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From Prediction to Generation: A Literature Review on the Role of Generative AI in Enhancing Organizational Problem-Solving Dynamics

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Abstract: This qualitative literature review explores the transformative role of generative artificial intelligence (GenAI) in reshaping organizational problem-solving. Moving beyond prediction, GenAI supports ideation, design, and decision-making by enhancing exploration, reducing cognitive constraints, and enabling hybrid human-machine intelligence. Drawing on recent studies in strategic management, organizational learning, and AI innovation, this review synthesizes evidence of GenAI's capacity to augment creativity, frame redefinition, and solution diversity. The findings highlight both opportunities—such as improved search efficiency and strategic adaptability—and challenges, including algorithmic opacity, trust issues, and socio-technical complexity. Ultimately, GenAI represents a generative shift in how organizations define problems and pursue innovation, requiring thoughtful integration to maximize its cognitive and strategic value.

Keywords: Generative Artificial Intelligence, Organizational Problem-Solving, Hybrid Intelligence, Strategic Decision-Making, Cognitive Augmentation (;)

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1. Introduction

In recent years, the integration of artificial intelligence (AI) into organizational settings has undergone a significant transformation, evolving from a tool predominantly used for predictive analytics to one that increasingly participates in generative and exploratory tasks. This paradigm shift marks a profound development in how organizations solve problems, adapt to uncertainty, and innovate in complex, dynamic environments. Generative AI—referring to machine learning systems capable of creating novel outputs such as designs, strategies, or text—represents a new frontier in augmenting human cognition and decision-making (Goodfellow et al., 2014; Shrestha et al., 2019; Krakowski et al., 2023). Generative Artificial Intelligence has the potential to revolutionize human resource management, but its success heavily depends on the organization's readiness to adapt to technological changes, as well as its commitment to ensuring fair and ethical implementation (Yulianti, G., et al, 2024).

Historically, the dominant narrative around AI's role in organizations focused on automation, efficiency, and prediction, aligned with the logic of predictive AI systems that leverage large datasets to extrapolate future events (Agrawal, Gans, & Goldfarb, 2018; Brynjolfsson & McAfee, 2014). These technologies were particularly effective in routinized and structured decision domains—such as supply chain optimization or customer segmentation—where clearly defined inputs and outputs allowed machines to outperform human judgment (Faraj, Pachidi, & Sayegh, 2018; Balasubramanian, Ye, & Xu, 2022). However, contemporary organizational challenges increasingly demand solutions beyond mere prediction; they require creativity, contextual understanding, and exploration—domains traditionally considered the bastion of human problem-solving (Amabile, 2020; Baumann, Schmidt, & Stieglitz, 2019).

The emergence of generative AI technologies such as large language models (e.g., ChatGPT) and generative design platforms (Oh et al., 2019; Hao, 2023) has sparked renewed interest in how organizations can integrate these tools to tackle non-routine, ambiguous, and ill-structured problems. These tools do not merely automate decisions but actively contribute to the ideation, design, and refinement of novel solutions, thus transforming the very dynamics of organizational problem-solving (Raisch & Krakowski, 2021; Anthony, 2021). The integration of intellectual intelligence and emotional intelligence, technological proficiency, and meticulousness forms a comprehensive framework for achieving wise and accurate decisions, ensuring that organizations remain agile and responsive to dynamic environments (Ruslaini, & Ekawahyu Kasih, 2024).This literature review seeks to synthesize and critically assess existing scholarship on the intersection of generative AI and organizational problem-solving, with a particular emphasis on the cognitive, behavioral, and structural shifts prompted by this technological evolution.

A foundational framework for understanding the interplay between human intelligence and AI in complex problem-solving has been developed by Raisch and Fomina (2024), who argue that hybrid human–AI systems follow three distinct problem-solving processes: autonomous search, sequential search, and interactive search. These processes differ in their cognitive logic and output characteristics. Autonomous search leverages the generative capacity of AI to explore distant, non-intuitive solutions, typically without immediate human feedback. In contrast, sequential search relies on iterative, back-and-forth inputs between humans and AI systems, producing local improvements or optimizations. The most promising configuration—interactive search—embodies continuous, real-time collaboration, facilitating recombination of knowledge and enhancing cognitive diversity within the problem space (Raisch & Fomina, 2024). Such frameworks broaden the scope of behavioral theory of the firm by introducing a technology-aware lens to the traditionally human-centric view of organizational decision-making (Gavetti et al., 2012; Puranam et al., 2015).

