

The Impact of Netflix's AI Powered Recommendation System on Consumers' Behavioral Intentions

Mehmet Etlioglu (corresponding author)

Department of International Trade and Business Administration, Faculty of Social Sciences and Humanities, Konya Food and Agriculture University, Merkez Kampüs, 42080 Meram / Konya, Türkiye
Email: mehmet.etlioglu@gidatarim.edu.tr

Article History

Received: 23 Aug 2025 Revised: 25 Nov 2025 Accepted: 06 Dec 2025 Published: 31 Dec 2025

Abstract

Current studies primarily focus on the recommender systems (RSs) through the algorithmic accuracy, and which insufficient to fully measure accurately the practical effectiveness of the RSs and understand user experience. There is an urge examine the dynamic interactions on the critical user context of "beyond accuracy" features such as diversity, novelty, and serendipity to understand RS's value creation mechanism holistically. The aim of the study is to explore the multidimensional effects of key features (Stimuli) of artificial intelligence (AI)-RSs on consumer behavior (Response) based on the Stimulus-Organism-Response (S-O-R) theoretical framework which is a gap in the literature. The study was modeled four key features of RSs (accuracy, diversity, novelty, serendipity) as stimuli, user engagement, satisfaction, and perceived risk as organism (mediating constructs), and behavioral intentions as the response. Data was collected from 437 participants, and analyses were conducted using the covariance-based structural equation modeling (CB-SEM) by AMOS 24.0 and SPSS 25.0 statistical programs. The findings explains that the empirical assumptions of the S-O-R model were met to a high degree, successfully explaining 61% of the variance in behavioral intentions. Specifically, satisfaction and engagement have strongest positive effects on behavioral intentions. The findings suggest that the effectiveness of AI-RSs should no longer be evaluated solely through algorithmic accuracy, but rather through the dynamics of user-centered value creation (satisfaction, engagement, and risk management). Furthermore, serendipity have the strongest direct effect on engagement, highlighting the importance of "beyond-accuracy objectives" that trigger curiosity. Accuracy and diversity significantly and negatively reduce risk, demonstrating a critical role in increasing system trustworthiness. Contrary to the accuracy-diversity trade-off problem, a strong positive relationship exists between accuracy and diversity, suggesting that these multiple goals reinforce each other in the context of user perception. These results provide important theoretical and practical consequences for the design of multi-objective recommender systems (MORS).

Keywords: AI-Powered Recommendation Systems, Accuracy, Novelty, Diversity, Serendipity, Engagement, Satisfaction, Perceived Risk, Netflix viewers, Türkiye.

1. Introduction

AI powered recommendation systems (AI-RSs) have emerged as critical tools for reducing information overload and offering personalized products/services in areas such as e-commerce, financial services, and content streaming with the rapid expansion of the digital age and the transformation of social and economic lifestyles by globalization (Haenlein & Kaplan, 2019). AI capability significantly contributes to businesses' understanding of dynamic customer behavior based on consumers' interests, tastes, trends, and preferences (Nikitha et al., 2025). In this regard, AI-RS is a strategic tool that reduces information overload, retains users longer on the platform, increases satisfaction, and reduces risk—in short, enhances the consumer experience. (Chatterjee et al. 2019; Schafer et al., 2001; Verma et al. 2021).

While traditional RS research has long focused on algorithmic efficiency and predictive accuracy (Herlocker et al., 2004; Jannach & Adomavicius, 2016; Pu et al., 2012), the primary motivation for this study stems from the academic shift that the ultimate business value of a system and long-term customer loyalty are built on user-centric experience, service quality, and risk management, rather than pure algorithmic performance. This motivation is reinforced by the idea that measuring long-term customer loyalty and business value in AI-RS requires focusing on elements such as service quality and customer experience. There are criticisms in the literature that optimizing accuracy is insufficient and can even be detrimental (accuracy metrics have hurt RSs). Therefore, academic attention has shifted beyond accuracy to the importance of "beyond-accuracy objectives" (diversity, novelty and serendipity).

Furthermore, AI-RS researches have focused primarily on developed economies such as US, the UK, China, and Germany (Efendioğlu, 2023; Jain et al. 2024; Li, 2019), This creates a significant limitation in the applicability of RSs to emerging economies like Türkiye, which may have different cultural dynamics and regional perceptions (Sharma, 2023). RSs should be regarded as social-technical systems that shape the user experience (Konstan & Terveen, 2021; Troussas et al. 2021). Therefore, it is crucial for business and platform managers to adapt RS strategies to the regional/cultural/sectoral contexts and the level of perceived risk in order to succeed globally (e.g., It requires thinking global, act locally approach of producing content) and to gain the trust of regional users. In this context, a key research gap and theoretical tension in the literature was the lack of a holistic structural model demonstrating how the impact of RS attributes (Stimuli: accuracy, diversity, novelty, and serendipity) on consumer behavioral intentions (Response) is mediated through cognitive and emotional internal processes (Organism) such as engagement, satisfaction, perceived risk (Jugovac & Jannach, 2017; Konstan & Terveen, 2021; Shi et al., 2014). The theoretical tension that the accuracy-diversity trade-off, often

assumed dilemma in traditional RS, needs to be empirically examined at the user perception level is also addressed.

High levels of personalization and the use of Big Data have made risk management indispensable, increasing not only consumers' privacy concerns but also the risk of locking users into narrow preferences (filter bubble). This suggests that RS design requires MORS optimization approach, which requires simultaneously optimizing conflicting objectives such as utility, variety, and fairness, and a multi-stakeholder recommender system (MRS) approach, which requires balancing the interests of multiple stakeholders. Furthermore, the "black box" nature of algorithmic decisions necessitates the integration of explainable artificial intelligence (XAI) mechanisms to enhance the reliability and understandability of recommendations, in accordance with the principles of fairness, accountability, transparency, and ethics (FATE).

To address these critical theoretical and geographical gaps, this study empirically examines the quality of AI-Rs based on the S-O-R framework. Four core RS attributes (accuracy, diversity, novelty, and serendipity) are modeled as stimuli; consumer psychological states (engagement, satisfaction, risk) as organism; and the ultimate marketing objective (behavior intentions) as Response. This study offers strong practical implications for guiding AI-RS strategies for emerging economies like Türkiye. In line with this motivation, the following fundamental research questions were defined:

1. What is the direct effect of stimuli on organism?
2. What is the direct effect of organism on response?
3. What is the mediating role of organism in the relationship between stimuli and response?

2. Theoretical Background

2.1 The S-O-R Theoretical Framework

The S-O-R model establishes a robust and dynamic theoretical foundation for explaining how external stimuli (accuracy, diversity, novelty, and serendipity) affect individuals' internal states as organisms (engagement, satisfaction, and perceived risk) and lead to behavioral intentions (response) (Mehrabian & Russell, 1974). It is widely employed to investigate consumer behavior researches (Wang & Benbasat, 2016; Xiao & Benbasat, 2007). Stimuli components are typically taken the core features of RS such as accuracy, diversity, novelty, and serendipity, supported by AI in this model. These stimuli are processed through organism variables such as engagement, satisfaction, and risk, which representing the consumer's internal reactions and perceptions which play mediating role. The final output of the model is response, which is modeled as the resulting patterns (purchase, continued use, or adoption intention).

The selection of four core RS attributes (accuracy, diversity, novelty, and serendipity) is grounded core RS evaluation methodologies that emphasize the importance of "beyond-accuracy objectives." (Foster & Keane, 2013; Gan et al., 2020; Khanagha et al., 2017; Trattner et al., 2023). Herlocker et al. (2004) conclude that pure accuracy metrics are insufficient for evaluating algorithm performance and suggested using user-centered fidelity measures such as coverage and novelty/serendipity. This legitimizes quantitative modelling which is employed to assess how four core are influential on user experience and engagement.

2.2 The Recommendation System of Netflix

RSs are types of information filtering systems extensively used in streaming services that predict users' interests and offer proper contents. Netflix RS utilizes benefit from AI and machine learning (ML). The core approach utilizes collaborative filtering (content liked by similar users) and content-based filtering (similar content to what you've watched) as hybrid filtering to take into account viewing history, user preferences, and interactions with people with similar tastes (Bell et al., 2010; Reddy et al., 2019) to provide better-personalized user experiences (Gomez-Uribe & Hunt, 2015). In addition, RS algorithms analyze the details such as genres, actors, and directors that the user has previously watched, as well as contextual information such as the user's entry time, language, device type, and duration (Netflix, 2025). Netflix offers real time personalized recommendations after evaluating user data based on past habits for the purpose of increasing engagement, satisfaction in order to strengthen user loyalty (Gomez-Uribe & Hunt, 2015). Netflix's strategy both improves user experience and increase retention old customer, while attracting new customers, and optimizes by reducing customer churn (Amatriain, 2013; Njomo, 2022).

Netflix's RS facilitates optimization of data which is accurate, diverse, novel, and serendipitous recommendations to increase user engagement and satisfaction (Khandelwal et al., 2023). The achievement of Netflix's RS is assessed through performance and quality factors specifically accuracy, novelty, diversity, and serendipity (Castells et al., 2022). The need for recommendation algorithms to optimize accuracy, diversity, novelty and serendipity are significant challenges facing the system because of dynamic industry and the ever-changing customer behavior (González et al., 2020).

2.3 Accuracy

Accuracy means the agreement between the user's current and expected preferences (Bobadilla et al., 2013; Lu et al., 2015; Smyth & McClave, 2001), complying the recommendations with the user's current and past preferences, interest, and tastes (Shi et al., 2014). It exerts a considerable influence on increasing engagement and satisfaction (He et al., 2017; Lee & Lee, 2023), and decreasing risk in the long term (Bobadilla et al., 2013; Gomez-Uribe & Hunt, 2015). Making the most relevant and precise recommendations aligned with users' interests is vital for the success of RS (Gomez-Uribe & Hunt, 2015), ensuring the accuracy is also a challenging area. The relationship between accuracy and

diversity has traditionally presented a fundamental challenge in system design: the accuracy-diversity trade-off in the RSs literature (Kaminskas & Bridge, 2016; Kunaver & Požrl, 2017; Wu et al., 2018). This dilemma stems from the tendency of systems to recommend best-selling items or items befitting when aiming for high accuracy; this leads to a narrow and homogeneous recommendation list, thus reducing diversity (Cai et al., 2005; Matt et al., 2014). However, there are studies suggesting that can be regarded as dilemma and can be overcome with MORS (Wang et al., 2023; Zheng & Wang, 2022).

2.4 Diversity

Users may be interested in different topics. Therefore, a RS should be able to cater to these different tastes and create diverse recommendation lists. Diversity measures the effectiveness of recommending items that customers have not previously purchased (Lu et al., 2015). It also indicates to the ability of the resulting lists to handle uncertainty or under specification (Clarke et al., 2008). The performance of recommendation algorithms has been measured primarily by using accuracy and diversity metric (Bag et al., 2019; Zhou et al., 2010). Studies on recommendation diversity center on how well RSs suggest different items that the customer has not purchased before, at a certain level of accuracy (Kotkov et al., 2020).

2.5 Novelty

Novelty is the quality of being new or different from what is known (Knijnenburg et al., 2012), and complementary concept with diversity (Castells et al., 2022). The word “novel” means “new – unknown, original and unprecedented,”; and “refreshing – pleasantly new or different” (Zhang, 2013) and highly desirable feature for a RS (Mendoza & Torres, 2020). Novelty measure the tendency to recommend items that are relevant to users yet not yet seen, known or experienced (Karimi et al., 2018). It is directly linked to the idea that the primary goal of RSs should be to elicit discovery by exposing users to relevant experiences they wouldn't otherwise find. Therefore, novelty is often considered a perceived criterion from the user's perspective, determining how unusual an item is relative to the user's typical tastes (Castells et al., 2022).

2.5 Serendipity

Serendipity is a stronger concept of novelty that refers to items that are novel because of unexpected, yet new, relevant, and a positive surprise for the user. (Kotkov et al., 2020). Serendipity involves the user's positive emotional response to previously unknown serendipity (Adamopoulos & Tuzhilin, 2014). Serendipity is a system's performance measure that indicates how well a recommendation system is at recommending serendipitous items (Gunawardana & Shani, 2015), which should be unpopular and significantly different from a user's profile (Zhang et al., 2012). Recommended serendipitous contents substantially stimulate user curiosity to enhance user experience, foster loyalty, and build trust with users (Bellogín et al., 2013).

3. Hypotheses Development

The following hypotheses were created in order to examine the direct and indirect effects relationships between accuracy, diversity, novelty, serendipity (Stimuli) and behavior intentions (Response), and engagement, satisfaction, and perceived risk (Organism) on the basis of the S-O-R framework.

