine how GenAI collaboration influences employee work engagement, as illustrated in Figure 1.

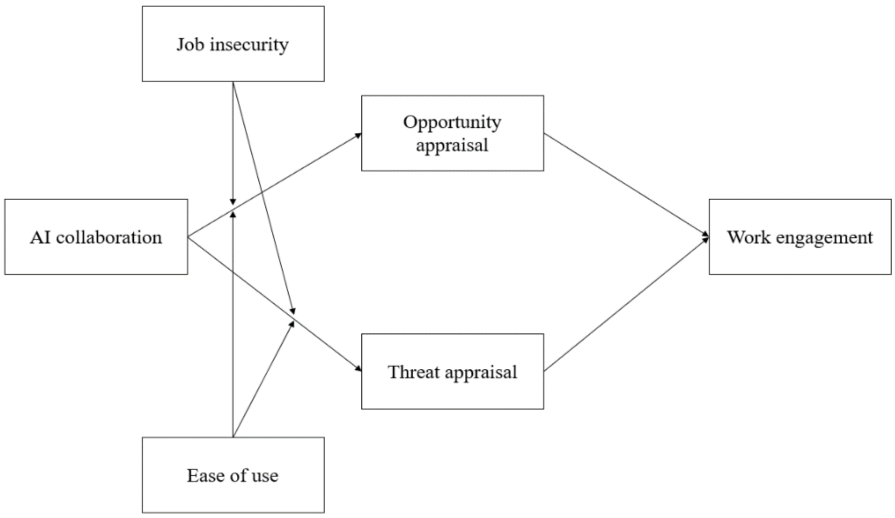

Figure 1. Conceptual framework

3. RESEARCH METHOD

3.1 Sample and data collection

To empirically test our conceptual model, we collected survey data from employed professionals using the online participant platform Prolific Academic Ltd. This platform was chosen for its high data quality, demographic diversity, and ability to target specific participant characteristics (Peer et al., 2017). Participants were pre-screened to ensure they (1) were currently employed and (2) worked in environments where GenAI tools were part of their workflow. These criteria ensured that respondents had direct exposure to GenAI technologies in their work context, allowing them to provide informed responses related to AI collaboration and its psychological and behavioral implications.

A total of 395 valid responses were retained after removing inattentive responses and incomplete submissions. Attention checks were embedded throughout the questionnaire to ensure data quality. All participants were employed and based in the United States, representing a diverse set of industries including business-to-business (B2B), business-to-consumer (B2C), and other sectors. The largest age group (33.7%) was 31–40 years old, followed by 31.4% aged 20–30, and 17.5% each in the 41–50 and over 50 categories. Regarding gender, 50.6% identified as male, 48.4% as female, and less than 1% as non-binary or preferring not to say. Educational attainment was relatively high, with 49.9%

holding a bachelor's degree and 36.7% holding a master's degree or above. In terms of work experience, 50.6% reported more than 10 years, while organizational size was most commonly medium (44.3%) or large (34.4%).

3.2 Measures

All constructs were measured using established multi-item scales adapted from prior research. Respondents rated their agreement with each item on a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). Minor wording adjustments were made to align items with the context of AI collaboration in the workplace and ensure content validity.

AI collaboration (AIC): This construct was assessed with a four-item scale adapted from Ma et al. (2024), capturing how employees engage with AI tools in their routine work activities. Items reflect the integration of AI into daily workflows to support knowledge acquisition, problem-solving, and decision- making. Sample items include: "I use AI tools to acquire solutions to work problems" and "I use AI tools in my daily work to obtain knowledge." While the items focus on perceived usage, we frame this construct as collaboration due to the iterative, context-sensitive, and co-creative nature of GenAI interactions. These forms of engagement align with emerging views of lightweight human–AI collaboration, where users prompt, refine, and integrate AI-generated outputs into their tasks.

Opportunity appraisal (OPA): A four-item scale adapted from Skinner and Brewer (2002) was used to evaluate employees' perceptions of AI as a source of growth, task enhancement, and future success. The items emphasize positive expectations about how AI contributes to performance and development. Sample items include: "I often think about how AI can help me perform very well in my tasks" and "I anticipate that AI will help me succeed in my work pursuits rather than cause problems."

Threat appraisal (THA): To assess perceived risks associated with AI use, a four-item scale from Skinner and Brewer (2002) was employed. Items reflect concerns about competence, potential mistakes, and judgment by others when interacting with AI systems. Sample items include: "I worry that I might make mistakes when working with AI technologies" and "I am concerned that my use of AI might be judged negatively by others."

Work engagement (WOE): This variable was captured through a four-item scale adapted from Shuck et al. (2017), reflecting employees' emotional and cognitive involvement in their work. The items address key aspects of vigor, dedication, and absorption. Sample items include: "I concentrate on my job when I am at work" and "Working at my current organization has a great deal of personal meaning to me."

Job insecurity (JOI): Adapted from Vander et al. (2014), the four-item scale for job insecurity focuses on perceived vulnerability to job loss or diminished role stability due to AI integration. Sample items include: "I feel secure in my ability to maintain my job despite AI- driven changes" and "I believe my job is at risk because of increasing AI adoption in my field."

Ease of use (EOU): Employees' perceptions of how intuitive and user-friendly GenAI tools are were assessed using a three-item scale adapted from Segars and Grover (1993). Items highlight clarity, simplicity, and ease of use. Sample items include: "I find it easy to get GenAI to do what I want it to do" and "Learning to operate GenAI is easy for me."

All scale items were randomized within sections to reduce common method bias. Prior to analysis, reliability and validity of all constructs were assessed using Cronbach's alpha and confirmatory factor analysis (CFA), reported in the results section.

3.3 Analytical approach

To test the proposed conceptual model and hypotheses, we used structural equation modeling (SEM) in Mplus. Before conducting SEM, we first evaluated the reliability of all latent constructs and conducted confirmatory factor analysis (CFA) to assess model fit and examine factor loadings. SEM was then employed to estimate the structural relationships among latent variables, while simultaneously testing mediation and moderation effects. This method was selected for its ability to handle complex models, account for measurement error, and assess both direct and indirect effects within a unified framework (Ullman & Bentler, 2012).

The hypothesized model includes direct effects (e.g., AI collaboration on cognitive appraisals; appraisals on work engagement), indirect effects through mediation (i.e., appraisals mediating the relationship between AI collaboration and engagement), and moderation effects (i.e., job insecurity and perceived ease of use moderating the relationships between AI collaboration and appraisals). All effects were tested using Mplus with bootstrapping procedures based on 5,000 resamples. This approach allowed for the examination of conditional effects and model robustness while accounting for measurement error.

Model fit was assessed using multiple standard goodness-of-fit indices: the chi-square divided by degrees of freedom (Cmin/df), comparative fit index (CFI), Tucker–Lewis index (TLI), and root mean square error of approximation (RMSEA). Consistent with established guidelines, acceptable model fit was indicated by Cmin/df values less than 3.00, CFI and TLI values above 0.90, and RMSEA below 0.08 (Hu & Bentler, 1999).

4. DATA ANALYSIS AND RESULTS

4.1 Reliability and construct validity

To assess the adequacy of the measurement model, we assessed internal consistency, convergent validity, discriminant validity, and overall model fit. All constructs demonstrated satisfactory reliability, with Cronbach's alpha values exceeding the recommended threshold of 0.70: AI Collaboration ($\alpha = 0.84$), Opportunity Appraisal ($\alpha = 0.89$), Threat Appraisal ($\alpha = 0.86$), Work Engagement ($\alpha = 0.84$), Job Insecurity ($\alpha = 0.87$), and Perceived Ease of Use ($\alpha = 0.86$) (Tavakol & Dennick, 2011). Table 2 shows the correlation matrix among the key study variables.

Table 2. Correlation matrix

Correlations						
	AIC	OPA	THA	WOE	JOI	EOU
AIC	1	.633**	-0.073	.350**	-0.056	.385**
OPA	.633**	1	-.129*	.530**	-.228**	.548**
THA	-0.073	-.129*	1	-.178**	.527**	-.230**
WOE	.350**	.530**	-.178**	1	-.303**	.345**
JOI	-0.056	-.228**	.527**	-.303**	1	-.234**
EOU	.385**	.548**	-.230**	.345**	-.234**	1

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Confirmatory factor analysis (CFA) was conducted to evaluate construct validity. The measurement model demonstrated a good fit to the data: $\chi^2/df = 2.24$, CFI = 0.963, TLI = 0.954, RMSEA = 0.056, and SRMR = 0.044, all within acceptable thresholds. All standardized factor loadings were statistically significant ($p < .001$) and exceeded 0.70, indicating strong item reliability. Composite reliability (CR) values for all constructs were above 0.70, and average variance extracted (AVE) values exceeded 0.50, supporting internal consistency and convergent validity. Discriminant validity was established as the square root of AVE for each construct exceeded its inter-construct correlations, and all heterotrait–monotrait (HTMT) ratios were below the conservative threshold of 0.85. Overall, these results confirm the robustness of the measurement model and support the use of structural equation modeling for hypothesis testing.

4.2 Hypothesis testing

Our model posits that AI collaboration influences work engagement indirectly through two distinct psychological appraisals: opportunity and threat. As hypothesized, AI collaboration exerted a significant positive effect on opportunity appraisal ($\beta = .728$, $p < .001$), supporting H1a. This suggests that when employees perceive AI as a collaborative partner in their workflow, they are more likely to see it as a source of growth, learning, and role enrichment. However, the path from AI collaboration to threat appraisal ($\beta = -.089$, $p = .128$) was not statistically significant, providing no support for H1b. This finding implies that collaboration with AI, in itself, may not be sufficient to trigger feelings of threat unless moderated by other contextual or dispositional variables.

With respect to the consequences of appraisal, opportunity appraisal was found to be positively associated with work engagement (β = .595, p < .001), consistent with H2a. Employees who perceived AI as enhancing their work capabilities reported greater vigor, dedication, and absorption—core dimensions of engagement. Threat appraisal was found to be negatively associated with work engagement (β = –.119, p = .019), providing support for H2b. This result suggests that employees who perceive AI as threatening are more likely to experience reduced engagement, possibly due to heightened anxiety, uncertainty, or diminished psychological safety in the workplace.

We further tested for mediation effects. The indirect effect of AI collaboration on work engagement through opportunity appraisal was significant (indirect effect = .32, p < .001, 95%CI [.22, .43]), supporting H3a. This mediation confirms that the way employees cognitively frame their relationship with AI, particularly as an opportunity, plays a key role in shaping motivational outcomes. However, the mediation pathway through threat appraisal (indirect effect = 0.008, p > .05, 95%CI [-.003, .024]) was not significant, thus H3b was not supported. Together, these findings point to an asymmetry in how opportunity versus threat appraisals function in relation to engagement outcomes, underscoring the importance of positive meaning-making in technology adoption contexts.

