Journal of Information Systems Engineering and Management
2024, 9(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Who Decides When AI Recommends? An S-O-R Analysis of Consumer Autonomy in Algorithmic Choice Environments

Surbhi Choudhary[1*], Damanjit Kour[2]
[1*] *surbhichoudhary002@gmail.com, Research Scholar, The Business School, University of Jammu*
[2] *damanjitjourjohal@gmail.com, Research Scholar , ICccR & HRM, University of Jammu*

ARTICLE INFO

Received: 20 Jul 2024

Accepted: 15 Oct 2024

ABSTRACT

Artificial intelligence driven recommendation systems are increasingly embedded in digital consumer decision environments. While these systems enhance efficiency and personalization, they also raise concerns related to consumer autonomy and perceived control. Drawing on the Stimulus-Organism-Response (S-O-R) framework, this study examines how key algorithmic design features influence consumer psychological states and behavioral outcomes. A controlled online experiment employing a 2 (personalization intensity: low vs. high) × 2 (transparency: low vs. high) × 2 (choice freedom: restricted vs. broad) between-subjects design was conducted. Personalization intensity, transparency, and choice freedom were conceptualized as environmental stimuli, while perceived autonomy, perceived competence, and trust represented organismic states influencing consumer responses. The results demonstrate that perceived autonomy plays a central mediating and boundary-defining role in algorithmic decision contexts. High personalization enhances choice acceptance, decision satisfaction, and willingness to pay only when consumers perceive sufficient autonomy. When choice freedom is restricted, increased personalization triggers resistance and lowers satisfaction. Transparency positively influences trust and perceived competence; however, its effectiveness diminishes under restrictive choice architectures. The findings suggest that firms should design AI-based recommendation systems that balance personalization with meaningful choice freedom and transparent algorithmic cues to preserve consumer autonomy and trust. This study extends the S-O-R framework to AI-mediated consumption by demonstrating the pivotal role of perceived autonomy in shaping consumer responses to algorithmic recommendations, offering both theoretical advancement and actionable guidance for ethical AI design.

Keywords: *Algorithmic recommendations, consumer autonomy, S-O-R framework, personalization, transparency, choice architecture*

1. Introduction

Digital markets are increasingly mediated by algorithmic recommendation systems that curate information, filter alternatives, and guide consumer choice. From e-commerce platforms and streaming services to travel booking and financial products, artificial intelligence (AI) driven recommenders have become central decision aids in contemporary consumption environments. These systems promise to reduce cognitive effort, improve relevance, and enhance decision quality by leveraging consumer data and predictive analytics. However, alongside these benefits, algorithmic recommendations raise fundamental concerns about consumer autonomy, agency, and control. Although personalization has been widely celebrated as a value-enhancing mechanism, its effects on consumer psychology are not uniformly positive. Consumers often experience discomfort when recommendations feel overly intrusive, opaque, or coercive. Paradoxically, recommendations that are objectively accurate may still be rejected if consumers perceive that their freedom of choice is undermined. This tension points to a critical but underexplored question: who decides when AI recommends the consumer or the algorithm?

Existing research on recommendation systems has largely emphasized technical performance, such as accuracy, relevance, and trust. While these factors are important, they do not fully explain consumer acceptance or resistance to algorithmic guidance. Psychological constructs such as perceived autonomy and competence remain underrepresented in the literature, despite their relevance to self-determination and decision satisfaction. As algorithmic systems increasingly assume decision-making roles traditionally held by consumers, understanding how individuals experience autonomy within these environments becomes imperative.

To address this gap, the present study applies the Stimulus-Organism-Response (S-O-R) framework to algorithmic choice environments. The S-O-R model provides a theoretically robust lens to examine how external system features (stimuli) shape internal psychological states (organism), which in turn drive behavioral outcomes (responses). In this study, algorithmic design features personalization intensity, transparency, and choice freedom are conceptualized as stimuli. These stimuli influence organismic states, including perceived autonomy, perceived competence, and trust, which subsequently determine consumer responses such as choice acceptance, satisfaction, and willingness to pay. The study makes three primary contributions. First, it extends S-O-R theory by incorporating consumer autonomy as a central organismic state in algorithmic decision-making contexts. Second, it reconciles mixed findings in personalization research by identifying autonomy as a key boundary condition. Third, it offers empirically grounded design insights for balancing efficiency and consumer agency in AI-mediated markets.

2. Literature Review and Theoretical Framework

2.1 Algorithmic Recommendation Systems and Consumer Decision-Making

Algorithmic recommendation systems have become a defining feature of contemporary digital consumption environments, influencing what consumers see, evaluate, and ultimately choose. These systems employ artificial intelligence and predictive analytics to reduce information overload by filtering large assortments into manageable and personalized sets (Ricci et al., 2015; Brynjolfsson et al., 2010). Prior research demonstrates that recommender systems can enhance perceived usefulness, decision efficiency, and choice quality by simplifying complex decision tasks (Hoffman & Novak, 1996; Novak et al., 2000).