3.1 The Effect of Accuracy of RS on Engagement, Satisfaction and Perceived Risk

High precision in AI-RS refers to the system's ability to adapt to user behavior and respond in real time, meaningfully promoting user engagement and satisfaction (Gomez-Uribe & Hunt, 2015; Ricci et al., 2011). When users believe that the RS understands and meets their current and past needs, tastes, preferences, and interests, their engagement, loyalty, and reuse intensify (Oestreicher & Sundararajan, 2012). Highly relevant and personalized recommendations promote consumer engagement and satisfaction, while reducing risk (Adamopoulos & Tuzhilin, 2014; Alabi, 2024; Ge et al., 2010; Jannach et al., 2022). While low recommendation accuracy can increase perceived risk, this leads to negative behavioral intentions (Gefen, 2000; Pavlou, 2003). When customers trust the accuracy of recommendations, their risk perception decreases, thus increasing their likelihood of purchasing. As a result of these comments and discussions, these hypotheses are proposed:

H1: Accuracy has positive effect on user engagement.

H2: Accuracy has positive effect on satisfaction.

H3: Accuracy has negative effect on perceived risk.

3.2 The Effect of Recommendation Diversity on Engagement, Satisfaction, and Perceived Risk

Different, distinct, and relevant recommendations are founded on users' areas of interest, tastes and preferences in order to encourage them to engage and stay on the platform by providing a diverse options (Zhou et al., 2019), and positively impact user satisfaction (Yoon & Lee, 2021). Platforms offer a mix of recommendations aligned with users' past tastes and preferences thus new recommendations makes interactions more personalized and satisfying. If the recommendations do not correctly align with users' tastes and preferences, they will fail to engage and abandon the platform (Alabi, 2024; Yoon & Lee, 2021). However, if the RS suggests the same product constantly, customer satisfaction and risk perception will decrease even if the accuracy is high (Aggarwal, 2016; Bobadilla et al., 2013). Users may distrust irrelevant and different recommendations, or surprising recommendations may increase risk by reducing the risk of "filter bubbles" (Zhang et al., 2012). Also, personal data usage may increase risk perception in the generating diversification process (Zhou et al., 2019). As a result of these comments and discussions, the hypothesized are proposed:

H4: Diversity has positive effect on user engagement.

H5: Diversity has positive effect on satisfaction.

H6: Diversity has negative effect on perceived risk.

3.3 The Effect of Novelty on Engagement, Satisfaction, and Perceived Risk

Novel recommendations encourage exploration and intensify users' interest in the platform by presenting them with products or content that they have not encountered before (Zhou et al., 2010). This paves the way for users to spend more time on the platform and become engaged. Novel recommendations while in attracting users' attention and retaining them on the platform actively (Ge et al., 2010; Vargas & Castells, 2011) is pivotal element their loyalty and satisfaction with the platform increases (McNee et al., 2006) risk perception reduce (Herlocker et al., 2004). The reduction of perceived risk positively affects users' purchase intentions and increases their likelihood of making purchases on the platform (Tuzhilin, 2009). The novel recommend has direct impact on user's spending time, satisfaction, and perceived risk to attract and retain users in long term in the online platforms (Vargas & Castells, 2011; Herlocker et al., 2004). Therefore, these hypotheses are proposed:

H7: Novelty has positive effect on user engagement.

H8: has positive effect on satisfaction.

H9: Novelty has negative effect on perceived risk.

3.4 The Effect of Serendipity on Engagement, Satisfaction, and Perceived Risk

Online retailers increasingly value serendipity as a key driver of consumer satisfaction (Yi & Nataraajan, 2018), which have positive effect (Matt et al., 2014), and engagement (Sun et al., 2021). Serendipitous items facilitate overcoming the overspecialization problem (Adamopoulos & Tuzhilin, 2014), while broadening user preferences (Sun et al., 2021; Yoon & Lee, 2021; Zhang et al., 2012), enriches the discovery process of users (Rashid et al., 2002), and increase user satisfaction with interesting recommendations (Adamopoulos & Tuzhilin, 2014; Chen et al., 2019; Sun et al., 2021), it reduce risk by offering unexpected, new, relevant, and a surprise (Adamopoulos & Tuzhilin, 2014; McNee et al., 2006). In this context, Serendipity in RSs is reflected as a important factor that improves user experience (Ziegler et al., 2005). Therefore, the hypotheses are proposed:

H10: Serendipity has positive effect on user engagement.

H11: Serendipity has positive effect on satisfaction.

H12: Serendipity has negative effect on perceived risk.

3.5 The Effect of Engagement, Perceived Risk, and Satisfaction on Behavioral Intentions

Engagement significantly influences online purchase intentions by enhancing the personalization and relevance of recommendations in AI-based RSs (Tam & Ho, 2006; Wang & Benbasat, 2007). More engaged users are more likely to perceive recommendations as credible and useful, which increase trust and satisfaction, reduces

perceived risk and leads to positive behavior or heighten the profitability of purchase (Kim & Ko, 2012; Komiak & Benbasat, 2006; Pu et al., 2011; Schafer et al., 2001). Satisfaction is not only related to how well the system provides accurate recommendations, also to how well it supports user decision-making in AI-powered RSs (Murakami et al., 2008). Positive experiences generate to more satisfied users and positive behavior (Komiak & Benbasat, 2006). While higher personalization can contribute to greater user satisfaction and purchase likelihood (Haenlein & Kaplan, 2019), also raises concern about data privacy and security, thus increasing risk (Konstan & Terveen, 2021). In addition, unmet expectations, data gathering and unethically usage of personal information can negatively impact users' trust in the system and leading to perception risk (Tintarev & Masthoff, 2012) and decrease purchase likelihood (Featherman & Pavlou, 2003; Haridasan & Fernando, 2018). In the light of information and discussion presented, the hypotheses are proposed;

H13: Engagement has positive effect on behavioral intentions.

H14: Satisfaction has positive effect on behavioral intentions.

H15: Perceived risk has negative effect on behavioral intentions.

3.6 The Mediation Role of Engagement, Satisfaction, and Risk between and RS Features and Behavioral Intentions

Accuracy, diversity, novelty, and serendipity boosts users' interest in the RS and escalate the level of interaction (Pu et al., 2011), while users' low perceived risk facilitates system adoption and users' development of positive behavioral intentions (Ricci et al., 2015). Higher engagement does not only enhances users' satisfaction towards the platforms also positively affects their behavioral intentions (Herlocker et al., 2004). User engagement is considered an important mediator variable in the relationship between RS features and behavioral intentions (Ricci et al., 2015). Satisfaction is directly related to the quality of RSs and the level of meeting user expectations. Accuracy and diversity make users more satisfied, and thus helping to develop positive attitudes and behavioral intentions towards the RS (Pu et al., 2011). The mediating impact of of satisfaction on behavioral intentions is essential for the sustainable success of RSs (Tintarev & Masthoff, 2012). Risk perception also reflects users' trust and hesitation towards RSs. High perceived risk can negatively affect users' engagement with the system and behavioral intentions (Jannach et al., 2022). In the light of information and discussion presented, the hypotheses are proposed;

H16: The relationship between RS features and behavioral intentions is mediated by engagement.

H17: The relationship between RS features and behavioral intentions is mediated by satisfaction.

H18: The relationship between RS features and behavioral intentions is mediated by perceived risk.

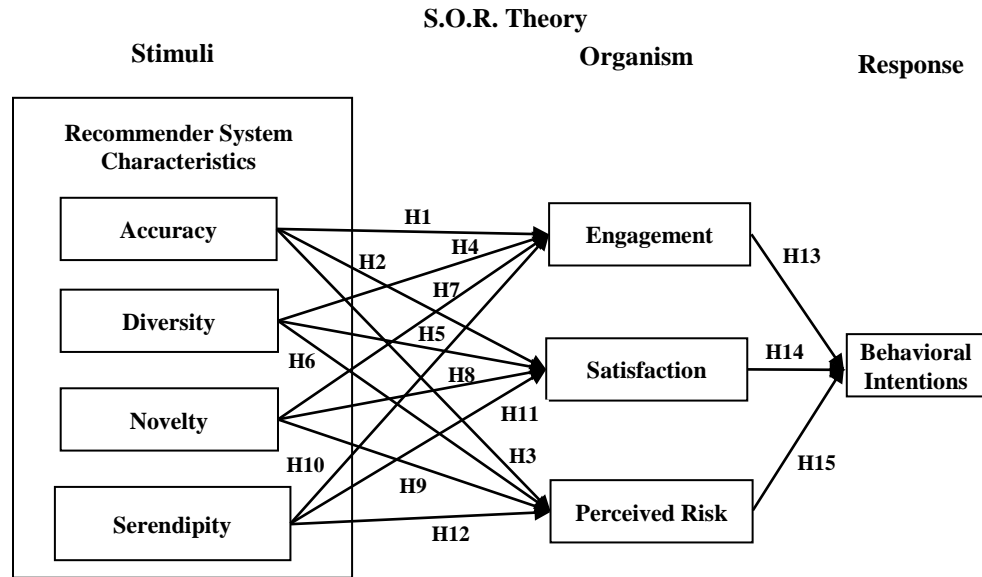


Figure 1: Research Model

4. Methodology

4.1 Data Collection

The convenience sampling method has been employed to obtain data. Primary data has been obtained by reaching out to the Netflix viewers in Türkiye. For eligibility, participants are required to have a Netflix subscription and have watched the movie(s). Face validity testing and content scale testing have been conducted before collecting primary data. Firstly, a pilot study has been conducted with 30 respondents. Some items were redesigned that would cause any uncertainty or misunderstanding regarding the items in the questions. 437 Netflix users have completed the survey, which has been conducted online in Türkiye.

4.2 Measures

Measurements in the study related to the conceptual model are taken from previous studies and have been proven to be validity and reliability in the study. Accuracy, diversity, novelty, and serendipity were measured with a single-item adapted from studies in the literature (Es, 2023; Pu et al., 2011). User engagement (O'Brien et al., 2018), satisfaction (Liang et al., 2006), perceived risk (Featherman & Pavlou, 2003) and behavioral intentions scale are adapted by (Pu et al., 2011). The measurement of all items are rated on seven-point Likert scales (Table 1). In addition, control variables were not used in order to protect

theoretical parsimony of the S-O-R model and isolate the main mechanism and prevent creating multicollinearity risk in the study (Bagozzi & Yi, 2012).

Scales	Items	Factor Loadings	Alpha	CR	AVE	MSV	Max R(H)
Perceived Risk (PRSK)	PRSK1	0.78	0.98	0.98	0.68	0.28	0.985
	PRSK2	0.768					
	PRSK3	0.79					
	PRSK4	0.804					
	PRSK5	0.797					
	PRSK6	0.761					
	PRSK7	0.796					
	PRSK8	0.762					
	PRSK9	0.811					
	PRSK10	0.874					
	PRSK11	0.832					
	PRSK12	0.842					
	PRSK13	0.697					
	PRSK14	0.86					
	PRSK15	0.886					
	PRSK16	0.875					
	PRSK17	0.874					
	PRSK18	0.879					
	PRSK19	0.875					
	PRSK20	0.885					
	PRSK21	0.893					
	PRSK22	0.91					
	PRSK23	0.897					
	PRSK24	0.885					
	PRSK25	0.886					
Satisfaction (STF)	STF1	0.798	0.970	0.975	0.76	0.732	0.976
	STF2	0.824					
	STF3	0.891					
	STF4	0.902					
	STF5	0.864					
	STF6	0.864					
	STF7	0.861					
	STF8	0.84					
	STF9	0.916					
	STF10	0.893					
	STF11	0.895					
	STF12	0.903					

Behavioral Intentions (BINT)	BINT1	0.938	0,950	0,955	0,782	0,601	0,972
	BINT2	0.958					
	BINT3	0.924					
	BINT4	0.937					
	BINT5	0.812					
	BINT6	0.71					
Engagement (ENG)	ENG1	0.716	0,96	0,963	0,683	0,732	0,966
	ENG1	0.814					
	ENG2	0.779					
	ENG3	0.887					
	ENG4	0.793					
	ENG5	0.824					
	ENG6	0.872					
	ENG7	0.834					
	ENG8	0.89					
	ENG9	0.84					
	ENG10	0.766					
ENG11	0.883						

5. Data Analysis and Results

CB-SEM was used, as it is the most suitable method for this purpose (Hair et al., 2014), because the study aimed to validate pre-specified theoretical relationships within the S-O-R model, the model provides global fit indices ($\chi^2=15.99$, $Df=4$, $CFI=1.0$, $RMSEA=.08$) that demonstrate the overall fit of the model (Hu & Bentler, 1999), indicating that the S-O-R structure strongly validates in the examined context. The model explains 61% of the variance in the behavioral intentions variable in total, 71% of user engagement, 59% of satisfaction and 22% of perceived risk. CB-SEM is compatible with our data set due to its sample size of 437 and its sensitivity in examining latent psychological constructs such as engagement, satisfaction, and risk (Bagozzi & Yi, 2012). CB-SEM approach directly connects to the methodology of previous research examining mediating effects (Kim et al., 2025; Zuva & Zuva, 2017) and causal chains in complex conceptual relationships (e.g., indirect effects of transparency or perceptual cues on satisfaction and purchase intention) (Benbasat & Wang, 2005).