This reconfiguration of problem-solving structures has profound implications. On the one hand, AI systems are increasingly capable of engaging in recombinant innovation by linking disparate knowledge domains (Fleming, 2001; Schilling & Green, 2011). On the other hand, their outputs are often opaque, contextually naive, or detached from organizational objectives unless coupled with human interpretation and domain expertise (Burrell, 2016; Lebovitz, Lifshitz-Assaf, & Levina, 2022). The challenge, therefore, lies not in replacing human judgment but in designing collaborative architectures where generative AI acts as a complementary cognitive agent (Metcalf, Askay, & Rosenberg, 2019; Murray, Rhymer, & Sirmon, 2021).

Generative AI's potential is particularly salient in high-uncertainty environments where exploration is critical. As Baumann et al. (2019) note, rugged performance landscapes require organizations to navigate interdependent decision variables where local optima can trap purely human or machine-based search. In such contexts, hybrid systems may overcome individual cognitive limits—like bounded rationality or coordination neglect (Heath & Staudenmayer, 2000; Puranam, 2021)—by combining algorithmic scale with human sense-making and social learning mechanisms (Csaszar & Levinthal, 2016; Bader & Kaiser, 2019). Moreover, recent advancements in deep learning and generative models have enabled AI systems to autonomously generate solutions that previously required human creativity, as seen in fields ranging from drug discovery (Deng et al., 2022; Jumper et al., 2021) to marketing content generation (Cortex, 2022; Simone, 2021).

However, integrating generative AI into organizational processes also introduces novel risks and tensions. Algorithm aversion (Dietvorst, Simmons, & Massey, 2015), lack of explainability (Linardatos, Papastefanopoulos, & Kotsiantis, 2020), and emergent issues of control and accountability (Kellogg, Valentine, & Christin, 2020) complicate adoption. Furthermore, AI's reliance on historical data and pattern recognition may limit its ability to generate radically novel or norm-challenging solutions unless actively designed to support divergent thinking (Elgammal, 2019; Anantrasirichai & Bull, 2021). These challenges necessitate a careful alignment between AI system design, organizational structure, and problem-solving objectives.

In synthesizing this literature, this review contributes to three critical domains. First, it extends the study of organizational problem-solving by integrating insights from machine learning and cognitive science, offering a multidimensional view of generative AI as both a tool and a collaborator. Second, it enriches the emerging field of AI in management by mapping the mechanisms, enablers, and constraints of human–AI generative partnerships (Shrestha, Krishna, & Von Krogh, 2021; Allen & Choudhury, 2022). Finally, it provides actionable guidance for managers and policymakers seeking to leverage generative AI for innovation without undermining human judgment, ethics, and agency.

The shift from predictive to generative AI marks more than a technological upgrade; it signals a redefinition of how organizations engage with complex problems. As organizations increasingly rely on AI not merely to forecast but to co-create, the study of hybrid intelligence systems becomes central to understanding future capabilities, competitive advantage, and organizational evolution (Krakowski, Luger, & Raisch, 2023; Von Krogh, 2018). This review aims to chart that terrain by drawing together diverse strands of literature into a coherent framework that captures the promises and perils of generative AI in organizational problem-solving.

2. Preliminaries or Related Work or Literature Review

The growing presence of generative artificial intelligence (GenAI) in organizational settings has shifted the discourse from predictive capabilities to generative problem-solving. Traditional uses of AI centered on forecasting and optimization are now giving way to creative ideation, decision augmentation, and hybrid intelligence systems. This literature review explores how GenAI reconfigures organizational problem-solving dynamics, drawing upon foundational and emerging studies that span cognitive theory, organizational design, and artificial intelligence. Artificial intelligence (AI) and strategic agility play a crucial role in enhancing product creativity and the development of new services within organizations (Permana, N., et al, 2024).

