# The Dual Role of Self-Efficacy and Perceived Privacy Risk in Shaping Consumer Responses to Recommendation Algorithms

**Hui Shi[1,2], Li Wang[1,2]**
[1]*Guangzhou Huashang College, Guangzhou, Guangdong, China*
[2]*Graduate University of Mongolia, Ulaanbaatar, Mongolia*

**Abstract: Recommendation algorithms have become a routine part of digital platforms, especially in e-commerce and online information environments. Much of the existing literature explains their adoption in terms of technical quality and system performance. Yet users do not respond to these systems on technical grounds alone. Their reactions are also shaped by whether they feel able to use algorithmic features effectively and whether the underlying personalization process feels acceptable from a privacy standpoint. This study examines how self-efficacy and perceived privacy risk jointly shape consumer responses to recommendation algorithms. Drawing on the Technology Acceptance Model, Task-Technology Fit theory, Social Cognitive Theory, and prior privacy research, the paper develops a dual capability-risk framework and tests it using survey data from 515 valid respondents. The results indicate that self-efficacy is positively associated with perceived ease of use, perceived usefulness, satisfaction, and consumer response, whereas perceived privacy risk is significantly related to satisfaction and consumer response. The findings suggest that recommendation systems are more likely to be accepted when users both feel capable of using them and feel reasonably comfortable with the way personal data are involved.**

**Keywords: Recommendation Algorithms; Self-efficacy; Perceived Privacy Risk; Consumer Response; Perceived Usefulness; Perceived Ease of Use; Satisfaction**

## 1. Introduction

### 1.1 Research Background

Recommendation algorithms are widely embedded in digital platforms to help users cope with information overload, identify relevant options, and make decisions more efficiently. In online shopping and content environments, they do more than improve matching accuracy. They also shape what users notice, how they compare alternatives, and how they move toward a final choice. For this reason, recommendation systems matter not only as technical tools, but also as part of the broader user experience [1].

At the same time, user response to recommendation systems cannot be explained by technical performance alone. Even when a system is accurate or efficient, users may respond differently depending on how they experience the interaction process. Some users engage readily because the system feels manageable and useful, while others remain cautious because the personalization process raises concerns about privacy and data use [2]. Recent work likewise shows that recommendation transparency, privacy-calculus considerations, and AI transparency signaling continue to shape user trust and acceptance in digital settings [3].

### 1.2 Research Gap

Prior research has offered strong explanations of recommendation-system adoption through technology-centered perspectives, especially perceived usefulness, perceived ease of use, and task-technology alignment. These perspectives are valuable, but they do not fully explain why technically effective recommendation systems still generate uneven or ambivalent responses [4]. One reason is that the literature has often treated user capability and privacy-related concern as separate issues. In recommendation environments, however, these two sides often operate at the same time. Users may be willing to engage because they feel confident in handling the system, yet still hesitate because they are uneasy about tracking, profiling, or data collection. A model that considers these forces together can therefore offer a more complete explanation of consumer response [5].

 

Recent studies suggest that recommendation use now differs from the classic one-time IT adoption setting assumed in much of the early acceptance literature. Li et al. show that recommendation-system transparency can strengthen consumer trust, but that effect depends on whether transparency increases perceived effectiveness without creating additional discomfort [6]. Wang et al. likewise demonstrate that recommendation acceptance is shaped by a privacy-calculus trade-off in which users weigh personalization benefits against perceived privacy violation [7]. These findings imply that user acceptance is already a negotiated judgment rather than a simple reaction to system accuracy or relevance. Recent work on AI-mediated communication further shows that transparency signals can transfer into stronger trust and relational satisfaction [8], while new review evidence indicates that privacy and security remain central conditions for the credibility of recommender systems [9]. For that reason, the recommendation context is theoretically more demanding than ordinary system adoption: users are not only asking whether a system works, but whether it remains understandable, controllable, and acceptable over time.