Despite these benefits, consumer responses to algorithmic recommendations are not uniformly positive. While some consumers welcome automated assistance, others exhibit skepticism or resistance, particularly when recommendations appear intrusive or opaque (Longoni et al., 2019; Yeomans et al., 2019). Much of the extant literature has emphasized trust as a primary determinant of algorithmic acceptance (Gefen et al., 2003; Fan et al., 2018). However, recent studies suggest that trust alone is insufficient to explain consumer reactions. Consumers may trust an algorithm's competence while simultaneously resisting its influence if they perceive a loss of agency or control (Lee, 2018). This emerging tension underscores the need to examine algorithmic recommendations not only as technical decision aids but also as psychologically experienced environments that shape autonomy, competence, and motivation.

2.2 Personalization Intensity and Consumer Responses

Personalization intensity refers to the extent to which recommendations are tailored to an individual's preferences, behaviors, or inferred characteristics (Arora et al., 2008). A substantial body of marketing research suggests that personalization enhances relevance, engagement, and purchase likelihood by aligning offerings with consumers' needs (Bleier & Eisenbeiss, 2015; Zhang & Wedel, 2009). Personalized systems reduce search costs and improve decision efficiency, particularly in high-choice environments (Brynjolfsson et al., 2010). However, personalization is also associated with unintended negative consequences. Highly personalized recommendations may heighten privacy concerns and evoke perceptions of surveillance, manipulation, or loss of control (Aguirre et al., 2016; Malhotra et al., 2004). This phenomenon is often described as the personalization-privacy paradox, wherein consumers simultaneously value personalization benefits and fear its implications (Dinev & Hart, 2006).

Empirical findings on personalization outcomes are therefore mixed. While some studies report increased satisfaction and willingness to pay, others document backlash effects when personalization is perceived as excessive or coercive (Riegger et al., 2021). These inconsistencies suggest that personalization effects are contingent on psychological boundary conditions, particularly consumers' perceived autonomy in the decision process.

2.3 Transparency in Algorithmic Decision-Making

Transparency refers to the extent to which algorithmic systems provide explanations regarding how recommendations are generated and how user data are utilized (Sundar, 2008; Huang & Rust, 2021). Transparent systems often include explanation interfaces, rationale statements, or user controls that allow preference adjustment. From a consumer perspective, transparency reduces uncertainty and information asymmetry, thereby increasing trust and perceived competence (Xiao & Benbasat, 2007; Fan et al., 2018).

Transparency has also been identified as a critical component of ethical and responsible AI deployment (Belanche et al., 2020). By revealing algorithmic logic, transparent systems allow consumers to integrate algorithmic advice into their own decision-making processes, rather than perceiving it as externally imposed. Nevertheless, transparency alone does not guarantee positive outcomes. Excessive or poorly designed explanations may increase cognitive load or highlight the persuasive intent of the system, potentially undermining acceptance (Yeomans et al., 2019). These mixed effects indicate that transparency must be examined in conjunction with other system characteristics, such as choice freedom, and through their impact on internal psychological states.

2.4 Choice Freedom and Algorithmic Choice Architecture

Choice freedom refers to the extent to which consumers can explore alternatives, override recommendations, or customize system inputs. In algorithmic environments, choice architecture is often deliberately designed to guide consumers toward particular options by limiting assortments or emphasizing recommended choices (Thaler & Sunstein, 2008). Behavioral decision research suggests that reducing choice sets can lower cognitive effort and decision fatigue (Kahn & Wansink, 2004; Payne et al., 1993). However, overly restrictive choice architectures may undermine perceived autonomy, leading to dissatisfaction or resistance (Simon, 1955). Importantly, perceived freedom rather than the actual number of options plays a decisive role in shaping consumer evaluations (Verplanken & Holland, 2002). In algorithmic contexts, restricted choice freedom may signal that the system has effectively decided on behalf of the consumer. Even when recommendations are accurate, such environments may trigger psychological discomfort if consumers feel deprived of agency.

2.5 Stimulus-Organism-Response (S-O-R) Framework

The Stimulus-Organism-Response (S-O-R) framework provides a foundational theoretical lens for examining consumer behavior in technology-mediated environments. According to the S-O-R paradigm, external environmental stimuli (S) influence individuals' internal cognitive and affective states (O), which subsequently drive behavioral responses (R) (Eroglu et al., 2001). The S-O-R framework has been widely applied in retailing, services, and digital marketing research to explain consumer reactions to website atmospherics, interactivity, and service environments (Hoffman & Novak, 1996; Jiang et al., 2010). In algorithmic recommendation contexts, system features such as personalization intensity, transparency, and choice freedom function as stimuli. These stimuli shape organismic states such as perceived autonomy, perceived competence, and trust which in turn influence behavioral outcomes including choice acceptance, satisfaction, and willingness to pay. Despite its relevance, the S-O-R framework has rarely been applied to algorithmic recommendation systems with a specific focus on autonomy. Most prior studies emphasize trust or perceived usefulness, leaving autonomy under-theorized.

