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The Algorithmic Mediation of Human Judgment: A Hybrid Systematic-Bibliometric Review of AI's Impact on Cognitive Decision-Making and Automation Bias

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Systematic Review

Keywords: Artificial intelligence, cognitive offloading, automation bias, human-AI collaboration, hybrid intelligence, strategic decision-making, systematic-bibliometric review

Posted Date: April 30th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9565332/v1

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Additional Declarations: The authors declare no competing interests.

Abstract

Organizations increasingly rely on artificial intelligence (AI) to support complex decision-making. While these tools improve efficiency, researchers caution that over-reliance on algorithms may cause cognitive offloading, automation bias, and the erosion of professional expertise. To map how this issue is being studied, the researcher conducted a hybrid systematic-bibliometric review of the literature published between 2015 and 2026. Our bibliometric network analysis yielded three primary research clusters: (1) Automation Bias and Algorithmic Aversion, (2) Cognitive Offloading and Deskilling, and (3) Human-AI Collaboration in Strategic Management. A targeted qualitative synthesis of the core texts within these clusters shows that the immediate operational benefits of AI often come at the expense of long-term critical thinking and independent verification. The study argue that safeguarding human agency requires moving beyond simple human-in-the-loop oversight. The paper concludes by outlining a research agenda centered on the structural integration of hybrid intelligence and interface models that utilize "friction-by-design."

I. INTRODUCTION

Artificial intelligence (AI) has shifted from a peripheral computational aid to a core component of human judgment. In fields ranging from healthcare and law to public administration and finance, professionals now routinely rely on automated decision support systems (ADSS) and generative AI to process information and formulate strategies (Danelid, 2026; Gillespie et al., 2026; Monteith et al., 2026; Waqar Ahmad et al., 2025).

While the operational advantages of these tools are evident, researchers are increasingly focused on the psychological and cognitive trade-offs of heavy AI reliance. Issues such as *automation bias*—the tendency for users to defer to machine-generated advice over their own judgment—and *cognitive offloading* challenge traditional models of human agency and expertise (Cook, 2026; Laux & Ruschemeier, 2025; Pearson et al., 2026; Udoh et al., 2025).

Currently, the literature addressing these phenomena is fragmented across various disciplines, including computer science, psychology, and organizational management. Existing systematic reviews tend to miss the broader structural map of the field, while standalone bibliometric studies generally fail to capture the nuanced qualitative findings regarding actual cognitive outcomes. To address this gap, this paper applies a hybrid systematic-bibliometric methodology.

Research Questions

1. What is the intellectual structure and thematic evolution of research regarding AI's impact on human decision-making?
2. Which primary thematic clusters define the current research front?
3. Within these clusters, what does the empirical evidence reveal about AI's effect on cognitive offloading, automation bias, and strategic decision-making?

II. METHODOLOGY

This study adopted a dual-stage Hybrid Systematic-Bibliometric workflow (Donthu et al., 2021; Paul et al., 2021) to ensure reproducibility, structured in accordance with PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines (Page et al., 2021).

- *Data Collection and Search Strategy*

A systematic search was conducted across the Web of Science and Scopus databases to capture literature published between January 2015 and March 2026, capturing the modern era of AI deployment. The Boolean query was structured as follows: Artificial Intelligence, AI, Generative AI, Machine Learning, Decision-Making, Judgment, Strategic Management, Cognitive Offloading, Automation Bias, Algorithmic Aversion, Deskilling, and Trust.

Corpus A (Macro-Level Bibliometric Dataset) - This initial search established the overall bibliographic landscape. After removing duplicate records, the metadata (titles, abstracts, keywords, and citations) was extracted, resulting in Corpus A (n = 46).

Corpus B (Micro-Level Systematic Dataset) - A two-stage screening process was applied to Corpus A. Two independent reviewers evaluated the titles and abstracts, followed by a full-text assessment. Articles were included if they were (a) peer-reviewed or published by recognized academic/industry institutions, (b) available in English, and (c) specifically focused on human cognitive or behavioral outcomes during AI interaction. Purely technical papers detailing algorithmic architecture without a human-in-the-loop component were excluded. The remaining texts formed Corpus B, which was used for the qualitative synthesis.

- *Analytical Approach*

Bibliometric Mapping (Stage 1) - *Corpus A* underwent co-word analysis and bibliographic coupling. Descriptive performance metrics were generated using the *bibliometrix* R package (Aria & Cuccurullo, 2017), and network visualizations were mapped via VOSviewer (van Eck & Waltman, 2010). The researcher applied association strength normalization and fractional counting to accurately map the intellectual structure and generate thematic clusters.