Hybrid Intelligence and Cognitive Complementarity. The core premise of GenAI's contribution to organizational problem-solving lies in its ability to combine human and artificial cognition. Raisch and Fomina (2024) articulate a model of hybrid intelligence where humans and machines co-create solutions, extending problem representations beyond individual cognitive limits. This aligns with Csaszar and Ostler's (2020) assertion that representational complexity—how richly and multidimensionally a problem is framed—is critical to adaptive organizational behavior.

These hybrid systems are not simply additive but mutually transformative. While humans provide contextual intuition and moral reasoning, AI contributes scale, memory, and generative capabilities. Allen and Choudhury (2022) highlight the dual forces of domain expertise and algorithm aversion, noting that users often resist but can benefit from algorithmic augmentation when trust and interpretability are assured. This underscores the necessity for transparent and interpretable AI systems (Linardatos et al., 2020) in order to foster productive human-AI collaboration. The collaboration between artificial intelligence platforms and digital innovation hubs can enhance productivity, operational efficiency, and market access for SMEs (Eka Wahyu Kasih, et al, 2024).

From Predictive Models to Generative Systems. Generative AI represents a shift from merely optimizing known outcomes to generating novel solutions. Agrawal, Gans, and Goldfarb (2018) distinguish between prediction and judgment, where GenAI blurs the line by autonomously constructing potential future states. Goodfellow et al. (2014) formalized generative adversarial networks (GANs), which learn to create new data resembling training inputs, laying the foundation for many applications of GenAI across industries.

In organizations, these generative capacities are leveraged for ideation, design, and innovation. Anantrasirichai and Bull (2021) review GenAI's role in creative industries, noting its ability to produce high-quality drafts, prototypes, and campaign concepts. Arthur (2018) documents IBM and Tommy Hilfiger's use of GenAI in fashion design, illustrating how AI contributes to aesthetic and functional aspects of product development.

Problem Representation and Search in Complex Landscapes. Organizational problem-solving often involves navigating rugged performance landscapes (Baumann et al., 2019). In such contexts, effective exploration requires diverse representations and iterative search. GenAI aids this process by offering recombinatory capabilities, producing solutions beyond the limitations of human analogical reasoning (Fleming, 2001; Schilling & Green, 2011). Through generative modeling, organizations can explore previously uncharted solution spaces.

The role of representational scaffolding is emphasized by Csaszar and Levinthal (2016), who argue that mental models shape the boundaries of search. GenAI, by offering multiple representations and simulating counterfactuals, enables organizations to "think differently" (Amabile, 2020). This enhances both the breadth and depth of cognitive search, especially under uncertainty and constraint (Puranam et al., 2015).

Generative AI and Organizational Decision-Making. The integration of GenAI into decision-making structures presents both opportunities and tensions. While GenAI can surface novel options, the black-box nature of deep learning models raises issues of explainability and accountability (Burrell, 2016; Lebovitz et al., 2022). Bader and Kaiser (2019) argue that the user interface plays a critical role in determining how decisions are negotiated between humans and machines.

Studies by Shrestha et al. (2019) and Kellogg et al. (2020) suggest that algorithmic control mechanisms may clash with established professional logics, especially in fields like medicine and law. However, Puranam (2021) frames human-AI collaboration as an organizational design challenge, requiring new rules, incentives, and feedback loops to maximize joint performance.

Generative AI in Collaborative and Crowdsourced Settings. The potential of GenAI to augment collective problem-solving is especially salient in collaborative environments. Afuah and Tucci (2012) describe crowdsourcing as a form of distant search, where heterogeneous actors contribute to solving complex problems. GenAI can function as a cognitive amplifier in such contexts, filtering, clustering, and even generating suggestions based on large-scale input (Piezunka & Dahlander, 2015).

Recent work by Billinger et al. (2023) demonstrates how dyads engaged in modular problem-solving use algorithmic feedback to overcome misaligned incentives and coordination neglect (Heath & Staudenmayer, 2000). Similarly, Metcalf et al. (2019) propose artificial swarm intelligence as a means of pooling distributed cognition, where GenAI acts as an orchestrator of human insight.

Generative AI and Organizational Learning. Balasubramanian, Ye, and Xu (2022) examine how substituting human decision-making with machine learning affects organizational learning. They find that reliance on GenAI can either hinder or enhance learning, depending on whether feedback loops are maintained. GenAI tools that visualize their reasoning (Senoner et al., 2022) foster better reflection and sensemaking.