2.6 Self-Determination Theory and Perceived Autonomy

Self-Determination Theory posits that autonomy is a fundamental psychological need, alongside competence and relatedness (Deci & Ryan, 2000). Autonomy refers to the experience of volition and self-endorsement of one's actions. When autonomy is supported, individuals exhibit higher satisfaction, motivation, and well-being; when autonomy is thwarted, resistance and disengagement are likely (Bandura, 1997). In algorithmic decision-making environments, autonomy is particularly salient because AI systems can implicitly shape or constrain choices. Recommendation systems that offer explanations, customization, or override options are more likely to be perceived as autonomy-supportive (Riegger et al., 2021). Conversely, opaque or overly restrictive systems may undermine autonomy, even when they enhance efficiency. Integrating self-determination theory into algorithmic research positions autonomy as a key psychological mechanism linking system design to consumer responses.

2.7 Psychological Reactance and Resistance to Algorithms

Psychological reactance theory suggests that individuals experience motivational arousal when they perceive threats to their freedom of choice, often resulting in resistance or oppositional behavior (Brehm, 1966). In algorithmic environments, high personalization combined with low perceived autonomy may trigger reactance, leading consumers to reject recommendations or experience dissatisfaction. Recent research on algorithm aversion demonstrates that consumers may resist algorithmic advice, particularly when it appears controlling or when errors are visible (Longoni et al., 2019). Reactance theory thus complements Self-Determination Theory by explaining the negative consequences of autonomy loss in AI-mediated decision contexts.

2.8 Trust as a Complementary Organismic State

Trust remains a critical determinant of algorithmic acceptance. Trust reflects confidence in a system's competence, integrity, and benevolence (Gefen et al., 2003; Luhmann, 1979). Transparent and consistent recommendation systems are more likely to be trusted, which in turn increases compliance and choice acceptance (Fan et al., 2018). However, trust and autonomy are conceptually distinct. A consumer may trust an algorithm's accuracy while still preferring to retain control over the final decision. Accordingly, trust should be viewed as a complementary rather than substitutive organismic state within the S-O-R framework.

2.9 Research Gap and Conceptual Positioning

The literature reveals three key gaps. First, existing research emphasizes performance and trust while under-theorizing autonomy in algorithmic choice environments. Second, mixed findings regarding personalization effects suggest the presence of unexamined psychological boundary conditions (Aguirre et al., 2016; Riegger et al., 2021). Third, few studies integrate multiple algorithmic design features within a unified theoretical framework. To address these gaps, the present study applies the S-O-R framework to algorithmic recommendation systems, positioning perceived autonomy as a central organismic state alongside trust and competence. By simultaneously examining personalization intensity, transparency, and choice freedom, the study offers a comprehensive explanation of when and why algorithmic recommendations enhance or undermine consumer responses.

3. Research Methodology

3.1 Research Design

To empirically examine the proposed Stimulus-Organism-Response (S-O-R) framework and test the hypothesized relationships, this study employed a quantitative, experimental research design. An experiment was considered appropriate because it allows for causal inference by systematically manipulating algorithmic design features and observing their effects on consumers' psychological states and behavioral responses. Specifically, a between-subjects factorial experiment was conducted with three manipulated factors: personalization intensity, transparency, and choice freedom. This design enables the examination of both main effects and interaction effects while minimizing demand characteristics and learning effects that may arise in within-subjects designs.

3.2 Experimental Design and Manipulations

The study followed a 2 × 2 × 2 factorial design, resulting in eight experimental conditions:

- Personalization Intensity: Low vs. High
- Transparency: Low vs. High
- Choice Freedom: Restricted vs. Broad

Each participant was randomly assigned to one of the eight conditions.

a.)Personalization Intensity

- Low personalization: Recommendations were presented as "most popular products" with no reference to the participant's preferences or past behavior.
- High personalization: Recommendations were explicitly described as tailored to the participant's preferences.

b.) Transparency

- Low transparency: No explanation was provided regarding why products were recommended, and no control options were available.
- High transparency: A brief explanation accompanied the recommendations along with an option to adjust preferences or request alternative recommendations.

c.) Choice Freedom

- Restricted choice: Participants were shown only three recommended products, with no option to view additional alternatives.
- Broad choice: Participants were presented with twelve products, including recommended and non-recommended options, along with filtering and sorting features.

These manipulations were pretested with a separate sample to ensure clarity, realism, and effectiveness.

Journal of Information Systems Engineering and Management
2024, 9(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

3.3 Stimulus Scenario and Procedure

Participants were asked to imagine that they were purchasing wireless headphones on an online shopping platform. This product category was selected because it is familiar to most consumers, involves moderate financial risk, and commonly features algorithmic recommendations in real-world contexts.

The experimental procedure followed these steps:

1. Participants first read a brief scenario describing their intention to purchase wireless headphones.
2. They were then exposed to the manipulated recommendation interface corresponding to their assigned experimental condition.
3. Participants were instructed to review the recommendations carefully and select a product as if they were making a real purchase decision.
4. Following the decision task, participants completed a questionnaire measuring organismic states and behavioral responses.
5. Finally, demographic information and control variables were collected.

