From Artificial Intelligence to Rational Intelligence: How Algorithmic Rationality Reshapes Consumer Decision-Making

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Abstract: This study develops a conceptual framework to clarify the influence of algorithmic rationality on consumer decision-making by analyzing its psychological mechanisms and identifying its limiting conditions. The framework demonstrates that algorithmic ranking and personalization narrow evaluation sets and redefine decision criteria, thereby reshaping the processes of searching, evaluating, and selecting options. Decision quality improves when algorithmic outputs enable meaningful user control and reduce information friction and cognitive load. These conditions foster calibrated trust rather than uncritical conformity. However, the same features may induce conformity, overconfidence, or reactive behaviors if algorithmic authority replaces critical judgment, or if transparency and personalization raise concerns about manipulation or legitimacy. The framework also clarifies how decision risk, consequence severity, product characteristics, and consumer understanding moderate these effects. These factors determine whether algorithms serve as effective decision support tools or as sources of welfare-related errors and resistance. The article highlights that rational intelligence can both enhance and undermine consumer decision quality. The theory-driven propositions contribute to research on consumer decision-making and algorithmic rationality, providing a foundation for future empirical investigation.

Keywords: artificial intelligence, algorithmic rationality, consumer decision-making

JEL Classification codes: D11, D91, O33

INTRODUCTION

This research begins with a scenario that illustrates the potential negative consequences of artificial intelligence systems. Imagine working on a project that is crucial for your career, with a presentation scheduled for the following day. On the morning of the presentation, your advanced smartwatch detects elevated blood pressure and transmits data on your sleep patterns, stress levels, and recent habits to both health and insurance systems. The insurance company determines that your stress tolerance is low and increases your risk premium, while your workplace also receives this information. Although the meeting proceeds, your holographic AI twin delivers the presentation, and human resources assigns you a negative performance evaluation. The smartwatch automatically calls an ambulance, and when you force the door open, the system interprets this as an escape attempt and reports it, further increasing your risk score. As a result, you lose your weekly free taxi ride.

Upon leaving your home, you are unable to board taxis, as their autonomous systems deny you access. Attempts to use the metro and buses are similarly unsuccessful, as these systems

have also been notified of your high-risk status. City sensors alert security forces to your presence as a health risk, and security personnel transport you to the hospital by ambulance. At the hospital, your repeated assurances that you are fine are interpreted by the system as denial. Despite your insistence, integrated AI and banking systems classify you as high-risk and restrict your financial transactions. After receiving treatment, you return home.

The following summarizes the day's outcomes: you may have high blood pressure; your health insurance premium increases; your spending is restricted; your workplace performance indicator becomes negative; your presentation is delivered by a hologram; and your general citizenship score decreases.

It is important to consider the potential positive aspects of AI systems in this scenario. Upon receiving an alert from your smartwatch, you visit the nearest hospital, where a physician identifies elevated blood pressure and recommends a new regimen. In this instance, you experience satisfaction and a sense of control over your health. However, even in this case, your health insurance premium increases; your workplace performance indicator becomes negative; and your presentation is delivered by your hologram.

This comparison highlights that, despite potential benefits, the overwhelming negative outcomes underscore a significant concern: in these scenarios, control over key decisions affecting your health, career, and daily life ultimately rests with AI systems, not with you. Recognizing this shift in authority is crucial as we consider the broader implications of artificial intelligence in society. The more critical point to emphasize here is that public policies themselves may be heavily influenced by AI–based decisions and assessments, or even delegate decision-making entirely to AI systems. As algorithmic rationality increases, it cannot be overlooked that this development may contribute to greater transparency in public policy. However, the cost of such transparency may be the realization of the scenario described above. The increasing transparency of public authority may, in turn, impose transparency on citizens as well, potentially rendering the surveillance of citizens systematic.

Algorithmic systems are increasingly prevalent in consumer contexts. However, prior research has examined the effects of algorithmic systems in a relatively fragmented manner, often emphasizing either observable performance outcomes or specific psychological responses rather than integrating these dimensions within a common framework (Chen, 2024; Mourali et al., 2025; Ribeiro et al., 2025). An integrated framework that systematically connects algorithmic system features, psychological mechanisms, and decision outcomes is currently lacking. This study addresses this gap by proposing a conceptual framework that clarifies how algorithmic rationality influences consumer decision-making.