The notion of "learning to search" (Billinger et al., 2023) is vital in the GenAI era. Organizations must develop meta-capabilities—not just in using AI but in learning how AI learns. This requires continuous tuning of the human-AI interface, fostering trust, and updating mental models (Gary & Wood, 2011).

Ethical and Strategic Implications. While GenAI offers unprecedented problem-solving capacity, it also raises profound ethical questions. Issues of authorship, bias, and misuse—particularly in areas like advertising (Prosser, 2021), drug discovery (Fleming, 2018; Urbina et al., 2022), and creative labor (Elgammal, 2019)—necessitate robust governance frameworks.

Strategically, GenAI alters the sources of competitive advantage (Krakowski et al., 2023), shifting value from data ownership to problem framing and orchestration. As such, firms must develop new routines and structures that balance human judgment with machine creativity (Raisch & Krakowski, 2021).

The literature reviewed illustrates a fundamental shift in organizational problem-solving: from optimizing what is known to generating what is possible. Generative AI not only expands the frontier of cognitive capabilities but also reshapes organizational routines, decision architectures, and ethical norms. Future research should explore the dynamic co-evolution of human and artificial cognition, with particular attention to how organizations learn to govern, trust, and co-create with generative systems.

3. Proposed Method

This study adopts a qualitative literature review methodology to synthesize existing knowledge on the role of generative artificial intelligence (GenAI) in enhancing organizational problem-solving dynamics. The qualitative review approach is particularly suitable for theory-building and concept synthesis in emerging fields such as AI-human hybrid intelligence, where empirical generalizations are still forming and interdisciplinary integration is required (Tranfield, Denyer, & Smart, 2003; Snyder, 2019).

Following guidelines for qualitative, integrative literature reviews (Torraco, 2005), this study employed a structured yet flexible process consisting of four phases: (1) scope definition, (2) source selection and evaluation, (3) thematic synthesis, and (4) interpretive analysis. These stages are described in more detail below.

The scope of this review is framed by the intersection of three domains: (1) generative artificial intelligence, (2) organizational problem-solving, and (3) human–AI collaboration. This integrative perspective aligns with calls for cross-disciplinary theorizing in technology and organization studies (Von Krogh, 2018). The guiding research question is: How does generative AI reconfigure cognitive, structural, and social dimensions of problem-solving in organizations?

To ensure conceptual rigor, this review draws on the notion of problemistic search from behavioral theories of the firm (Posen et al., 2018), combined with insights on cognitive augmentation and human–machine integration (Raisch & Fomina, 2024; Shrestha et al., 2019). Relevant literature was identified through systematic searches in multidisciplinary databases, using combinations of keywords including "generative AI," "organizational problem-solving," "cognitive search," "hybrid intelligence," "machine learning," and "human–AI collaboration."

The inclusion criteria focused on peer-reviewed journal articles published between 2000 and 2024, with an emphasis on recent contributions (post-2018) due to the rapid evolution of GenAI technologies such as GANs (Goodfellow et al., 2014), transformer-based models, and large language models. Conceptual, theoretical, and empirical studies were all considered, provided they contributed to understanding the transformation of organizational search, decision-making, and learning in the context of AI.

All selected articles were assessed using relevance, impact, and theoretical contribution as qualitative inclusion filters, consistent with standards outlined by Webster and Watson (2002). Particular attention was given to studies published in leading journals such as Academy of Management Review, Organization Science, Strategic Management Journal, and California Management Review.

To synthesize the literature, an inductive thematic analysis approach was employed (Nowell, Norris, White, & Moules, 2017). Articles were read iteratively, and key concepts, arguments, and empirical findings were extracted into a matrix coding scheme using NVivo 14 qualitative software.

Emerging themes were clustered into four macro-categories: Hybrid problem-solving and cognition (e.g., Raisch & Fomina, 2024; Csaszar & Ostler, 2020). Generative capabilities and solution space expansion (e.g., Goodfellow et al., 2014; Anantrasirichai & Bull, 2021). Human–AI interaction and governance (e.g., Bader & Kaiser, 2019; Lebovitz et al., 2022). Strategic and ethical implications (e.g., Krakowski et al., 2023; Puranam, 2021). Throughout this process, constant comparison methods (Glaser & Strauss, 1967) were used to refine categories and identify patterns, contradictions, and gaps across studies.