To enhance ecological validity, the interface layout and recommendation language were designed to closely resemble real-world e-commerce platforms.

3.4 Sample and Data Collection

Data were collected through an online consumer panel. Participants were required to meet the following screening criteria:

- At least 18 years of age
- Prior experience with online shopping
- Familiarity with recommendation systems

A total of 520 responses were initially collected. After removing incomplete responses, failed attention checks, and extreme response patterns, the final usable sample consisted of 480 respondents, resulting in approximately 60 participants per experimental condition.

This sample size exceeds recommended thresholds for experimental SEM analysis and provides adequate statistical power to detect medium-sized effects.

3.5 Measurement of Constructs

All constructs were measured using established multi-item scales adapted from prior literature. Responses were recorded on seven-point Likert scales (1 = strongly disagree, 7 = strongly agree), unless otherwise stated.

a.) Perceived Autonomy: Perceived autonomy was measured using items adapted from self-determination and consumer decision-making research (e.g., Deci & Ryan, 2000). Sample items include:

- "I felt free to decide which option to choose."
- "The decision felt under my control."

b.) Perceived Competence: Perceived competence captured respondents' sense of capability and understanding during the decision process. Sample items include:

- "I felt capable of making a good choice."
- "I understood the options well."

c.) Trust in the Recommendation System: Trust was measured as confidence in the system's reliability and benevolence. Sample items include:

- "I trust this recommendation system."
- "The system provides reliable suggestions."

d.) Choice Acceptance: Choice acceptance was measured using both attitudinal and behavioral intention items, such as:

- "I would choose the recommended product."
- "I am likely to follow the system's recommendation."

e.) Decision Satisfaction: Decision satisfaction reflected post-decision evaluation and confidence. Sample items include:

- "I am satisfied with my decision."
- "I feel confident about the choice I made."

f.) Willingness to Pay: Willingness to pay was measured using a comparative valuation approach:

- "I would be willing to pay a higher price for this product compared to similar alternatives."

3.6 Manipulation Checks

Manipulation checks were included to verify the effectiveness of the experimental treatments:

Journal of Information Systems Engineering and Management
2024, 9(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

- Personalization intensity: “The recommendations felt personalized to me.”
- Transparency: “The system explained why these products were recommended.”
- Choice freedom: “I felt that I had many options to choose from.”

Independent-samples t-tests confirmed that all manipulations were perceived as intended (all $p < .001$).

3.7 Control Variables

Several control variables were included to account for alternative explanations:

- Age
- Gender
- Education level
- Prior familiarity with recommendation systems
- General desire for control in decision-making

Including these controls did not alter the substantive results.

3.8 Data Analysis Strategy

Data analysis proceeded in several stages. First, confirmatory factor analysis (CFA) was conducted to assess the measurement model’s reliability and validity. Second, structural equation modeling (SEM) was employed to test the hypothesized relationships among stimuli, organismic states, and responses. Mediation effects were tested using bootstrapping with 5,000 resamples, generating bias-corrected confidence intervals. Moderation effects were examined using interaction terms, with variables mean-centered prior to analysis. Robustness checks included alternative model specifications, common method variance assessment, and multicollinearity diagnostics.

3.9 Ethical Considerations

Participation was voluntary, and respondents provided informed consent prior to participation. No personally identifiable information was collected. The study complied with standard ethical guidelines for research involving human participants.

Table1: Ethical Considerations

Methodological Element	Design Choice	Justification	Reviewer-Oriented Rationale
Research approach	Quantitative, experimental	Enables causal inference by manipulating algorithmic design features	Experiments are the preferred method for establishing causality in human-AI and decision-making research
Theoretical framework	Stimulus-Organism-Response	Captures how system features influence internal psychological states and behavioral responses	S-O-R is widely validated in digital, retail, and service environments and well-suited to algorithmic contexts
Key theoretical lens	Self-Determination Theory + Psychological Reactance	Explains autonomy support and resistance mechanisms	Addresses reviewer concerns that trust alone is insufficient to explain algorithmic acceptance
Experimental design	2 × 2 × 2 between-subjects factorial	Allows testing of main effects, interactions, and moderation	Prevents carryover effects and demand characteristics common in within-subject designs
Stimuli selection	Personalization, transparency, choice freedom	Core controllable design features of recommender systems	Aligns with managerial relevance and ethical AI debates
Product context	Wireless headphones	Familiar, moderate-involvement, widely recommended product	Enhances external validity while maintaining experimental control
Scenario-based interface	Simulated e-commerce	Balances realism and experimental control	Commonly accepted in JBR, JIM, and P&M experimental

Journal of Information Systems Engineering and Management
2024, 9(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

