

ENHANCING MARKETING PERSONALIZED SHOPPING RECOMMENDATIONS IN THE UAE: LEVERAGING LOGIC MINING AND ADVANCED TECHNOLOGIES

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Abstract: This study investigates how personalized recommendation systems in e-commerce operate, using Social Exchange Theory as its theoretical basis. Through empirical research, we analyze the effects of improving consumer experiences, enhancing product suggestions, and building trust and satisfaction on the effectiveness of personalized recommendation systems. Our study combines practical techniques with theoretical knowledge to improve user engagement and build long-lasting brand loyalty. This research provides valuable insights for e-commerce stakeholders, suggesting that individualized recommendations might enhance consumer satisfaction in the digital marketplace.

Keywords: Personalized Recommendation Systems, Consumer Challenges, Trust and Satisfaction, User Engagement, Digital Marketplace.

JEL Classification: M300.

1 Introduction

Customized purchasing suggestions are essential in contemporary e-commerce platforms to improve user satisfaction and increase sales. Utilizing advanced technologies like logic mining is critical for enhancing the precision and pertinence of these recommendations. Multiple research has examined the complexities of personalized recommendation systems, emphasizing the significance of novel methodologies in this field (El-Deen, Morsi and Magdi, 2018; Stalidis, et al., 2023). Scholars have focused extensively on improving customized buying suggestions in the online retail industry. Research conducted by Yan, et al. (2022) and El-Deen, et al. (2018) showcases the application of sophisticated technologies, including fuzzy logic, Semantic Web Technology, and data mining, in creating robust recommendation systems. Stalidis, et al. (2023) also emphasize the necessity of inventive methods to address the difficulties encountered by recommendation systems in e-commerce settings (Dahu, et al., 2022; Khadragy, et al., 2022; Shwedeh, Aburayya, et al., 2022).

Nevertheless, despite notable progress, enduring obstacles impedes the efficacy of customized purchasing

suggestions, especially in areas such as the UAE. Personalized purchasing recommendations face considerable challenges in the UAE due to many circumstances. Compared to larger markets, the smaller population worsens data scarcity (Stalidis, et al., 2023). In addition, cultural diversity in the UAE adds intricacies to comprehending and anticipating user preferences, making the recommendation process more intricate (Shanthi and Rajagopalan, 2018; Tian, Shi and Li, 2023). Furthermore, the exponential expansion of online commercial transactions in the area requires the implementation of increasingly advanced recommendation systems to match the ever-changing patterns of customer actions (Guo, Wang and Li, 2017). Therefore, tackling these obstacles and creating customized strategies to improve individualized purchasing suggestions in the UAE are crucial. Consequently, this study aims to:

- examine the significant influence of challenges (data scarcity and cultural diversity) associated with customers' preferences and personalized recommendations (PRs; social media engagements, emotional connections, and social media platforms);

- investigate the significant influence of product attributes (price, product brand, and product quality) on PRs (social media engagements, emotional connections, and social media platforms);
- examine the significant influence of customers' trust and satisfaction on PRs (social media engagements, emotional connections, and social media platforms).

2 Literature Review

2.1 Personalized Shopping Recommendations

Personalized shopping recommendations involve offering customized product suggestions to individual users, considering their preferences, behaviors, and past interactions with the platform (Fayyaz, et al., 2020; Sharma, Rana and Kumar, 2021). Amidst the current digital environment, characterized by abundant choices, tailored recommendations are crucial in helping users find suitable products and enhancing their overall purchasing process as fast as possible (Ko, et al., 2022). Customized recommendations are important because they strengthen user involvement and satisfaction, increasing sales and revenue for e-commerce platforms (Tran, et al., 2021).

The significance of personalized purchasing recommendations in e-commerce has grown and become more crucial with the progression of technology (Karthik and Ganapathy, 2021; Alam, et al., 2021). Initially, recommendation systems relied on basic rule-based methods (Aburayya, et al., 2023; Alkashami, et al., 2023). However, machine learning, deep learning, and fuzzy logic have evolved into more advanced and proficient systems capable of delivering exact and pertinent suggestions (Sohn and Kim, 2020; Serrano-Guerrero, et al., 2021). PRs have become a strategic tool for enterprises in the competitive e-commerce industry to distinguish themselves, retain clients, and establish long-term connections (Hallikainen, et al., 2022).