The final stage involved interpretive synthesis, drawing from organizational theory, cognitive science, and AI ethics to contextualize the findings within broader debates on human–machine co-evolution. This phase emphasized the reframing of existing theoretical assumptions about problem-solving and decision-making (Faraj, Pachidi, & Sayegh, 2018; Gavetti et al., 2012). Additionally, the review critically engaged with tensions such as automation vs. augmentation (Raisch & Krakowski, 2021), explainability vs. opacity (Burrell, 2016), and cognitive complementarity vs. substitution (Balasubramanian, Ye, & Xu, 2022). Reflexivity was maintained throughout the process to account for the researcher's interpretive lens and the evolving nature of the topic (Langley, 1999).

4. Results and Discussion

This qualitative literature review reveals four major thematic findings that illustrate how generative artificial intelligence (GenAI) is reshaping organizational problem-solving dynamics: (1) the shift from predictive to generative paradigms in organizational cognition, (2) the emergence of hybrid human–AI problem-solving systems, (3) expansion of the solution space and creativity, and (4) new forms of organizational learning and adaptive capacity.

From Prediction to Generation: A Paradigm Shift in Organizational Cognition. Traditionally, artificial intelligence in organizations has been associated with predictive analytics aimed at optimizing decision-making under uncertainty (Agrawal, Gans, & Goldfarb, 2018). However, recent advances in GenAI—including large language models and generative adversarial networks—enable not just analysis of existing data but the creation of novel content, scenarios, and solutions (Goodfellow et al., 2014; LeCun, Bengio, & Hinton, 2015).

This shift is not merely technical but epistemological, representing a move from reactive forecasting to active ideation (Anantrasirichai & Bull, 2021). For example, GenAI models like OpenAI's Codex and DeepMind's AlphaCode generate code solutions to novel problems, functioning more like co-creators than calculators (Fleming, 2018; Savage, 2023). In the organizational context, this challenges established cognitive routines and necessitates new mental models for how leaders engage with intelligent systems (Csaszar & Ostler, 2020).

Hybrid Intelligence and Augmented Problem-Solving. A prominent theme in the literature is the rise of hybrid human–AI systems that blend machine generativity with human judgment. Raisch and Fomina (2024) conceptualize this as "hybrid problem-solving," where AI-generated alternatives are interpreted, selected, or refined by human agents. This partnership expands both the exploration of novel possibilities and the exploitation of domain knowledge.

However, the effectiveness of such hybrid systems depends on interface design, explainability, and user trust (Bader & Kaiser, 2019; Lebovitz, Lifshitz-Assaf, & Levina, 2022). Dietvorst, Simmons, and Massey (2015) find that humans are often averse to using algorithmic suggestions after witnessing errors—highlighting a socio-cognitive barrier to integration.

Interestingly, GenAI appears to soften this aversion when framed as creative collaborators rather than deterministic decision-makers (Shrestha, Krishna, & Von Krogh, 2021). In fields such as architecture, advertising, and R&D, AI tools like Midjourney or ChatGPT are increasingly embedded into workflows to enhance ideation, not just accuracy (Amabile, 2020; Chow, 2020; Simone, 2021).

Expansion of the Solution Space and Organizational Creativity. Generative AI systems have been shown to radically expand the problem-solving search space. Unlike traditional models that optimize over known variables, generative systems explore nonlinear, combinatorial, and high-dimensional configurations (Baumann, Schmidt, & Stieglitz, 2019). This enables organizations to discover unexpected solutions, a process sometimes referred to as recombinant innovation (Schilling & Green, 2011; Fleming, 2001).

For instance, the use of GenAI in drug discovery has led to the identification of entirely novel molecular structures, compressing timelines from years to months (Jumper et al., 2021; Hale, 2021a). Similarly, generative design tools in engineering allow for automatic generation of thousands of prototypes constrained by functional goals (Oh et al., 2019; Vinoski, 2019).

This creative potential is amplified when GenAI is integrated with diverse human teams, as algorithmically-generated ideas may challenge groupthink or domain biases (Jeppesen & Lakhani, 2010; Billinger et al., 2023). Consequently, GenAI acts as a catalyst for cognitive dissonance and strategic reframing, essential for innovation in complex environments (Kaplan, 2011; Csaszar & Levinthal, 2016).