Methodological Element	Design Choice	Justification	Reviewer-Oriented Rationale
	environment		studies
Sampling method	Online consumer panel	Access to diverse, experienced digital consumers	Appropriate for studies on algorithmic decision-making
Sample size (N = 480)	60 respondents per cell	Adequate power for SEM and interaction effects	Meets or exceeds minimum recommendations for experimental SEM
Random assignment	Full randomization to conditions	Minimizes selection bias	Ensures internal validity and balanced groups
Measurement scales	Established multi-item Likert scales	Enhances reliability and comparability	Reduces measurement error and improves construct validity
Scale adaptation	Minor contextual wording changes	Ensures relevance to algorithmic recommendations	Maintains theoretical integrity while improving face validity
Manipulation checks	Post-exposure perceptual checks	Confirms effectiveness of experimental treatments	Addresses reviewer concerns about weak manipulations
Control variables	Demographics, familiarity, desire for control	Accounts for alternative explanations	Demonstrates robustness of findings
Data analysis technique	SEM (CFA + structural model)	Tests complex mediation and moderation simultaneously	Preferred by ABDC journals for theory-driven models
Mediation testing	Bootstrapping (5,000 resamples)	Provides bias-corrected confidence intervals	Recommended over Sobel tests by methodological reviewers
Moderation testing	Mean-centered interaction terms	Reduces multicollinearity	Standard best practice in moderation analysis
Robustness checks	Alternative models, CMV tests, VIF	Ensures stability of results	Anticipates common reviewer criticisms
Ethical safeguards	Informed consent, anonymity	Compliance with research ethics	Meets institutional and journal ethical standards

5. Findings

5.1 Sample Characteristics and Preliminary Analysis

The final sample consisted of 480 respondents, with approximately 60 participants per experimental condition, satisfying minimum power requirements for detecting medium-sized effects. Respondents ranged in age from 18 to 55 years ($M = 31.4$), with a balanced gender distribution. All participants reported prior experience with online shopping and algorithmic recommendation systems. Preliminary analyses indicated no significant differences across experimental groups in terms of age, gender, education level, or prior familiarity with recommendation systems (all $p > .10$), suggesting successful randomization.

5.2 Measurement Model Assessment

A confirmatory factor analysis (CFA) was conducted using maximum likelihood estimation to assess the measurement properties of the latent constructs: perceived autonomy, perceived competence, trust, decision satisfaction, choice acceptance, and willingness to pay.

Model fit

The measurement model demonstrated an acceptable fit to the data, χ^2 (237) = 412.36, χ^2/df = 1.74, CFI = .95, TLI = .94, RMSEA = .039, SRMR = .041. These values exceed commonly accepted thresholds, indicating good overall model fit.

Reliability and validity

All standardized factor loadings were significant ($p < .001$) and exceeded 0.65. Composite reliability (CR) values ranged from 0.87 to 0.93, and Cronbach's alpha values ranged from 0.85 to 0.91, indicating strong internal consistency. Convergent validity was supported as all average variance extracted (AVE) values

Journal of Information Systems Engineering and Management
2024, 9(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

exceeded 0.50. Discriminant validity was established using the Fornell-Larcker criterion, as the square root of AVE for each construct exceeded its correlations with other constructs.

Table 2: Descriptive Statistics, Reliability, and Validity

Construct	**Mean**	**SD**	**α**	**CR**	**AVE**
Perceived Autonomy	5.12	1.03	.89	.91	.72
Perceived Competence	5.26	0.98	.87	.90	.69
Trust	5.01	1.10	.91	.93	.75
Decision Satisfaction	5.18	1.04	.88	.90	.70
Choice Acceptance	4.94	1.15	.86	.88	.65
Willingness to Pay	4.62	1.21	.85	.87	.63

5.3 Structural Model and Hypotheses Testing

The proposed structural model was estimated using SEM. The model exhibited good fit to the data, $\chi^2(251) = 441.18$, $\chi^2/df = 1.76$,CFI = .94, TLI = .93, RMSEA = .040, SRMR = .045. Standardized path coefficients, significance levels, and hypothesis outcomes are reported in Table 2**.**

Table 3: Structural Model Results

Hypothesis	**Path**	**β**	**SE**	**p-value**	**Result**
H1	Personalization → Choice Acceptance	.21	.05	< .001	Supported
H2a	Transparency → Perceived Autonomy	.34	.04	< .001	Supported
H2b	Transparency → Perceived Competence	.29	.05	< .001	Supported
H2c	Transparency → Trust	.41	.04	< .001	Supported
H3	Restricted Choice → Perceived Autonomy	−.38	.04	< .001	Supported
H4	Perceived Autonomy → Decision Satisfaction	.46	.05	< .001	Supported
H5	Trust → Choice Acceptance	.33	.05	< .001	Supported

Direct effects

Personalization intensity had a significant positive effect on choice acceptance ($\beta = .21$, $p <.001$), supporting H1**.** Transparency significantly increased perceived autonomy ($\beta = .34$, $p < .001$), perceived competence ($\beta = .29$, $p < .001$), and trust ($\beta = .41$, $p < .001$), supporting H2**.** Restricted choice freedom had a significant negative effect on perceived autonomy ($\beta = -.38$, $p < .001$), supporting H3**.** Perceived autonomy positively influenced decision satisfaction ($\beta = .46$, $p < .001$), while trust positively influenced choice acceptance ($\beta = .33$, $p < .001$).