Systematic Synthesis (Stage 2) - *Corpus B* was analyzed using deductive thematic synthesis. A standardized coding matrix was used to extract data on research design, context, psychological mechanisms, and cognitive outcomes. These qualitative findings were then directly mapped onto the macro-level clusters identified in Stage 1.

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III. RESULTS

- *Part A: The Bibliometric Landscape (Macro-Level)*

The initial bibliometric analysis of *Corpus A* charted the structural evolution of the field. A review of publication dates showed a distinct concentration of research published post-2022, aligning with the widespread adoption of advanced generative AI models.

Keyword and thematic co-occurrence analyses revealed a network of 118 high-frequency keywords. The current literature structurally divides into three highly centralized clusters:

Cluster 1 (Red): Automation Bias, Trust, and Algorithmic Aversion. This domain focuses heavily on user reliance. Dominant keywords include automation bias, algorithmic aversion, trust, clinical decision support, and explainable AI.

Cluster 2 (Blue): Cognitive Offloading, Deskilling, and Educational Impacts. This cluster captures the developmental and psychological aspects of AI use, featuring terms like cognitive offloading, deskilling, critical thinking, education, and generative AI.

Cluster 3 (Green): Strategic Decision-Making and Human-AI Collaboration. Bridging cognition and organizational systems, this cluster centers on strategic decision-making, human-AI collaboration, enterprise, and data analytics.

- *Part B: Systematic Synthesis (Micro-Level)*

Using the bibliometric network as an organizational framework, this study synthesized the empirical and theoretical findings from *Corpus B* across the three identified clusters.

- *Synthesis of Cluster 1: Automation Bias and Algorithmic Aversion*

This cluster examines the volatility of human trust in automated systems, mapping a spectrum from over-reliance to complete rejection.

Early evidence of algorithms restructuring clinical judgment emerged decades ago (Hillson et al., 1995), but modern implementations carry unprecedented societal weight. In public policy, tools used to predict recidivism have exhibited systematic bias against specific demographics (Angwin et al., 2016), and algorithmic tenant screening heavily influences landlord assessments in real estate (So, 2022). Despite awareness of these flaws, decision-makers in public administration routinely defer to automated support systems (Danelid, 2026). In recruitment contexts, human reviewers selectively adhere to biased AI outputs, effectively exacerbating systemic prejudice rather than correcting it (Alon-Barkat & Busuioc, 2023; Marieke & Sach, 2024).

When humans inherit these biases, their subsequent reactions to system failures fluctuate between misplaced trust and outright algorithmic aversion (Cao et al., 2024; Jones, 2021; Pearson et al., 2026; Vicente & Matute, 2023). User perceptions of the "algorithmic imaginary" heavily dictate this engagement and trust (Bucher, 2016). System updates can further disrupt this fragile collaboration if not managed transparently (Mohanty et al., 2025). Furthermore, users often develop complex workaround strategies to bypass biased systems (Overbye-Thompson & Rice, 2025), while poorly designed AI interfaces can lead to manipulative algorithmic behaviors (Zhang et al., 2025).

A critical finding across this cluster is that Explainable AI (XAI) does not reliably cure automation bias. Providing users with technical explanations often creates a false sense of security, elevating trust without improving decision accuracy (Chen et al., 2023; Han & Ko, 2025; Jones-Jang & Park, 2022; Treiman et al., 2024). Similarly, legal frameworks like the European AI Act rely heavily on mandated "human oversight," but without targeted behavioral interventions, simply placing a human in the loop remains an ineffective legal remedy (Laux & Ruschemeier, 2025; Shamszare & Choudhury, 2023). Building genuine trust requires proactively mitigating aversion triggers before

deploying decision aids (Burton et al., 2020), considering ethical algorithmic approaches in human resource management (Rodgers et al., 2022), and understanding how test types and explanations alter applicant acceptance (Wesche et al., 2022).

- *Synthesis of Cluster 2: Cognitive Offloading and Deskilling*

Research in this cluster evaluates the neurological and developmental consequences of outsourcing cognitive labor to machines.

While offloading routine tasks to AI frees up mental bandwidth, it actively alters how individuals cope with complex problems (Chirayath et al., 2025; P V, 2026; Shalu et al., 2025). This dependency carries physiological consequences; LLM-assisted writers exhibit significantly weaker brain interconnectivity and deep processing on EEG scans compared to unassisted individuals (Kosmyna et al., 2025).