The significance of technology in enhancing personalized shopping suggestions cannot be underestimated (Shwede, et al., 2022; Shwede, et al., 2023), as it enables the analysis of vast quantities of data, intricate algorithms, and innovative approaches to recommendation modeling (Almahmood and Tekerek, 2022; Zimmermann, et al., 2023). Data mining, semantic web, augmented reality, and artificial intelligence (AI)

technologies monitor user behavior, extract valuable insights, and deliver personalized suggestions in real time (El-Deen, et al., 2018; Sharma, Rana and Kumar, 2021). In addition, the integration of explainable AI and user interaction mechanisms enhances the transparency and efficacy of recommendation systems, hence promoting user trust and confidence (Xu, et al., 2020; Ko, et al., 2022). Technology remains crucial in shaping the future of personalized shopping recommendations, fostering creativity, and providing benefits for businesses and customers (Alimour, et al., 2024; Shwede, 2024).

2.2 Existing Approaches and Technologies

Many recommendation systems and methodologies are currently used in personalized purchasing recommendations. These systems strive to optimize the user experience and boost revenue by offering personalized product recommendations. A survey of recommendation systems demonstrates the utilization of diverse models and algorithms for examining user preferences and behaviors (Bleize and Antheunis, 2019; Ko, et al., 2022). These systems utilize machine learning, deep learning, and fuzzy logic to create personalized suggestions by analyzing past user interactions and item characteristics (Fayyaz, et al., 2020; Sharma, Rana and Kumar, 2021). Furthermore, recommendation systems have various applications in various sectors, such as e-commerce, social commerce, health care, and entertainment, underscoring their adaptability and importance in contemporary digital settings (Tran, et al., 2021; Ko, et al., 2022).

Logic mining is becoming increasingly crucial in tailored suggestions since it provides valuable insights into user preferences and behaviors (Sohn and Kim, 2020; Cui, 2021). Logic mining algorithms utilize logical reasoning and pattern recognition to extract significant correlations and rules from extensive datasets. This process aids in identifying pertinent product recommendations (Serrano-Guerrero, et al., 2021; Karthik and Ganapathy, 2021). These algorithms utilize user interactions, such as browsing history, purchase trends, and feedback, to deduce implicit preferences and anticipate future behavior (Sohn and Kim, 2020; Sharma, Rana and Kumar, 2021). In addi-

tion, logic mining techniques are being more frequently combined with other recommendation approaches, such as collaborative filtering and content-based filtering, to improve the accuracy and effectiveness of recommendations (Alam, et al., 2021; Hallikainen, et al., 2022).

Integrating logic mining into PR systems yields several advantages such as higher recommendation precision, improved user contentment, and increased sales revenue (Yang and Yan, 2011; Xu, Ferwerda and Lee, 2020). Using logical thinking and insights derived from data, these systems may effectively address obstacles such as limited data availability, uncertainty in user preferences, and cultural differences (Shwede, et al., 2020; Ravikumar et al., 2023). As a result, they can provide users with more pertinent recommendations tailored to their individual needs and preferences (Karthik and Ganapathy, 2021; Alam, et al., 2021). In addition, combining logic mining with explainable AI allows users to comprehend the reasoning behind recommendations, promoting confidence and transparency in the recommendation process (Almahmood and Tekerek, 2022; Zimmermann, et al., 2023). Logic mining offers a promising solution for dealing with the difficulties of tailored buying recommendations and improving the user experience in e-commerce (Shwede, et al., 2020; Ravikumar, et al., 2023).

2.3 Challenges in Personalized Shopping Recommendations

The intricacies of the e-commerce landscape give rise to numerous challenges in tailored buying recommendations. Data sparsity and cold-start difficulties are significant obstacles in this context (Almahmood and Tekerek, 2022; Zimmermann, et al., 2023). The efficacy of recommendation systems is impeded by the scarcity of user data and the challenge of creating tailored recommendations for new users or items. In addition, the suggestion process is further complicated by the ambiguity of user preferences (Xu, Ferwerda and Lee, 2020; Almahmood and Tekerek, 2022). Comprehending and forecasting user preferences in the face of diverse individual likes and preferences poses a daunting problem for recommendation systems.