### 1.3 Research Objective and Contribution

This study addresses that gap by examining self-efficacy as an enabling factor and perceived privacy risk as a constraining factor in recommendation environments. Rather than treating these as isolated influences, the paper considers how they jointly shape consumer response, both directly and through perceived ease of use, perceived usefulness, and satisfaction.

The study contributes in two ways. First, it extends technology-centered explanations of recommendation acceptance by incorporating psychological capability and privacy-related concern into the same framework. Second, it gives that framework an empirical form by testing it with survey data, allowing the argument to move beyond conceptual discussion and into a more explicitly evidence-based model. In this sense, the present study does more than combine two familiar constructs. It reframes recommendation acceptance as a continuing boundary process in which users judge whether the system remains both usable and legitimate. That distinction matters because recommendation systems rely on repeated exposure, implicit profiling, and ongoing preference inference, all of which make continued acceptance more fragile than a single adoption decision. By foregrounding this dual condition, the paper shifts the discussion from whether the technology can be used to whether users are willing to keep engaging under conditions of persistent personalization.

## 2. Literature Review and Hypothesis Development

### 2.1 Recommendation Algorithms and Consumer Responses

Recommendation algorithms help users filter information, narrow large sets of options, and reduce search costs in online settings. Their influence, however, extends beyond technical matching. They also affect how users allocate attention, evaluate alternatives, and act on what they see. A recommendation does not merely present an option; it can shape what appears worth considering in the first place.

For that reason, consumer response is best treated as a broader outcome rather than a single behavioral event. It includes cognitive evaluation, affective reaction, and behavioral follow-through [10].

### 2.2 TAM and TTF as the Baseline Logic

The Technology Acceptance Model offers a useful starting point for understanding responses to recommendation systems. Its central claim is that users are more likely to adopt a system when they regard it as useful and easy to use. In recommendation environments, these two perceptions remain highly relevant.

Task-Technology Fit adds a related perspective by emphasizing the match between what a technology can do and what users are trying to accomplish. Together, TAM and TTF explain why usability, usefulness, and fit matter in recommendation-system acceptance, while still leaving room for additional factors tied to confidence and privacy-related concern [11].

### 2.3 The Enabling Role of Self-Efficacy

Self-efficacy plays an enabling role in recommendation environments because users are more likely to engage with algorithmic systems when they feel capable of using them. In Social Cognitive Theory, self-efficacy refers to a person's belief in their ability to perform actions and achieve intended outcomes. In the context of recommendation systems, that belief matters because users are required to interpret suggestions, compare options, and make judgments in settings where information is abundant and attention is limited.

Users who feel more capable are generally more likely to see a recommendation system as easier to use. Once interaction feels manageable, the system is also more likely to be viewed as useful. In this study, the empirical results follow that pattern: self-efficacy is positively associated with perceived ease of use, perceived usefulness, satisfaction, and consumer response.

H1: Self-efficacy positively influences perceived ease of use.

H2: Self-efficacy positively influences perceived usefulness.

H3: Self-efficacy positively influences user satisfaction.

H4: Self-efficacy positively influences consumer responses to recommendation algorithms.

### 2.4 The Constraining Role of Perceived Privacy Risk

If self-efficacy helps explain why users engage, perceived privacy risk helps explain why they may hesitate. Recommendation systems depend heavily on user data collection, behavioral tracking, and the inference of personal preferences. These processes make personalization possible, but they can also raise concerns about surveillance, data misuse, unauthorized sharing, and loss of control over personal information [12]. Recent reviews further note that privacy and security concerns remain central to user trust, system credibility, and the overall effectiveness of recommender systems.

A recommendation may be relevant and convenient, yet still produce discomfort if it appears overly intrusive or insufficiently transparent. The empirical results in this study reflect that tension: perceived privacy risk is significantly related to both satisfaction and consumer response.

H5: Perceived privacy risk significantly influences user satisfaction.

H6: Perceived privacy risk significantly influences consumer responses to recommendation algorithms.