AMOS 24.0 and SPSS 25.0 statistical programs were used for analyzing. For the normal distribution test of the data, skewness ($-0.98 \leq \text{skewness} \leq 0.59$) and kurtosis ($-0.56 \leq \text{kurtosis} \leq 0.57$) values has been examined and that the values are within ± 1 range (Tabachnick & Fidell, 2019). This finding shows that the data meets the normal distribution assumption. Cook distance values are to be below 1, indicating that there are no multivariate extreme values in the data set (Field, 2013). VIF values are less than 3, which confirms that no multicollinearity problem (Yurt, 2023). It is observed that all the assumptions required

for multivariate analysis, such as linear relationship, normality of error terms, and homogeneity of variance, are met (Byrne, 2013).

5.1 Measurement Model

Values of Cronbach's alpha (α), composite reliability (CR), and maximal reliability (MaxR(H)) are above 0.70 for all scales (Table 1). It is accepted for the factor loading value to be above 0.4 and the Average Variance Extracted (AVE) to be above 0.5 for convergent validity. The square root of each AVE must be greater than the correlation values among the constructs for discriminant validity (Jörg et al., 2016). AVE values are above 0.67, indicating that the model has reliable and convergent validity (Table 1). In addition, since the square root of the AVE value of each structure is greater than the correlations between other structures, it has been concluded that the model meets the criteria for discriminant validity. Alpha, CR, AVE and factor loading values haven't been calculated since the accuracy, diversity, novelty and serendipity variables measured with a single item. All items (PRSK1-25, STF1-12, BINT1-6, ENG-11) have high factor loadings (generally well above 0.71), indicating that the items strongly represent the construct to which they belong.

5.2 Common Method Bias (CMB)

Obtaining the data from a single source and in a single survey session may create CMB (Podsakoff et al., 2003). To minimize risk, procedural measures are implemented during the data collection phase to ensure anonymity and confidentiality to avoid social desirability pressure and to ensure psychological separation to prevent participant response consistency (Podsakoff et al., 2012). In addition to procedural measures, Harman's single-factor assessment (Podsakoff et al., 2003) has been utilized to evaluate the presence of CMB. The outcomes of the un-rotated factor analysis, has exhibited that the primary factor accounted for merely 27% of the overall variance.

5.3 Structural Model

Pearson correlation coefficients, maximum and minimum values, arithmetic means (M) and standard deviations (SD) among the variables in the study. The significance level for all correlation analyses was determined as $p < .01$ and the analysis is performed with data obtained from 437 participants (Table 2).

Table 2: Descriptive Statistics

	Variables	N	Min.	Max.	M	SD
1.	Accuracy	437	1	7	4.98	1.49
2.	Diversity	437	1	7	5.12	1.44
3.	Novelty	437	1	7	5.14	1.43
4.	Serendipity	437	1	7	4.91	1.44
5.	Engagement	437	17	82	58.11	15.50
6.	Satisfaction	437	12	84	59.31	16.05
7.	Perceived Risk	437	25	159	74.67	31.51
8.	Behavioral Intentions	437	6	42	28.20	8.69

When Table 3 is examined, a positive and strong relationship is revealed between accuracy and diversity ($r = .81, p < .01$). Similarly, positive and significant relationships were found between accuracy and novelty ($r = .82, p < .01$) and accuracy and serendipity ($r = .75, p < .01$). Engagement is profoundly related to accuracy ($r = .76, p < .01$) and satisfaction ($r = .83, p < .01$). Correlations between risk and other variables are negative. Especially, the relationship between risk and behavioral intentions is negative and significant ($r = -.48, p < .01$). Conversely, there is a positive and substantial relationship between behavioral intentions and satisfaction ($r = .76, p < .01$).

Table 3: Pearson Correlation Coefficients of Relationships between Variables

	Variables	1.	2.	3.	4.	5.	6.	7.	8.
1.	Accuracy	1.0							
2.	Diversity	.81**	1.0						
3.	Novelty	.82**	.83**	1.0					
4.	Serendipity	.75**	.77**	.77**	1.0				
5.	Engagement	.76**	.77**	.78**	.78**	1.0			
6.	Satisfaction	.73**	.69**	.68**	.69**	.83**	1.0		
7.	Perceived Risk	-.45**	-.44**	-.38**	-.39**	-.52**	-.52**	1.0	
8.	Behavioral Intentions	.67**	.63**	.65**	.62**	.73**	.76**	-.48**	1.0

** $p < 0.01, N = 437$

Created a path model is analyzed to test the research hypotheses. Accuracy, diversity, novelty, serendipity, engagement, satisfaction, and risk are included as endogenous variables, and behavioral intentions were included as exogenous variables in the model. The fit values ($\chi^2 = 15.99, Df = 4, p < .01, \chi^2/Df = 3.99, GFI = .99, AGFI = .92, TLI = .97, CFI = 1.0, RMSEA = .08, \text{ and } RMR = .02$) indicates that the model shows a good fit with the data set. This result constitutes evidence for the validation. The tested path analysis model is shown in Figure 2. The path coefficients, significance levels, and confidence intervals obtained by testing the model are given in Table 4.

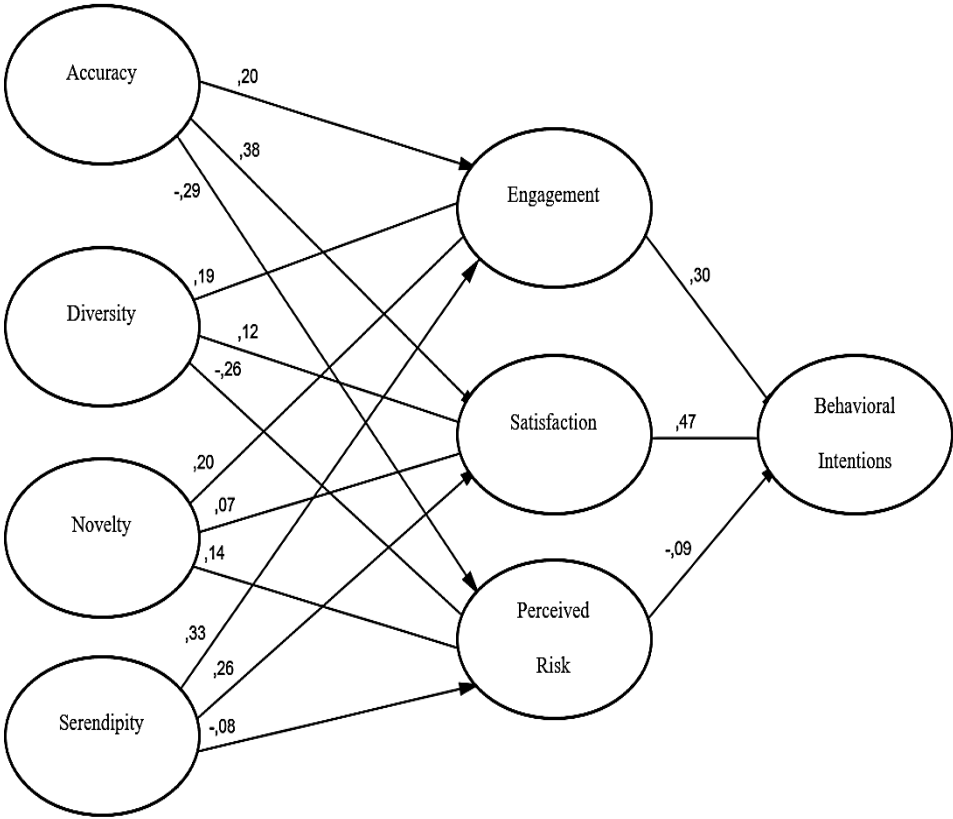


Figure 2: Tested Path Analysis Model

The direct relationships (Stimuli → Organism → Response), examines the effects of four RS characteristics (Stimuli) on organism (engagement, satisfaction, perceived risk) and the ultimate goal (response: behavioral intentions).

Table 4 presents the relationships and impacts among the variables included in the path analysis model. Accuracy is the strongest driver of satisfaction ($\beta = .38, p < .001, 95\% \text{ CI } [.25, .51]$) (H2 accepted), and also has a positive impact on user engagement ($\beta = .20, p < .001, 95\% \text{ CI } [.09, .31]$) (H1 accepted). A critical theoretical finding reveals that accuracy exert a substantial negative influence on perceived risk ($\beta = -.29, p < .001, 95\% \text{ CI } [-.44, -.13]$) (H3 accepted), indicating that accurate recommendations reduce users' perception of risk. Current studies imply that accuracy metrics alone are not sufficient in algorithmic evaluation (e.g., accuracy metrics have hurt RSs) also reinforce these findings (Jannach & Adomavicius, 2016; Jannach & Bauer, 2020; Jannach & Jugovac, 2019; Chia et al., 2022;

Cremonesi & Jannach, 2021; Jin et al., 2019). It is concluded that in applications using Big Data for personalization, not only accurate predictions also diverse recommendation is fundamental to mitigate perceived downsides (privacy concerns and filter bubble risks). This in-depth interpretation highlights that RS's success depends not only on the algorithm's technical accuracy also on the complex interactions of these features on user psychological states (satisfaction, engagement, risk). The result offers a critical in-depth interpretation of the perceived risk variable. The noteworthy negative impact of risk on behavioral intentions ($\beta=-.09$) emphasize the indispensability of trust and risk management variables, particularly in applications that collect Big Data for personalization (Kim, 2025; Saxborn et al., 2024; Nilashi et al., 2016; Wang & Benbasat, 2016).

Table 4: Structural Model Results and Hypothesis Testing

Path			β	SE	p	% 95 CI		Hypothesis
						Lower	Upper	
Accuracy	-->	Engagement	.20	.52	***	.09	.31	H1 Supported
Accuracy	-->	Satisfaction	.38	.64	***	.25	.51	H2 Supported
Accuracy	-->	Perceived Risk	-.29	1.73	***	-.44	-.13	H3 Supported
Diversity	-->	Engagement	.19	.57	***	.08	.30	H4 Supported
Diversity	-->	Satisfaction	.12	.70	.061	-.02	.25	H5 Not Supp
Diversity	-->	Perceived Risk	-.26	1.88	.002	-.43	-.09	H6 Supported
Novelty	-->	Engagement	.20	.59	***	.08	.31	H7 Supported
Novelty	-->	Satisfaction	.07	.72	.255	-.07	.21	H8 Not Supp
Novelty	-->	Perceived Risk	.14	1.95	.113	-.02	.30	H9 Not Supp
Serendipity	-->	Engagement	.33	.48	***	.24	.43	H10 Supported
Serendipity	-->	Satisfaction	.26	.59	***	.16	.38	H11 Supported
Serendipity	-->	Perceived Risk	-.08	1.59	.242	-.22	.05	H12 Not Supp
Engagement	--->	Behavioral Intentions	.30	.03	***	.15	.44	H13 Supported
Satisfaction	--->	Behavioral Intentions	.47	.03	***	.32	.61	H14 Supported
Perceived Risk	--->	Behavioral Intentions	-.09	.01	.013	-.17	-.01	H15 Supported

***p < .001

Although the diversity has no effect on satisfaction ($\beta = .12, p = .061, 95\% \text{ CI } [-.02, .25]$), positive and significant effect on engagement ($\beta = .19, p < .001, 95\% \text{ CI } [-.08, .30]$) (H4 accepted). However, diversity negatively and significantly affects perceived risk ($\beta = -.26, p = .002, 95\% \text{ CI } [-.43, -.09]$) (H6 accepted). The most important and the most useful analytical outcome is that accuracy ($\beta = -.29$) and diversity ($\beta = -.26$), contribute significantly to mediate risk reduction by affecting perceived risk. It is stated that diversity, particularly, is pivotal in mitigating potential downsides (such as filter bubble risk or privacy concerns). This outcome compatible with the researches on Trustworthy/Responsible AI (Arrieta et al., 2020; Matt et al., 2014; Nguyen et al., 2014; Raza et al., 2024), demonstrating that algorithmic transparency and bias reduction (diversity) are central to establishing user trust. Increasing the diversity can reduce risk by increasing user confidence in the generated profile. Within the scope of these findings, these results demonstrate that the achievement of AI-based personalization relies not only on accurate predictions but also so on reducing risk perception via diversity and serendipity. This can be supported by theoretical frameworks such as Mutual Domestication (Siles et al., 2019), which strengthen relevance of the results. Conversely, the direct effect of diversity on satisfaction is not significant (H5 rejected). Although the accuracy-diversity trade-off is often assumed in RSs (Dawson, 2014; Mutambik et al., 2023), studies also focus on resolving this apparent dilemma (Zhou et al., 2010; Zeng et al., 2014), there is positive and strong correlations between accuracy ($r = .81$) and novelty ($r = .82$). This offers significant logical justification. In the context under study (e-commerce), it follows that satisfaction increases when accurate recommendations also include undiscovered/new elements at the user's perceptual level, therefore the traditional trade-off becomes invalid. This is an essential observation indicating when algorithmic performance becomes beneficial for the user experience. This finding demonstrates that traditionally separate goals can be combined into a single, high-quality experience from the user's perspective, suggesting that the traditional algorithmic dilemma is overcome at the perceptual level.