In recent years, organizations have increasingly relied on algorithms to enhance their decision-making processes. Algorithmic decision-making systems have become an integral part of many fields, highlighting a growing dependence on the outputs these algorithms provide. These systems automate decision-making by following established rules and defined goals. More important than simply ensuring that algorithmic decisions are accurate and consistent compared to human decisions is the establishment of lasting rationality as the foundational principle of these systems (Lindebaum et al., 2020). Algorithmic rationality addresses problems by adhering to specific steps and established rules. In contrast, probabilistic methods rely on known probabilities to guide each step. As a result, the outcomes from probabilistic methods are generally viewed as less reliable compared to those produced by algorithmic approaches (Rybalko, 2024). Algorithms find extensive applications across various fields, including finance, healthcare, the Internet of Things, public administration, autonomous vehicles, and social media (Bilić, 2018). Transformations in consumer behavior can be examined through established decision-making frameworks. Traditional models, such as the Engel–Blackwell–Miniard model (Engel et al., 1995) and the Howard–Sheth model (Howard & Sheth, 1969), conceptualize consumer decision-making as a structured process involving need recognition,

information search, alternative evaluation, and choice. Algorithmic systems influence these stages by filtering information, organizing available alternatives, and shaping evaluation criteria. Therefore, algorithmic rationality does not replace existing models but reconfigures their internal dynamics.

Algorithmic suggestions become more important in human–AI decision-making and can improve decision quality. Research suggests that even simple statistical models can outperform human experts, with about 10% higher accuracy on average (Grove et al., 2000). However, this improvement can reduce critical scrutiny and increase unreflective acceptance of suggestions; even for tasks humans can perform well, misleading suggestions labeled as AI calculations can be highly convincing (Liel & Zalmanson, 2020). In human–algorithm collaboration, the goal is to use algorithmic insights accurately and selectively, knowing when to rely on the algorithm and when to trust one's own judgment. Evidence indicates that people and algorithms together can outperform either alone, yet algorithmic errors can quickly erode trust and increase demands for control, sometimes leading users either to follow advice without thinking or to reject helpful suggestions to feel autonomous, neither of which reliably improves decisions (Burton et al., 2020). Informing individuals that an algorithm can make accurate predictions increases trust and compliance, but this trust and compliance are recalibrated over time as users encounter algorithmic errors (de Jong et al., 2025). Artificial intelligence, a branch of computer science, explores the limits of computability and computational cognition (Rapaport, 2020). In contrast, algorithmic rationality views algorithms as components of larger systems that include data, software, infrastructure, and human use, and evaluates them based on overall system performance. Evaluation extends beyond accuracy to include efficiency, speed, and cost-effectiveness, all of which shape knowledge production (Lowrie, 2017). The bounded rationality of software engineers, data biases, and the judgmental nature of artificial intelligence can also lead to biased or suboptimal decisions (Nishant et al., 2024).

1 LITERATURE REVIEW

Research on consumer behavior has systematically investigated decision-making processes from cognitive and behavioral perspectives. Foundational studies, such as those by Engel et al. (1995) and Howard and Sheth (1969), provide structured frameworks for understanding how consumers process information and make choices. More recent scholarship highlights the experiential and affective dimensions of consumption (Holbrook & Hirschman, 1982), as well as the roles of habits and automaticity in decision-making (Wood & Neal, 2009). Collectively, these perspectives extend behavioral economics by demonstrating that decision-making is shaped by context, routines, and psychological constraints, rather than being exclusively rational. The classical assumption of rationality asserts that decision-makers correctly evaluate all information, predict outcomes, and make optimal choices. However, Simon (1955) argued that humans possess bounded rationality and that when they lack the information necessary for rational decision-making, they employ approaches that reduce the need for rational judgment. The concept of heuristic judgment is a central mechanism within the bounded rationality approach. Tversky and Kahneman (1974) suggested that individuals use heuristics to simplify complex judgments when making decisions under uncertainty, and that these heuristics lead to systematic errors. Gigerenzer and Gaissmaier (2011), on the other hand, argue that simple heuristic methods can achieve similar predictive accuracy to more complex approaches in certain contexts.

Algorithmic decision environments in markets

Algorithmic decision environments increasingly shape consumer information search and personalized recommendations, influencing choices. Brin and Page (1998) showed that large-

scale search engines transform information access by providing tailored content. Building on this, Liu (2009) found that algorithmic sorting outperforms intuitive rules, further guiding user decisions.