A stark developmental divide has emerged. Experienced professionals face a slow erosion of existing skills, but students risk *skill foreclosure*—never developing foundational analytical skills in the first place (Cook, 2026; Lodge & Loble, 2026; Shen & Tamkin, 2026). Unstructured AI use boosts short-term performance but severely stunts deeper knowledge acquisition (Nosta, 2025). Unchecked reliance on large language models also correlates with self-reported declines in cognitive effort (Lee et al., 2025; Royce & Bennette, 2025) and risks homogenizing human thought and collective creativity (Doshi et al., 2024; Sourati et al., 2026). This dynamic creates widespread anxiety and decision fatigue (Ahmad, Han, et al., 2023; Sternberg, 2026), threatening the self-efficacy central to modern knowledge work (Winter et al., 2025).

Professional deskilling is particularly acute in specialized fields (El Tarhouny & Farghaly, 2026). In healthcare, relying heavily on diagnostic AI threatens to erode the clinical empathy and intuition of future practitioners, reinforcing pre-existing biases (Ahmed, 2025; Monteith et al., 2026). Legal professionals similarly find that AI integration demands a deliberate recalibration of academic and professional expertise (Greggwirth, 2025; Lin & Sohail, 2026). To counteract these declines, educators must reframe AI as a "dialogic partner" to encourage active critical questioning rather than passive acceptance (Colleague AI, 2025; Gerlich, 2025; Tang et al., 2024; Tian et al., 2026; Zhu & Yang, 2026).

- *Synthesis of Cluster 3: Human-AI Collaboration and Strategic Management*

The third cluster shifts the focus from individual psychology to organizational strategy and enterprise integration.

Effectively integrating AI into strategy requires balancing machine learning outputs with human intuition (Bakr et al., 2025; Balbaa & Abdurashidova, 2024; Waqar Ahmad et al., 2025). AI fundamentally reshapes strategic intuition but cannot replace the causal reasoning and analogical imagination unique to human cognition (Csaszar et al., 2024; Felin & Holweg, 2024; Rindova & Martins, 2024). This reality is forcing rapid changes in enterprise workflows, compelling organizations to align AI adoption with business processes to generate measurable value (Couture, 2025; Gorka et al., 2025; Kim et al., 2025; Taguimdje et al., 2020).

To successfully adopt digital technologies, enterprises require an entrepreneurial orientation (Vrontis et al., 2022) and must overcome executive-level algorithm aversion (Harrell, 2016). Financial sectors and supply chains increasingly rely on deep-learning models for risk management (Belanche et al., 2019; Wong et al., 2022), while healthcare leverages AI for macro-level pandemic preparedness (Syrowatka et al., 2021). However, workforce audits indicate that strategic planning must carefully differentiate between tasks suitable for full automation and those requiring human augmentation (Shao et al., 2025).

When managers evaluate AI-generated strategic options, they inevitably introduce their own "bias in the loop" (Beck et al., 2025). Furthermore, human-AI collaboration can enhance task performance but inadvertently undermine a worker's intrinsic motivation (Wu et al., 2025) and requires careful alignment of financial incentives (Yin et al., 2013). Group dynamics and composition also heavily dictate collective performance when using AI tools (Almaatouq et al., 2023). Ultimately, organizations achieve the best results through "Hybrid Intelligence" frameworks—symbiotic environments where human intuition is systematically validated against algorithmic data (Bouha & Benhayoun, 2026; Jarrahi, 2018; Mallon et al., 2026). Cultivating this requires robust governance frameworks and strong digital literacy across the workforce (Fragiadakis et al., 2024; Gillespie et al., 2026; Khosravi et al., 2024; Nofal et al., 2025; Tyagi et al., 2026; Xu et al., 2025; Yamani et al., 2025).

- *Summary Tables*

To contextualize the findings of the hybrid review, Table 1 details the core thematic clusters derived from the network parameters of the bibliometric mapping. Table 2 provides a structured extraction of the key studies systematically synthesized in the micro-level analysis, explicitly mapping them back to their originating bibliometric clusters.

Table 1

Bibliometric Cluster Summary and Network Characteristics

Cluster	Thematic Focus	Keyword Nodes	Core Bibliometric Keywords	Primary Application Domains
1	Automation Bias & Algorithmic Aversion	42	Automation bias	Public sector
			Algorithmic aversion	Legal
			Trust	Recruitment
			Clinical decision support	Clinical diagnostics
			Explainable AI	
2	Cognitive Offloading & Deskilling	38	Cognitive offloading	Education
			Deskilling	Cognitive psychology
			Critical thinking	Professional development
			Education	
			Generative AI	
3	Human-AI Collaboration & Strategic Management	38	Strategic decision-making	Enterprise strategy
			Human-AI collaboration	Finance
			Enterprise	Entrepreneurship
			Data analytics	Organizational management