Table 3 summarizes the results of the structural equation modeling analysis, including direct, indirect, and interaction effects for all hypothesized paths, along with model fit statistics. Table 4 presents the results of the mediation analysis, showing the total and indirect effects of AI collaboration on work engagement through opportunity and threat appraisals, along with their corresponding confidence intervals.

Table 3. Structural model results

Hypothesis	Path	β	p-value
H1a	AIC → OPA	0.728	0.000
H1b	AIC → THA	-0.089	0.13
H2a	OPA → WOE	0.595	0.000
H2b	THA → WOE	-0.119	0.019
H3a	AIC → OPA→WOE (indirect)	0.32	0.000
H3b	AIC → THA→WOE (indirect)	0.008	0.23
H4a	JOI × AIC → OPA	0.08	0.000
H4b	JOI × AIC → THA	0.152	0.000
H5a	EOU × AIC → OPA	-0.13	0.000
H5b	EOU × AIC → THA	-0.169	0.000
Control: Gender	Gender → WOE	0.136	0.004
Age	Age → WOE	-0.038	0.413
Education	Education → WOE	-0.08	0.089
Industry	Industry → WOE	0.010	0.841
Working tenure	Tenure → WOE	-0.06	0.199
Organization size	Size → WOE	-0.007	0.886

Fit Statistics: CMIN/DF = 2.23, CFI = 0.962, TLI = 0.955, RMSEA = 0.056.

Table 4. Mediation analysis results

Independent variable	Mediator	Dependent variable	Total effects	95% CI (Total effects)	Indirect effects	95% CI (Indirect effects)
AIC	OPA	WE	0.352	[0.236, 0.474]	0.317	[0.218, 0.427]
AIC	THA	WE	0.325	0.227, 0.432]	0.008	[–0.003, 0.024]

4.3 Moderation analysis

To assess the boundary conditions under which AI collaboration influences cognitive appraisals, we tested moderation effects using Mplus. Job insecurity significantly moderated the relationship between AI collaboration and opportunity appraisal ($\beta = .08$, $p < .01$, 95%CI [.07, .23]), supporting H4a. Interestingly, the negative interaction suggests that higher job insecurity weakens the positive association between AI collaboration and opportunity appraisal. This implies that employees who feel insecure about their jobs are less likely to interpret AI collaboration as an opportunity, possibly due to heightened concerns about job displacement. The moderating effect of job insecurity on the AI collaboration, threat appraisal relationship was also significant ($\beta = .152$, $p < .01$, 95%CI [.06, .25]), offering support for H4b.

Perceived ease of use moderated both appraisal pathways. Specifically, it weakened the positive relationship between AI collaboration and opportunity appraisal ($\beta = -.13$, $p < .01$, 95%CI [-.22, -.04]), supporting H5a. It also weakened the positive relationship between AI collaboration and threat appraisal ($\beta = -.169$, $p < .01$, 95%CI [-.3, -.04]), supporting H5b. These findings suggest that when AI systems are perceived as easy to use, employees may view them as less threatening but also less enriching, indicating a more passive perception of the technology.

5. CONCLUSION

5.1 Key findings

This study provides new insight into how employees psychologically engage with GenAI in the workplace by applying a dual-path cognitive appraisal framework. First, our results indicate that AI collaboration significantly enhances opportunity appraisal. Employees who engage with GenAI are more likely to interpret the technology as a source of task improvement, skill development, and personal growth, an interpretation that strongly predicts elevated work engagement. This aligns with prior findings that opportunity appraisals are positively associated with proactive behavioral responses and motivational states (Lazarus & Folkman, 1984). It reinforces the notion that when AI is perceived as a developmental partner, it fosters a more dedicated and absorbed workforce (Wu et al., 2025).

Interestingly, AI collaboration did not significantly predict threat appraisal, suggesting that GenAI, particularly in collaborative, interactive contexts, is not inherently experienced as psychologically threatening. This departs from earlier studies on rule-based or opaque AI systems, which often trigger both opportunity and threat appraisals simultaneously (e.g., Dong et al., 2025). A key differentiator lies in the nature of the AI studied. Prior work typically focused on predictive or decision-automation tools, whereas GenAI enables co-creation, transparency, and interpretability through natural language interfaces. These features likely mitigate ambiguity and cognitive strain by offering users greater explainability and a sense of control (Lu & Kim, 2025). As employees better understand how outputs are generated and retain agency over final decisions, they may perceive less role encroachment, reducing the likelihood of threat-based interpretations. This supports a more optimistic view of GenAI as a collaborative augmentation tool rather than a replacement mechanism.

Second, our findings reveal an asymmetrical influence of cognitive appraisals. Only opportunity appraisal significantly mediated the relationship between AI collaboration and work engagement, highlighting that positive evaluations are central to the motivational benefits of GenAI. This adds conceptual precision to existing models of work engagement by identifying appraisal dynamics as a critical interpretive filter between technology use and psychological outcomes (Lu & Kim, 2025; Kiefer, 2005). While threat appraisal did not serve as a mediator in this context, it still had a significant negative direct effect on engagement, consistent with prior work showing that even low levels of perceived threat can erode motivational energy and reduce task absorption (Sonnentag et al., 2010). These results reinforce the theoretical utility of a dual-path model, in which opportunity and threat appraisals operate via distinct routes, with the former facilitating engagement and the latter suppressing it.

Finally, the study underlines the importance of individual context in shaping appraisal formation. Job insecurity moderated both appraisal paths: it weakened the positive link between AI collaboration and opportunity appraisal and strengthened the link with threat appraisal. This supports earlier findings that resource-scarce conditions heighten risk sensitivity and reduce developmental interpretations of change (Lu & Kim, 2025). Employees who feel uncertain about their job future may view GenAI as a symbol of obsolescence, heightening anxiety and defensive responses. Perceived ease of use also had a dampening effect on both appraisal pathways, reducing anxiety, but also blunting enthusiasm. This suggests that overly seamless AI systems may paradoxically reduce perceptions of skill acquisition or challenge, potentially weakening the motivational impact of the collaboration.

5.2 Theoretical implications

This study offers several important theoretical contributions by advancing a psychologically grounded understanding of how employees engage with GenAI in the workplace. While prior research on AI adoption has often emphasized factors, such as perceived usefulness and ease of use, central to widely used models like the Technology Acceptance Model, these approaches do not fully account for how employees interpret and emotionally respond to AI collaboration. By drawing on cognitive appraisal theory, this study foregrounds the subjective meaning-making processes that shape employees' experience of GenAI. This lens offers a novel contribution by explaining why the same AI system may elicit motivational engagement in some employees and emotional withdrawal in others. In particular, GenAI's interactive, explainable, and co-creative features allow employees to understand how outputs are produced and to acquire contextualized knowledge through natural language interaction. These characteristics reduce ambiguity and foster agency, enabling employees to appraise AI collaboration as an opportunity rather than a threat. Our findings show that opportunity appraisal significantly mediates the relationship between AI collaboration and work engagement, while threat appraisal does not. This asymmetry highlights that positive, value-oriented framing, rather than mere avoidance of fear or uncertainty, is essential for sustaining motivation in AI-enabled work environments. Therefore, this positions appraisal formation as a proactive and interpretive process extends prior models that treat user responses as largely rational or unidimensional.

Second, the inclusion of job insecurity and ease of use as moderators provides insight into the boundary conditions that shape how employees interpret AI. Contrary to assumptions that insecure workers are more likely to reject or fear AI, our results suggest a more complex picture: job insecurity may actually heighten sensitivity to opportunity cues, possibly because employees under threat are more attuned to the benefits of performance-enhancing tools. Similarly, ease of use was not uniformly beneficial; instead, it appeared to dampen the motivational relevance of AI, perhaps because overly intuitive systems reduce perceptions of growth potential or opportunity. Together, these findings call attention to the nonlinear and sometimes counterintuitive pathways through which technological characteristics and individual dispositions interact, urging future research to consider contextual subtleties rather than assuming direct or universal effects.

5.3 Practical implications

This study provides actionable guidance for organizations seeking to foster employee engagement through GenAI collaboration. Our findings suggest that employee motivation is shaped not only by the technological features of GenAI, but by how employees interpret the experience of working alongside AI, either as an opportunity for growth or a threat to their role, autonomy, or value.

First, organizations should adopt implementation strategies that actively promote opportunity appraisals, encouraging employees to view GenAI as a developmental partner rather than a replacement threat. This begins with how AI is introduced: emphasizing how GenAI can enhance creative thinking, support complex decision-making, and facilitate access to contextualized knowledge can shift employee perceptions toward growth and empowerment. Practical steps include integrating GenAI into learning and development programs, offering hands-on workshops that allow experimentation, and highlighting examples of employees using GenAI to augment (not replace) their professional capabilities. Rather than limiting communication to technical training or cost-saving benefits, leaders should deliberately craft value-based narratives that position AI collaboration as a source of enrichment and personal mastery. Over time, this framing reinforces the idea that GenAI is not just a tool, but a cognitive partner that can elevate the quality and meaningfulness of work.

Second, our findings show that threat appraisals do not automatically lead to disengagement, but they require careful managerial intervention. When employees perceive AI collaboration as threatening, whether due to concerns about job displacement, loss of control, or diminished relevance, leaders should respond with strategies that restore clarity, agency, and psychological security. This includes maintaining open communication about the goals, limitations, and boundaries of GenAI integration, while consistently reinforcing the irreplaceable value of human judgment, creativity, and emotional intelligence in areas where AI falls short. Managers should create an environment where employees feel safe to express uncertainty, ask questions, and seek clarification, thereby reducing the stigma around AI-related apprehension. Importantly, framing GenAI as a tool for augmentation, rather than replacement, can help reorient employees' perspectives toward growth and partnership. In this way, threat appraisals should not be treated as resistance to change, but as an invitation for leadership to engage in active sensemaking and reassurance.

Third, the role of job insecurity as a moderator reveals an important and nuanced opportunity for targeted engagement strategies. Rather than viewing job insecurity solely as a barrier to AI adoption, organizations can leverage it as a motivational lever, provided that appropriate framing and support structures are in place. Employees who feel vulnerable in the face of change may be particularly receptive to tools that enhance their visibility, adaptability, and perceived value. To convert anxiety into action, managers can clearly articulate how GenAI integration will impact existing roles and offer structured pathways for skill development that align with future job demands. Involving employees in co-designing use cases, decision-making processes, or pilot implementations can enhance their sense of ownership and control. Additionally, recognizing and celebrating early examples of successful employee–AI collaboration can help foster a forward-looking mindset in teams facing uncertainty.