In addition, the presence of cultural diversity and market dynamics introduces an additional level of intricacy to tailored buying recommendations (Hallikainen, et al., 2022; Zimmermann, et al., 2023). In regions characterized by many cultural origins, such as the UAE, it becomes progressively challenging to accommodate the distinct preferences and behaviors of various consumer segments. The issues are further exacerbated by the rapidly changing consumer behaviors, which require regular adjustment of recommendation algorithms due to shifting trends and preferences (Sohn and Kim, 2020; Alam, et al., 2021). To stay current and successfully provide individualized purchasing experiences, recommendation systems must be adaptable and responsive to evolving customer habits.

To tackle these ongoing issues, it is necessary to employ inventive strategies and robust frameworks that consider the ever-changing character of e-commerce settings (Almahmood and Tekerek, 2022; Chakraborty and Paul, 2023). By using sophisticated technologies such as explainable AI and augmented reality, the precision and pertinence of PRs can be improved (Zimmermann, et al., 2023). Moreover, it is imperative to cultivate cooperation among industry players and researchers to create customized solutions that address personalized shopping recommendations' distinct requirements and difficulties (Dahu, et al., 2022; Khadragy, et al., 2022; Shwede, Aburayya, et al., 2022). E-commerce platforms can seize new chances for growth and innovation by providing individualized shopping experiences and directly addressing and resolving these difficulties (Shwede, et al., 2022; Shwede, et al., 2023).

2.4 Influencing Factors for Personalized Shopping Recommendations

Various variables impact customers' inclination to purchase tailored shopping recommendations. Product attributes, such as price, brand, and quality, substantially impact customers' buying choices (Chang and Wildt, 1994; Lee, Cheng and Shih, 2017; Sohn and Kim, 2020). The cost of a product directly influences consumers' intention to acquire it since they typically evaluate the product's perceived value concerning its price (Chang and Wildt, 1994). Furthermore, the repu-

tation of a brand and the perceived quality of its products significantly impact how customers perceive the value and trustworthiness of the brand, which in turn affects their intentions to make a purchase (Lee, Cheng and Shih, 2017). Furthermore, user engagement metrics, such as click-through rate and dwell duration, are markers of customer interest and involvement, impacting purchase intention (Shareef, et al., 2008; Ma, et al., 2020).

Trust and satisfaction are crucial in influencing purchase intention in personalized shopping recommendations (Lin and Lu, 2010; Chiu, et al., 2012). Consumers' confidence in the transaction process is enhanced by their trust in the e-sellers' reputation and the overall business image, increasing their purchase intention (Shareef, et al., 2008). In addition, consumer trust and the probability of future purchases are increased by both contentment with past purchases and positive word-of-mouth recommendations (Lin and Lu, 2010). Furthermore, the impact of trust on the intention to make repeat purchases online is regulated by the habits developed as a result of repeated pleasant experiences. This highlights the significance of trust in motivating the intention to make purchases (Chiu, et al., 2012).

Furthermore, personalized buying recommendations are influenced by social media interactions and elements related to the source and substance of the recommendations (Onofrei, Filieri, and Kennedy, 2022). The level of consumer engagement and intentions to make online purchases are influenced by the relationships they develop and the emotional connections they establish through social commerce platforms (Ma, et al., 2020; Qi, Yu, and Ploeger, 2020). In addition, the intention to acquire health-care apps is influenced by consumption values, representing consumers' judgments of the usefulness and advantages of these applications (Chakraborty and Paul, 2023). Thorough comprehension of the factors that influence consumers' intention to purchase emphasizes the intricate nature of consumer behavior in personalized shopping suggestions. It reinforces the significance of addressing various variables to enhance the effectiveness of recommendation systems.

2.5 Research Framework

The following research framework that led to the research hypotheses is given based on the relevant articles and publications reviewed for the issues under investigation (Figure 1).

2.6 Research Hypotheses

H1: A significant relationship exists between perceived challenges (data scarcity and cultural diversity) associated with customers' preferences and PRs (social media engagements, emotional connections, and social media platforms).

H2: Product attributes (price, product brand, and product quality) have a significant relationship with PRs (social media engagements, emotional connections, and social media platforms).

H3: Customers' perceived trust and satisfaction significantly influence PRs (social media engagements, emotional connections, and social media platforms).