Table 2

Systematic Extraction of Key Empirical and Theoretical Literature (Corpus B)

Authors (Year)	Cluster	Study Design & Sample	Domain / Context	Key Findings & Strategic Implications
Ahmad, Han, et al. (2023)	2	Theoretical Framework	Education	**Finding**: AI use reduces student effort and creates "laziness" and decision fatigue in educational contexts.
Almaatouq et al. (2023)	3	Empirical Analysis	Cognitive Science / Teams	**Finding**: Analyzes the effects of group composition and dynamics on collective performance. **Implication**: AI tools must be calibrated to team dynamics, not just individual decision-makers.
Alon-Barkat & Busuioc (2023)	1	Experimental Survey	Public Sector / Recruitment	**Finding**: Human reviewers selectively adhere to biased AI outputs, exacerbating rather than correcting systemic prejudice. **Implication**: Human-in-the-loop oversight is insufficient for mitigating systemic algorithmic bias.
Angwin et al. (2016)	1	Investigative Analysis	Public Policy / Justice	**Finding**: Software used to predict recidivism exhibited systematic bias against specific demographics. **Implication**: Algorithms deployed in high-stakes public contexts require rigorous auditing for disparate impact.
Bakr et al. (2025)	3	Thematic Analysis	Strategic Management	**Finding**: Explores the tension between human intuition and machine learning algorithms in modern management frameworks.
Balbaa & Abdurashidova (2024)	3	Literature Review	Economics / Enterprise	**Finding**: AI acts as a primary transformative force in economic business processes and overarching strategic management.
Beck et al. (2025)	3	Randomized Experiment (N = 2,784)	Strategy / Management	**Finding**: Humans evaluating AI-generated strategic suggestions inherently introduce their own biases. **Implication**: Organizations require engineered "hybrid intelligence" frameworks to structure evaluations.
Belanche et al. (2019)	3	Empirical Analysis	Fintech / Finance	**Finding**: Analyzes the psychological and operational drivers of AI adoption within financial technology ecosystems. **Implication**: Understanding user and institutional adoption drivers is necessary before scaling algorithmic tools.
Ahmed (2025)	2	Editorial Review	Medical Education	**Finding**: Generative AI tools frequently encode bias, fabricate sources, and lead to early over-reliance. **Implication**: Medical curricula must urgently adjust to mitigate the likelihood of deskilling novice learners.
Bouha & Benhayoun (2026)	3	Framework Development	Enterprise Strategy	**Finding**: Proposes an employee-focused, context-aware framework of AI adoption to balance performance with cognitive load.
Bucher (2016)	1	Empirical Analysis	Social Media	**Finding**: Explores the "algorithmic imaginary" and the ordinary effects of Facebook algorithms on users. **Implication**: User perceptions of algorithms heavily dictate their engagement and trust.
Burton et al. (2020)	1	Systematic Review	Decision Science	**Finding**: Evaluates the systematic factors leading to algorithm aversion in augmented decision-making contexts. **Implication**: Trust building requires mitigating aversion triggers before deploying decision aids.
Cao et al. (2024)	1	Empirical Analysis	HCI / Chatbot Interaction	**Finding**: Cognitive and affective pathways heavily dictate how users understand, respond to, and forgive AI chatbot errors.