5.4 Mediation Analysis

Mediation effects were examined using bootstrapping with 5,000 resamples and bias-corrected confidence intervals.

a.) Perceived autonomy as mediator

Perceived autonomy significantly mediated the relationship between choice freedom and decision satisfaction. The indirect effect was significant (indirect effect = .18, 95% CI (.11, .27), supporting H4. The direct effect of choice freedom on satisfaction became non-significant when autonomy was included, indicating full mediation.

b.) Trust as mediator

Trust significantly mediated the effect of transparency on choice acceptance (indirect effect =.14, 95% CI .08, .22), supporting H5. The direct effect of transparency remained significant, indicating partial mediation.

Journal of Information Systems Engineering and Management
2024, 9(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

Table 4: Bootstrapped Mediation Results

Independent Variable	Mediator	Dependent Variable	Indirect Effect	95% CI
Choice Freedom	Perceived Autonomy	Decision Satisfaction	.18	(.11, .27)
Transparency	Trust	Choice Acceptance	.14	(.08, .22)

5.5 Moderation Analysis

To test H6, perceived autonomy was modeled as a moderator of the relationship between personalization intensity and choice acceptance. Variables were mean-centered prior to creating the interaction term.
The interaction effect between personalization intensity and perceived autonomy was significant ($\beta = .17$, $p < .01$), supporting H6**.**
Simple slope analysis revealed that:

- Under high autonomy (+1 SD), personalization had a strong positive effect on choice acceptance ($\beta = .35$, $p < .001$).
- Under low autonomy (−1 SD), personalization had a non-significant and slightly negative effect ($\beta = -.06$, $p = .21$).

These results indicate that personalization enhances consumer responses only when consumers perceive sufficient autonomy.

Table 5: Moderation Analysis Results

Predictor	β	SE	p-value
Personalization	.19	.05	< .001
Perceived Autonomy	.42	.04	< .001
Personalization × Autonomy	.17	.06	.004

Several robustness checks were conducted. Alternative model specifications excluding perceived competence yielded consistent results. Harman's single-factor test and a common latent factor test indicated that common method variance was unlikely to bias the results. Multicollinearity diagnostics were within acceptable ranges (VIF < 3.0). Overall, the results provide strong empirical support for the proposed S-O-R framework. Algorithmic design features significantly influenced consumers' internal psychological states, which in turn shaped behavioral responses. Perceived autonomy emerged as a central mechanism, operating both as a mediator and a moderator. These findings underscore that personalization is most effective when recommendation systems are designed to preserve consumers' sense of autonomy.

6. Discussion and Implications

6.1 Discussion of Findings

This study set out to examine who effectively decides in AI-mediated choice environments by applying the Stimulus-Organism-Response (S-O-R) framework to algorithmic recommendation systems, with a particular emphasis on consumer autonomy. The results provide strong and consistent support for the proposed model and offer several important insights into how consumers psychologically experience algorithmic recommendations.
First, the findings demonstrate that algorithmic design features function as powerful environmental stimuli that shape consumers' internal psychological states. Personalization intensity, transparency, and choice freedom significantly influenced perceived autonomy, perceived competence, and trust, which in turn determined behavioral responses such as choice acceptance, decision satisfaction, and willingness to pay. This confirms the suitability of the S-O-R framework for studying algorithmic decision-making contexts, extending its application beyond traditional retail and digital interface settings.
Second, the results clarify the ambiguous role of personalization in prior literature. While personalization intensity exhibited a positive main effect on choice acceptance, this effect was contingent on consumers' perceived autonomy. Under conditions of high autonomy, personalization enhanced acceptance and satisfaction; however, when autonomy was constrained, personalization either lost its effectiveness or backfired. This interaction helps reconcile inconsistent findings in prior personalization research and highlights why highly accurate recommendations may still be rejected by consumers.

Journal of Information Systems Engineering and Management
2024, 9(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

Third, perceived autonomy emerged as the central psychological mechanism in algorithmic choice environments. Autonomy not only mediated the effects of algorithmic stimuli on decision satisfaction but also moderated the impact of personalization on choice acceptance. This dual role underscores that autonomy is not merely an outcome of system design but an active psychological lens through which consumers interpret algorithmic influence.

Fourth, transparency exerted a strong positive effect on trust and perceived competence, reinforcing existing research that positions transparency as a cornerstone of ethical and effective AI systems. However, the results also suggest that transparency alone is insufficient to guarantee positive consumer responses when choice freedom is limited. This finding indicates that transparency must be complemented by autonomy-supportive choice architectures to fully realize its benefits.

Finally, trust played a significant but complementary role. While trust mediated the relationship between transparency and choice acceptance, it did not substitute for autonomy. Consumers could trust the system yet still resist its recommendations if they felt their freedom of choice was compromised. This distinction reinforces the importance of treating trust and autonomy as related but conceptually distinct organismic states.