Novelty have a positive and significant effect only on engagement ($\beta = .20, p < .001, 95\% \text{ CI } [.08, .31]$) (H7 accepted). The effects on satisfaction ($\beta = .07, p = .255, 95\% \text{ CI } [-.07, .21]$) (H8 rejected) and perceived risk ($\beta = .14, p = .113, 95\% \text{ CI } [-.02, .30]$) is not significant (H9 rejected). Serendipity has the strongest direct effect on engagement among the RS attributes ($\beta = .33, p < .001, 95\% \text{ CI } [.24, .43]$) (H10 accepted), providing a critical interaction detail indicating that to achieve long-term behavioral intentions, the system must provide serendipitous experiences that exceed user expectations. This result offers a profound implication that the success of an RS lies not in hitting the user's known preferences but in stimulating curiosity by offering unexpected but interesting (serendipity) suggestions (Adamopoulos & Tuzhilin, 2014; Zuva & Zuva, 2017; Kim et al., 2025; Maccatrozzo et al., 2017). Current studies confirm the importance of "beyond-accuracy objectives" such as exploration and surprise for user experience (Ge et al., 2010; Trattner et al., 2023; Foster & Keane, 2013; Khanagha et al., 2017). Serendipity has also

positive and significant effect on satisfaction ($\beta = .26, p < .001, 95\% \text{ CI } [.16, .38]$) (H11 accepted). However, the effect of serendipity on perceived risk ($\beta = -.08, p = .242, 95\% \text{ CI } [-.22, .05]$) is not significant (H12 rejected).

Related to the effects of organism (O) on behavioral intentions (R), satisfaction (O) is the strongest positive predictor of behavioral intentions (R) ($\beta = .47, p < .001, 95\% \text{ CI } [.32, .61]$) (H14 accepted). Engagement (O) also has a positive and significant effect on behavioral intentions (R) ($\beta = .30, p < .001, 95\% \text{ CI } [.15, .44]$) (H13 accepted). Perceived risk (O) have a negative and significant impact on behavioral intentions (R) ($\beta = -.09, p = .013, 95\% \text{ CI } [-.17, -.01]$) (H15 accepted). This suggests that privacy concerns and trust issues arising from the use of Big Data in personalization applications reduce final behavioral intentions.

5.4 Mediating effects

Mediation analyses indicate indirect effects of independent variables, such as accuracy, diversity, novelty and serendipity, on behavioral intentions through satisfaction, engagement and risk variables (Table 5). Related to mediating role of user engagement (S \rightarrow Engagement \rightarrow R), engagement (O) have significant mediating role in the positive indirect effects of all examined RS features (accuracy, diversity, novelty, serendipity) on behavioral intentions (R) (All p values $< .001$) (H16 accepted). This finding demonstrates that RS features foster interaction dynamics among users before reaching final behavior.

Table 5: Mediating Analysis Results

Indirect Paths	B	%95 CI		p	Decision
		Lower	Upper		
Accuracy --> Satisfaction --> Behavioral Intentions	1.024	0.649	1.491	0.001	Significant
Accuracy --> Engagement --> Behavioral Intentions	0.34	0.154	0.594	0.001	Significant
Accuracy --> Perceived Risk --> Behavioral Intentions	0.148	0.042	0.32	0.016	Significant
Diversity --> Satisfaction --> Behavioral Intentions	0.329	0.021	0.684	0.081	Not Sig
Diversity --> Engagement --> Behavioral Intentions	0.346	0.172	0.599	0.001	Significant
Diversity --> Perceived Risk --> Behavioral Intentions	0.139	0.03	0.327	0.018	Significant
Novelty --> Satisfaction --> Behavioral Intentions	0.207	-0.128	0.571	0.286	Not Sig
Novelty --> Engagement --> Behavioral Intentions	0.352	0.161	0.642	0.001	Significant
Novelty --> Perceived Risk --> Behavioral Intentions	-0.08	-0.225	-0.009	0.046	Significant
Serendipity --> Satisfaction --> Behavioral Intentions	0.74	0.444	1.123	0.001	Significant
Serendipity --> Engagement --> Behavioral Intentions	0.592	0.358	0.882	0.001	Significant
Serendipity --> Perceived Risk --> Behavioral Intentions	0.045	-0.002	0.141	0.113	Not Sig

***p < 0.001, **p < 0.010, *p < 0.05

Particularly, the Accuracy → Satisfaction → Behavioral Intentions path exhibits the strongest positive effect among all indirect paths (B = 1.024, $p < 0.001$), engagement (B = 0.34, $p < 0.001$) and risk (B = 0.148, $p = 0.016$). In particular, satisfaction and engagement exhibit strong positive effects, while risk shows a low level of effect. Diversity also has significant indirect effect on behavioral intentions through engagement (B = 0.346, $p < 0.001$) and risk (B = 0.139, $p = 0.018$), while its effect through satisfaction is not significant ($p = 0.081$). Related to mediating role of risk (S → Risk → R), risk (O), accuracy (B = 0.148, $p = 0.016$), and diversity (B = 0.139, $p = 0.018$) (H18 accepted) plays a significant role in the indirect effects of the variables on behavioral intentions (R).

These findings demonstrate that accuracy and diversity indirectly support behavioral intentions by reducing risk perception and play a risk-reducing mediating role. The indirect impact of the novelty through perceived risk is negative and significant ($B = -0.08, p = 0.046$).

Novelty has significant influence on behavioral intentions through engagement ($B = 0.352, p < 0.001$), while its effect through satisfaction isn't significant ($p = 0.286$). In addition, the serendipity has significant indirect impacts on behavioral intentions through satisfaction ($B = 0.74, p < 0.001$) and engagement ($B = 0.592, p < 0.001$), while its effect through risk isn't significant ($p = 0.113$). However, the satisfaction mediation for diversity and novelty is not significant (consistent with the rejection results of H5 and H8).

Related to mediating role of satisfaction ($S \rightarrow \text{Satisfaction} \rightarrow R$), satisfaction (O) is the strongest mediator driver of behavioral intentions ($\beta=0.47, p<0.001$) (H17 accepted). This finding, in line with recent studies (Jannach & Jugovac, 2019; Jannach, 2023; Jannach & Bauer, 2020), confirms that measuring long-term customer loyalty and business value in AI-enabled applications requires focusing on and optimizing elements such as service quality and customer experience (Bag et al., 2022; Chen et al., 2022; Kumar et al. 2025). From the S-O-R perspective, the fact that the mediating role of satisfaction is much more dominant than perceived risk suggests that shifting the focus of AI marketing strategies from perceived risk management to maximizing consumer benefit and service quality is the most effective approach. This requires focusing on service quality and experience (satisfaction/engagement) to measure long-term customer loyalty in AI-RSs (Kumar et al., 2025; Bag et al., 2022). Engagement, satisfaction, and risk variables as organism role, absorb the stimulus effects and shape the final response, that is, behavioral intentions. These findings explain that the success of RS is based on user-centered experience (satisfaction and engagement), user centric value creation, and perceived risk management rather than pure algorithmic accuracy performance (Karimi et al., 2018; Knees et al., 2019; Knijnenburg et al. 2012; Konstan & Terveen, 2021; Lobschat et al., 2021).

These results provide theoretical background that, from an S-O-R perspective, the user experience (satisfaction, engagement, perceived risk) created by RS (Stimuli) is central to the final behavioral outcomes (Response), and these mediating factors shift the success of RS toward user-centered satisfaction and risk management rather than solely technical accuracy (De Gemmis et al., 2015; Jannach & Bauer, 2020; Jannach, 2023).

6. Discussions and Implications

It is concluded that the accuracy, novelty, diversity, and serendipity influence user engagement. It shows that providing accurate and diverse content that meets users' expectations enables users to interact with RSs more frequently and intensively. Increasing engagement is of strategic importance, especially for platform providers who

wish to extend the interaction time of users with the system and strengthen their loyalty to the platform. It is concluded that although accuracy and serendipity affect satisfaction, diversity and novelty do not affect satisfaction. The finding that accuracy and serendipity criteria positively affect user satisfaction that user satisfaction levels increase when recommendation systems meet user expectations in terms of accuracy and serendipity with unexpectedly surprising but pleasant content. But, absence of a substantial impact of diversity and novelty on satisfaction can illustrate that user satisfaction is not always related to the diversity or novelty of content directly. Users can perceive this situation differently. Therefore, diversity and novelty can often conflict with users' basic expectation of recommendation relevance. If novel or diverse recommendations are not sufficiently relevant, the discovery value offered by RS will not offset the dissatisfaction of missing accurate items and will not impact overall satisfaction (McNee et al., 2006). Users expect personalized recommendations to be relevant to their interests, tastes, and preferences (Vargas & Castells, 2011; Ziegler et al., 2005). The number and variety of recommendations lose their importance. Hence it must be relevant users' interests, tastes, and preferences. According to Vargas & Castells (2011), the impacts of diversity on user satisfaction have not been fully validated in RSs, as the effect of diversity on satisfaction often needs to be balanced with predictive accuracy. Diversity often complicate decision-making processes and causes problems like "information overload". Ziegler et al. (2005) concludes that while diversity may be attractive to users in certain situations, it is not always accepted, due to different user segmentations perceive diversity differently.

The study ascertains that while accuracy and diversity have an effect on perceived risk, novelty and serendipity have no effect on perceived risk. Accurate and diverse recommendations increase users' trust and reduce uncertainty in the RS. If users believe accurate contents which align with their interest, tastes and preferences, they do not perceive risky. In addition, users wish and evaluate different contents which align with their interest, tastes and preferences. If users perceive these contents irrelevant and different, they develop negative behavior leading to risk (McNee et al., 2006; Tintarev & Masthoff, 2012). Generating a wide diversity of recommendations can also influence users risk perception about their personal data and data privacy. The finding of risk-reducing role of accuracy and diversity (Rohden & Zeferino, 2023; Yu et al., 2022) provides an important theoretical bridge to recent AI and consumer behavior literature focusing on users' trust in data privacy and algorithmic decisions (Sohn et al., 2025). The mitigating role of accuracy and diversity directly aligns with recent discussions in responsible AI (Lopez-Avila & Du, 2025) and FATE (Anand et al., 2025). It validates the role of algorithmic accuracy and diversity in increasing the reliability of AI systems by demonstrating that high accuracy and diversity reduce the perceived risk that may be associated with the use of Big Data (Raza et al., 2024; Zhao et al., 2025). Current studies focus on the need to simultaneously optimize algorithm design for multiple objectives, such as not only accuracy but also diversity and fairness (Wang et al., 2023; Zheng & Wang, 2022), emphasize that transparency, explain ability (XAI), and trustworthiness in

AI systems (Arrieta et al., 2020; Matt et al., 2014; Nguyen et al., 2014; Raza et al., 2024) are critical for user adoption intentions and risk perceptions. The finding explains that the impact of RS attributes on behavioral intentions through engagement and satisfaction is significant underscoring this "beyond-utility" perspective (Hollebeek et al., 2019; Kang et al., 2023). The negative effect of risk on behavioral intentions reflects the need for multi-stakeholder evaluation frameworks in particular (Adomavicius & Kwon, 2011; Burke et al., 2025; Jannach & Abdollahpouri, 2023). These frameworks argue that the impact of RSs should be evaluated by balancing the objectives of different stakeholders both the consumer (user satisfaction/intention) and system providers (business value), and society (ethics/risk/fairness) (Adomavicius & Kwon, 2011; Burke et al., 2025).

Approaches to resolving the diversity-accuracy trade-off (Zhou et al., 2010; Zeng et al., 2014). The apparent dilemma identified in the study's correlation results (a strong positive relationship between accuracy and diversity) should be interpreted as suggesting that this dilemma can be overcome at the user perceptual level, and this should be closely aligned with these current discussions (Vargas & Castells, 2011). The finding of a positive correlation between accuracy and novelty/diversity strengthens the importance of multi-objective optimization perspectives, which pay particular attention to explore a Pareto frontier between these conflicting or similar objectives rather than assuming a single "best" solution for algorithms (Martijn et al., 2016; Qingfu & Hui, 2007). This result means that accurate recommendations can also be useful and unexplored at the user-perceived level and compatible with recent studies suggesting that increased diversity and novelty increase user engagement and loyalty (Barata & Coelho, 2021; Dokoupil et al., 2025; Jannach & Abdollahpouri, 2023), compatible with recent studies on the importance of MORS. (Wang et al., 2023; Zheng & Wang, 2022). In addition, consistent with McNee et al. (2006)'s critique that "accuracy metrics are detrimental to RSs," current RS research has shifted its focus from pure algorithmic accuracy to multi-objectives such as long-term user experience, retention, and business value (Jannach, & Jugovac, 2019; Jannach & Abdollahpouri, 2023; Lü et al., 2012).

Serendipity has the strongest direct effect ($\beta = .33$) on engagement, triggers a sense of exploration and curiosity in the user. The strong role of serendipity in user engagement is supported by current trends through integrating of Large Language Models (LLMs) and Deep Learning (DL) techniques into RSs and the potential of these next-generation systems to burst filter bubbles and deliver serendipitous recommendations (Carraro & Bridge, 2024; Xi et al., 2025). With the integration of DL techniques (Raza et al., 2024; Zonghan et al., 2025) and LLMs (Lopez-Avila and Du, 2025; Raza et al., 2024; Xi et al., 2025), the RSs experience a major change and transformation. LLMs are used not only for generating recommendations, also for their ability to reason about beyond-accuracy objectives (diversification, re-ranking, and serendipity) (Carraro & Bridge, 2024; Wang et al., 2025). This demonstrates potential for bursting the filter bubbles of traditional

LLMs by integrating external world knowledge and better identifying serendipitous items (Xi et al., 2025).