### 2.5 Mediating Roles of PEU, PU, and Satisfaction

The effects of self-efficacy and privacy risk are unlikely to be purely direct. In recommendation contexts, users typically move through a set of intermediate evaluations before arriving at a behavioral response. They first decide whether the system feels manageable, then whether it seems useful, and finally whether the overall experience is satisfactory enough to support continued engagement.

The empirical results support this logic. Perceived ease of use is positively associated with perceived usefulness and satisfaction. Perceived usefulness is positively related to both satisfaction and consumer response. Satisfaction also remains positively linked to consumer response.

### 2.6 Proposed Research Model

This study proposes a dual capability-risk model of consumer responses to recommendation algorithms. The model treats self-efficacy and perceived privacy risk as the two main antecedents, while recognizing that their effects are partly carried through perceived ease of use, perceived usefulness, and satisfaction. The proposed research model is shown in Figure 1

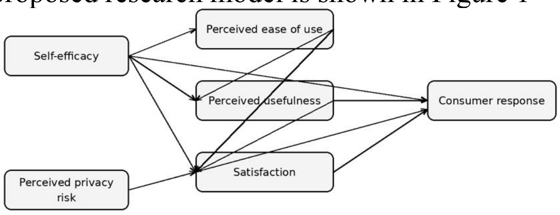


**Figure 1. Proposed Research Model**

## 3. Methodology

### 3.1 Sample and Data Collection

To test the proposed model, this study used a questionnaire survey targeting consumers with experience in online personalized recommendation environments. Data collection was conducted from January to July 2024. During this period, 550 questionnaires were distributed, 535 were returned, and 515 valid responses were retained for analysis. This corresponds to a response rate of 97.27% and a valid-response rate of 96.26% as shown in Table 1.

**Table 1. Survey Distribution and Valid Response Rate**

| Item | Value |
| --- | --- |
| Distributed questionnaires | 550 |
| Returned questionnaires | 535 |
| Valid questionnaires | 515 |

| | |
|---|---|
| Response rate | 97.27% |
| Valid-response rate | 96.26% |

### 3.2 Respondent Profile

The sample reflects an active online consumer group. In terms of gender, 47.20% of respondents were male and 52.80% were female. The age distribution is concentrated among younger adults, with the largest group in the 25-30 range (33.80%), followed by 31-34 (22.90%) and 18-24 (20.40%) as shown in Table 2.

The educational profile also indicates a relatively well-educated sample, with 60.00% of respondents holding a university degree. These characteristics make the sample suitable for studying user evaluations and behavioral responses in recommendation-rich digital environments.

**Table 2. Respondent Characteristics**

| Dimension | Category | Percentage |
|---|---|---|
| Gender | Male | 47.20% |
| Gender | Female | 52.80% |
| Age | 18-24 | 20.40% |
| Age | 25-30 | 33.80% |
| Age | 31-34 | 22.90% |
| Age | Other age groups | 22.90% |
| Education | University degree | 60.00% |

### 3.3 Measures

The study focuses on six constructs: self-efficacy (SE), privacy risk (PRIR), perceived ease of use (PEU), perceived usefulness (PU), satisfaction (SAT), and consumer response (Y). These variables correspond directly to the theoretical model developed in the paper. Self-efficacy and privacy risk are treated as the two main antecedents, while perceived ease of use, perceived usefulness, and satisfaction capture the evaluative process through which users arrive at a behavioral response.

In the measurement design, self-efficacy was measured with five items, privacy risk with three items, perceived ease of use with three items, perceived usefulness with four items, satisfaction with four items, and consumer response with three items.

### 3.4 Reliability and Validity

The measurement results indicate that the scale is suitable for empirical analysis. For the full instrument, Cronbach's alpha is 0.918, the KMO value is 0.891, and the cumulative explained variance reaches 73.29% as shown in Table 3. These values suggest strong internal consistency and adequate factorability for the present dataset.