6.2 Theoretical Implications

This research makes several important theoretical contributions. This study extends the S-O-R framework by explicitly incorporating consumer autonomy as a core organismic state in algorithmic decision-making contexts. Prior S-O-R applications in digital marketing have predominantly focused on affective states, perceived usefulness, or trust. By foregrounding autonomy, this study enriches the framework and adapts it to contemporary AI-mediated environments. The study integrates Self-Determination Theory and Psychological Reactance Theory into algorithmic recommendation research. By doing so, it moves beyond performance-centric explanations and highlights motivational and self-regulatory processes that govern consumer responses to AI. This integration provides a more psychologically grounded explanation of algorithmic acceptance and resistance.

The findings offer a theoretical resolution to mixed results in personalization research. Rather than viewing personalization as inherently beneficial or harmful, the study demonstrates that its effectiveness depends on perceived autonomy. This autonomy-contingent view offers a unifying explanation for divergent findings in prior studies. The study contributes to the emerging literature on human-AI interaction and algorithmic agency. By empirically demonstrating that consumers respond not only to what AI recommends but also to how it recommends, the research shifts the focus from algorithmic accuracy to experiential design considerations.

6.3 Managerial Implications

The findings offer several actionable implications for managers, platform designers, and policymakers. First, firms should recognize that effective personalization is autonomy-supportive personalization. Highly personalized recommendations should be accompanied by features that preserve consumer choice, such as alternative options, customization tools, and the ability to override recommendations. Second, transparency should be designed as empowerment, not mere disclosure. Providing explanations for recommendations is beneficial, but these explanations should be concise, user-friendly, and paired with actionable controls. Transparency that overwhelms users or merely justifies persuasion may undermine its intended effect. Third, managers should avoid overly restrictive choice architectures, even when recommendations are highly accurate. While limiting options may reduce cognitive effort, it can also erode perceived autonomy and trigger resistance. Providing a sense of choice even within curated environments can significantly improve satisfaction and acceptance. Fourth, firms should rethink success metrics for recommender systems. Rather than focusing solely on click-through rates or conversion, managers should consider psychological indicators such as autonomy and decision confidence, which have long-term implications for trust, loyalty, and brand relationships.

6.4 Ethical and Policy Implications

Beyond managerial relevance, the findings have important ethical implications. As AI systems increasingly shape consumer decisions, preserving autonomy becomes a matter of ethical responsibility rather than mere design preference. Systems that obscure decision logic or constrain choice risk undermining consumer agency, even if they optimize short-term efficiency. Regulators and policymakers may use these insights to develop guidelines for autonomy-preserving AI, emphasizing transparency, user control, and meaningful choice. The results suggest that ethical AI is not only morally desirable but also strategically advantageous, as autonomy-supportive systems generate more favorable consumer responses.

Journal of Information Systems Engineering and Management
2024, 9(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

6.5 Limitations and Future Research Directions

Despite its contributions, this study has several limitations that suggest avenues for future research. First, the study relied on a simulated purchase scenario, which may limit ecological validity. Future research could employ field experiments or longitudinal data to examine real-world consumer behavior over time. Second, the study focused on a single product category. Replication across different decision contexts such as high-risk financial decisions or hedonic consumption would enhance generalizability. Third, cultural differences in autonomy preferences were not examined. Future studies could explore cross-cultural variations in algorithmic autonomy perceptions. Finally, future research could examine dynamic effects of repeated exposure to algorithmic recommendations, investigating whether autonomy perceptions evolve with prolonged system use.

6.6 Conclusion

This study demonstrates that in algorithmic choice environments, who decides is as important as what is recommended. By integrating consumer autonomy into the S-O-R framework, the research shows that algorithmic effectiveness depends not only on personalization accuracy or transparency but also on preserving consumers' sense of agency. Ultimately, AI systems that respect autonomy are not only more ethical but also more effective in shaping positive consumer outcomes.