5.4 Limitations and future research

This study advances our understanding of how employees engage with GenAI collaboration through the lens of cognitive appraisal theory. Nonetheless, several limitations provide valuable opportunities for future research.

First, the cross-sectional design limits our ability to infer causality or temporal dynamics, particularly in mediation and moderation pathways. Although the model is theoretically grounded and statistically robust, employee appraisals of AI are likely to evolve over time in response to shifting contexts, such as role changes, exposure to new AI capabilities, or organizational messaging. Longitudinal or experimental designs would be valuable in tracking how appraisals shift and whether sustained collaboration with AI influences work engagement differently over time.

Secondly, the data were collected through self-reported questionnaires, which may introduce common method bias. Although steps were taken to minimize this risk (e.g., item randomization, statistical controls), self-report data remain vulnerable to biases such as social desirability and recall error. Future research could strengthen methodological rigor by integrating behavioral indicators, usage logs, or supervisor assessments to triangulate employee perceptions and outcomes.

Thirdly, while the study examined job insecurity and perceived ease of use as moderators, these are only part of the broader set of individual and organizational conditions that may shape AI-related appraisals. For instance, leadership communication, organizational climate, AI literacy, or employees' prior experiences with digital tools may also influence how collaboration with AI is evaluated. Future work could test these boundary conditions to uncover additional leverage points for fostering positive appraisal formation.

Finally, this study focused on work engagement as the primary outcome, but employee responses to AI are likely multi-dimensional. Variables such as innovation behavior, learning orientation, burnout, or turnover intentions may also be shaped by how employees appraise their interactions with AI. Future studies could broaden the outcome space to capture both the beneficial and adverse effects of sustained AI collaboration in the workplace.

REFERENCE

Akhtar, P., Ghouri, A. M., Ashraf, A., Lim, J. J., Khan, N. R., & Ma, S. (2024). Smart product platforming powered by AI and Generative AI: Personalization for the circular economy. *International Journal of Production Economics*, *273*, 109283.

Ashford, S. J. (1988). Individual strategies for coping with stress during organizational transitions. *The Journal of Applied Behavioral Science*, *24*(1), 19–36.

Bakker, A. B., Schaufeli, W. B., Leiter, M. P., & Taris, T. W. (2008). Work engagement: An emerging concept in occupational health psychology. *Work & Stress*, *22*(3), 187–200.

Bonnefon, J. F., Rahwan, I., & Shariff, A. (2024). The moral psychology of artificial intelligence. *Annual Review of Psychology*, *75*, 653–675.

Boussioux, L., Lane, J. N., Zhang, M., Jacimovic, V., & Lakhani, K. R. (2024). The crowdless future? Generative AI and creative problem-solving. *Organization Science*, *35*(5), 1589–1607.

Chowdhury, S., Budhwar, P., & Wood, G. (2024). Generative artificial intelligence in business: towards a strategic human resource management framework. *British Journal of Management*, *35*(4), 1680–1691.

Crawford, E. R., LePine, J. A., & Rich, B. L. (2010). Linking job demands and resources to employee engagement and burnout: A theoretical extension and meta-analytic test. *Journal of Applied Psychology*, *95*(5), 834–848.

Dong, X., Tian, Y., He, M., & Wang, T. (2025). When knowledge workers meet AI? The double-edged sword effects of AI adoption on innovative work behavior. *Journal of Knowledge Management*, *29*(1), 113–147.

Doshi, A. R., Bell, J. J., Mirzayev, E., & Vanneste, B. S. (2025). Generative artificial intelligence and evaluating strategic decisions. *Strategic Management Journal*, *46*(3), 583–610.

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., . . . Wright, R. (2023). Opinion Paper:"So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, *71*, 102642.

Faraj, S., Pachidi, S., & Sayegh, K. (2018). Working and organizing in the age of the learning algorithm. *Information and Organization*, *28*(1), 62–70.

Fügener, A., Grahl, J., Gupta, A., & Ketter, W. (2022). Cognitive challenges in human–artificial intelligence collaboration: Investigating the path toward productive delegation. *Information Systems Research*, *33*(2), 678–696.

Greenhalgh, L., & Rosenblatt, Z. (1984). Job insecurity: Toward conceptual clarity.

Academy of Management Review, *9*(3), 438–448.

Hai, S., Long, T., Honora, A., Japutra, A., & Guo, T. (2025). The dark side of employee-generative AI collaboration in the workplace: An investigation on work alienation and employee expediency. *International Journal of Information Management*, *83*, 102905.

He, C., Teng, R., & Song, J. (2024). Linking employees' challenge-hindrance appraisals toward AI to service performance: the influences of job crafting, job insecurity and AI knowledge. *International Journal of Contemporary Hospitality Management*, *36*(3), 975–994.

Hu, B., Mao, Y., & Kim, K. J. (2023). How social anxiety leads to problematic use of conversational AI: The roles of loneliness, rumination, and mind perception. *Computers in Human Behavior*, *145*, 107760.

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1–55.

Jia, N., Luo, X., Fang, Z., & Liao, C. (2024). When and how artificial intelligence augments employee creativity. *Academy of Management Journal*, 67(1), 5–32.

Kiefer, T. (2005). Feeling bad: Antecedents and consequences of negative emotions in ongoing change. *Journal of Organizational Behavior*, *26*(8), 875-897.

Kong, H., Yin, Z., Baruch, Y., & Yuan, Y. (2023). The impact of trust in AI on career sustainability: The role of employee–AI collaboration and protean career orientation. *Journal of Vocational Behavior*, *146*, 103928.

Kusiak, A. (2020). Convolutional and generative adversarial neural networks in manufacturing. *International Journal of Production Research*, *58*(5), 1594–1604.

Lazarus, R., & Folkman, S. (1984). *Stress, appraisal, and coping*. Springer.

LePine, J. A., Podsakoff, N. P., & LePine, M. A. (2005). A meta-analytic test of the challenge Stressor-hindrance stressor framework: An explanation for inconsistent relationships among Stressors and performance. *Academy of Management Journal*, *48*(5), 764–775.

Liang, C., Du, H., Sun, Y., Niyato, D., Kang, J., Zhao, D., & Imran, M. A. (2024). Generative AI-driven semantic communication networks: Architecture, technologies and applications. *IEEE Transactions on Cognitive Communications and Networking*, *11*(1), 27–47.

Lin, H., Tian, J., & Cheng, B. (2024). Facilitation or hindrance: The contingent effect of organizational artificial intelligence adoption on proactive career behavior. *Computers in Human Behavior*, *152*, 108092.

Lu, X., & Kim, J. (2025). Keeping up with generative AI: effects of engagement characteristics, cognitive appraisals, and affective reactions on user adaptation. *Behaviour & Information Technology*, *44*(18), 4523-4537.

Ma, L., Yu, P., Zhang, X., Wang, G., & Hao, F. (2024). How AI use in organizations contributes to employee competitive advantage: The moderating role of perceived organization support. *Technological Forecasting and Social Change*, *209*, 123801.

Newman, D. T., Fast, N. J., & Harmon, D. J. (2020). When eliminating bias isn't fair: Algorithmic reductionism and procedural justice in human resource decisions. *Organizational Behavior and Human Decision Processes*, *160*, 149–167.

Peer, E., Brandimarte, L., Samat, S., & Acquisti, A. (2017). Beyond the Turk: Alternative platforms for crowdsourcing behavioral research. *Journal of Experimental Social Psychology*, *70*, 153–163.

Rai, A., Constantinides, P., & Sarker, S. (2019). Next generation digital platforms: Toward human-AI hybrids. *MIS Quarterly*, *43*(1), iii-ix.

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review*, *46*(1), 192–210.

Salanova, M., & Schaufeli, W. B. (2008). A cross-national study of work engagement as a mediator between job resources and proactive behaviour. The *International Journal of Human Resource Management*, *19*(1), 116–131.

Seeber, I., Bittner, E., Briggs, R. O., de Vreede, T., de Vreede, G. J., Elkins, A., Maier, R., Merz, A. B., Oeste-Reiß, S., Randrup, N., Schwabe, G., & Söllner, M. (2020). Machines as teammates: A research agenda on AI in team collaboration. *Information & Management*, *57*(2), 103174.

Segars, A. H., & Grover, V. (1993). Re-examining perceived ease of use and usefulness: A confirmatory factor analysis. *MIS Quarterly*, *17*(4), 517–525.

Shuck, B., Adelson, J. L., & Reio Jr, T. G. (2017). The employee engagement scale: Initial evidence for construct validity and implications for theory and practice. *Human Resource Management*, *56*(6), 953–977.

Singla, A., Sukharevsky, A., Yee, L., Chui, M., & Hall, B. (2025). *The state of AI: How organizations are rewiring to capture value*. McKinsey.

Skinner, N., & Brewer, N. (2002). The dynamics of threat and challenge appraisals prior to stressful achievement events. *Journal of Personality and Social Psychology*, *83*(3), 678–692.

Sonnentag, S., Kuttler, I., & Fritz, C. (2010). Job stressors, emotional exhaustion, and need for recovery: A multi-source study on the benefits of psychological detachment. *Journal of Vocational Behavior*, *76*(3), 355-365.

Sowa, K., Przegalinska, A., & Ciechanowski, L. (2021). Cobots in knowledge work: Human – AI collaboration in managerial professions. *Journal of Business Research*, *125*, 135–142.

Sundar, S. S. (2020). Rise of Machine Agency: A Framework for Studying the Psychology of Human-AI Interaction (HAII). *Journal of Computer-Mediated Communication*, *25*(1), 74–88.

Sverke, M., Hellgren, J., & Näswall, K. (2002). No security: a meta-analysis and review of job insecurity and its consequences. *Journal of Occupational Health Psychology*, *7*(3), 242-264.

Talaei-Khoei, A., Yang, A. T., & Masialeti, M. (2024). How does incorporating ChatGPT within a firm reinforce agility-mediated performance? The moderating role of innovation infusion and firms' ethical identity. *Technovation*, *132*, 102975.

Tang, P. M., Koopman, J., Mai, K. M., De Cremer, D., Zhang, J. H., Reynders, P., Ng, T. S., & Chen, I. H. (2023). No person is an island: Unpacking the work and after-work consequences of interacting with artificial intelligence. *Journal of Applied Psychology*, *108*(11), 1766–1789.

Tarafdar, M., Cooper, C. L., & Stich, J. (2019). The technostress trifecta-techno eustress, techno distress and design: Theoretical directions and an agenda for research. *Information Systems Journal*, *29*(1), 6–42.

Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. *International Journal of Medical Education*, *2*, 53-55.

Tims, M., Bakker, A. B., & Derks, D. (2013). The impact of job crafting on job demands, job resources, and well-being. *Journal of Occupational Health Psychology*, *18*(2), 230–240.