Recommendation systems create personalized and individualized decision environments using user data. Adomavicius and Tuzhilin (2005) state that recommendation systems rely on partial and predictive utility information and incorporate preference assumptions when tailoring choices to the individual. Koren et al. (2009) demonstrate that matrix factorization improves recommendation accuracy by capturing latent preference dimensions. Rendle et al. (2009) emphasize that personalization goes beyond mere prediction, enabling ranking choices and providing superior ranking performance. Furthermore, it is stated that explanations in recommendation systems affect trust and acceptance. Herlocker et al. (2000) suggest that the transparency and explainability of the algorithm can increase user acceptance and perception of control.

Behavioral evidence shows that consumer trust in algorithmic recommendations varies across contexts. For example, Logg et al. (2019) describe this as algorithm appreciation, noting that individuals place more trust in algorithmic advice than human advice on judgment and prediction tasks, particularly when domain expertise is low. However, in contrast, Dietvorst et al. (2015) state that observing an algorithmic error can significantly reduce trust, a phenomenon they term "algorithm aversion." This finding suggests that the perceived probability of error can rapidly weaken action, even if algorithms outperform humans. Extending these insights to e-commerce, Yin et al. (2025) found that personalized recommendations by AI increased click intent through perceived relevance, inspiration, and insight via immersive experience and technology adoption, but privacy concerns weakened these effects. Ultimately, through mechanisms such as ranking, personalization, and recommendations, algorithms are shaping what consumers see and evaluate, influencing trust and loyalty, and reshaping the balance between decision support and consumer autonomy.

Algorithmic Rationality and Rational Intelligence

In contemporary decision systems, algorithmic rationality is closely linked to improvements in prediction accuracy and performance across tasks. Specifically, empirical evaluations reveal that algorithmic decision systems generally outperform traditional human or single-model approaches in predictive environments (Lakshminarayanan et al., 2017; Ovadia et al., 2019).

Rational intelligence involves explaining and understanding decision-making processes. As algorithms are increasingly used in high-risk areas, the demand for clear explanations grows (Mahmud et al., 2022; Munch et al., 2024). Despite their high performance, users may develop negative perceptions of algorithms when their decisions lack transparency or involve significant risks (Mahmud et al., 2022). Overall, research indicates that predictive success alone is not enough; legitimacy, accountability, and explainability are also crucial components of algorithmic rationality in markets.

Key psychological pathways and boundary conditions

Algorithmic decision environments activate various psychological processes that influence how consumers interpret and respond to algorithmic outputs. Notably, trust in algorithmic advice tends to remain strong, even when it contradicts individuals' own judgments or presents inconsistencies. In incentivized decision-making tasks, simply indicating that the advice came from AI can enhance the quality of decisions. This trust can endure even when there are legitimate reasons to question the advice. Additionally, the broader implications of this trust such as lower individual outcomes and effects on others impacted by the decision suggest that trust can serve as a pathway for the spread of welfare-related errors (Klingbeil et al., 2024).

Providing more information about how an AI system operates does not necessarily enhance users’ perception of control and autonomy. True autonomy is strengthened when users actively

participate in decision-making processes during system design. Research on generative AI services shows that user engagement, task difficulty, and system transparency influence autonomy and related outcomes, such as satisfaction and usage intentions (Han & Ko, 2025). Moreover, under uncertainty and time pressure, users often exhibit overconfidence, relying on algorithmic advice as a default. This can lead to a perceived sense of informed decision-making even when outcomes are suboptimal, with confidence remaining high despite reduced decision quality (Klingbeil et al., 2024).

The reviewed studies demonstrate methodological diversity, encompassing experimental designs, field data, and conceptual analyses. These methodological differences affect the interpretation of results, especially in terms of external validity and generalizability. As a result, the effects of algorithmic decision-making differ depending on context, data type, and research design.

2 METHODOLOGY

General approach

This article offers a synthesis of conceptual and narrative literature reviews. The purpose of the research is to integrate specific areas of literature to illustrate how and why algorithmic systems impact consumer decision-making rationality. While previous studies have focused on how algorithmic features influence consumer outcomes through causal and psychological processes, this article specifically explores algorithmic rationality as a form of rationality that emerges from the interaction between technological systems and human cognition.