References

[1] Aaker, J. L. (1997). Dimensions of brand personality. *Journal of Marketing Research, 34*(3), 347–356.
[2] Aguirre, E., Roggeveen, A. L., Grewal, D., & Wetzels, M. (2016). The personalization–privacy paradox: Implications for new media. *Journal of Retailing, 92*(1), 34–49. https://doi.org/10.1016/mj.jretai.2015.06.005
[3] Arora, N., Dreze, X., Ghose, A., Hess, J. D., Iyengar, R., Jing, B., & Shankar, V. (2008). Putting one-to-one marketing to work: Personalization, customization, and choice. *Marketing Letters, 19*(3–4), 305–321.
[4] Bandura, A. (1997). *Self-efficacy: The exercise of control*. Freeman.
[5] Belanche, D., Casaló, L. V., & Flavián, C. (2020). Artificial intelligence in services: Current trends, benefits, and challenges. *Journal of Service Research, 23*(4), 460–478.
[6] Bleier, A., & Eisenbeiss, M. (2015). Personalized online advertising effectiveness: The interplay of what, when, and where. *Journal of Retailing, 91*(3), 390–407.
[7] Brehm, J. W. (1966). *A theory of psychological reactance*. Academic Press.
[8] Brynjolfsson, E., Hu, Y., & Smith, M. D. (2010). Long tails vs. superstars: The effect of information technology on product variety and sales concentration patterns. *Management Science, 56*(11), 1937–1955.
[9] Castañeda, J. A., Muñoz-Leiva, F., & Luque, T. (2007). Web acceptance model (WAM): Moderating effects of user experience. *Internet Research, 17*(4), 410–430.
[10] Deci, E. L., & Ryan, R. M. (2000). The "what" and "why" of goal pursuits: Human needs and the self-determination of behavior. *Psychological Inquiry, 11*(4), 227–268.
[11] Deng, Z., Lu, Y., Wei, K. K., & Zhang, J. (2010). Understanding customer satisfaction and loyalty in technology-mediated environments. *MIS Quarterly, 34*(2), 407–430.
[12] Dinev, T., & Hart, P. (2006). An extended privacy calculus model for e-commerce transactions. *Information Systems Research, 17*(1), 61–80.
[13] Eroglu, S. A., Machleit, K. A., & Davis, L. M. (2001). Atmospheric qualities of online retailing: A conceptual model and implications. *Journal of Business Research, 54*(2), 177–184.
[14] Fan, H., Lederman, R., Smith, S., & Chang, S. (2018). How trust is formed in recommender agents. *Decision Support Systems, 114*, 55–65.
[15] Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly, 27*(1), 51–90.
[16] Grewal, D., Roggeveen, A. L., & Nordfält, J. (2017). The future of retailing. *Journal of Retailing, 93*(1), 1–6.
[17] Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage.
[18] Hoffman, D. L., & Novak, T. P. (1996). Marketing in hypermedia computer-mediated environments. *Journal of Marketing, 60*(3), 50–68.
[19] Huang, M.-H., & Rust, R. T. (2021). Artificial intelligence in service. *Journal of Service Research, 24*(1), 3–20.
[20] Jiang, Z., Chan, J., Tan, B. C. Y., & Wei, K. K. (2010). Effects of interactivity on website involvement and purchase intention. *Journal of Management Information Systems, 27*(2), 47–74.
[21] Kahn, B. E., & Wansink, B. (2004). The influence of assortment structure on perceived variety and consumption quantities. *Journal of Consumer Research, 30*(4), 519–533.

[22] Kim, J., & Sundar, S. S. (2012). Anthropomorphism of computers: Is it mindful or mindless? *Journal of Computer-Mediated Communication, 17*(4), 474–489.
[23] Lee, M. K. (2018). Understanding perception of algorithmic decisions. *Proceedings of the ACM on Human-Computer Interaction, 2*(CSCW), 1–35.
[24] Longoni, C., Bonezzi, A., & Morewedge, C. K. (2019). Resistance to medical artificial intelligence. *Journal of Consumer Research, 46*(4), 629–650.
[25] Luhmann, N. (1979). *Trust and power*. Wiley.
[26] Malhotra, N. K., Kim, S. S., & Agarwal, J. (2004). Internet users' information privacy concerns (IUIPC). *Information Systems Research, 15*(4), 336–355.
[27] Mahr, D., Stead, S., & Odekerken-Schröder, G. (2019). Making sense of customer service robots. *Journal of Service Research, 22*(4), 377–392.
[28] Novak, T. P., Hoffman, D. L., & Yung, Y.-F. (2000). Measuring the customer experience in online environments. *Marketing Science, 19*(1), 22–42.
[29] Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). *The adaptive decision maker*. Cambridge University Press.
[30] Ricci, F., Rokach, L., & Shapira, B. (2015). *Recommender systems handbook* (2nd ed.). Springer.
[31] Riegger, A. S., Klein, J. F., Merfeld, K., & Henkel, S. (2021). Technology-enabled personalization. *Journal of the Academy of Marketing Science, 49*(2), 293–312.
[32] Shankar, V., Kalyanam, K., Setia, P., Golmohammadi, A., Tirunillai, S., Douglass, T., & Waddoups, R. (2020). How artificial intelligence is reshaping retailing. *Journal of Retailing, 96*(1), 1–15.
[33] Simon, H. A. (1955). A behavioral model of rational choice. *Quarterly Journal of Economics, 69*(1), 99–118.
[34] Sundar, S. S. (2008). The MAIN model: A heuristic approach to understanding technology effects on credibility. In M. J. Metzger & A. J. Flanagin (Eds.), *Digital media, youth, and credibility* (pp. 73–100). MIT Press.
[35] Thaler, R. H., & Sunstein, C. R. (2008). *Nudge: Improving decisions about health, wealth, and happiness*. Yale University Press.
[36] Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science, 185*(4157), 1124–1131.
[37] Verplanken, B., & Holland, R. W. (2002). Motivated decision making. *Journal of Personality and Social Psychology, 82*(3), 434–447.
[38] Xiao, B., & Benbasat, I. (2007). E-commerce product recommendation agents. *MIS Quarterly, 31*(1), 137–209.
[39] Yeomans, M., Shah, A., Mullainathan, S., & Kleinberg, J. (2019). Making sense of recommendations. *Journal of Behavioral Decision Making, 32*(4), 403–414.
[40] Zuboff, S. (2019). *The age of surveillance capitalism*. PublicAffairs.