Authors (Year)	Cluster	Study Design & Sample	Domain / Context	Key Findings & Strategic Implications
				Implication: Trust repair mechanisms must account for emotional and cognitive responses to automation failure.
Chen et al. (2023)	1	Mixed Methods Study (N = 26)	Explainable AI (XAI)	**Finding**: XAI mechanisms frequently create a false sense of security, elevating human trust without improving actual decision accuracy. **Implication**: Interface design must prioritize cognitive friction over mere transparency.
Chirayath et al. (2025)	2	Theoretical Review	Psychology	**Finding**: Cognitive offloading fundamentally alters the mental architecture required for deep coping. **Implication**: Long-term over-reliance diminishes human autonomy in coping with complex problem-solving.
Colleague AI (2025)	2	Case Study / Tools	Education / Teaching	**Finding**: Outlines mechanisms for fostering critical thinking via the active engagement between students and AI tools.
Cook (2026)	2	Theoretical Review	Education / Development	**Finding**: A generational divide exists where experienced professionals experience skill atrophy, but developing students face skill foreclosure. **Implication**: Educational models must prioritize the foundational building of critical analysis before AI integration.
Couture (2025)	3	Industry Analysis	Legal Profession	**Finding**: Details how artificial intelligence acts as a disruptive technology redefining traditional law firm business models.
Csaszar et al. (2024)	3	Randomized Controlled Trial	Enterprise / Investment	**Finding**: AI reshapes, rather than replaces, strategic intuition. **Implication**: Effective use requires combining AI insights with high data literacy and an entrepreneurial orientation.
Danelid (2026)	1	Systematic Review (N = 13 studies)	Public Sector	**Finding**: Decision-makers routinely defer to automated support systems even when explicitly aware of the system's potential flaws. **Implication**: Training alone cannot overcome deeply ingrained automation bias.
Doshi et al. (2024)	2	Empirical Analysis	Strategy / Content Generation	**Finding**: Generative AI assistance boosts individual creativity scores but causes outputs to become highly similar to each other. **Implication**: AI use can artificially enhance individual performance at the direct expense of collective creativity and diversity.
El Tarhouny & Farghaly (2026)	2	Thematic Review	Medicine	**Finding**: The increasing reliance on automation in medicine fundamentally threatens human cognitive skill retention ("brain over automation").
Felin & Holweg (2024)	3	Theoretical Analysis	Strategy / Causal Reasoning	**Finding**: Disputes the notion that AI's data-based models can replace human decision-making under genuine uncertainty. **Implication**: Human causal reasoning remains an irreplaceable asset for navigating novel strategic environments.
Fragiadakis et al. (2024)	3	Methodology Review	HCI	**Finding**: Proposes an updated methodological framework for the proper evaluation of human-AI collaborative workflows.
Gerlich (2025)	2	Mixed Methods (N = 666 survey, 50 interviews)	Education & Society	**Finding**: Increased reliance on AI for complex decisions reduces critical thinking, while using it for administrative offloading preserves it.

Authors (Year)	Cluster	Study Design & Sample	Domain / Context	Key Findings & Strategic Implications
				Implication: Policies should restrict offloading of core analytical tasks to prevent cognitive decline.
Gillespie et al. (2026)	3	Thematic Review	Healthcare Operations	**Finding**: Integrating LLMs into strategy supplements human judgment, but requires strict governance to realize organizational objectives. **Implication**: Robust governance frameworks must be instituted to safely scale AI in operations.
Gorka et al. (2025)	3	Thematic Review	Enterprise / Business Process	**Finding**: Investigates the direct impact of artificial intelligence integration on the enterprise decision-making process. **Implication**: Enterprises must fundamentally adjust operational workflows to accommodate algorithmic insights.
Greggwirth (2025)	2	Industry Analysis	Legal Profession	**Finding**: Outlines the specific risks and opportunities for legal professionals relying on AI for critical analysis.
Han & Ko (2025)	1	Behavioral Analysis	Finance	**Finding**: Evaluates trust formation, the impact of AI errors, and trust repair strategies within human-AI financial advisory systems.
Harrell (2016)	3	Expert Commentary	Management	**Finding**: Argues that managers should not fear algorithm-based decision making. **Implication**: Overcoming executive algorithm aversion is a prerequisite for enterprise modernization.
Hillson et al. (1995)	1	Empirical Analysis	Medical Diagnostics	**Finding**: Computer-assisted interpretations significantly alter physicians' diagnostic decisions. **Implication**: Early baseline evidence that algorithmic assistance fundamentally restructures clinical judgment.
Jarrahi (2018)	3	Theoretical Review	Organizational Behavior	**Finding**: Proposes a "Human-AI Symbiosis" model for the future of work and organizational decision-making. **Implication**: Strategic planning should focus on symbiotic augmentation rather than direct human replacement.
Jones (2021)	1	Reference Guide	Psychology	**Finding**: Defines algorithm aversion and details the psychological mechanisms that cause humans to reject algorithmic advice.
Jones-Jang & Park (2022)	1	Empirical Analysis	HCI / Trust Repair	**Finding**: Overly technical explanations can inadvertently reinforce misplaced trust among users with low AI literacy. **Implication**: User engagement and independent verification efforts are mandatory to overcome system complacency.
Khosravi et al. (2024)	3	Thematic Analysis	Medical Diagnostics	**Finding**: Provides a thematic overview of AI frameworks applied directly to high-stakes healthcare operations.
Kim et al. (2025)	3	Systematic Review & AHP Analysis	Legal Domain	**Finding**: Integrating AI into legal practice presents distinct operational barriers that outpace purely technological concerns. **Implication**: Expert-driven, structured frameworks are necessary to safely integrate AI into legal workflows.
Kosmyna et al. (2025)	2	Controlled EEG Experiment	Education / Writing	**Finding**: LLM-assisted writers showed the weakest brain interconnectivity (EEG patterns) compared to unassisted participants.