Ullman, J. B., & Bentler, P. M. (2012). *Structural equation modeling. Handbook of Psychology*. John Wiley & Sons, Inc.

Vander Elst, T., De Witte, H., & De Cuyper, N. (2014). The Job Insecurity Scale: A psychometric evaluation across five European countries. *European Journal of Work and Organizational Psychology*, *23*(3), 364–380.

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, *46*(2), 186–204.

Wamba, S. F., Queiroz, M. M., Jabbour, C. J. C., & Shi, C. V. (2023). Are both generative AI and ChatGPT game changers for 21st-Century operations and supply chain excellence? *International Journal of Production Economics*, *265*, 109015.

Wilson, H. J., & Daugherty, P. R. (2018). Collaborative intelligence: Humans and AI are joining forces. *Harvard Business Review*, *96*(4), 114–123.

Wu, T., Zhang, R., & Zhang, Z. (2025). Navigating the human-artificial intelligence collaboration landscape: Impact on quality of work life and work engagement. *Journal of Hospitality and Tourism Management*, *62*, 276-283.

Xanthopoulou, D., Bakker, A. B., Demerouti, E., & Schaufeli, W. B. (2009). Reciprocal relationships between job resources, personal resources, and work engagement. *Journal of Vocational Behavior*, *74*(3), 235–244.

Xu, Y. W., Cai, R. R., & Gursoy, D. (2024). When disclosing the artificial intelligence (AI) technology integration into service delivery backfires: Roles of fear of AI, identity threat and existential threat. *International Journal of Hospitality Management*, *122*, 103829.

Zang, J., Shao, Q., & Li, H. (2024). Challenge and hindrance: Yin and Yang paths of AI usage's effects on Chinese employee innovative behaviour. *Asia Pacific Business Review*, 1-27.

PAPER 4

Generative AI collaboration and sustainable careers: A career construction perspective on expatriates' adaptability and development

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Abstract

The rise of generative AI (GenAI) is transforming knowledge work by enabling dynamic human–AI collaboration. While much research has examined GenAI's impact on task efficiency, its implications for long-term career development remain underexplored, particularly for expatriates navigating complex global work environments. Drawing on Career Construction Theory, this study investigates how GenAI-enabled collaboration influences expatriates' career adaptability and, in turn, supports career sustainability. Using survey data from 361 expatriates, the findings reveal that GenAI collaboration enhances career adaptability captured by concern, control, curiosity, and confidence, which mediates its positive effect on career sustainability. Furthermore, AI trust and job insecurity moderate these relationships, amplifying the benefits of GenAI for adaptive and sustainable career development. Notably, the direct effect of GenAI collaboration on career sustainability is not significant, highlighting adaptability as a critical pathway. These results advance theoretical understanding of how digital technologies interact with individual psychological resources in shaping career trajectories. Practical insights are offered for global talent managers and organizations aiming to foster resilient, future-ready careers in AI-mediated work settings.

Keywords: Generative AI, GenAI-enabled collaboration, global career, career adaptability, career sustainability

1. INTRODUCTION

Recent advancements in generative artificial intelligence (GenAI) models have significantly improved performance compared to earlier AI systems, leading to their rapid and widespread adoption across industries (Noy & Zhang, 2023). These technologies enable users to complete a variety of complex tasks, such as writing, coding, data analysis, and design, without requiring advanced technical expertise (Dwivedi et al., 2023). As GenAI becomes increasingly integrated into organizational workflows, it has the potential to fundamentally reshape the role of human capital by augmenting rather than replacing worker capabilities (Chowdhury et al., 2024). While there are ongoing concerns about automation and job displacement (Zhao et al., 2024), growing evidence suggests that GenAI can improve productivity, support creativity, and enhance learning and decision-making (Doshi & Hauser, 2024; Hao et al., 2024; Noy & Zhang, 2023). This shift positions GenAI not only as a disruptive force in the labor market, but also as a tool that may help individuals build more adaptive, fulfilling, and sustainable careers in an increasingly digital economy.

In an increasingly globalized workforce, expatriates, who temporarily live and work outside their country of origin, play a central role in cross-border knowledge exchange and organizational development (McNulty & Brewster, 2017). Whether assigned by organizations or self-initiated, expatriates often face a host of challenges as they adjust to new cultural, institutional, and professional environments. These challenges include adapting to unfamiliar norms, managing language barriers, and working without access to established social and organizational support systems (Reiche et al., 2011). Successfully responding to these demands requires more than technical expertise. It calls for psychological resources that help individuals remain effective in the face of uncertainty. Career adaptability has emerged as a key construct in this regard. Defined as a psychosocial competency comprising concern, control, curiosity, and confidence (Savickas & Porfeli, 2012), career adaptability equips individuals to manage transitions, anticipate future demands, and respond constructively to change. Research shows that expatriates with high adaptability are more likely to take initiative in shaping their career paths, explore new environments proactively, and maintain confidence in dynamic and unfamiliar settings (Presbitero & Quita, 2017). These adaptive strengths are critical for sustaining meaningful and resilient careers across international contexts.

As work becomes increasingly shaped by global mobility, digital transformation, and shifting life priorities, the notion of a career has expanded beyond linear advancement to encompass broader questions of how individuals design meaningful lives. In this context, the concept of career sustainability has gained prominence as a way to capture how individuals maintain productive, satisfying, and healthy careers over time (De Vos & Van der Heijden, 2015). Rather than viewing career development as a discrete or isolated process, sustainability reflects a long-term, evolving trajectory that unfolds across different social contexts and life domains (De Vos & Van der Heijden, 2015). It emphasizes the individual's agency in shaping career paths while also acknowledging the influence of personal circumstances, institutional conditions, and changing aspirations. For expatriates, whose career experiences are often marked by temporary contracts, cultural transitions, and limited support structures, sustainable careers require more than short-term adjustment. Instead, they demand the capacity to integrate work and life in ways that preserve continuity, purpose, and well-being. As de Vos et al. (2020) note, sustainable careers are co-constructed over time by the individual and their surrounding context, making the expatriate experience an especially relevant case for examining how careers endure across geographic, cultural, and temporal boundaries.

Despite growing interest in the impact of AI on work and careers, several important gaps remain in the existing literature. First, very few studies have specifically examined how AI, particularly GenAI, affects expatriates, even as this group increasingly interacts with AI tools in global work environments. Second, limited attention has been given to how GenAI supports the development of career adaptability, despite its potential to enhance individuals' capacity to respond to complex, evolving work conditions. Third, research linking GenAI to long-term career outcomes such as career sustainability remains scarce, with most studies focusing narrowly on short-term task efficiency rather than holistic career development. Addressing these gaps is not only timely but also critical, as the widespread diffusion of GenAI is reshaping the nature of international work. Understanding how GenAI intersects with expatriates' adaptive processes and long-term career trajectories is essential for organizations, policymakers, and individuals seeking to foster resilient and sustainable global careers in the digital age.

To address these gaps, this study investigates how GenAI-enabled collaboration influences expatriates' career adaptability and, in turn, contributes to their career sustainability. Drawing on career construction theory, we propose a framework in which GenAI serves not only as a technological resource but also as a contextual enabler of adaptive career development. We further examine the moderating roles of AI trust and job insecurity, two critical factors that may condition how expatriates interpret and respond to GenAI in their professional lives. Accordingly, the study is guided by the following research question: How does GenAI-enabled collaboration affect expatriates' career adaptability and sustainability, and under what conditions are these effects strengthened or weakened? This study contributes to research on career development, GenAI, and global work by introducing GenAI-enabled collaboration as a novel contextual factor that shapes career adaptability. Extending Career Construction Theory, we position interaction with GenAI tools as an active influence on individuals' concern, control, curiosity, and confidence. We further show that career adaptability mediates the relationship between GenAI collaboration and long-term career sustainability, offering a psychological pathway through which technology affects career outcomes. Finally, we identify AI trust and job insecurity as key moderators, highlighting how individual-level factors shape the benefits of AI collaboration in dynamic work environments.

2. LITERATURE REVIEW

2.1 GenAI-enabled collaboration

The rise of GenAI has introduced a new paradigm in human–machine collaboration. GenAI refers to advanced AI systems, typically powered by large language models (LLMs), that are capable of generating coherent, context-sensitive outputs such as text, code, images, or audio based on human prompts (Dwivedi et al., 2023) Unlike traditional rule-based or classification-driven AI systems, GenAI enables dynamic co-creation and interactive problem-solving, allowing users to iteratively refine content, explore alternatives, and simulate decisions in real-time (Jackson et al., 2025). Within this evolving technological landscape, AI collaboration is conceptualized as the process through which humans and AI agents engage in complementary interactions to achieve shared goals (Sowa et al., 2021). Such collaboration can involve delegating tasks to AI, integrating AI-generated outputs into workflows, or engaging in iterative back-and-forth communication with AI tools.

GenAI technologies are rapidly reshaping knowledge work across industries, offering advanced capabilities in language processing, content generation, data interpretation, and creative problem-solving. In the workplace, tools such as ChatGPT are increasingly used to draft documents, synthesize information across languages, generate reports, and simulate decision alternatives, thereby streamlining tasks that traditionally required high cognitive input (van Dis et al., 2023). For globally mobile employees, particularly expatriates working in unfamiliar cultural and linguistic environments, GenAI offers significant utility. It can serve as a real-time translator, a cultural mediator, and an information assistant, helping expatriates understand local norms, reduce miscommunication, and perform knowledge-intensive tasks more efficiently (Chen, 2024). These benefits are shaped by two key dimensions of GenAI-enabled collaboration: AI adoption, which refers to the extent to which expatriates incorporate GenAI tools into their daily work routines, and AI interaction, which captures the quality, depth, and responsiveness of their engagement with the technology. While high levels of adoption provide access to valuable resources, meaningful interaction enables expatriates to co-create solutions, explore alternatives, and receive tailored support in context-specific situations (Jackson et al., 2025). This technological shift not only introduces new demands for digital adaptability, but also offers important opportunities for expatriates to better adjust to unfamiliar work environments and cultural settings.