**Table 3. Reliability and Convergent Validity of the Focal Constructs**

| Construct | Items | Cronbach's alpha | CR | AVE |
|---|---|---|---|---|
| Self-efficacy (SE) | 5 | 0.885 | 0.886 | 0.607 |
| Privacy risk (PRIR) | 3 | 0.822 | 0.825 | 0.612 |
| Perceived usefulness (PU) | 4 | 0.819 | 0.821 | 0.535 |
| Perceived ease of use (PEU) | 3 | 0.810 | 0.811 | 0.588 |
| Satisfaction (SAT) | 4 | 0.859 | 0.859 | 0.605 |
| Consumer response (Y) | 3 | 0.825 | 0.825 | 0.611 |

## 4. Results

### 4.1 Measurement Model Assessment

The measurement model performs adequately across the main diagnostic criteria. Reliability is acceptable for all focal constructs, and the convergent validity results indicate that the indicators load appropriately on their intended latent variables. The AVE values all exceed 0.50, which supports the view that the constructs capture a meaningful share of variance in their indicators.

### 4.2 Structural Model Results

The structural model results are consistent with the main theoretical expectations as shown in Table 4. Self-efficacy is positively associated with perceived ease of use, perceived usefulness, satisfaction, and consumer response. Perceived privacy risk is significantly associated with satisfaction and consumer response.

### 4.3 Mediating Effects

As shown in Table 5 .The indirect-effect results reinforce the idea that consumer response develops through a sequence of intermediate judgments. Self-efficacy affects consumer response through several mediated paths, and privacy risk also affects consumer response indirectly through satisfaction.

**Table 4. Structural Path Estimates for the Focal Model**

| Path | Beta | p-value | Direction | Decision |
|---|---|---|---|---|
| SE -> PEU | 0.150 | 0.003 | Positive | Supported |
| SE -> PU | 0.247 | < 0.001 | Positive | Supported |
| SE -> SAT | 0.116 | 0.021 | Positive | Supported |
| SE -> Y | 0.139 | 0.003 | Positive | Supported |
| PRIR -> SAT | 0.175 | < 0.001 | Significant | Supported |
| PRIR -> Y | 0.228 | < 0.001 | Significant | Supported |

 

| | | | | |
|---|---|---|---|---|
| PEU -> PU | 0.244 | < 0.001 | Positive | Supported |
| PEU -> SAT | 0.145 | 0.004 | Positive | Supported |
| PU -> SAT | 0.264 | < 0.001 | Positive | Supported |
| PU -> Y | 0.197 | < 0.001 | Positive | Supported |
| SAT -> Y | 0.148 | 0.005 | Positive | Supported |

**Table 5. Indirect Effects of Self-Efficacy and Privacy Risk**

| Indirect path | Estimate | p-value | Decision |
|---|---|---|---|
| SE -> PU -> Y | 0.049 | 0.006 | Supported |
| SE -> PU -> SAT -> Y | 0.002 | 0.009 | Supported |
| SE -> PEU -> SAT -> Y | 0.003 | 0.013 | Supported |
| SE -> SAT -> Y | 0.017 | 0.025 | Supported |
| PRIR -> SAT -> Y | 0.026 | 0.024 | Supported |

## 5. Discussion

### 5.1 The Enabling Role of Self-Efficacy

The results indicate that self-efficacy matters at more than one point in the response process. It is linked not only to consumer response itself, but also to perceived ease of use, perceived usefulness, and satisfaction. This pattern suggests that confidence in using recommendation systems helps reduce the friction users may otherwise experience when interacting with algorithmic features.

### 5.2 The Constraining Role of Privacy Risk

The findings also show that recommendation effectiveness is limited by perceived privacy risk. Even when a system offers relevant or efficient recommendations, users may respond cautiously if they are uneasy about data collection, profiling, or information control.