Authors (Year)	Cluster	Study Design & Sample	Domain / Context	Key Findings & Strategic Implications
				Implication: AI assistance in cognitive tasks physically reduces brain engagement and deep processing.
Laux & Ruschemeier (2025)	1	Policy / Legal Review	AI Regulation (EU AI Act)	**Finding**: Current legal mandates for human oversight fail to properly account for the psychological realities of automation bias. **Implication**: Regulatory frameworks must integrate targeted behavioral and psychological interventions.
Lee et al. (2025)	2	Survey of Knowledge Workers	HCI / General Use	**Finding**: Widespread generative AI use correlates with self-reported reductions in cognitive effort and independent verification among users. **Implication**: Systems should prompt users to independently verify claims to combat decision fatigue.
Lin & Sohail (2026)	2	Thematic Essay	Academic Research	**Finding**: Generative AI is forcing a complete recalibration of what defines academic expertise and scholarly independence.
Lodge & Loble (2026)	2	Institutional Report	Education Infrastructure	**Finding**: Unstructured AI use creates a profound risk that students will outsource the cognitive work necessary for lifelong learning. **Implication**: Institutions must actively safeguard the human "thinking infrastructure."
Mallon et al. (2026)	3	Industry Report	Enterprise Strategy	**Finding**: Treating AI as mere software leads to failure; leading organizations treat AI systems as "agentic workers." **Implication**: Achieving strategic outcomes requires adopting hybrid intelligence architectures to manage these agents.
Marieke & Sach (2024)	1	Experimental Study (N = 132)	HR / Recruitment	**Finding**: Participants exposed to biased applicant scoring systems exhibit selective adherence to automated recommendations. **Implication**: Evaluating the behavioral perils of AI requires closely monitoring user interactions with biased scoring.
Mohanty et al. (2025)	1	Empirical Analysis	HCI / Systems	**Finding**: Explores the impact of underlying AI model updates in AI-infused systems. **Implication**: System updates can disrupt human-AI collaboration if not managed transparently.
Monteith et al. (2026)	2	Thematic Review	Medicine / Healthcare	**Finding**: Over-reliance on diagnostic algorithms erodes clinical intuition and reinforces pre-existing cognitive biases in practitioners. **Implication**: Medical curricula must be adjusted to deliberately test unassisted diagnostic proficiency.
Nofal et al. (2025)	3	Empirical Program	Healthcare	**Finding**: Analyzes the positive impact of an AI enhancement program on healthcare providers' knowledge and workplace flourishing.
Nosta (2025)	2	Expert Commentary	Psychology	**Finding**: Cognitive offloading to AI boosts immediate performance metrics but actively hinders deep knowledge acquisition. **Implication**: Relying heavily on AI for analysis sacrifices long-term knowledge acquisition for short-term gains.
Overbye-Thompson & Rice (2025)	1	Theoretical & Empirical	Information Systems	**Finding**: Users detect bias through cue routes and develop complex adaptive workaround strategies through action routes to bypass biased ADSS. **Implication**: Designers must understand how users subvert algorithms to build better collaborative

Authors (Year)	Cluster	Study Design & Sample	Domain / Context	Key Findings & Strategic Implications
				systems.
P V (2026)	2	Narrative Review	Education / Professional	**Finding**: Excessive dependency degrades cognitive autonomy, though balanced use maintains it. **Implication**: AI literacy and self-regulation skills are mandatory to prevent cognitive decline while maximizing benefits.
Pearson et al. (2026)	1	Experimental Study (N = 295)	Facial Authenticity Judgments	**Finding**: Participants receiving AI guidance with positive AI attitudes showed poorer discriminability between real and synthetic faces. **Implication**: AI-derived guidance is uniquely placed to engender biases, requiring structural safeguards beyond unaided human judgment.
Rindova & Martins (2024)	3	Theoretical Framework	Strategic Theory Building	**Finding**: Strategists develop theories by combining knowledge and imagination through analogy, an epistemic stance unique to human cognition. **Implication**: Human analogical reasoning should guide strategic direction, with AI acting only as a supporting knowledge base.
Rodgers et al. (2022)	1	Theoretical Framework	HR Management	**Finding**: Proposes an AI algorithmic approach specifically geared toward maintaining ethical decision-making in human resource processes.
Royce & Bennette (2025)	2	Thematic Analysis	Critical Thinking	**Finding**: Investigates the fundamental conflict between rapid AI answers and the slow, deliberate process required for critical thinking skills.
Shalu et al. (2025)	2	Cognitive Analysis	Daily Technology Use	**Finding**: Anxiety toward AI correlates directly with increased decision fatigue and cognitive strain during daily technology interactions.
Shamszare & Choudhury (2023)	1	Thematic Analysis	Clinical Integration	**Finding**: Maps clinicians' complex perceptions of AI, specifically focusing on the tension between clinical trust and perceived risk.
Shao et al. (2025)	3	Workforce Audit	U.S. Workforce	**Finding**: Audited the automation and augmentation potential of AI agents across the U.S. workforce. **Implication**: Strategic planning must differentiate between tasks suitable for agentic automation versus human augmentation.
Shen & Tamkin (2026)	2	Thematic Analysis	Skill Formation	**Finding**: Routine AI use fundamentally alters the trajectory of how humans form and maintain complex skills. **Implication**: Continued AI substitution poses a severe risk of permanent skill foreclosure for developing learners.
So (2022)	1	Empirical Analysis	Housing Policy / Real Estate	**Finding**: Measured landlord assessments of tenant screening reports to determine which information matters. **Implication**: Algorithmic screening reports heavily influence human decision-makers in high-stakes socio-economic domains.
Sourati et al. (2026)	2	Thematic Review	Cognitive Science	**Finding**: Unchecked use of large language models is leading to a quantifiable homogenizing effect on human expression, thought, and creativity. **Implication**: The loss of cognitive diversity requires structural interventions to maintain independent analytical skills.
Sternberg (2026)	2	Theoretical Framework	Education	**Finding**: Explores the dual capacity of AI to simultaneously increase baseline cognitive output while decreasing genuine individual cognitive abilities.