2.2 Career adaptability and career construction theory

Career construction theory provides a foundational perspective for understanding how individuals shape their careers amid changing environments (Savickas, 2005). Central to this theory is the concept of career adaptability, which refers to the psychological resource individuals draw upon to manage career-related transitions, tasks, and uncertainties. It is composed of four key dimensions: concern, control, curiosity, and confidence (Savickas, 2005). Career concern denotes a future-oriented mindset that involves planfulness, a belief in the value of preparing for what lies ahead, and the ability to engage in purposeful career planning. Without this orientation, individuals may become passive, pessimistic, or disengaged from their future trajectories. Career control reflects the degree to which individuals take ownership of their career decisions, believe they are responsible for shaping their paths, and possess the decision-making skills needed to act on that belief. A lack of control is often associated with indecisiveness and a sense of external dependency. Career curiosity involves inquisitiveness about both oneself and the world of work, along with a desire to explore and discover options that could lead to a better person-environment fit. When curiosity is low, individuals may show unrealistic expectations or limited awareness of their possibilities. Finally, career confidence refers to the expectation of success in one's efforts to construct a meaningful career, encompassing the ability to solve problems, overcome obstacles, and acquire new competencies. In the context of GenAI, these resources are especially critical. Expatriates must anticipate how GenAI might reshape their responsibilities, take initiative in adapting their work practices, experiment with new ways of collaborating across cultural and technological boundaries, and remain resilient in the face of novel and ambiguous challenges. Thus, career adaptability serves as a central mechanism through which expatriates respond to both the opportunities and complexities of GenAI-enabled collaboration.

For expatriates working in fast-changing and demanding environments, GenAI-enabled collaboration can serve as a vital resource for strengthening career adaptability. It enhances career concern by supporting future-oriented thinking through scenario generation and trend forecasting tools that help individuals proactively prepare for unfolding developments (Bankins et al., 2024). It contributes to career control by enabling users to independently adapt AI-generated outputs, exercise decision-making autonomy, and maintain task ownership, even in contexts with limited support structures (Bankins et al., 2024). Through its interactive and exploratory capabilities, GenAI stimulates career curiosity, introducing users to unfamiliar ideas, alternative work strategies, and new possibilities (Chowdhury et al., 2024). Finally, GenAI reinforces career confidence by aiding task completion, facilitating skill acquisition, and offering real-time feedback, helping expatriates sustain a sense of competence in complex professional settings (Kong et al., 2023). Together, these mechanisms highlight GenAI's potential to meaningfully enhance all four adaptability dimensions and support career sustainability in international assignments.

Therefore, we propose:

H1: AI collaboration positively influences expatriates' career adaptability.

2.3 Career sustainability

In today's globalized and technology-driven economy, career sustainability has become an increasingly important concern, particularly for individuals working in cross-border and culturally diverse environments. Career sustainability refers to the capacity to maintain a productive, meaningful, and healthy work life over time, despite changing roles, environments, and personal circumstances (De Vos & Van der Heijden, 2015). For expatriates, sustaining a career often involves more than adjusting to a new job or organization (Kohonen, 2008). It requires navigating institutional unfamiliarity, balancing personal and professional identities, and managing evolving expectations across multiple life domains. Challenges such as work–life conflict, social isolation, and limited long-term security are common, especially for those in flexible or transitional employment arrangements (Mäkelä et al., 2017). In this context, sustainable careers depend not only on performance and skill but also on an individual's ability to preserve a sense of purpose, direction, and psychological well-being while adapting to continual change.

Career sustainability is commonly conceptualized through three core subdimensions: life satisfaction, career satisfaction, and productivity (De Vos & Van der Heijden, 2015). Life satisfaction reflects the individual's overall sense of well-being and harmony across life domains, including personal, familial, and social spheres. Career satisfaction refers to the degree to which individuals feel fulfilled, valued, and successful in their professional journey over time. Productivity captures one's ability to perform effectively and consistently at work, despite shifting job demands or external pressures (De Vos & Van der Heijden, 2015). For expatriates, these dimensions are particularly interdependent. For instance, challenges in adapting to a host culture can affect not only work performance but also personal fulfillment and emotional balance. A sustainable career, therefore, is one that supports continued engagement, satisfaction, and functioning across both personal and professional spheres.

GenAI-enabled collaboration offers transformative potential for strengthening career sustainability, particularly within international, knowledge-intensive roles (Budhwar et al., 2023). By automating routine tasks, delivering real-time insights, and supporting complex decision-making, GenAI allows expatriates to manage demanding assignments with greater efficiency and redirect their efforts toward higher-value, meaningful work (Hessari et al., 2024). These functions directly enhance productivity by reducing cognitive load and improving task execution, especially under high-stakes or ambiguous conditions. GenAI also supports career satisfaction by affording expatriates greater autonomy, enabling tailored solutions that align with local demands, and reinforcing competence through visible performance gains (Kong et al., 2023). Furthermore, by easing communication challenges, facilitating contextual understanding, and saving time, GenAI indirectly promotes life satisfaction, allowing expatriates to conserve energy for personal well-being and maintain engagement in non-work domains (Chen, 2024). Collectively, these capabilities suggest that GenAI does more than streamline work. Instead, it creates the conditions for expatriates to sustain fulfilling and balanced careers in global environments.

Therefore, we hypothesize the following:

H2a: AI collaboration enhances expatriates' career sustainability.

While GenAI collaboration may contribute directly to career sustainability, its effects are unlikely to be uniform or automatic. The ability to benefit from GenAI depends on how individuals engage with and adapt to these technologies in their specific work contexts. Career adaptability plays a critical mediating role in this process (Rudolph et al., 2017). Expatriates who demonstrate high levels of concern, control, curiosity, and confidence are better equipped to integrate GenAI tools into their work meaningfully. These adaptability resources allow individuals to anticipate how GenAI might reshape their roles, take initiative in modifying work practices, explore new career possibilities, and persist through uncertainty (Bankins, et al., 2024). Through this adaptive engagement, individuals are more likely to translate GenAI-driven changes into long-term career benefits. Thus, rather than acting as a direct enabler alone, GenAI collaboration enhances career sustainability most effectively when filtered through the lens of career adaptability, especially for expatriates operating in fluid and demanding environments.

Accordingly, we propose:

H2b: Career adaptability mediates the relationship between AI collaboration and expatriates' career sustainability.

2.4 The moderating role of AI trust and job insecurity

Although GenAI collaboration can enhance career adaptability, the extent to which individuals benefit from these technologies depends in part on their trust in AI. AI trust refers to the belief that AI systems are reliable, helpful, and aligned with one's goals, and it influences how individuals engage with and rely on such tools in their work (Kong et al., 2023). For expatriates, who often face unfamiliar systems and institutions, trust in GenAI becomes even more critical. A high level of AI trust can facilitate experimentation, increase willingness to rely on AI-generated outputs, and reduce anxiety associated with using unfamiliar technologies. In contrast, low trust may lead to avoidance or underutilization, limiting the developmental benefits of GenAI collaboration. When expatriates trust AI tools, they are more likely to actively incorporate them into their workflows, explore their potential applications, and build confidence through successful interaction, all of which reinforce the dimensions of career adaptability. Therefore, AI trust strengthens the positive influence of GenAI collaboration on career adaptability by shaping users' openness and responsiveness to these emerging technologies.

Therefore, we propose the following hypothesis:

H3a: AI trust moderates the relationship between AI collaboration and career adaptability.

The extent to which expatriates benefit from GenAI-enabled collaboration in sustaining their careers may depend significantly on their level of trust in AI. Trust in AI functions as a critical moderator that can amplify or constrain the positive effects of AI collaboration on career sustainability. When expatriates perceive AI systems as reliable, transparent, and aligned with their goals, they are more likely to engage with them confidently, integrate AI support into their workflows, and leverage AI recommendations in high-stakes decision-making (Shin, 2021). This trusting engagement enhances the likelihood that GenAI will support productivity, increase career satisfaction, and reduce stress, thus, contributing positively to all three dimensions of career sustainability (Kong et al., 2023). Conversely, low trust in AI may lead to resistance or superficial use, limiting the effectiveness of collaboration and reducing the potential career benefits that AI can offer. In this way, trust serves as a psychological gateway: it shapes whether and how expatriates fully capitalize on GenAI's affordances to build sustainable, high-quality careers in dynamic global contexts.

Therefore, we propose the following hypothesis:

H3b: AI trust moderates the relationship between AI collaboration and career sustainability.

Job insecurity, defined as the perceived threat of job loss or role obsolescence, is another key factor that can shape how individuals respond to GenAI collaboration (Koo et al., 2021). As GenAI becomes more capable of performing cognitive and creative tasks, concerns about being replaced or devalued may intensify, particularly for expatriates whose positions may already be considered peripheral or temporary. This sense of insecurity can affect how individuals engage with GenAI. On one hand, moderate levels of job insecurity may act as a motivator, prompting individuals to upskill, adopt new tools, and enhance their adaptability to protect their roles (Shoss et al., 2023). In such cases, insecurity may strengthen the positive effect of GenAI collaboration on career adaptability by encouraging proactive behavior and learning. On the other hand, high levels of insecurity can be debilitating, leading to withdrawal, resistance to new technologies, and diminished confidence (Brougham & Haar, 2020). Thus, the moderating effect of job insecurity is likely nonlinear and context-dependent, with its influence contingent on whether it is perceived as a challenge to be overcome or a threat to be feared. Therefore, we propose:

H4a: Job insecurity positively moderates the relationship between AI collaboration and career adaptability.

In addition to shaping adaptability, job insecurity may also moderate the direct relationship between GenAI collaboration and career sustainability. Even when GenAI tools enhance productivity or reduce workload, the long-term career benefits may not materialize if individuals remain uncertain about their future employment (Nam, 2019). For expatriates in particular, whose assignments are often fixed-term or subject to local labor market fluctuations, job insecurity can undercut the stability and continuity that career sustainability requires. If GenAI is perceived as a force that increases volatility by threatening role stability, reducing human decision-making, or reinforcing short-term employment arrangements, it may erode the sense of purpose and direction needed for sustaining a meaningful career. Conversely, in contexts where job insecurity is managed or mitigated, individuals may be better positioned to integrate GenAI into their professional lives in ways that support long-term career development. In this sense, job insecurity acts as a boundary condition that can either enable or constrain the extent to which GenAI collaboration translates into sustainable career outcomes. Therefore, we propose:

H4b: Job insecurity moderates the relationship between AI collaboration and career sustainability.

Grounded in career construction theory, the research framework presented in Figure 1 illustrates the hypothesized relationships among GenAI-enabled collaboration, career adaptability, and career sustainability in the expatriate context. We propose that AI collaboration, encompassing both adoption and interaction with GenAI tools, enhances expatriates' capacity to manage transitions and uncertainties by strengthening their career adaptability. In turn, adaptability supports sustained engagement, satisfaction, and productivity in international careers. The model further suggests that career adaptability mediates the relationship between AI collaboration and career sustainability. Additionally, two contextual factors, AI trust and job insecurity, are introduced as moderators. AI trust is expected to strengthen the positive effect of AI collaboration on adaptability and career sustainability, while job insecurity may function as a motivational amplifier or constraint, shaping the influence of AI collaboration on both adaptability and sustainability outcomes. This framework captures the dynamic interplay between technological collaboration and individual psychological resources in shaping sustainable career development among globally mobile professionals.