2.7 Social Exchange Theory As Philosophical Underpinning

Social Exchange Theory offers a conceptual framework for comprehending the dynamics of interpersonal relationships and interactions in many situations, such as online platforms and e-commerce environments. Liao, et al. (2021) and Akarsu, et al. (2020) suggest that people participate in social interactions online to maximize benefits and minimize drawbacks. These factors play a crucial role in the decision-making process in online environments. This idea suggests that individuals are driven to participate in mutual behaviors with the anticipation of gaining advantages or rewards from their contacts (Davlembayeva, et al., 2020; Ferm and Thaichon, 2021). Within the realm of e-commerce, individuals engage in social commerce platforms and online communities with the anticipation of acquiring important insights, endorsements, and assistance from fellow users (Zhang and Liu, 2022). Sharing information and resources fosters trust, dedication, and allegiance among users (Almahmood and Tekerek, 2022; Alimamy and Gnoth, 2022).

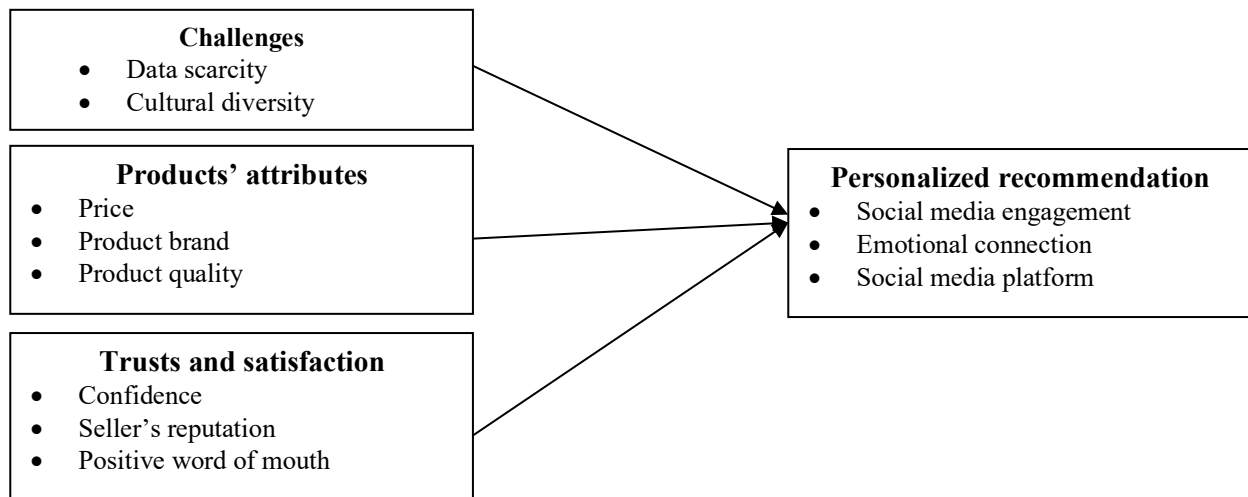


Figure 1. Research framework
(Source: Authors' own research)