The study's focus on the only Netflix clearly limits the applicability of the findings (Yudhistira & Wang 2025), but it can conclude critical details related to RSs-human interactions. The literature highlights that users' perceptions of RS features and the impact of psychological factors such as satisfaction are domain-dependent (Burke et al., 2025; Dokoupil et al., 2025; Wu et al., 2018). For example, results obtained from e-commerce data may require different user responses in different geographical/cultural contexts, tourism (Wang et al., 2025; Werneck et al., 2021) or film/music (Chinese context) (Chen et al., 2019; Yudhistira and Wang, 2025). Related AI-RS researches show geographically differences (China, India, the United States, Greece, Korea, Australia, Germany, France, and the United Kingdom) (Efendioğlu, 2023; Jain et al., 2024; Li et al., 2019). This geographic differences provides a significant framework for understanding how perceived risk attributes (accuracy, diversity) are perceived in the context of regional/cultural differences (Bianchi & Andrews, 2012; Erdoğan, 2023), for example, a research of the perceived risk in financial services (Hawamleh et al., 2020) and e-commerce (e.g., from a Chilean perspective). From this perspective, AI-RS marketing strategies should take consider regional user perceptions (trust, satisfaction, and risk) into account. Finally, current studies review indicate a lack of sample size in the field of AI and consumer behavior, particularly in South America and Africa. Therefore, it is critical that the results require additional validation and contextual analysis before they can be applied to other regions/cultures/sectors (Jain et al., 2024).

6.1 Theoretical Implications

This study empirically empower the S-O-R model framework in the context of modern AI-RSs and presents a holistic causal mechanism that bridges the methodological gap between technology-human centered researches. Satisfaction as the strongest driver in the model, explaining 61% of the variance in behavior intention ($\beta=.47$), support excellent model fit values. This theoretical finding corroborates the current studies, which posits that the assessment of RS success should be predicated on subjective, user-centered organizational variables such as service quality and superior customer experience, as opposed to the exclusive utilization of objective metrics such as algorithmic accuracy (Root Mean Square Error-RMSE). Moreover, the significant function of engagement ($\beta=.30$) on behavioral intentions is reinforced.

This study highlights the importance of elements that are considered secondary in traditional RS — namely, those that go “beyond-accuracy objectives” — and explains that a system's success lies in encouraging discovery motivation. Serendipity (stimulus) has the strongest direct effect on user engagement (organism) ($\beta=.33$) in among RS features. This means that a system's success does not lie in addressing the user's known preferences, but rather in fostering long-term engagement (i.e. discovery motivation) by providing unexpected yet surprising recommendations. Another important theoretical

finding is the questioning of the accuracy and diversity trade-off, a fundamental premise of RS engineering, at the level of user perception. The strong positive relationship ($r = .81$) between accuracy and diversity, offers a new theoretical interpretation of the support that these two features provide to users in an e-commerce context, necessitating a rethink of theoretical models in line with the MORS approach.

This research significantly contributes to the field of reliability by presenting the role of perceived risk as a two-way process in the scope of the S-O-R context. While it has been confirmed that risk has a significant negative impact on behavioral intention ($\beta = -.09$), the most significant theoretical contribution is that risk-related characteristics such as accuracy ($\beta = -.29$) and diversity ($\beta = -.26$) have a significant negative effect on this risk. This finding opens up a new theoretical issue for evaluating how RS features operate as risk-reducing or buffering agents that manage users' internal organizational states, such as privacy concerns and trust issues, rather than merely providing benefits. In this context, although diversity and novelty (discovery-oriented features) fail to trigger the expected direct satisfaction pathway, they preserve the S-O-R integrity by strongly increasing user engagement and reducing the perceived risk users experienced when trying less familiar items. Overall, the S-O-R framework has been validated, but these features' primary role isn't to provide instant gratification; rather, they established psychological bridges that encouraged users to explore and reduce uncertainty. These results suggest that algorithmic quality should be directly incorporated into reliability models of AI systems.

6.2 Practical Implications

This study suggests that businesses and platform managers implementing AI-based personalization in the Netflix context should strategically target organizational factors to increase users' long-term behavioral intentions (Response). Depending on S-O-R framework, the focus of the system should shift from RMSE to satisfaction an engagement (organism). The primary focus should be on maximizing satisfaction, the strongest driver of behavioral intentions. To achieve this goal, businesses should prioritize the core behavioral intention, as providing accurate and relevant offers enhances service quality and fosters long-term customer loyalty. Second, to support users' desire for discovery and reduce monotony, priority should be given to serendipity, which has the strongest direct impact through engagement. This means that algorithms should mitigate the "filter bubble" problem by offering unexpected yet appealing suggestions that not only reflect known preferences but also trigger curiosity. Third, given the noteworthy negative effect of risk (Organism) on behavioral intentions, enhancing platform security and addressing privacy concerns is critical. This risk should be mitigated through strong stimuli such as accuracy and diversity, as these factors play an instrumental role in enhancing system reliability. Herein, managers should incorporate transparency (XAI) mechanisms into RS interfaces, explaining to users why a particular recommendation is made. Finally, contrary to what is traditionally seen as a dichotomy,

the strong positive correlation observed between accuracy and diversity demonstrates that developers should simultaneously optimize these two objectives to maximize satisfaction without conflict. The practical implementation of these theoretical implications requires the integration of AI into CRM systems, transforming existing customer data into action using analytical approaches, and enabling complex CRM capabilities such as sentiment analysis.

6.3 Limitations and Future Directions

The study's focus on Netflix RSs, which offer only service Subscription Video-On-Demand (SVOD) and whose content is limited to film/video shows, limits the generality of the findings (Bennett & Lanning, 2007; Chiny et al., 2022). Netflix's algorithm primarily serves the goal of maximizing long-term subscriber retention and customer loyalty (Gomez-Uribe & Hunt, 2015), these results cannot be directly generalized to other RSs, typically those with different business objectives (revenue or transaction maximization), such as e-commerce (Amazon) or mobile banking (Shen, 2014). Furthermore, as Netflix uses complex algorithmic and customization techniques adapted to constantly changing and diverse contexts, rather than a single model, transferring these findings to RSs outside this specialized vertical becomes difficult (González-Chans et al., 2020).

The research's reliance on single-point-of-time data, which falls short of fully capturing dynamic user preferences and long-term effects, is a limitation. In this regard, integrating longitudinal studies and more comprehensive online A/B testing is suggested. Furthermore, causal relationships can be established through studies that directly manipulate the effects of perceived risk or satisfaction (organism) variables using mixed methods or experimental designs. Empirical studies analyzing bidirectional causality, examining the feedback loop between platform recommendations and user responses, could be focused on. Furthermore, the integration of concept of drift techniques, which model continuous changes in user preferences in dynamic environments, into RSs can be considered another important area.

A MRS framework that balances the objectives of other stakeholders (platform providers and content creators) should be adopted in terms of theoretical and structural deficiencies, since the S-O-R approach focuses primarily on the end user. To strengthen the findings on perceived risk, algorithms, and the role of critical constructs such as trust and privacy, has not been thoroughly investigated as an independent construct. To address this shortcoming, it is important to combine XAI with the model and examine its impact on consumer behavior. It requires combining DL and LLM. To overcome the study's limitation of focusing on individual users, future studies should focus on solving Group Recommender Systems (GRSs) and joint viewing/purchasing scenarios involving different business groups or customer groups. Finally, utilizing economic models (business value metrics such as ROI and LTV) to balance user satisfaction with business

metrics (business profitability, sales, and customer retention) is an important theory-based future direction.

7. Conclusion

The study emphasizes that the effectiveness of AI-assisted personalization is contingent both algorithmic accuracy and on users' cognitive and emotional engagement with the accuracy, diversity, novelty, and serendipity. The S-O-R model is integrated to create a robust framework that explains the psychological processes that effect how users behavior. The study highlights a theoretical contribution to the literature on AI-based personalization. Being achieved by incorporating the emotional and cognitive dimensions of user experience, it facilitates a more profound comprehension of personalization (Adapa et al., 2020; Aloysius et al., 2018; Habil et al., 2023; Hossain et al., 2020). The findings extend beyond the purely technical capability of algorithms, underscoring the necessity of human-centered design to optimize behavioral intention. It can be concluded that enhancing behavioral intention necessitates achieving a strategic balance between accuracy, the primary objective of RSs, and the multidimensional, "beyond accuracy" features such as novelty, diversity, and serendipity that enrich the user experience, in light of the findings and the prevailing consensus in the RS literature.

Accuracy positively affect both engagement and satisfaction while reducing risk significantly. This means that the system's core advantages (relevance and accuracy) is essential in users' perception of it as a trustworthy tool. Accuracy has significant positive indirect effects on behavioral intention through engagement, satisfaction, and risk. In addition to accuracy, serendipity is found to strongly increase both engagement and satisfaction. Serendipity also positively and significantly influences behavioral intention through satisfaction and engagement. This result reflects the need to focus on objectives beyond traditional accuracy metrics, frequently mentioned in the literature (Kaminskas & Bridge, 2016). The potential of providing users with novel yet relevant content to broaden engagement and enrich the user experience has been confirmed (McBirnie, 2008; Rubinstein, 2002). While diversity and novelty enhance engagement, they fail to have a significant direct effect on satisfaction. This may reflect the accuracy-diversity trade-off in the literature (Kunaver & Požrl, 2017; Liu et al., 2012; Zhou et al., 2010; Ziegler et al., 2005). Moreover, the fact that the accuracy and diversity significantly and negatively affect the risk and have a function of reducing the risk and the accuracy-diversity trade-off in the RS is refuted by the positive correlation at the user perception level confirms that AI powered personalization is a fundamental strategy that comprehensively shapes the customer experience in the interactive marketplace. While users find the presence of diversity (topic diversity) beneficial (increasing engagement and reducing risk), these features alone do not guarantee satisfaction (Cai, 2005). Nevertheless, diversity and novelty have significant indirect effects on behavioral intention through the engagement and perceived risk paths.

In terms of balancing independent variables to enhance behavioral intentions, the success of an AI-RS in generating behavioral intention (purchase intention or continued use) depends on the balanced management of four key characteristics (accuracy, diversity, novelty, and serendipity). For this purpose;

1. **Prioritizing Satisfaction and Exploration:** Since satisfaction primarily enhances behavioral intention, managers and designers should focus on the two characteristics that contribute most to this emotional response: Accuracy and serendipity. A RS should deliver content that users know and expect with high precision, while also satisfying the sense of discovery by surprising them with unexpected (but relevant) content. Serendipity can also be enhanced through placement strategies within recommendation lists (Kaminskas & Bridge, 2016).

2. **Managing Risk and Sustaining Engagement with Diversity:** Diversity plays two important roles such as reducing risk and increasing user engagement, while diversity may not directly increase satisfaction. Diversity can provide transparency and a sense of control by giving users the impression that the system is neutral and comprehensive (Awad & Krishnan, 2006; Heilbroner et al., 1980). Therefore, diversity should be used as a complementary control mechanism to manage the system's long-term sustainability and user trust rather than being the primary objective.

3. **Positioning Novelty:** Marketers should focus on offering novelty through coincidences that create satisfaction when introducing new products or lesser-known content as novelty has no direct and significant effect on satisfaction and risk indicates. Although novelty is attractive on its own, it does not lead to satisfaction, which is the main driver of behavioral intention, unless it meets or exceeds user expectations

In conclusion, optimizing behavioral intention necessitates a transition from a solitary metric to a multifaceted approach, encompassing numerous objectives that strategically balance accuracy and serendipity (key satisfaction drivers) with diversity (for risk management and participant confidence).

This balance is analogous to a dynamic portfolio selection between accuracy and exploration, much like an investor combining assets that not only offer high returns (accuracy), but also offer new opportunities (serendipity) and diversify risk (diversity). This strategy explains digital platforms to make systems that meet users' needs, build trust, and keep users retained for a long time. This study emphasizes the importance of RS design should focus on the delicate balance between user-centered experience (engagement, satisfaction, and serendipity) and risk-reducing features (accuracy and diversity), and that human perception, rather than pure algorithmic accuracy, is critical.

Research Funding

The authors received no research grant or support for this research study.

Availability of Data

The data set is available on reasonable request from the corresponding author.

Declaration of AI Use

I declare that no generative AI tools were used in the creation or writing of the main text of this article. Limited use was made of Google Translate and similar language checkers for the sole purpose of improving grammar and spelling. The conceptual framework, data analysis, interpretation of findings, and all scientific content of the article were written entirely by the author.