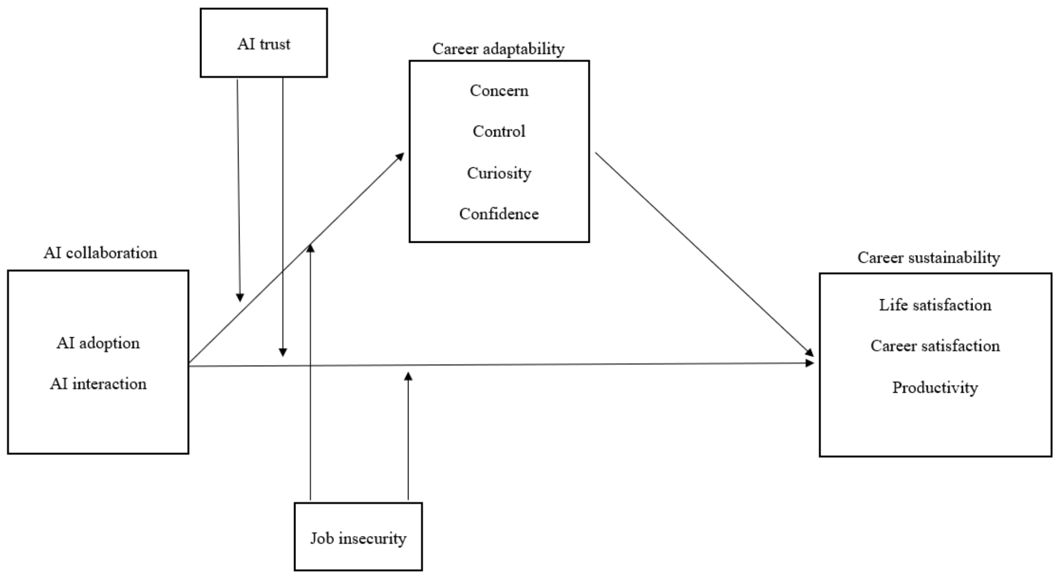

Figure 1. Theoretical framework

3. METHOD

3.1 Data collection

We conducted a survey of employed expatriates to empirically examine our conceptual model, using the online platform Prolific Academic Ltd. This platform was selected for its reputation for high-quality, diverse participant pool, and the ability to target specific respondent characteristics (Peer et al., 2017). Participants were pre-screened to confirm that they (1) were currently expatriates for at least half year and (2) worked in environments where Gen-AI tools were used in their workflows. These criteria ensured that respondents had first-hand experience with Gen-AI technologies, enabling them to provide informed insights into AI collaboration and its impact to the career adaptability and career sustainability.

Data were collected by using non-random convenience sampling between May to June 2025. Participants were informed that their involvement was voluntary and that the results would be anonymous and used only for academic purposes. Additionally, an expert panel comprising academic scholars and doctoral researchers reviewed the survey instrument to assess the clarity, relevance, and comprehensibility of each item, thereby supporting the instrument's content and face validity (Huang et al., 2017).

A pilot test with small samples (n=50) was firstly conducted to validate the survey's clarity and readability. A total of 401 samples were collected. After removing inattentive and incomplete responses, 361 valid entries were retained.

3.2 Measurement

The constructs used in this study were measured by adopting or adapting well-established scales from prior research. First, AI collaboration (AIC), conceptualized as a second-order construct comprising AI adoption and AI interaction, was measured using three items for each subdimension, adapted from Ma et al. (2024) and McAllister (1995). Second, Career adaptability (CAA), a second-order construct covering concern, control, curiosity, and confidence, was measured by thirteen items adapted from Savickas and Porfeli (2012). Third, Career sustainability (CASU) was operationalized through three dimensions: life satisfaction, career satisfaction, and productivity. Life satisfaction (LIS) was assessed using a three-item scale adapted from Diener et al. (1985). Career satisfaction (CAS) was measured with a three-item scale adapted from Greenhaus and Wormley (1990), and productivity was assessed using a three-item scale from Williams and Anderson (1991). Fourth, AI trust (AIT) was measured using a three-item scale adapted from Kong et al. (2023). Lastly, job insecurity (JOI) was measured by three items adapted from Vander et al. (2014). Moreover, control variables collected in the survey include task complexity, age, gender, education level, years of work experience, industry type, and organizational size.

3.3 Data analysis

We employed IBM SPSS Statistics Version 27 to conduct initial data screening, which involved identifying and removing incomplete, duplicate, or missing entries. This process yielded a final sample of 361 valid responses suitable for analysis (Pallant, 2020). To test the hypothesized model, we applied structural equation modeling (SEM), an analytical approach well-established in socio-technical research (Kong et al., 2023; Ma et al., 2024). The analysis was conducted using AMOS Version 21 in conjunction with SPSS Version 28 (Hair et al., 2014). The modeling process followed a two-step approach. First, confirmatory factor analysis (CFA) was used to assess the measurement model, including overall model fit and construct validity. Internal consistency was evaluated using composite reliability (CR) and Cronbach's alpha (α), both of which should exceed the recommended threshold of 0.70. Convergent validity was supported by average variance extracted (AVE) values above 0.50, while discriminant validity was verified following the Fornell-Larcker criterion (Fornell & Larcker, 1981). Second, the structural model was estimated using maximum likelihood estimation to examine the hypothesized relationships among latent variables.

3.4 Common method variance (CMV) bias check

We assessed the potential influence of common method variance (CMV) by applying Harman's single-factor test, as recommended by Fuller et al. (2016). In the single-factor test, all measurement items were loaded onto a single latent factor to determine whether a single source accounted for most of the variance. The analysis showed that the first factor accounted for 29.02 percent of the total variance, which falls below the accepted threshold of 50 percent. This result suggests that CMV was not a serious concern in this study.

4. RESULTS

4.1 Descriptive analysis

The sample reflects a broadly balanced gender distribution, with 50.6% identifying as male and 48.4% as female. A small number of participants identified as non-binary (0.5%) or preferred not to disclose their gender (0.5%). Participants spanned various age groups, with the largest proportion aged between 31 and 40 years old (33.7%), followed by those aged 20–30 (31.4%), and equal proportions aged 41–50 and over 50 (both 17.5%). Regarding education, nearly half of the respondents held a bachelor's degree (49.9%), while 36.7% had obtained a master's degree or higher, and fewer had completed high school (7.6%) or vocational training (5.8%). In terms of organizational context, 49.6% of participants worked in business-to-consumer (B2C) settings, 38.5% in business-to-business (B2B), and 11.9% in other types of organizations. Half of the respondents (50.6%) had over ten years of work experience, whereas 21.5% had between four to six years, and only 2% had less than one year of experience. Organizational size was varied, with most participants employed in medium-sized firms (44.3%), followed by those in large (34.4%), small (13.7%), and micro (7.6%) organizations. This distribution suggests a mature and professionally diverse sample, suitable for examining AI collaboration in workplace contexts.

4.2 The measurement model

We assessed the reliability and validity of the measurement model using a two-step approach. First, internal consistency was evaluated using Cronbach's alpha values calculated in SPSS. All constructs demonstrated acceptable reliability, with alpha values exceeding the recommended threshold of 0.70. Next, confirmatory factor analysis (CFA) was conducted in AMOS to examine both convergent and discriminant validity. Convergent validity was assessed by calculating the Average Variance Extracted (AVE) and Composite Reliability (CR) for each construct. The results (see Table 1) showed that AVE values ranged from 0.51 to 0.82, surpassing the 0.50 benchmark, while CR values ranged from 0.75 to 0.93, exceeding the recommended threshold of 0.70 (Fornell & Larcker, 1981). These results indicate that each construct demonstrates adequate convergent validity. To evaluate discriminant validity, we compared the square root of the AVE for each construct with its inter-construct correlations (see Table 2). In most cases, the square root of the AVE was greater than the corresponding correlation coefficients, supporting discriminant validity as per Fornell and Larcker's (1981) criterion. However, one exception emerged: the square root of the AVE for AIA (0.74) was lower than its correlation with AII (r = 0.83) and AIT (r = 0.78), indicating a potential overlap in construct measurement.

Table 1. CFA result

Latent variables	Indicators	Standardized factor loading	AVE	Square root of AVE	C.R.	P
AIA	AIA1	0.84	0.55	0.74	0.78	***
	AIA2	0.75				
	AIA3	0.61				
AII	AII1	0.87	0.57	0.75	0.79	***
	AII2	0.53				
	AII3	0.81				
CONC	CONC1	0.79	0.51	0.71	0.75	***
	CONC2	0.62				
	CONC3	0.72				
CONT	CONT1	0.70	0.51	0.71	0.75	***
	CONT2	0.67				
	CONT3	0.76				
CURI	CURI1	0.77	0.67	0.73	0.89	***
	CURI2	0.88				
	CURI3	0.80				
	CURI4	0.82				
CONF	CONF1	0.66	0.51	0.72	0.76	***
	CONF2	0.74				
	CONF3	0.74				
LIS	LIS1	0.82	0.73	0.86	0.89	***
	LIS2	0.86				
	LIS3	0.89				
CAS	CAS1	0.84	0.75	0.87	0.90	***
	CAS2	0.91				
	CAS3	0.85				
TAP	TAP1	0.75	0.59	0.77	0.81	***
	TAP2	0.80				
	TAP3	0.76				
JOI	JOI1	0.91	0.82	0.90	0.93	***
	JOI2	0.88				
	JOI3	0.92				
AIT	AIT1	0.73	0.58	0.76	0.80	***
	AIT2	0.73				
	AIT3	0.82				

Table 2. Correlation result

	JOI	TAP	CAS	LIS	CONF	CURI	CONT	CONC	AII	AIA	AIT
JOI	1.00										
TAP	-0.03	1.00									
CAS	-0.18	0.40	1.00								
LIS	-0.22	0.41	0.83	1.00							
CONF	-0.17	0.33	0.67	0.58	1.00						
CURI	-0.24	0.18	0.26	0.18	0.42	1.00					
CONT	-0.21	0.22	0.47	0.40	0.71	0.47	1.00				
CONC	-0.18	0.41	0.59	0.52	0.69	0.42	0.71	1.00			
AII	0.09	0.53	0.29	0.25	0.32	0.18	0.23	0.31	1.00		
AIA	-0.02	0.52	0.28	0.35	0.39	0.27	0.32	0.39	0.83	1.00	
AIT	-0.09	0.70	0.46	0.40	0.51	0.28	0.51	0.55	0.68	0.78	1.00

To further evaluate the distinctiveness of the constructs and support the discriminant validity of the measurement model, we conducted a series of chi-square difference tests comparing our proposed model with several alternative, more constrained models. This approach enables us to determine whether the hypothesized eleven-factor model provides a significantly better fit to the data than models in which conceptually related constructs are merged. The results of the CFA indicated that the eleven-factor model (model 1) exhibited a good fit (X2=818.45, df=475, CFI = 0.95, TLI = 0.94, RMSEA = 0.05, and SRMR = 0.04). All standardized factor loadings were above 0.50, indicating strong item reliability. Given the high correlations among AIA, AII, and AIT, we compared Model 1 with ten alternative constrained models. In Model 2, the measurement items of AIA and AII were combined into one factor. Model 3 further combined AIA, AII, and CURI items into a single factor. Model 4 grouped AIA, AII, CURI, and LIS. Model 5 extended this by combining AIA, AII, CURI, LIS, and CONT. Model 6 added CAS into the merged group. Model 7 included CONC along with the previous six constructs. Model 8 included TAP, while Model 9 combined AIA through CONF into one factor. Model 10 grouped all constructs except for one (AIT) into a single factor, and finally, Model 11 placed all measurement items onto a single general factor. Results of the chi-square difference tests (Table 3) indicated that the eleven-factor model fit the data significantly better than all alternative models. These findings support the discriminant validity of the constructs by demonstrating that each construct captures unique variance not explained by other constructs.