Analysis

The literature was selected based on thematic relevance and theoretical contribution, rather than publication count or database coverage. The review encompasses four interconnected domains: (i) foundations of consumer decision-making and bounded rationality, (ii) algorithmic decision environments in markets, (iii) algorithmic rationality and rational intelligence, and (iv) psychological mechanisms and boundary conditions shaping algorithmic impact. Studies were included if they contributed to at least one of the following: clear definition of algorithmic features in decision-making (accuracy, personalization, consistency, uncertainty management); explanation of psychological responses to algorithmic systems (trust, perceived control, overconfidence, resistance); or analysis of contextual and user-level boundary conditions (risk severity, product type, expertise).

This study adopts a conceptual and narrative literature review approach. The synthesis integrates four principal domains: (i) consumer decision-making and bounded rationality, (ii) algorithmic decision environments, (iii) algorithmic rationality and rational intelligence, and (iv) psychological mechanisms and boundary conditions. The analysis follows a three-stage structure: first, identifying core algorithmic features; second, linking these features to psychological mechanisms; and third, connecting these mechanisms to decision outcomes such as decision quality, information processing, and resistance.

The synthesis proceeds in three layers. First, it identifies the core elements of rational intelligence in algorithmic systems (predictive accuracy, cross-context consistency, efficiency, uncertainty management, explainability). Second, it relates these features to psychological mechanisms and mediating factors (trust, perceived autonomy, dependency behavior, suspicion of manipulation). Third, it connects these mechanisms to decision outcomes, including information seeking, adherence to recommendations, decision quality, welfare effects, and resistance. This layered synthesis aims to reveal the central tension in the study, improved decision quality versus increased conformity, and to identify the conditions under which either side may predominate.

3 RESULTS AND DISCUSSION

This study introduces a framework for understanding how algorithm-driven systems reshape consumer decision-making. It links algorithmic features to underlying psychological processes and presents a structured comparison of their dual effects in Table 1.

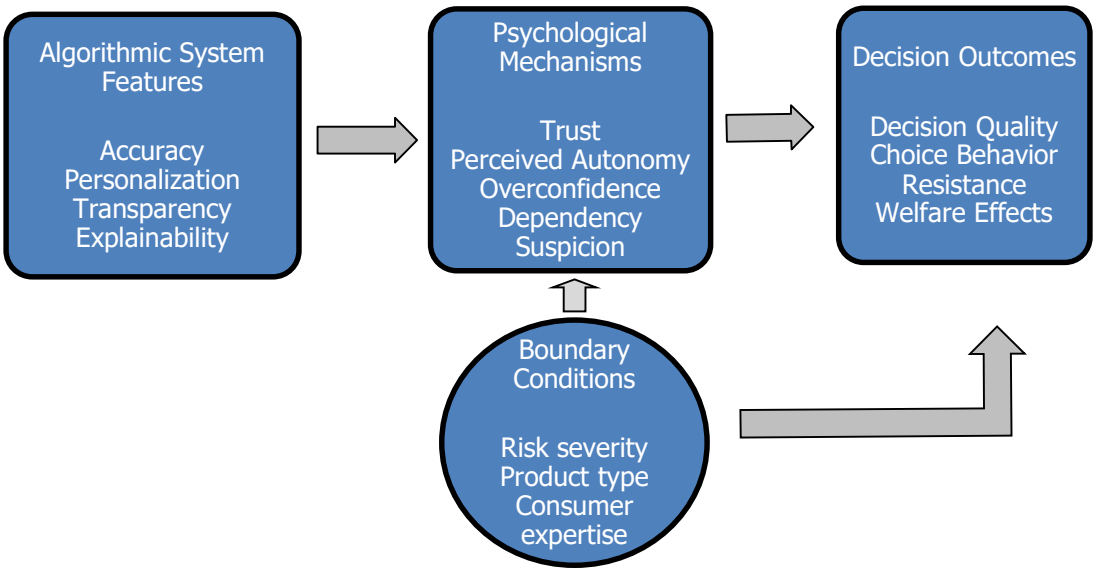
Tab. 1 Algorithmic rationality effects on consumer decisions

Dimension	Positive Effects	Negative Effects	References
Trust	Increased reliance, efficiency	Over-reliance, blind acceptance	Logg et al. (2019); Dietvorst et al. (2015)
Autonomy	Perceived control with explanations	Reduced autonomy, dependency	Han & Ko (2025)
Decision quality	Reduced search costs	Lower quality under overconfidence	Klingbeil et al. (2024)
Information processing	Higher accuracy and relevance	Narrowed consideration sets	Liu (2009); Rendle et al. (2009)
Transparency	Increased accountability	Suspicion of manipulation	Mahmud et al. (2022)
Personalization	Higher relevance	Privacy concerns and resistance	Yin et al. (2025)

Source: Author's own elaboration

As shown in Table 1, each advantage is paired with a behavioral risk, highlighting the dual nature of algorithmic rationality.