### 5.3 A Dual Capability-Risk Interpretation

Taken as a whole, the results support a dual capability-risk interpretation of consumer response. Positive reactions to recommendation systems are more likely when users feel both able to use the system and reasonably secure about the way personal data are involved.

This dual mechanism is best understood as a psychological boundary condition for algorithmic acceptance rather than as two independent predictors operating in parallel. Self-efficacy lowers cognitive strain because it helps users interpret recommendations, compare alternatives, and recover from minor mismatches without feeling overwhelmed. Privacy risk, by contrast, changes the perceived legitimacy of personalization itself: when profiling appears excessive or opaque, the same recommendation may be read as manipulative rather than helpful. Recent evidence supports this interpretation. Li et al. find that transparency improves trust only when it enhances perceived effectiveness without simultaneously increasing discomfort [11], and Wang et al. show that users evaluate recommender systems through a benefit-risk trade-off tied to privacy calculus. Related research also indicates that transparency signaling can strengthen trust and relational satisfaction in AI-mediated settings. Taken together, these studies suggest that recommendation acceptance is not a linear extension of system quality. It is an ongoing judgment shaped by whether users feel competent enough to engage and secure enough to accept the underlying data logic.

## 6. Theoretical and Practical Implications

### 6.1 Theoretical Implications

The main theoretical contribution of this study is that it brings together strands of research that are often discussed separately. By introducing self-efficacy and privacy risk into the same explanatory framework, the paper shows that recommendation-system acceptance is shaped by more than functional performance. Users respond not only to what the system can do, but also to whether they feel able to use it and whether the personalization process feels acceptable.

This perspective also refines how TAM and TTF should be read in algorithmic settings. Here, usefulness and ease of use are not simply proximal beliefs; they are partly conditioned by whether users feel in control of the interaction and whether the recommendation process appears trustworthy. Likewise, even a technically appropriate task-technology fit does not guarantee acceptance if privacy concerns weaken users' willingness to rely on the system. Theoretical progress therefore lies in showing that recommendation acceptance is a joint outcome of functional fit, psychological readiness, and informational assurance rather than a product of technical performance alone.

### 6.2 Practical Implications

For platform designers, the findings suggest that recommendation quality should not be treated as a purely technical issue. Improving relevance or accuracy remains important, but those improvements may have limited effect if users do not feel comfortable using the system or remain uneasy about how their data are handled.

The results point to two practical priorities. First, platforms should support user confidence through clearer interface design, better onboarding, concise explanations of recommendation features, and interaction flows that reduce confusion. Second, platforms need to treat privacy assurance as part of the recommendation experience itself through visible privacy controls, clearer consent language, and transparent explanations of data use. Recent studies on recommendation transparency and AI transparency signaling suggest that these design choices can strengthen trust and reduce discomfort in digital interactions.

## 7. Conclusion

This study argues that consumer responses to recommendation algorithms are shaped by both enabling and constraining forces. Self-efficacy supports engagement by making users more willing and more able to work with recommendation features, whereas perceived privacy risk influences whether those same features are experienced as acceptable and trustworthy.

The findings also suggest that these influences do not operate in isolation. Their effects are partly carried through perceived ease of use, perceived usefulness, and satisfaction, which together help explain how users move from initial perception to behavioral response. For this reason, the effectiveness of recommendation systems should be understood as more than a matter of technical optimization. It also depends on whether users feel competent in using the system and comfortable with the conditions of personalization.

Future research could extend this work by testing the model in different platform settings, using broader samples, or introducing additional variables such as trust, transparency, or explainability. Recent studies indicate that transparency design, privacy calculus, and privacy-security governance remain promising directions for extending recommender-system research. For platform designers, the implication is clear: improving recommendation performance remains important, but it is unlikely to be sufficient unless users also feel confident and protected.

**Acknowledgments**

This paper is supported by the 2023 Youth Academic Research Project of Guangzhou Huashang College, titled “Research on Consumer Behavior from the Perspective of Recommendation Algorithms” (Project No. 2023HSQX046).

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