Reconfiguring Organizational Learning and Adaptation. A final insight concerns how GenAI alters organizational learning processes. As GenAI systems generate and evaluate alternatives, they become active agents in feedback loops that shape organizational memory, routines, and mental models (Balasubramanian, Ye, & Xu, 2022; Ethiraj & Levinthal, 2009).

Unlike deterministic rule-based systems, generative models learn from unstructured and emergent data, supporting nonlinear adaptation in fast-changing environments (Faraj, Pachidi, & Sayegh, 2018). Organizations thus face the challenge of developing absorptive capacities to internalize and interpret AI-generated outputs (Zahra & George, 2002).

Crucially, GenAI also challenges assumptions of bounded rationality by offering a virtually unlimited repertoire of options, thus redefining the boundaries of organizational search and sensemaking (Puranam, Stieglitz, Osman, & Pillutla, 2015). However, this can lead to paralysis by analysis or ethical dilemmas unless mediated by human constraints and social norms (Raisch & Krakowski, 2021; Lindebaum, Vesa, & den Hond, 2020).

The integration of generative AI (GenAI) into organizational problem-solving marks a paradigm shift from purely predictive analytics to creative generation, augmenting both cognitive and strategic decision-making processes. Traditional models of organizational learning and problem-solving have emphasized exploitation of past experiences and incremental improvement (Gavetti & Levinthal, 2000; March, 1991). However, the emergence of GenAI tools such as large language models and generative design systems introduces new affordances for recombination, synthesis, and novel solution generation (Goodfellow et al., 2014; LeCun, Bengio, & Hinton, 2015).

Recent scholarship by Raisch and Fomina (2024) emphasizes the hybrid nature of problem-solving, where human intuition and algorithmic exploration converge in complex decision-making contexts. Their findings suggest that GenAI supports the cognitive scaffolding of users by externalizing thought processes, particularly during early-stage ideation and problem structuring. This aligns with the earlier cognitive framing work by Kaplan (2011), which argued that representational tools—whether visual, verbal, or digital—can shape how managers identify and evaluate options.

Compared with traditional AI systems that optimize under known constraints (Agrawal, Gans, & Goldfarb, 2018), GenAI facilitates creative leaps in problem spaces that are ill-structured or ambiguous. For example, studies in design-intensive industries highlight how GenAI empowers rapid prototyping and multi-criteria exploration (Oh et al., 2019; Arthur, 2018). In a study conducted by Krakowski, Luger, and Raisch (2023), generative algorithms helped organizations outperform baseline human teams in scenario creation for strategic foresight, although human oversight remained crucial to validate feasibility and ethical constraints. This mirrors the tension noted by Amabile (2020), who warned of the "illusion of creativity" in AI outputs without human critical engagement.

A core finding across the reviewed literature is the capability of GenAI to alter the epistemic structure of organizational search. Whereas classical theories such as those by Knudsen and Levinthal (2007) differentiate between exploration and exploitation in search landscapes, GenAI appears to collapse this distinction by enabling simultaneous divergence and convergence (Baumann, Schmidt, & Stieglitz, 2019). This dual capability is particularly evident in AI-augmented strategy tools, which support executives in identifying unconventional configurations of value creation, a feature rarely achievable through conventional means (Puranam, 2021).

Moreover, GenAI's role in distributed cognition transforms the way knowledge is represented and shared within teams. The work of Metcalf, Askay, and Rosenberg (2019) on artificial swarm intelligence demonstrates that AI systems can harness collective intelligence to refine organizational decisions. This is reinforced by the empirical results of Shrestha, Krishna, and Von Krogh (2021), who show that deep learning models, when embedded in organizational workflows, improved decision accuracy by 18–23% in financial forecasting tasks.

A comparative analysis with the work of Allen and Choudhury (2022) reveals that algorithm-augmented decision-making leads to a paradox of empowerment and aversion. While GenAI enhances the abilities of domain experts, it also introduces a psychological barrier—algorithm aversion—especially when outputs challenge conventional wisdom (Dietvorst, Simmons, & Massey, 2015). In contrast, Lebovitz, Lifshitz-Assaf, and Levina (2022) argue that professionals who engage reflexively with GenAI systems tend to co-evolve their judgment strategies, thereby reducing cognitive dissonance and improving confidence in AI-enhanced decisions.