Table 3. Chi-square difference test result

Model comparison	ΔX^2	Δdf	P
Theoretical model (11 factors)			
VS 11 factors	72	10	***
VS 11 factors	892	19	***
VS 11 factors	1683	27	***
VS 11 factors	1924	34	***

VS 11 factors	2135	40	***
VS 11 factors	2254	45	***
VS 11 factors	2572	49	***
VS 11 factors	3550	58	***
VS 11 factors	3021	57	***
VS 11 factors	3913	56	***

4.3 Hypothesis tests

The structural path analysis yielded several key findings. First, AI collaboration was found to significantly predict career adaptability (AIC → CAA = 0.435, $p < 0.001$), providing support for Hypothesis 1a. In contrast, the direct effect of AI collaboration on career sustainability was not statistically significant (AIC → CASU = 0.074, $p = 0.245$), thus offering no support for Hypothesis 1b. Nevertheless, a mediation analysis using 5,000 bootstrap samples revealed a significant indirect effect of AI collaboration on career sustainability through career adaptability (AIC → CAA → CASU = 0.295, $p < 0.001$, 95% CI [0.203, 0.424]). This result confirms the mediating role of career adaptability and supports Hypothesis 2.

Subsequently, we examined the moderating effects of AI trust and job insecurity using the same bootstrapping approach. The results indicated that AI trust significantly moderated the relationship between AI collaboration and career adaptability (AIC × AIT → CAA = 0.502, $p < 0.001$, 95% CI [0.118, 1.255]), supporting Hypothesis 3a. However, the moderating effect of AI trust on the relationship between AI collaboration and career sustainability was not statistically significant (AIC × AIT → CASU = 0.139, $p = 0.079$, 95% CI [–0.095, 1.088]), providing no support for Hypothesis 3b. Furthermore, job insecurity demonstrated a significant positive moderating effect on the relationship between AI collaboration and career adaptability (AIC × JOI → CAA = 0.196, $p < 0.001$, 95% CI [0.015, 0.342]), thereby supporting Hypothesis 4a. Additionally, job insecurity was found to significantly moderate the relationship between AI collaboration and career sustainability (AIC × JOI → CASU = 0.185, $p < 0.001$, 95% CI [0.034, 1.132]). Notably, the direction of this interaction suggests that higher levels of job insecurity enhance the positive association between AI collaboration and career sustainability. A comprehensive summary of these results is presented in Table 4.

Table 4. Hypotheses test result

Hypotheses Paths	Standardized estimation	P-Value	Decision
H1: AIC->CAA	0.44	***	Accept
H2a: AIC->CASU	0.07	0.245	Reject
H2b: AIC->CAA->CASU	0.295	***	Accept
H3a: AIC*AIT->CAA	0.502	***	Accept
H3b: AIC*AIT->CASU	0.139	0.079	Reject

H4a: AIC*JOI->CAA	0.196	***	Accept
H4b: AIC*JOI->CASU	0.185	***	Accept

5. CONCLUSION

5.1 Key findings

The current study proposed and empirically tested a theoretically grounded model examining how GenAI-enabled collaboration influences expatriates' career adaptability and sustainability. Our findings supported most of the hypothesized relationships. Specifically, the results revealed that GenAI collaboration had a significant positive effect on expatriates' career adaptability (H1), supporting the idea that engaging with GenAI tools can enhance individuals' readiness to manage change, uncertainty, and transitions in complex global environments. This aligns with prior research emphasizing the developmental potential of technology-enabled work settings in fostering proactive career behaviors (Presbitero & Quita, 2017; Savickas & Porfeli, 2012). However, the direct relationship between GenAI collaboration and career sustainability (H2a) was not significant. A possible explanation lies in the dual nature of AI interaction: while it can enhance task performance, it may also create psychological strain, reduce social connectedness, and blur boundaries between work and personal life factors that have been shown to negatively affect well-being. This ambivalence helps explain why GenAI collaboration alone may not directly promote sustainable careers. Importantly, we found a significant indirect effect through career adaptability (H2b), highlighting adaptability as a critical mechanism that allows expatriates to transform their engagement with GenAI into long-term, positive career outcomes. This finding reinforces the value of career adaptability in navigating technology-mediated work and supports its role as a central construct in contemporary career development theory (De Vos et al., 2020).

The results of the current research also provide insights into how individual-level factors condition the impact of GenAI collaboration on career-related outcomes. First, we found that AI trust significantly moderated the relationship between GenAI collaboration and career adaptability (H3a), such that the effect was stronger among expatriates who exhibited higher levels of trust in AI systems. This result supports earlier research highlighting the role of trust in shaping individuals' openness toward AI-supported tools (Glikson & Woolley, 2020), and suggests that when expatriates perceive GenAI as competent and reliable, they are more likely to use it in ways that enhance their adaptive capacity. However, AI trust did not significantly moderate the relationship between GenAI collaboration and career sustainability (H3b), indicating that trust may be more relevant to immediate adaptive behaviors than to long-term career outcomes. Second, job insecurity was found to positively moderate both the GenAI–career adaptability (H4a) and GenAI–career sustainability (H4b) relationships. These findings suggest that expatriates experiencing greater job insecurity may be more motivated to actively engage with GenAI tools as a strategy to maintain their value and relevance in competitive global job markets. This pattern reflects prior literature on job preservation motivation theory (Shoss, 2017), in which insecurity can trigger constructive responses when individuals perceive available tools, such as GenAI, as offering career protection or growth potential. Taken together, these results underscore the importance of psychological and situational factors in shaping the impact of technological collaboration on expatriate careers.

5.2 Theoretical implications

This study offers several theoretical contributions to the literature on career development, GenAI, and global work. First, it extends Career Construction Theory by positioning GenAI as a socio-technical career enabler, which is a digital context that shapes how individuals develop and apply adaptability in their careers. Career Construction Theory traditionally emphasizes how people draw on psychological resources (e.g., concern, control, curiosity, confidence) to navigate career transitions (Savickas & Porfeli, 2012). Our findings suggest that GenAI-enabled collaboration provides more than task support. It helps individuals construct adaptable careers by enabling future planning, autonomous decision-making, exploration of new possibilities, and successful problem-solving. By integrating GenAI into the theory, we show that adaptability is not only internally driven but also shaped through interaction with intelligent technologies, especially in complex or uncertain contexts like expatriation.

Second, much of the existing literature treats GenAI as a tool for automating tasks or improving efficiency. Our study reframes GenAI as a developmental context that shapes how individuals experience and manage their careers. We find that GenAI indirectly contributes to career sustainability through adaptability, rather than delivering immediate career benefits on its own. This shift in focus from task outcomes to long-term psychological development adds depth to research on AI in the workplace. It suggests that technology should be viewed as part of the environment in which career resources are activated and strengthened, not merely as an external tool used by individuals.

By identifying career adaptability as the mediating mechanism, this study explains how GenAI-enabled collaboration influences career sustainability. This mechanism clarifies that the benefits of GenAI arise when users become more future-oriented, agentic, exploratory, and confident in their work. We also show that AI trust and job insecurity condition this process: trust in AI strengthens the impact of GenAI on adaptability, while job insecurity can increase individuals' motivation to use AI constructively. These findings highlight that individual differences and work-related concerns shape how people engage with AI, adding nuance to existing models of AI–human interaction.

Finally, this study contributes to the global careers literature by showing how GenAI can help expatriates navigate the challenges of working across cultural and institutional boundaries. GenAI enables real-time translation, local adaptation, and autonomous learning features that are especially valuable when traditional support systems are weak or absent. In this way, GenAI acts as a contextual support mechanism, helping expatriates manage complexity and maintain career continuity. This adds a digital dimension to the study of global careers, suggesting that technology is becoming an essential part of how international professionals construct sustainable career paths.

5.3 Practical implications

This study provides several practical insights for organizations, HR professionals, and global talent managers aiming to foster adaptive and sustainable careers in increasingly AI-mediated and globally mobile work environments. Our findings underscore the critical role of career adaptability in transforming GenAI-enabled collaboration into long-term career benefits. Since GenAI does not automatically enhance sustainability outcomes, organizations must take an active role in building employees' adaptive capacity—especially among expatriates facing cultural unfamiliarity and limited support systems. HR teams can implement training programs that go beyond technical AI literacy to include psychological adaptability skills, such as future planning (concern), self-direction (control), exploratory learning (curiosity), and confidence building. These programs could incorporate scenario-based exercises using GenAI tools, reflective coaching, and microlearning modules designed to simulate real-world challenges in global roles. By fostering these adaptive resources, organizations can equip employees not only to use GenAI, but to thrive through it.

Although GenAI offers clear benefits for productivity and efficiency, it can also introduce risks, such as cognitive overload, increased work expectations, and depersonalization, if poorly implemented. Our results suggest that career sustainability is not a guaranteed outcome of GenAI adoption. Instead, it depends on how individuals experience and internalize their interactions with the technology. Managers should carefully design AI-supported workflows that preserve human agency and psychological safety. This includes clearly defining which tasks are best supported by GenAI, providing room for human discretion in decision-making, and ensuring that AI use does not displace opportunities for collaboration, creativity, or rest. Regular check-ins with expatriate employees can help identify emerging stressors and support recalibration. By embedding GenAI in ways that respect the human side of work, firms can avoid the "dark side" of AI while reinforcing sustainable career development.