REFERENCES

Adamopoulos, P., & Tuzhilin, A. (2014). On Unexpectedness in Recommender Systems. *ACM Transactions on Intelligent Systems and Technology*, 5(4), 1-32. <https://doi.org/10.1145/2559952>

Adapa, S., Fazal, S. M., Makam, S. B., Azeem, M. M., & Mortimer, G. (2020). Examining the antecedents and consequences of perceived shopping value through smart retail technology. *Journal of Retailing and Consumer Services*, 52, 101901. <https://doi.org/10.1016/j.jretconser.2019.101901>

Adomavicius, G., & Kwon, Y. (2011). Improving aggregate recommendation diversity using ranking-based techniques. *IEEE Transactions on Knowledge and Data Engineering*, 24(5), 896-911. <https://doi.org/10.1109/TKDE.2011.15>

Aggarwal, C. C. (2016). *Recommender Systems* (1st ed.). Springer International Publishing, Cham.

Alabi, M. (2024). AI-Powered Product Recommendation Systems: Personalizing Customer Experiences and Increasing Sales. Available at Research Gate: <https://www.researchgate.net/profile/Moses-Alabi/publication/384931166>

Aloysius, J. A., Hoehle, H., Goodarzi, S., & Venkatesh, V. (2018). Big data initiatives in retail environments: Linking service process perceptions to shopping outcomes. *Annals of Operations Research*, 270(1), 25-51. <https://doi.org/10.1007/s10479-016-2276-3>

Amatriain, X. (2013). Big & personal: Data and models behind Netflix recommendations. Proceedings of the 2nd International Workshop on Big Data, Streams and Heterogeneous Source Mining: Algorithms, Systems, Programming Models and Applications Conference. Association for Computing Machinery. New York United States. (pp. 1-6). <https://doi.org/10.1145/2501221.2501222>

- Anand, V., & Maurya, A. K. (2025). A survey on recommender systems using graph neural network. *ACM Transactions on Information Systems*, 43(1), 1-49. <https://doi.org/10.1145/3694784>
- Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., ... & Herrera, F. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information fusion*, 58, 82-115. <https://doi.org/10.1016/j.inffus.2019.12.012>
- Awad, N. F., & Krishnan, M. S. (2006). The personalization privacy paradox: an empirical evaluation of information transparency and the willingness to be profiled online for personalization. *MIS quarterly*, 30(1), 13-28. <https://doi.org/10.2307/25148715>
- Bag, S., Ghadge, A., & Tiwari, M. K. (2019). An integrated recommender system for improved accuracy and aggregate diversity. *Computers & Industrial Engineering*, 130, 187-197. <https://doi.org/10.1016/j.cie.2019.02.028>
- Bag, S., Srivastava, G., Bashir, M. M. A., Kumari, S., Giannakis, M., & Chowdhury, A. H. (2022). Journey of customers in this digital era: Understanding the role of artificial intelligence technologies in user engagement and conversion. *Benchmarking: An International Journal*, 29(7), 2074-2098. <https://doi.org/10.1108/BIJ-07-2021-0415>
- Bagozzi, R. P., & Yi, Y. (2012). Specification, evaluation, and interpretation of structural equation models. *Journal of the academy of marketing science*, 40(1), 8-34. <https://doi.org/10.1007/s11747-011-0278-x>
- Barata, M. L., & Coelho, P. S. (2021). Music streaming services: Understanding the drivers of customer purchase and intention to recommend. *Heliyon*, 7(2):e07783. <https://doi.org/10.1016/j.heliyon.2021.e07783>
- Bell, R. M., Koren, Y., & Volinsky, C. (2010). All Together Now: A Perspective on the Netflix Prize. *Chance*, 23(1), 24-29. <https://doi.org/10.1080/09332480.2010.10739787>
- Bellofín, A., Cantador, I., Díez, F., Castells, P., & Chavarriaga, E. (2013). An empirical comparison of social, collaborative filtering, and hybrid recommenders. *ACM Transactions on Intelligent Systems and Technology*, 4(1), 1-29. <https://doi.org/10.1145/2414425.2414439>
- Benbasat, I., & Wang, W. (2005). Trust in and adoption of online recommendation agents. *Journal of the association for information systems*, 6(3), 4. <https://doi.org/10.17705/1jais.00065>
- Bennett, J., Lanning, S., 2007. The Netflix prize. In Proceedings of ACM SIGKDD Explorations Newsletter (51-52 pp). New York: USA. <https://doi.org/10.1145/1345448.1345459>

- Bianchi, C., & Andrews, L. (2012). Risk, trust, and consumer online purchasing behaviour: A Chilean perspective. *International Marketing Review*, 29(3), 253-275. <https://doi.org/10.1108/02651331211229750>
- Bobadilla, J., Ortega, F., Hernando, A., & Gutiérrez, A. (2013). Recommender systems survey. *Knowledge-Based Systems*, 46, 109-132. <https://doi.org/10.1016/j.knsys.2013.03.012>
- Burke, R., Adomavicius, G., Bogers, T., Di Noia, T., Kowald, D., Neidhardt, J., Özgöbek, Ö., Pera, M. S., Tintarev, N., & Ziegler, J. (2025). De-centering the (Traditional) user: Multistakeholder evaluation of recommender systems. *International Journal of Human Computer Studies*, 203, 103560. <https://doi.org/10.1016/j.ijhcs.2025.103560>
- Byrne, B. M. (2013). Structural equation modeling with Mplus: Basic concepts, applications, and programming. 1-432. Routledge: New York. <https://doi.org/10.4324/9781410600219-7>
- Cai-Nicolas Ziegler, Sean M. McNee, Joseph A. Konstan, and Georg Lausen. (2005). Improving recommendation lists through topic diversification. In Proceedings of the 14th International Conference on the World Wide Web. (pp. 22-32). <https://doi.org/10.1145/1060745.1060754>
- Carraro, D., & Bridge, D. (2024). Enhancing recommendation diversity by re-ranking with large language models. *ACM Transactions on Recommender Systems*. 4(2), 1-40. <https://doi.org/10.1145/3700604>
- Castells, P., Hurley, N., & Vargas, S. (2022). Novelty and diversity in recommender systems. F. Ricci, L. Rokach, & B. Shapira (Eds.), In *Recommender systems handbook* (pp. 603-646). Springer. https://doi.org/10.1007/978-1-0716-2197-4_16
- Chatterjee, S., Ghosh, S. K., Chaudhuri, R., & Nguyen, B. (2019). Are CRM systems ready for AI integration? *The Bottom Line*, 32(2), 144-157. <https://doi.org/10.1108/BL-02-2019-0069>
- Chen, L., Yang, Y., Wang, N., Yang, K., & Yuan, Q. (2019). How serendipity improves user satisfaction with recommendations? A Large-Scale User Evaluation. The World Wide Web Conference, (pp. 240-250). <https://doi.org/10.1145/3308558.3313469>
- Chen, S., Qiu, H., Zhao, S., Han, Y., He, W., Siponen, M., ... & Xiao, H. (2022). When more is less: The other side of artificial intelligence recommendation. *Journal of Management Science and Engineering*, 7(2), 213-232. <https://doi.org/10.1016/j.jmse.2021.08.001>
- Chia, P. J., Tagliabue, J., Bianchi, F., He, C., & Ko, B. (2022, April). Beyond NDCG: Behavioral testing of recommender systems with RecList. In Companion Proceedings of the Web Conference 2022 (pp. 99-104). <https://doi.org/10.1145/3487553.3524215>

- Chiny, M., Chihab, M., Bencharef, O. and Chihab, Y. (2022). Netflix Recommendation System based on TF-IDF and Cosine Similarity Algorithms. In Proceedings of the 2nd International Conference on Big Data, Modelling and Machine Learning - BML; ISBN 978-989-758-559-3, SciTePress, (pp. 15-20). <https://doi.org/10.5220/0010727500003101>
- Clarke, C. L. A., Kolla, M., Cormack, G. V., Vechtomova, O., Ashkan, A., Büttcher, S., & MacKinnon, I. (2008). Novelty and diversity in information retrieval evaluation. Proceedings of the 31st Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, USA. (pp. 659-666). <https://doi.org/10.1145/1390334.1390446>
- Cremonesi, P., & Jannach, D. (2021). Progress in recommender systems research: Crisis? What crisis?. *AI Magazine*, 42(3), 43-54. <https://doi.org/10.1609/aimag.v42i3.18145>
- Dawson, J. F. (2014). Moderation in management research: What, why, when, and how. *Journal of Business and Psychology*, 29(1), 1-19. <https://doi.org/10.1007/s10869-013-9308-7>
- De Gemmis, M., Lops, P., Semeraro, G., & Musto, C. (2015). An investigation on the serendipity problem in recommender systems. *Information Processing & Management*, 51(5), 695-717. <https://doi.org/10.1016/j.ipm.2015.06.008>
- Dokoupil, P., Boratto, L., & Peska, L. (2025, September). How Do Users Perceive Recommender Systems' Objectives?. In Proceedings of the Nineteenth ACM Conference on Recommender Systems (RecSys '25), September Prague, Czech Republic. 2025 (pp. 22-26). <https://doi.org/10.1145/3705328.3748066>
- Efendioğlu, İ. H. (2023). The power of artificial intelligence in personalized marketing. In 22nd International Business Congress, İstanbul, Turkey, (63-80).
- Erdoğan, Z. (2023). Netflix's machine learning, personalization, culture effect and its evolution in Covid-19. *Intermedia International E-journal*, 10(18), 1-14. <https://doi.org/10.56133/intermedia.1066604>
- Es, K. V. (2023). Netflix & Big Data: The strategic ambivalence of an entertainment company. *Television & New Media*, 24(6), 656-672. <https://doi.org/10.1177/15274764221125745>
- Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. *International Journal of Human-Computer Studies*, 59(4), 451-474. [https://doi.org/10.1016/S1071-5819\(03\)00111-3](https://doi.org/10.1016/S1071-5819(03)00111-3)
- Field, A. (2013). *Discovering statistics using IBM SPSS statistics*. Sage.
- Foster, M., & Keane, M. T. (2013). Surprise: You've got some explaining to do. Proceedings of the 35th Annual Conference of the Cognitive Science Society. Austin, TX:

- Cognitive Science Society. Berlin, Germany. 35. (pp. 2321-2326). <https://doi.org/10.48550/arXiv.1308.2236>
- Ge, M., Delgado-Battenfeld, C., & Jannach, D. (2010). Beyond accuracy. Proceedings of the Fourth ACM Conference on Recommender Systems, Barcelona, Spain. (pp. 257-260). <https://doi.org/10.1145/1864708.1864761>
- Gan, L., Nurbakova, D., Laporte, L., & Calabretto, S. (2020, July). Enhancing recommendation diversity using determinantal point processes on knowledge graphs. Proceedings of the 43rd international ACM SIGIR conference on research and development in information retrieval. China. (pp. 2001-2004). <https://doi.org/10.1145/3397271.3401213>
- Gefen, D. (2000). E-commerce: The role of familiarity and trust. *Omega*, 28(6), 725-737. [https://doi.org/10.1016/S0305-0483\(00\)00021-9](https://doi.org/10.1016/S0305-0483(00)00021-9)
- Gomez-Uribe, C. A., & Hunt, N. (2015). The netflix recommender system. *ACM Transactions on Management Information Systems*, 6(4), 1-19. <https://doi.org/10.1145/2843948>
- González-Chans, C., Membiela-Pollán, M., & Cortés-Cuns, M. (2020). Relational Marketing and Brand Community: The case of Netflix. *Redmarka. Revista de Marketing Aplicado*, 24(2), 251-274. <https://doi.org/10.17979/redma.2020.24.2.7157>
- Gunawardana, A., & Shani, G. (2015). Evaluating recommender systems. In recommender systems handbook (pp. 265-308). Springer US. https://doi.org/10.1007/978-1-4899-7637-6_8
- Habil, S., El-Deeb, S., & El-Bassiouny, N. (2023). AI-based recommendation systems: The ultimate solution for market prediction and targeting. In interactive marketing (pp. 683-704). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-031-14961-0_30
- Haenlein, M., & Kaplan, A. (2019). A Brief history of artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence. *California Management Review*, 61(4), 5-14. <https://doi.org/10.1177/0008125619864925>
- Hair, J., Gabriel, M. & Patel, V. (2014). AMOS Covariance-Based Structural Equation Modeling (CB-SEM): Guidelines on Its Application as a Marketing Research Tool. *Brazilian Journal of Marketing*, 13(2), 44-55. <https://doi.org/10.5585/remark.v13i2.2718>
- Haridasan, A. C., & Fernando, A. G. (2018). Online or in-store: Unravelling consumer's channel choice motives. *Journal of Research in Interactive Marketing*, 12(2), 215-230. <https://doi.org/10.1108/JRIM-07-2017-0060>
- Hawamleh, A. M. A., Alorfi, A. S. M., Al-Gasawneh, J. A., & Al-Rawashdeh, G. (2020). Cyber security and ethical hacking: The importance of protecting user data. *Solid State*

Technology, 63(5), 7894-7899. Available at: <https://www.researchgate.net/profile/Jassim-Al-Gasawneh/publication/347902323>

He, X., Liao, L., Zhang, H., Nie, L., Hu, X., & Chua, T. S. (2017, April). Neural collaborative filtering. Proceedings of the 26th international conference on world wide web (pp. 173-182). <https://doi.org/10.1145/3038912.3052569>

Heilbroner, R. L., Ajzen, I., Fishbein, M., & Thurow, L. C. (1980). Understanding attitudes and predicting social behavior. Prentice Hall.