Authors (Year)	Cluster	Study Design & Sample	Domain / Context	Key Findings & Strategic Implications
Syrowatka et al. (2021)	3	Scoping Review	Medicine / Public Health	**Finding**: Identified key use cases for leveraging artificial intelligence in pandemic preparedness and response. **Implication**: AI serves as a critical structural tool for macro-level healthcare strategy.
Taguimdje et al. (2020)	3	Empirical Analysis	Business Process Management	**Finding**: Identifies the business value and influence of AI-based transformation projects on overall firm performance. **Implication**: Strategic AI adoption must align with business processes to generate measurable value.
Tang et al. (2024)	2	Action Research (N = 4 teachers)	Secondary Education	**Finding**: Reframing generative AI as a "dialogic partner" successfully enhances active engagement and critical questioning among students. **Implication**: Educational integration should position AI as a tool for debate, requiring constant human validation.
Tian et al. (2026)	2	Empirical Analysis	HCI / Decision Making	**Finding**: Explores how systems designed specifically to elicit critical thinking alter the flow and outcomes of human-AI collaboration.
Treiman et al. (2024)	1	Experimental Analysis	Decision-Making	**Finding**: Training humans to rely on AI algorithms has lasting consequences on their unassisted, independent decision-making capabilities.
Tyagi et al. (2026)	3	Conceptual Review	Management	**Finding**: Reviews the integration layers required to facilitate effective and safe collaboration between human actors and AI tools.
Udoh et al. (2025)	1 & 2	Thematic Review	Human Agency	**Finding**: Algorithmic interventions are progressively redefining the boundaries of human capability, identity, and independent agency.
Vicente & Matute (2023)	1	Empirical Analysis	Psychology	**Finding**: Humans unconsciously absorb and inherit the biases present in the artificial intelligence systems they interact with.
Vrontis et al. (2022)	3	Empirical Analysis	SMEs / Strategy	**Finding**: Entrepreneurial orientation acts as a moderating role in the adoption of digital technologies for sustainability and value creation. **Implication**: Enterprise culture dictates the success of digital and algorithmic transformations.
Waqar Ahmad et al. (2025)	3	Thematic Analysis	Finance	**Finding**: Extensively reviews how AI integrations dictate modern financial decision-making and economic policy modeling.
Wesche et al. (2022)	1	Empirical Analysis	HR / Recruitment	**Finding**: Evaluated people's reactions to decisions by human versus algorithmic decision-makers and the role of explanations. **Implication**: Explanations and test types significantly alter applicant acceptance of AI decisions.
Winter et al. (2025)	2	Thematic Analysis	Knowledge Work / Ethics	**Finding**: The increasing presence of AI creates a peril for the future of knowledge work by threatening human self-efficacy. **Implication**: Preserving worker self-efficacy must be a central pillar of ethical AI deployment.
Wong et al. (2022)	3	PLS-SEM-ANN Analysis	Supply Chain Management	**Finding**: AI-driven risk management significantly enhances supply chain agility. **Implication**: Deep-learning predictive models are essential for robust enterprise risk management.
Wu et al. (2025)	3	Empirical Analysis	Human-AI Collaboration	**Finding**: Human-generative AI collaboration enhances task performance but undermines the human's intrinsic motivation.