Another key dimension is representational complexity. According to Csaszar and Ostler (2020), the complexity of internal models used by organizations affects their ability to engage in generative reasoning. GenAI lowers the threshold of representational complexity by producing analogies, prototypes, or scenarios that aid understanding. This supports the contingency theory of representation, where higher representational richness aligns with improved strategic flexibility under uncertainty (Csaszar & Levinthal, 2016).

In terms of organizational learning, GenAI contributes by broadening the learning loop. While traditional AI reinforces single-loop learning through optimization, GenAI promotes double-loop learning by challenging the assumptions behind decision rules (Argyris & Schön, 1978; Faraj, Pachidi, & Sayegh, 2018). The findings of Balasubramanian, Ye, and Xu (2022) further illustrate that when organizations substitute human judgment with GenAI systems in uncertain domains, they paradoxically improve long-term adaptive learning due to forced reframing of assumptions and priors.

Eight prior studies provide useful benchmarks to contextualize the impact of GenAI. Afuah and Tucci (2012) explored crowdsourcing for distant problem-solving and found that distributed knowledge access improves innovation breadth. In contrast, GenAI internalizes this diversity, simulating synthetic perspectives without requiring external crowds. Fleming (2001) and Fleming & Sorenson (2004) emphasized recombinant search in innovation processes. GenAI automates and scales this logic, producing thousands of variations and enabling organizations to escape local optima more effectively.

Piezunka & Dahlander (2015) observed that crowdsourced ideas often get filtered by organizational biases. GenAI reduces human filtering bias by treating all permutations with computational neutrality, although human evaluation bias remains. Jeppesen & Lakhani (2010) showed that marginal contributors are more effective in solving complex problems due to cognitive distance. GenAI models, trained on heterogeneous corpora, emulate this marginality synthetically.

Kaplan & Tripsas (2008) emphasized framing effects on innovation outcomes. GenAI reinforces or disrupts cognitive frames, depending on prompt structure and user intent, making the framing process itself an object of iterative design. Gavetti et al. (2012) proposed that strategic cognition shapes firm-level adaptation. The use of GenAI as a "cognitive copilot" enables managers to simulate forward-looking scenarios more comprehensively, enhancing adaptive capacity.

Shrestha et al. (2019) identified structural tensions in AI decision-making. GenAI exacerbates these tensions by increasing the volume and ambiguity of information, demanding new sensemaking structures. Anthony (2021) critiqued black-box algorithmic outputs. The emergence of explainable GenAI, as documented by Senoner, Netland, and Feuerriegel (2022), attempts to restore transparency through visual or textual rationalizations, although limitations remain.

Furthermore, the problem-solving value of GenAI must be considered in light of domain specificity. In high-regulation domains such as healthcare or law, generative models face greater constraints on actionability due to reliability and explainability concerns (Holzinger, 2016; Lebovitz et al., 2022). By contrast, in creative or semi-structured domains such as marketing or design, GenAI accelerates experimentation and personalization (Simone, 2021; Chow, 2020). For instance, Cortex AI helped Visit Utah improve content engagement by 23% through generative optimization of media assets (Cortex, 2022), showcasing immediate application value.

An important discussion also emerges around human-AI teaming. Murray, Rhymer, and Sirmon (2021) outline modes of conjoint agency, where humans and machines act interdependently to shape decisions. GenAI exemplifies this interdependence, requiring users to actively prompt, interpret, and refine outputs. This reflects a shift from automation to augmentation (Raisch & Krakowski, 2021), necessitating new literacies in prompt engineering, validation, and feedback tuning.

Ethical concerns and governance are becoming central in GenAI deployment. Issues of fairness, bias, and epistemic opacity are well documented (Newman, Fast, & Harmon, 2020; Burrell, 2016). As organizations embed GenAI into workflows, the need for algorithmic accountability and explainability becomes critical (Linardatos, Papastefanopoulos, & Kotsiantis, 2020). Early-stage experiments in explainable GenAI (XAI) suggest that textual rationales and confidence estimates can enhance user trust, although these features are still in their infancy (Deng et al., 2022).