Fig. 1 Conceptual framework of algorithmic rationality in consumer decision-making



Source: Author's own elaboration

Figure 1 presents the proposed framework in which algorithmic system features influence decision outcomes indirectly through psychological mechanisms, while boundary conditions moderate these relationships.

The article also examines what factors shape the strength and direction of these effects. Algorithms can help people make better decisions by increasing accuracy, consistency, and efficiency. Still, psychological factors can cause different reactions, such as conformity, overconfidence, or resistance. To structure the discussion more systematically, the proposed framework is organized into three interrelated analytical components.

The framework comprises three primary components. The first component involves attributes associated with rational intelligence that shape the environments in which algorithms operate. These attributes include predictive accuracy, performance, cross-contextual consistency, transparency, explainability, and justification of decisions. Such attributes influence the system by determining what consumers observe, how options are prioritized, and how effort is distributed during the decision-making process. The second component addresses consumer responses, which occur through various psychological mechanisms. These mechanisms include trust in algorithmic outputs, perceived control and autonomy, overconfidence, overesteem, and suspicion regarding manipulation or intent. These responses influence whether consumers perceive algorithmic outputs as supportive, advisory, or manipulative. The third component concerns the evaluation of alternatives, which encompasses changes in final choices, perceived decision quality, potential welfare outcomes, and resistance to decisions. Within this framework, a single attribute may either enhance or diminish decision quality, depending on its impact on trust, perceived autonomy, and perceived intent.

This synthesis shows that rational intelligence is connected to better decision quality. When systems predict more accurately and provide relevant information, it becomes easier to find what you need. This lowers search costs, makes choices simpler, and removes options that do not matter. Trust allows people to rely on these systems when needed. As algorithms become more capable, decision quality gets better too. When systems explain their suggestions, users can better understand why they trust or doubt them, which shapes how much they depend on the system. Studies with recommendation systems show that explanations help people accept suggestions, and good interfaces make it easier to judge options. In this setting, rational intelligence acts as a support tool that keeps people focused on their goals and reduces mental effort.

This review examines the adverse reactions and disadvantages associated with reliance on algorithmic advice. Trust in algorithmic recommendations can influence behavior and increase compliance with perceived authority, even when such advice contradicts users' own judgment or contextual information. Non-selective compliance may foster excessive trust, leading consumers to treat algorithmic outputs as default choices and to maintain trust despite declining decision quality. This dynamic can result in tangible costs, including negative effects on third parties. Human factors research characterizes these scenarios as the "misuse" or "abuse" of automation. Delegating judgment to automated systems introduces risks of inappropriate trust, which may accompany performance improvements (Parasuraman & Riley, 1997). Studies on automation bias demonstrate that users of flawed assistive tools may commit errors and omissions by following these tools, even in the presence of counter-evidence (Skitka et al., 1999). These findings indicate that algorithmic authority can impede critical evaluation and adversely affect outcomes, even when users possess relevant information.

Boundary condition propositions specify the circumstances in which effects are either amplified or diminished. Decision risk and the severity of consequences shape fault tolerance and influence the psychological impact of uncertainty. In high-risk contexts, individuals exhibit increased sensitivity to disagreement dynamics, perceived bias, and the sufficiency of justification. This heightened sensitivity may reinforce distrust or foster selective trust. When conflicts arise between algorithmic outputs and human expert judgment, particularly in situations with clear accountability and consequences, individuals may selectively adhere to one authority over another based on their evaluation of these competing information sources.

The characteristics of the product significantly influence these processes, as different product categories affect the relationship between recommendation features and consumer needs. This suggests that personalization strategies do not operate uniformly across all markets. Consumer understanding and expertise are critical factors in the adoption of and trust in recommendations, while task perception also plays a pivotal role. Consumers are more likely to resist recommendations when they perceive a task as subjective or as requiring exclusively human judgment, even if algorithmic performance is strong. Therefore, whether a task is perceived as objective or subjective constitutes a key boundary condition that determines whether rational intelligence is viewed as beneficial or as an inappropriate delegation of responsibility (Castelo et al., 2019).