Trust in GenAI was shown to significantly shape whether expatriates engage with these tools in a way that builds adaptability. When employees view AI systems as competent, fair, and aligned with their goals, they are more likely to explore their functions, incorporate outputs meaningfully, and rely on them during critical work tasks. To foster this trust, organizations must adopt transparent, user-centered AI practices. This includes educating users about how GenAI systems function, what data they use, and what their limitations are. Providing explainability features and allowing feedback on AI performance can reduce anxiety and increase psychological comfort. Furthermore, involving employees, including expatriates, in co-designing or testing AI systems can increase ownership and trust. These inclusive practices are essential not only for AI adoption, but for ensuring that it supports long-term career growth rather than short-term compliance.

Job insecurity emerged in our study as a complex moderator: while it can motivate greater engagement with GenAI, it can also reflect deeper concerns about professional obsolescence. Expatriates, often operating in precarious or fixed-term roles, may be particularly sensitive to technological disruption. Managers should therefore take a proactive role in framing GenAI not as a threat, but as a catalyst for career development. This involves clearly communicating how AI will complement rather than replace human expertise, offering training that highlights new skillsets required in AI-enhanced roles, and mapping out how employees can evolve with the technology. Embedding GenAI into broader upskilling initiatives and career planning frameworks can reduce fear and increase career ownership. In addition, creating internal mobility pathways that align with new GenAI-enabled competencies can provide employees with visible and attainable career futures, enhancing both motivation and retention.

5.4 Limitations and suggestions for future research

While this study offers valuable insights, several limitations should be acknowledged. First, the use of a cross-sectional research design limits the ability to infer causal relationships between GenAI collaboration, career adaptability, and career sustainability. Future research could employ longitudinal or experimental designs to better capture how these relationships evolve over time. Second, the data were collected through self-reported measures, which may introduce common method bias despite procedural precautions. Incorporating multi-source or behavioral data, such as AI usage logs or supervisor ratings, could strengthen the validity of future findings. Third, the sample focused on expatriates as a broad category without distinguishing between self-initiated and organization-assigned expatriates. Subsequent studies could explore subgroup differences to assess whether AI-related career dynamics vary across expatriate types, industries, or cultural contexts. Lastly, while this study examined two moderators, other contextual factors, such as organizational AI readiness, team climate, or cultural values may also shape how individuals experience GenAI at work. Exploring these conditions would further enrich the understanding of sustainable career development in the age of intelligent technologies.

REFERENCE

Bankins, S., Jooss, S., Restubog, S. L. D., Marrone, M., Ocampo, A. C., & Shoss, M. (2024). Navigating career stages in the age of artificial intelligence: A systematic interdisciplinary review and agenda for future research. *Journal of Vocational Behavior*, *153*, 104011.

Bankins, S., Ocampo, A. C., Marrone, M., Restubog, S. L. D., & Woo, S. E. (2024). A multilevel review of artificial intelligence in organizations: Implications for organizational behavior research and practice. *Journal of Organizational Behavior*, *45*(2), 159–182.

Brougham, D., & Haar, J. (2020). Technological disruption and employment: The influence on job insecurity and turnover intentions: A multi-country study.

Technological Forecasting and Social Change, *161*, 120276.

Budhwar, P., Chowdhury, S., Wood, G., Aguinis, H., Bamber, G. J., Beltran, J. R., . . . Varma, A. (2023). Human resource management in the age of generative artificial intelligence: Perspectives and research directions on ChatGPT. *Human Resource Management Journal*, *33*(3), 606–659.

Chen, Y. (2024). Generative Artificial Intelligence Empowering Translation: Current Status, Challenges, and Prospects. *The Educational Review USA*, *8*(12), 1447–1454.

Chowdhury, S., Budhwar, P., & Wood, G. (2024). Generative artificial intelligence in business: towards a strategic human resource management framework. *British Journal of Management*, *35*(4), 1680–1691.

Creswell, J. W. (2014). *Research design: qualitative, quantitative, and mixed methods approaches* (Fourth edition). SAGE.

De Vos, A., & Van der Heijden, B. (2015). *Handbook of research on sustainable careers*. Edward Elgar Publishing.

De Vos, A., Van der Heijden, B. I., & Akkermans, J. (2020). Sustainable careers: Towards a conceptual model. *Journal of Vocational Behavior*, *117*, 103196.

Diener, E. D., Emmons, R. A., Larsen, R. J., & Griffin, S. (1985). The satisfaction with life scale. *Journal of Personality Assessment*, *49*(1), 71–75.

Doshi, A. R., & Hauser, O. P. (2024). Generative AI enhances individual creativity but reduces the collective diversity of novel content. *Science Advances*, *10*(28), eadn5290.

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., . . . Wright, R. (2023). Opinion Paper:"So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, *71*, 102642.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50.

Fuller, C. M., Simmering, M. J., Atinc, G., Atinc, Y., & Babin, B. J. (2016). Common methods variance detection in business research. *Journal of Business Research*, *69*(8), 3192–3198.

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals*, *14*(2), 627–660.

Greenhaus, J. H., Parasuraman, S., & Wormley, W. M. (1990). Effects of Race on Organizational Experiences, Job Performance Evaluations, and Career Outcomes. *Academy of Management Journal*, *33*(1), 64–86.

Hair Jr., J. F., Gabriel, M. L. D. da S., & Patel, V. K. (2014). AMOS covariance- based structural equation modeling (CB-SEM): Guidelines on its application as a marketing research tool. *Brazilian Journal of Marketing*, *13*(2), 44–55.

Hao, X., Demir, E., & Eyers, D. (2024). Exploring collaborative decision-making: A quasi-experimental study of human and Generative AI interaction. *Technology in Society*, *78*, 102662.

Hessari, H., Bai, A., & Daneshmandi, F. (2024). Generative AI: Boosting Adaptability and Reducing Workplace Overload. *Journal of Computer Information Systems*, 1–14.

Huang, C. C., Chen, W. S., Tsai, M. W., & Wang, W. T. J. (2017). Comparing the Chinese versions of two knee-specific questionnaires (IKDC and KOOS): reliability, validity, and responsiveness. *Health and Quality of Life Outcomes*, *15*(1), 238.

Jackson, V., Vasilescu, B., Russo, D., Ralph, P., Prikladnicki, R., Izadi, M., D'Angelo, S., Inman, S., Andrade, A., & Van Der Hoek, A. (2025). The Impact of Generative AI on Creativity in Software Development: A Research Agenda. *ACM Transactions on Software Engineering and Methodology*, *34*(5), 1–28.

Kohonen, E. (2008). The impact of international assignments on expatriates' identity and career aspirations: Reflections upon re-entry. *Scandinavian Journal of Management*, *24*(4), 320–329.

Kong, H., Yin, Z., Baruch, Y., & Yuan, Y. (2023). The impact of trust in AI on career sustainability: The role of employee–AI collaboration and protean career orientation. *Journal of Vocational Behavior*, *146*, 103928.

Koo, B., Curtis, C., & Ryan, B. (2021). Examining the impact of artificial intelligence on hotel employees through job insecurity perspectives. *International Journal of Hospitality Management*, *95*, 102763.

Ma, L., Yu, P., Zhang, X., Wang, G., & Hao, F. (2024). How AI use in organizations contributes to employee competitive advantage: The moderating role of perceived organization support. *Technological Forecasting and Social Change*, *209*, 123801.

Mäkelä, L., Saarenpää, K., & McNulty, Y. (2017). International business travellers, short-term assignees and international commuters. In *Research handbook of expatriates* (pp. 276–294). Edward Elgar Publishing.

McAllister, D. J. (1995). Affect- and Cognition-Based Trust as Foundations for Interpersonal Cooperation in Organizations. *Academy of Management Journal*, *38*(1), 24–59.

McNulty, Y., & Brewster, C. (2017). The concept of business expatriates. In *Research handbook of expatriates* (pp. 21–60). Edward Elgar Publishing.

Nam, T. (2019). Technology usage, expected job sustainability, and perceived job insecurity. *Technological Forecasting and Social Change*, *138*, 155– 165.

Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. *Science*, *381*(6654), 187–192.

Pallant, J. (2020). *SPSS survival manual: A step by step guide to data analysis using IBM SPSS*. Routledge.

Peer, E., Brandimarte, L., Samat, S., & Acquisti, A. (2017). Beyond the Turk: Alternative platforms for crowdsourcing behavioral research. *Journal of Experimental Social Psychology*, *70*, 153–163.

Presbitero, A., & Quita, C. (2017). Expatriate career intentions: Links to career adaptability and cultural intelligence. *Journal of Vocational Behavior*, *98*, 118– 126.

Reiche, B. S., Kraimer, M. L., & Harzing, A. (2011). Why do international assignees stay? An organizational embeddedness perspective. *Journal of International Business Studies*, *42*(4), 521–544.

Rudolph, C. W., Lavigne, K. N., & Zacher, H. (2017). Career adaptability: A meta- analysis of relationships with measures of adaptivity, adapting responses, and adaptation results. *Journal of Vocational Behavior*, *98*, 17–34.

Savickas, M. L. (2005). The theory and practice of career construction. In *Career development and counseling: Putting theory and research to work*, *1*(1), 42-70. Wiley.

Savickas, M. L., & Porfeli, E. J. (2012). Career Adapt-Abilities Scale: Construction, reliability, and measurement equivalence across 13 countries. *Journal of Vocational Behavior*, *80*(3), 661–673.

Shin, D. (2021). The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. *International Journal of Human-Computer Studies*, *146*, 102551.

Shoss, M. K., Su, S., Schlotzhauer, A. E., & Carusone, N. (2023). Working hard or hardly working? An examination of job preservation responses to job insecurity. *Journal of Management*, *49*(7), 2387–2414.

Shoss, M. K. (2017). Job insecurity: An integrative review and agenda for future research. *Journal of Management*, *43*(6), 1911–1939.

Sowa, K., Przegalinska, A., & Ciechanowski, L. (2021). Cobots in knowledge work: Human – AI collaboration in managerial professions. *Journal of Business Research*, *125*, 135–142.

Van Dis, E. A. M., Bollen, J., Zuidema, W., Van Rooij, R., & Bockting, C. L. (2023).

ChatGPT: five priorities for research. Nature, 614(7947), 224–226.

Vander Elst, T., De Witte, H., & De Cuyper, N. (2014). The Job Insecurity Scale: A psychometric evaluation across five European countries. *European Journal of*

Work and Organizational Psychology, *23*(3), 364–380.

Williams, L. J., & Anderson, S. E. (1991). Job Satisfaction and Organizational Commitment as Predictors of Organizational Citizenship and In-Role Behaviors. *Journal of Management*, *17*(3), 601–617.

Zhao, H., Yuan, B., & Song, Y. (2024). Employees' perception of generative artificial intelligence and the dark side of work outcomes. *Journal of Hospitality and Tourism Management*, *61*, 191–199.