Authors (Year)	Cluster	Study Design & Sample	Domain / Context	Key Findings & Strategic Implications
				Implication: Organizations must balance efficiency gains against the potential loss of worker intrinsic motivation.
Xu et al. (2025)	3	Theoretical Review	Human-AI Reliance	**Finding**: Investigates how intuitive decision-making frameworks can be preserved and enhanced within collaborative AI interfaces.
Yamani et al. (2025)	3	Mixed Methods (Case study & Survey)	Enterprise Management	**Finding**: Data analytical skills and an entrepreneurial mindset are vital for optimizing AI advantages and avoiding unintended consequences. **Implication**: Organizations must cultivate digital literacy alongside entrepreneurial culture to maximize AI value.
Yin et al. (2013)	3	Empirical Analysis	Online Labor Markets	**Finding**: Analyzed the effects of performance-contingent financial incentives in online labor markets. **Implication**: Incentive structures must be carefully aligned with algorithmic task deployment to ensure quality.
Zhang et al. (2025)	1	Taxonomy Development	Human-AI Relationships	**Finding**: Identifies the "dark side" of AI companionship through a taxonomy of harmful algorithmic behaviors in user relationships. **Implication**: Interface design must safeguard users from manipulative or harmful long-term algorithmic interactions.
Zhu & Yang (2026)	2	Empirical Analysis	Education	**Finding**: Evaluates how generative AI impacts graduate research competence, heavily moderated by the student's baseline self-efficacy.

IV. DISCUSSION AND FUTURE RESEARCH AGENDA

The synthesis reveals a structural transition across professional domains: organizations are moving from using AI for basic task execution to relying on it as a core epistemic mediator. This creates several operational and psychological friction points that align with our bibliometric clusters.

The Myth of Human Oversight

As mapped in Cluster 1, simply placing a human in the loop fails to prevent algorithmic errors from becoming real-world decisions. Because people naturally conserve cognitive effort, they default to automation bias when confronted with complex, system-generated recommendations (Beck et al., 2025; Pearson et al., 2026). Relying on explainable AI (XAI) to fix this dynamic is ineffective; system transparency often breeds false confidence rather than genuine scrutiny (Chen et al., 2023).

Generational Deskilling

Findings from Cluster 2 expose a severe deskilling trajectory. While veteran professionals may experience a gradual softening of intuitive expertise, novice learners face a much higher risk of skill foreclosure. Bypassing the friction of initial learning by offloading tasks to AI prevents the formation of the neural and cognitive infrastructure necessary for critical analysis (Cook, 2026; Kosmyna et al., 2025). This over-reliance directly threatens cognitive diversity and worker self-efficacy (Sourati et al., 2026; Winter et al., 2025).

Designing Hybrid Intelligence

Cluster 3 demonstrates that enterprise success depends on treating AI as an agentic collaborator rather than an infallible oracle. High-performing organizations engineer hybrid environments where human traits—such as causal reasoning, imagination, and strategic intuition—are deliberately paired with algorithmic data aggregation (Felin & Holweg, 2024; Rindova & Martins, 2024; Yamani et al., 2025).

Future Research Directions

Based on the empirical gaps identified in this review, future research should prioritize the following areas:

1. Friction-by-Design - Developers need to investigate user interfaces that purposefully introduce "cognitive friction"—brief operational pauses that force users to critically assess an AI's output before accepting a decision.
2. Longitudinal Studies on Deskilling- There is a distinct lack of long-term data tracking the actual rate of cognitive skill degradation in high-AI environments (such as radiology or legal drafting).
3. Psychological Efficacy of XAI - Explainable AI models should be evaluated on whether they actually succeed in reducing automation bias in practice, not just on their technical clarity.
4. Frameworks for Hybrid Intelligence - Management research must clarify how organizations can successfully design workflows that balance automated data aggregation with human auditing (Gillespie et al., 2026).

V. CONCLUSION

This hybrid systematic-bibliometric review illustrates that AI's impact on decision-making is fundamentally a psychological and organizational challenge. By mapping the literature, the study identified a triad of pressing issues: the failure of explainability to curb automation bias, the distinct threat of cognitive deskilling, and the complexities of blending AI into strategic management. Moving forward, the primary challenge is not simply improving algorithm accuracy, but protecting and cultivating human cognitive agency. Ensuring that AI serves as a tool for augmentation rather than erosion requires organizations and policymakers to deliberately design collaborative, friction-based workflows that demand active human engagement.

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