Herlocker, J. L., Konstan, J. A., Terveen, L. G., & Riedl, J. T. (2004). Evaluating collaborative filtering recommender systems. *ACM Transactions on Information Systems*, 22(1), 5-53. <https://doi.org/10.1145/963770.963772>

Hollebeek, L. D., Srivastava, R. K., & Chen, T. (2019). S-D logic-informed customer engagement: Integrative framework, revised fundamental propositions, and application to CRM. *Journal of the Academy of Marketing Science*, 47(1), 161-185. <https://doi.org/10.1007/s11747-016-0494-5>

Hossain, M. A., Akter, S., & Yanamandram, V. (2020). Revisiting customer analytics capability for data-driven retailing. *Journal of Retailing and Consumer Services*, 56, 102187. <https://doi.org/10.1016/j.jretconser.2020.102187>

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural equation modeling: a multidisciplinary journal*, 6(1), 1-55. <https://doi.org/10.1080/10705519909540118>

Jain, V., Wadhvani, K., & Eastman, J. K. (2024). Artificial intelligence consumer behavior: A hybrid review and research agenda. *Journal of consumer behaviour*, 23(2), 676-697. <https://doi.org/10.1002/cb.2233>

Jannach, D., & Adomavicius, G. (2016). Recommendations with a purpose. 7-10. <https://doi.org/10.1145/2959100.2959186>

Jannach, D., Manzoor, A., Cai, W., & Chen, L. (2022). A survey on conversational recommender systems. *ACM Computing Surveys*, 54(5), 1-36. <https://doi.org/10.1145/3453154>

Jannach, D. (2023). Evaluating conversational recommender systems: A landscape of research. *Artificial Intelligence Review*, 56(3), 2365-2400. <https://doi.org/10.1007/s10462-022-10229-x>

Jannach, D., & Bauer, C. (2020). Escaping the McNamara fallacy: Towards more impactful recommender systems research. *AI Magazine*, 41(4), 79-95. <https://doi.org/10.1609/aimag.v41i4.5312>

Jannach, D., & Jugovac, M. (2019). Measuring the business value of recommender systems. *ACM Transactions on Management Information Systems*, 10(4), 1-23. <https://doi.org/10.1145/3370082>

- Jannach, D., & Abdollahpouri, H. (2023). A survey on multi-objective recommender systems. *Frontiers in big Data*, 6, 1157899. <https://doi.org/10.3389/fdata.2023.1157899>
- Jin, Y., Htun, N. N., Tintarev, N., & Verbert, K. (2019, June). Contextplay: Evaluating user control for context-aware music recommendation. In Proceedings of the 27th ACM conference on user modeling, adaptation and personalization (pp. 294-302). <https://doi.org/10.1145/3320435.3320445>
- Jörg, H., Hubona, G., & Ash, P. R. (2016). Using PLS path modeling in new technology research: Updated guidelines. *Industrial Management & Data Systems*, 116(1), 2-20. <https://doi.org/10.1108/IMDS-09-2015-0382>
- Jugovac, M., & Jannach, D. (2017). Interacting with recommenders overview and research directions. *Transactions on Interactive Intelligent Systems*, 7(3), 10-46. <https://doi.org/10.1145/3001837>
- Kaminskas, M., & Bridge, D. (2016). Diversity, serendipity, novelty, and coverage: A survey and empirical analysis of beyond-accuracy objectives in recommender systems. *ACM Transactions on Interactive Intelligent Systems (TiiS)*, 7(1), 1-42. <https://doi.org/10.1145/2926720>
- Kang, Y., Gu, H., Tang, X., He, Y., Zhang, Y., He, J., ... & Yang, Q. (2023). Optimizing privacy, utility and efficiency in constrained multi-objective federated learning. <https://doi.org/10.48550/arXiv.2305.00312>
- Karimi, M., Jannach, D., & Jugovac, M. (2018). News recommender systems - survey and roads ahead. *Information Processing & Management*, 54(6), 1203-1227. <https://doi.org/10.1016/j.ipm.2018.04.008>
- Khanagha, S., Volberda, H., & Oshri, I. (2017). Customer co-creation and exploration of emerging technologies: the mediating role of managerial attention and initiatives. *Long Range Planning*, 50(2), 221-242. <https://doi.org/10.1016/j.lrp.2015.12.019>
- Khandelwal, K., Patel, S., Patel, J., & Pnachal, M. (2023). A study to know-use of AI for personalized recommendation, streaming optimization, and original content production at Netflix. *International Journal of Scientific Engineering and Research*, 9(6), 1738-1743. <https://doi.org/10.61137/ijset.vol.9.issue6.119>
- Kim, A. J., & Ko, E. (2012). Do social media marketing activities enhance customer equity? An empirical study of luxury fashion brand. *Journal of Business Research*, 65(10), 1480-1486. <https://doi.org/10.1016/j.jbusres.2011.10.014>
- Kim, Y., Oh, S., Noh, C., Hong, E., & Park, S. (2025). Design of a serendipity-incorporated recommender system. *Electronics*, 14(4), 821. <https://doi.org/10.3390/electronics14040821>

- Komiak & Benbasat. (2006). The effects of personalization and familiarity on trust and adoption of recommendation agents. *MIS Quarterly*, 30(4), 941-960. <https://doi.org/10.2307/25148760>
- Knees, P., Schedl, M., Ferwerda, B., & Laplante, A. (2019). User awareness in music recommender systems. *Personalized human-computer interaction*, 29 (2019), 223-252. <https://doi.org/10.1515/9783110552485-009>
- Knijnenburg, B. P., Willemsen, M. C., Gantner, Z., Soncu, H., & Newell, C. (2012). Explaining the user experience of recommender systems. *User Modeling and User-Adapted Interaction*, 22(4), 441-504. <https://doi.org/10.1007/s11257-011-9118-4>
- Konstan, J. A., & Terveen, L. G. (2021). Human-centered recommender systems: Origins, advances, challenges, and opportunities. *AI Magazine*, 42(3), 31-42. <https://doi.org/10.1609/aimag.v42i3.18142>
- Kotkov, D., Veijalainen, J., & Wang, S. (2020). How does serendipity affect diversity in recommender systems? A serendipity-oriented greedy algorithm. *Computing*, 102(2), 393-411. <https://doi.org/10.1007/s00607-018-0687-5>
- Kumar, J., Rani, V., Rani, G., & Sandhu, K. (2025). What attracts me or prevents me from using AI-enabled neo-banking services? Unveiling the nexus between service quality and customer loyalty. *International Journal of Quality & Reliability Management*. 42(10): 2793-2814. <https://doi.org/10.1108/IJORM-11-2024-0421>
- Kunaver, M., & Požrl, T. (2017). Diversity in recommender systems - A survey. *Knowledge-Based Systems*, 123, 154-162. <https://doi.org/10.1016/j.knosys.2017.02.009>
- Lee, S. Y., & Lee, S. W. (2023). Normative or effective? The role of news diversity and trust in news recommendation services. *International Journal of Human-Computer Interaction*, 39(6), 1216-1229. <https://doi.org/10.1080/10447318.2022.2057116>
- Li, H. (2019). Special section introduction: Artificial intelligence and advertising. *Journal of advertising*, 48(4), 333-337. <https://doi.org/10.1080/00913367.2019.1654947>
- Liang, T.P., Lai, H.J., & Ku, Y.C. (2006). Personalized content recommendation and user satisfaction: Theoretical synthesis and empirical findings. *Journal of Management Information Systems*, 23(3), 45-70. <https://doi.org/10.2753/MIS0742-1222230303>
- Liu, J. G., Shi, K., & Guo, Q. (2012). Solving the accuracy-diversity dilemma via directed random walks. *Physical Review E-Statistical, Nonlinear, and Soft Matter Physics*, 85(1), 016118. <https://doi.org/10.1103/PhysRevE.85.016118>
- Lobschat, L., Mueller, B., Eggers, F., Brandimarte, L., Diefenbach, S., Kroschke, M., & Wirtz, J. (2021). Corporate digital responsibility. *Journal of Business Research*, 122, 875-888. <https://doi.org/10.1016/j.jbusres.2019.10.006>

- Lopez-Avila, A., & Du, J. (2025). A survey on large language models in multimodal recommender systems. <https://doi.org/10.48550/arXiv.2505.09777>
- Lu, J., Wu, D., Mao, M., Wang, W., & Zhang, G. (2015). Recommender system application developments: A survey. *Decision Support Systems*, 74, 12-32. <https://doi.org/10.1016/j.dss.2015.03.008>
- Lü, L., Medo, M., Yeung, C. H., Zhang, Y. C., Zhang, Z. K., & Zhou, T. (2012). Recommender systems. *Physics reports*, 519(1), 1-49. <https://doi.org/10.1016/j.physrep.2012.02.006>
- Maccatrozzo, V., Terstall, M., Aroyo, L., & Schreiber, G. (2017, March). SIRUP: Serendipity in recommendations via user perceptions. In Proceedings of the 22nd International Conference on Intelligent User Interfaces (pp. 35-44). <https://doi.org/10.1145/3025171.3025185>
- Martijn C. Willemsen, Mark P. Graus, and Bart P. Knijnenburg. 2016. Under-standing the role of latent feature diversification on choice difficulty and satisfaction. *User modeling and user-adapted interaction* 26, 4 (01 Oct 2016), 347-389. <https://doi.org/10.1007/s11257-016-9178-6>
- Matt, C., Benlian, A., Hess, T., Weiß, & ve, C. (2014, 14 December). Escaping from the filter bubble? The effects of novelty and serendipity on users' evaluations of online recommendations. In proceedings of the thirty fifth international conference on information systems, Auckland, New Zealand.
- McBirnle, A. (2008, November). Seeking serendipity: The paradox of control. In Aslib proceedings (Vol. 60, No. 6, pp. 600-618). Emerald Group Publishing Limited. <https://doi.org/10.1108/00012530810924294>
- McNee, S. M., Riedl, J., & Konstan, J. A. (2006). Being accurate is not enough. *CHI '06 Extended Abstracts on Human Factors in Computing Systems*, 1097-1101. <https://doi.org/10.1145/1125451.1125659>
- Mehrabian, A., & Russell, J. A. (1974). An approach to environmental psychology. Cambridge, MA: MIT Press.
- Mendoza, M., & Torres, N. (2020). Evaluating content novelty in recommender systems. *Journal of Intelligent Information Systems*, 54(2), 297-316. <https://doi.org/10.1007/s10844-019-00548-x>
- Murakami, T., Mori, K., Orihara, R. (2008). Metrics for evaluating the serendipity of recommendation lists. In: Satoh, K., Inokuchi, A., Nagao, K., Kawamura, T. (Eds). In New Frontiers in Artificial Intelligence. JSAI 2007. *Lecture Notes in Computer Science*, 4914(40-46). Springer. https://doi.org/10.1007/978-3-540-78197-4_5

- Mutambik, I., Lee, J., Almuqrin, A., Zhang, J. Z., & Homadi, A. (2023). The growth of social commerce: How it is affected by users' privacy concerns. *Journal of Theoretical and Applied Electronic Commerce Research*, 18(1), 725-743. <https://doi.org/10.3390/jtaer18010037>
- Netflix. (2025, November 20). How does Netflix's recommendations system work? <https://help.netflix.com/tr/node/100639>
- Nguyen, T. T., Hui, P. M., Harper, F. M., Terveen, L., & Konstan, J. A. (2014). Exploring the filter bubble: The effect of using recommender systems on content diversity. Proceedings of the 23rd International Conference on World Wide Web, (pp. 677-686). ACM. <https://doi.org/10.1145/2566486.2568012>
- Nikitha Reddy, K., Iyer, L. S., & Sophia Shalini, G. B. (2025). Pattern identification and recommender system based on skin undertone in apparel-A deep learning approach. In S. Kumar, E. A. Mary Anita, J. H. Kim, & A. Nagar (Eds.), Fifth Congress on Intelligent Systems. CIS 2024. Lecture Notes in Networks and Systems (Vol. 1277, pp. 245-256). Springer, Singapore. https://doi.org/10.1007/978-981-96-2700-4_21
- Nilashi, M., Jannach, D., bin Ibrahim, O., Esfahani, M. D., & Ahmadi, H. (2016). Recommendation quality, transparency, and website quality for trust-building in recommendation agents. *Electronic commerce research and applications*, 19, 70-84. <https://doi.org/10.1016/j.elerap.2016.09.003>
- Njomo, F. (2022). The perceived impact of video-on-demand services adoption on subscription tv services in South Africa [Master's thesis]. University of the Witwatersrand, Johannesburg (South Africa).
- O'Brien, H. L., Cairns, P., & Hall, M. (2018). A practical approach to measuring user engagement with the refined user engagement scale (UES) and new UES short form. *International Journal of Human-Computer Studies*, 112, 28-39. <https://doi.org/10.1016/j.ijhcs.2018.01.004>
- Oestreicher-Singer & Sundararajan. (2012). Recommendation networks and the long tail of electronic commerce. *MIS Quarterly*, 36(1), 65. <https://doi.org/10.2307/41410406>
- Qingfu Zhang and Hui Li. 2007. MOEA/D: A multiobjective evolutionary algorithm based on decomposition. *IEEE Transactions on Evolutionary Computation* 11, 6 (2007), 712-731. <https://doi.org/10.1109/TEVC.2007.892759>
- Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce*, 7(3), 101-134. <https://doi.org/10.1080/10864415.2003.11044275>
- Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of applied psychology*, 88(5), 879. <https://doi.org/10.1037/0021-9010.88.5.879>

- Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. *Annual review of psychology*, 63(1), 539-569. <https://doi.org/10.1146/annurev-psych-120710-100452>
- Pu, P., Chen, L., & Hu, R. (2011). A user-centric evaluation framework for recommender systems. In Proceedings of the Fifth ACM Conference on Recommender Systems. (pp. 157-164). <https://doi.org/10.1145/2043932.2043962>
- Pu, P., Chen, L., & Hu, R. (2012). Evaluating recommender systems from the user's perspective: Survey of the state of the art. *User Modeling and User-Adapted Interaction*, 22(4-5), 317-355. <https://doi.org/10.1007/s11257-011-9115-7>
- Rashid, A. M., Albert, I., Cosley, D., Lam, S. K., McNee, S. M., Konstan, J. A., & Riedl, J. (2002). Getting to know you. Proceedings of the 7th International Conference on Intelligent User Interfaces. (pp. 127-134). <https://doi.org/10.1145/502716.502737>
- Raza, S., Rahman, M., Kamawal, S., Toroghi, A., Raval, A., Navah, F., & Kazemeini, A. (2024). A comprehensive review of recommender systems: Transitioning from theory to practice. *Computer Science Review*, 59, 100849. <https://doi.org/10.1016/j.cosrev.2025.100849>
- Reddy, S. R. S., Nalluri, S., Kuniseti, S., Ashok, S., & Venkatesh, B. (2019). Content-based movie recommendation system using genre correlation. Smart Intelligent Computing and Applications: Proceedings of the Second International Conference on SCI. 2018 (Vol. 2, pp. 391-397). Springer. https://doi.org/10.1007/978-981-13-1927-3_42
- Ricci, F., Rokach, L., & Shapira, B. (2011). Introduction to recommender systems handbook. In recommender systems handbook (pp. 1-35). Springer US. https://doi.org/10.1007/978-0-387-85820-3_1
- Ricci, F., Rokach, L., & Shapira, B. (2015). Recommender systems: Introduction and challenges. In F. Ricci, L. Rokach, & B. Shapira (Eds.), Recommender Systems Handbook (pp.1-34). Springer US. https://doi.org/10.1007/978-1-4899-7637-6_1
- Rohden, S. F., & Zeferino, D. G. (2023). Recommendation agents: An analysis of consumers' risk perceptions toward artificial intelligence. *Electronic Commerce Research*, 23(4), 2035-2050. <https://doi.org/10.1007/s10660-022-09626-9>
- Rubinstein, M. (2002). Markowitz's" portfolio selection": A fifty-year retrospective. *The Journal of finance*, 57(3), 1041-1045. <https://doi.org/10.1111/1540-6261.00453>
- Saxborn, M., Pan, Y., & Said, A. (2024, March). Trust through recommendation in e-commerce. Proceedings of the 2024 Conference on Human Information Interaction and Retrieval (pp. 87-96). ACM. <https://doi.org/10.1145/3627508.3638294>

- Schafer, J. B., Konstan, J. A., & Riedl, J. (2001). E-commerce recommendation applications. *Data Mining and Knowledge Discovery*, 5(1/2), 115-153. <https://doi.org/10.1023/A:1009804230409>
- Sharma, A. (2023). Analyzing the role of artificial intelligence in predicting customer behavior and personalizing the shopping experience in ecommerce. *International Journal of Scientific Research in Engineering and Management*. 7(2), 1-8.
- Shen, A. (2014). Recommendations as personalized marketing: insights from customer experiences. *Journal of Services Marketing*, 28(5), 414-427. <https://doi.org/10.1108/JSM-04-2013-0083>
- Shi, Y., Larson, M., & Hanjalic, A. (2014). Collaborative filtering beyond the user-item matrix. *ACM Computing Surveys*, 47(1), 1-45. <https://doi.org/10.1145/2556270>
- Siles, I., Espinoza-Rojas, J., Naranjo, A., & Tristán, M. F. (2019). The mutual domestication of users and algorithmic recommendations on Netflix. *Communication, Culture & Critique*, 12(4), 499-518. <https://doi.org/10.1093/ccc/tcz025>
- Smyth, B., & McClave, P. (2001). Similarity vs. diversity. International Conference on Case-Based Reasoning. (pp. 347-361). https://doi.org/10.1007/3-540-44593-5_25
- Sohn, S., Labrecque, L., Siemon, D., & Morana, S. (2025). Artificial intelligence versus human service agents: How their presence shapes consumer information privacy concerns. *Journal of Retailing*. 101(2), 263-278. <https://doi.org/10.1016/j.jretai.2025.03.003>
- Sun, T., Zhang, M., & Mei, Q. (2021). Unexpected relevance: An empirical study of serendipity in retweets. Proceedings of the International AAAI Conference on Web and Social Media, 7(1), 592-601. <https://doi.org/10.1609/icwsm.v7i1.14435>
- Tabachnick, B. G., & Fidell, L. S. (2019). Using multivariate statistics (7th ed.). Pearson Education.
- Tam & Ho. (2006). Understanding the impact of web personalization on user information processing and decision outcomes. *MIS Quarterly*, 30(4), 865-890. <https://doi.org/10.2307/25148757>
- Tintarev, N., & Masthoff, J. (2012). Evaluating the effectiveness of explanations for recommender systems. *User Modeling and User-Adapted Interaction*, 22(4-5), 399-439. <https://doi.org/10.1007/s11257-011-9117-5>
- Trattner, C., Said, A., Boratto, L., & Felfernig, A. (2023). Evaluating group recommender systems. In Group recommender systems: an introduction (pp. 63-75). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-44943-7_3
- Troussas, C., Krouska, A., & Sgouropoulou, C. A. (2021). User-centric system for improving human-computer interaction through fuzzy logic-based assistive messages. Proceedings of the 17th International Conference on Web Information Systems and

- Technologies-WEBIST (pp. 365-370). SciTePress.
<https://doi.org/10.5220/0010702800003058>
- Tuzhilin, A. (2009). Personalization: The state of the art and future directions. In G. Adomavicius and A. Gupta (Eds). *Business Computing*, ser. Handbooks in Information Systems (pp. 47-68). Emerald Group Publishing Limited.
- Vargas, S., & Castells, P. (2011). Rank and relevance in novelty and diversity metrics for recommender systems. *Proceedings of the Fifth ACM Conference on Recommender Systems*. (pp. 109-116). <https://doi.org/10.1145/2043932.2043955>
- Verma, S., Sharma, R., Deb, S., & Maitra, D. (2021). Artificial intelligence in marketing: Systematic review and future research direction. *International Journal of Information Management Data Insights*, 1(1), 100002. <https://doi.org/10.1016/j.ijime.2020.100002>
- Wang, Z., Höpken, W., & Jannach, D. (2025). A survey on point-of-interest recommendations leveraging heterogeneous data. *Information Technology & Tourism*, 27(1), 29-73. <https://doi.org/10.1007/s40558-024-00301-3>
- Werneck H, Silva N, Viana M et al (2021) Points of interest recommendations: Methods, evaluation, and future directions. *Information Systems*, 101,101789. <https://doi.org/10.1016/j.is.2021.101789>
- Wang, W., & Benbasat, I. (2007). Recommendation agents for electronic commerce: Effects of explanation facilities on trusting beliefs. *Journal of Management Information Systems*, 23(4), 217-246. <https://doi.org/10.2753/MIS0742-1222230410>
- Wang, W., & Benbasat, I. (2016). Empirical assessment of alternative designs for enhancing different types of trusting beliefs in online recommendation agents. *Journal of management information systems*, 33(3), 744-775. <https://doi.org/10.1080/07421222.2016.1243949>
- Wang, Y., Lam, H. T., Wong, Y., Liu, Z., Zhao, X., Wang, Y., ... & Tang, R. (2023). Multi-task deep recommender systems: A survey. <https://doi.org/10.48550/arXiv.2302.03525>
- Wu, W., Chen, L., & Zhao, Y. (2018). Personalizing recommendation diversity based on user personality. *User Modeling and User-Adapted Interaction*, 28(3), 237-276. <https://doi.org/10.1007/s11257-018-9205-x>
- Xi, Y., Weng, M., Chen, W., Yi, C., Chen, D., Guo, G., ... & Zhang, W. (2025, August). Bursting filter bubble: Enhancing serendipity recommendations with aligned large language models. *Proceedings of the 31st ACM SIGKDD Conference on Knowledge Discovery and Data Mining* (Vol. 2, pp. 5059-5070). ACM. <https://doi.org/10.1145/3711896.3737199>

- Xiao, B., & Benbasat, I. (2007). E-commerce product recommendation agents: Use, characteristics, and impact. *MIS quarterly*, 31(1), 137-209. <https://doi.org/10.2307/25148784>
- Yi, Y., & Natarajan, R. (2018). Customer satisfaction in Asia. *Psychology & Marketing*, 35(6), 387-391. <https://doi.org/10.1002/mar.21093>
- Yoon, N., & Lee, H.K. (2021). AI recommendation service acceptance: Assessing the effects of perceived empathy and need for cognition. *Journal of Theoretical and Applied Electronic Commerce Research*, 16(5), 1912-1928. <https://doi.org/10.3390/jtaer16050107>
- Yudhistira, R. A., & Wang, G. (2025). Factors influencing recommender system effectivity on continuance usage intention in Indonesian e-commerce user. *Journal of Theoretical and Applied Information Technology*, 103(3), 848-874.
- Yurt, E. (2023). Practical insights for multivariate analyses in social sciences: SPSS and AMOS Applications. Ankara: Nobel.
- Yu, P., & Krutasaen, W. (2022). Consumer psychology of ethnic clothing based on artificial Intelligence decision-making and internet of things. *Wireless Communications & Mobile Computing*, 2(2022), 1-7. <https://doi.org/10.1155/2022/8805010>
- Zeng, W., Zeng, A., Liu, H., Shang, M. S., & Zhou, T. (2014). Uncovering the information core in recommender systems. *Scientific reports*, 4(1), 6140. <https://doi.org/10.1038/srep06140>
- Zhang, L. (2013). The definition of novelty in recommendation system. *Journal of Engineering Science and Technology Review*, 6(3), 141-145. <https://doi.org/10.25103/jestr.063.25>
- Zhang, Y. C., Séaghdha, D. Ó., Quercia, D., & Jambor, T. (2012). Auralist: Introducing serendipity into music recommendation. Proceedings of the Fifth ACM International Conference on Web Search and Data Mining, 13-22. <https://doi.org/10.1145/2124295.2124300>
- Zhao, Y., Wang, Y., Liu, Y., Cheng, X., Aggarwal, C. C., & Derr, T. (2025). Fairness and diversity in recommender systems: A survey. *ACM Transactions on Intelligent Systems and Technology*, 16(1), 1-28. <https://doi.org/10.1145/3664928>
- Zheng, Y., & Wang, D. X. (2022). A survey of recommender systems with multi-objective optimization. *Neurocomputing*, 474, 141-153. <https://doi.org/10.1016/j.neucom.2021.11.041>
- Zhou, G., Mou, N., Fan, Y., Pi, Q., Bian, W., Zhou, C., Zhu, X., & Gai, K. (2019). Deep interest evolution network for click-through rate prediction. Proceedings of the AAAI Conference on Artificial Intelligence. 33(01), 5941-5948. <https://doi.org/10.1609/aaai.v33i01.33015941>

- Zhou, T., Kuscsik, Z., Liu, J. G., Medo, M., Wakeling, J. R., & Zhang, Y. C. (2010). Solving the apparent diversity-accuracy dilemma of recommender systems. *Proceedings of the National Academy of Sciences*, 107(10), 4511-4515. <https://doi.org/10.1073/pnas.1000488107>
- Ziegler, C. N., McNee, S. M., Konstan, J. A., & Lausen, G. (2005). Improving recommendation lists through topic diversification. *Proceedings of the 14th International Conference on World Wide Web - WWW '05*, 22. <https://doi.org/10.1145/1060745.1060754>
- Zonghan Wu, Shirui Pan, Fengwen Chen, Guodong Long, Chengqi Zhang, and Philip S. Yu. A (2025). Comprehensive survey on graph neural networks. *IEEE Transactions on Neural Networks and Learning Systems*, 32(1), 4-24. <https://doi.org/10.1109/TNNLS.2020.2978386>
- Zuva, K., & Zuva, T. (2017, December). Diversity and serendipity in recommender systems. In *Proceedings of the International Conference on Big Data and Internet of Thing* (pp. 120-124). <https://doi.org/10.1145/3175684.3175694>