The literature suggests that GenAI augments organizational problem-solving through four primary mechanisms: (1) expanding the breadth and depth of cognitive search, (2) supporting hybrid cognition between humans and machines, (3) enhancing representational richness and reframing capabilities, and (4) enabling rapid iteration and scenario simulation. However, these benefits are contingent upon the design of socio-technical systems that embed GenAI responsibly and reflexively

5. Conclusion

This qualitative literature review highlights a significant shift in the organizational problem-solving paradigm: from prediction-focused analytics to generative, creative capabilities facilitated by advanced AI systems. Generative AI (GenAI), as evidenced across various studies (e.g., Raisch & Fomina, 2024; Goodfellow et al., 2014; Krakowski, Luger, & Raisch, 2023), serves not merely as a computational tool but as a cognitive and strategic partner. It enables organizations to expand their exploration space, simulate alternative futures, augment creative ideation, and support hybrid human-machine intelligence.

The integration of GenAI transforms how organizations frame problems, generate solutions, and make decisions under uncertainty. Rather than replacing human judgment, GenAI often complements it, enhancing representational richness and supporting bounded rationality (Puranam, 2021; Shrestha, Krishna, & Von Krogh, 2021). In domains such as design, marketing, and innovation strategy, GenAI significantly reduces the cost of experimentation and ideation, making it possible to explore broader solution landscapes at unprecedented speed (Oh et al., 2019; Cortex, 2022).

Furthermore, the review reveals a convergence between strategic cognition and generative technologies. GenAI helps decision-makers overcome cognitive limitations, challenge prevailing frames, and engage in double-loop learning (Faraj, Pachidi, & Sayegh, 2018; Csaszar & Ostler, 2020). At the same time, the literature calls for caution. As organizations increasingly depend on AI-generated outputs, ethical, epistemological, and practical concerns—such as opacity, bias, and over-reliance—become more pronounced (Burrell, 2016; Newman, Fast, & Harmon, 2020).

In sum, GenAI has the potential to reshape the problem-solving dynamics of organizations by blending computational creativity with human oversight. However, its effectiveness depends on the design of socio-technical systems that facilitate human-AI collaboration, ensure transparency, and build user trust. Future research and practice must focus on embedding these systems in ways that amplify organizational intelligence while safeguarding against cognitive, ethical, and operational blind spots.

6. Limitation

Despite the valuable insights derived from this review, several limitations must be acknowledged. Scope of Literature: This review focused on academic publications and selected industry case studies up to mid-2024. As the field of generative AI is rapidly evolving, newer developments—especially those in non-English or proprietary industry contexts—may not have been captured. The findings may therefore not fully reflect the most recent advancements or niche applications. Conceptual Diversity: Generative AI encompasses a wide array of technologies (e.g., large language models, GANs, generative design platforms), each with distinct affordances. This review treated GenAI as a somewhat unified category, which may oversimplify the nuanced differences between tools, sectors, and use cases.

Lack of Empirical Meta-Analysis: While the review synthesizes insights from qualitative and conceptual studies, it does not include a formal meta-analysis of empirical data or effect sizes. As such, conclusions about impact, adoption rates, and organizational outcomes remain interpretative rather than statistically validated. Disciplinary Bias: The majority of reviewed sources are situated within management, information systems, and organizational science literature. Important insights from adjacent fields such as cognitive science, ethics, and human-computer interaction may be underrepresented, which could narrow the interdisciplinary understanding of GenAI's organizational implications.

Human Factors Underexplored: While the review touches on issues such as algorithm aversion, hybrid teaming, and trust, it lacks deep engagement with user-centered studies on how employees, managers, and teams experience and interact with GenAI over time (Allen & Choudhury, 2022; Lebovitz, Lifshitz-Assaf, & Levina, 2022). Future research should examine behavioral, emotional, and cultural dynamics in more depth. Dynamic Contexts: The review primarily reflects GenAI's role in relatively stable organizational settings. Its application in crisis management, political decision-making, or non-profit contexts remains an open area. Moreover, the long-term effects of generative systems on strategic inertia, groupthink, or innovation fatigue have not yet been systematically studied.

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