This analysis demonstrates that rational intelligence fundamentally alters the processes of information search, evaluation, and selection. Ranking and personalization mechanisms shift attention from broad exploration to targeted assessments by reorganizing the prominence of information elements. Algorithmic systems shape perceptions of relevance and comparability, thereby increasing evaluation efficiency but potentially narrowing users' perspectives. In the selection phase, algorithmic outputs often function as decision-making shortcuts. When applied judiciously, these outputs can improve outcomes; however, reliance on them as default authorities may impede thorough deliberation. Although features of rational intelligence do not inherently remove user autonomy, particularly when users maintain trust and control, they do enhance decision quality by reducing search costs and information asymmetry. Conversely, risks intensify when systems exert excessive persuasive influence. Transparency indicators may prompt concerns regarding legitimacy or manipulation. Reduced autonomy can result in conformity, overconfidence, and reactive behaviors. These dynamics generate core tensions: personalization may increase relevance but threaten autonomy; transparency can support accountability yet amplify fears of manipulation; and efficiency may decrease cognitive effort but foster passive compliance. In privacy-sensitive contexts, responses become more nuanced, as perceived surveillance risks can provoke resistance that extends beyond concerns of accuracy or accessibility (Acquisti et al., 2015).

Theoretical inferences are grounded in mechanism-based explanations. Within this framework, algorithmic environments are defined as digital systems that structure information presentation and decision-making, serving as both tools and infrastructures that shape individuals' decision processes and rationality. Algorithmic rationality refers to a reasoning mode influenced by algorithms, which may diverge from traditional human rationality. Determinants such as trust, autonomous decision-making capacity, over-commitment, and perceptions of algorithmic intent influence rational behavior outcomes. The validity and effectiveness of algorithmic rationality as a decision-making norm should be assessed across varying conditions, including decision risk, product characteristics, and user competencies. This perspective posits that algorithmic rationality can enhance decision quality by increasing accuracy and speed. Conversely, insufficient alignment with psychological factors and human limitations may result in a transition to algorithmic management, potentially reducing compliance, causing welfare losses, and fostering resistance.

CONCLUSION

This article examines how algorithmic decision environments alter consumer rationality. Algorithm-powered systems are not neutral information tools; rather, they reshape market visibility, clarity, and possibilities through ranking, personalization, and automated recommendations. The concept of "rational intelligence" is defined by prediction accuracy, performance, contextual consistency, uncertainty management, and explainability. These characteristics influence how consumers search for, evaluate, and select products, shifting behavior from broad exploration to narrower, algorithm-driven choices.

The primary finding is that rational intelligence produces a bidirectional transformation. When algorithms reduce information friction and cognitive load while preserving user autonomy, decision quality improves. Trust facilitates selective dependence, and explainability enhances evaluation and calibration, providing users with meaningful control. However, these same features can foster over-reliance when algorithmic outputs are perceived as authoritative. In such cases, trust may override conflicting signals, diminishing critical thinking and increasing welfare costs, such as the spread of errors.

The proposed framework demonstrates that negative outcomes stem from psychological mechanisms and emphasizes that results depend on boundary conditions as well as system performance. Transparency and disclosure can undermine trust by raising legitimacy concerns, while personalization intensifies user reactions when persuasive intent is detected. These tensions manifest in practice: more relevant results may reduce perceived autonomy, and transparency intended for accountability may heighten concerns about manipulation.

The article advocates a probabilistic approach to illustrate how algorithmic features interact with trust, autonomy, overconfidence, and perceived intent. Decision risk and consequence severity amplify sensitivity to disagreements, justifications, and perceived bias. Conflicts between algorithmic and human recommendations prompt consumers to selectively follow advice. Product type influences the extent to which recommendations fulfill psychological needs. Consumer understanding and expertise can enhance judgment but may also increase skepticism. Ultimately, the impact of algorithmic rationality extends beyond accuracy improvements, as both benefits and risks emerge from the interplay among psychological mechanisms, boundary conditions, and system design.

This study has several limitations. First, as a conceptual synthesis, it does not provide empirical validation for the proposed framework. Second, the literature selection is based on thematic relevance rather than systematic review protocols, which may introduce selection bias. Third, the framework does not adequately account for differences across cultural contexts, which could influence consumer responses to algorithmic systems. Future research should empirically test the proposed mechanisms using experimental and longitudinal designs and investigate cross-cultural variations in algorithmic trust and resistance.

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