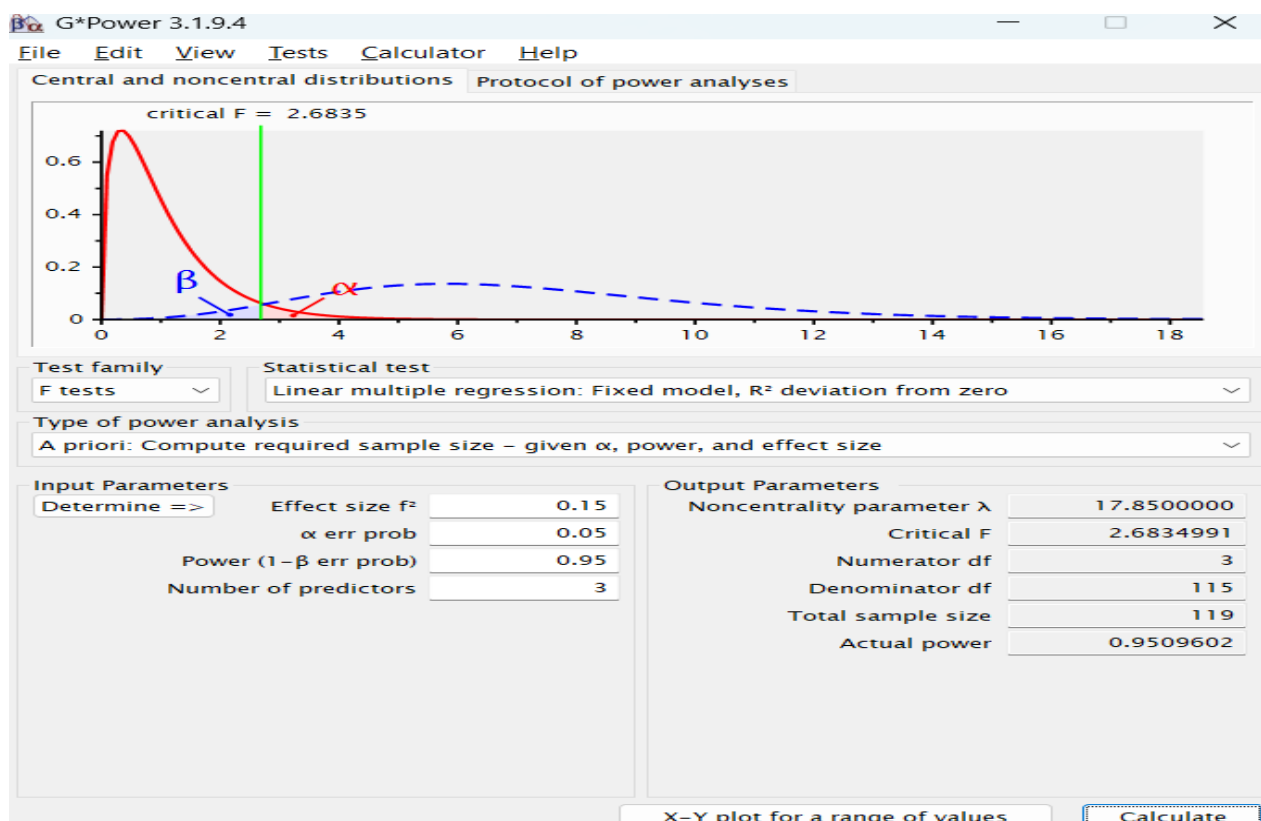


Figure 2. G*Power version 3.1.9.4 used to compute the sample size of the study
(Source: Authors' own research)

Comprehending the fundamental principles of Social Exchange Theory is essential for examining the behaviors and preferences of customers in online environments, specifically concerning tailored buying recommendations. Researchers can enhance recommendation systems in social commerce platforms by

analyzing the aspects that impact users' involvement, trust, and satisfaction

This analysis allows for the development of more efficient systems that cater to individual users' specific needs and preferences (Khanal, et al., 2020; Ko, et al., 2022). Moreover, Social Exchange Theory emphasizes the significance of reciprocity and mutual advantage in

online interactions. This can guide the development and execution of recommendation algorithms prioritizing user-centric experiences (Sharma, et al., 2021; Stalidis, et al., 2023). Researchers can improve the accuracy and significance of tailored recommendations in e-commerce by utilizing Social Exchange Theory insights. This can ultimately enhance user happiness, engagement, and purchase behavior (Tran, et al., 2021; Tian, et al., 2023).

3 Methodology

This study employs a quantitative research design utilizing survey methodology to investigate the factors influencing consumers' acceptance of personalized shopping recommendations in the context of e-commerce platforms. To achieve the study's objectives, we employed a survey approach to target UAE shoppers with experience in shopping recommendations. Since we have no definite database to determine the available population and the needed sample size, we employed a stratified random sampling where stratification is based on respondent age, level of income, gender, and online shopping frequency.

Moreover, the sample size was determined using power analysis software (G*Power version 3.1.9.4), as recommended by Kang (2021). The software was set to F-test based on the proposed analysis structural equation modeling (SEM) (Kang, 2021; Serdar, et al., 2021), and linear multiple regression was chosen with r^2 deviation from zero. With this, the power analysis suggested an estimate of 115 samples after computing the sample size using effect size, power, and error probability (Kang, 2021; Lakens, 2022). The output is presented in Figure 2.

In fact, the survey instruments were adapted from earlier investigations that include Almahmood and Tekerek (2022), Xu, et al. (2020), and Zimmermann et al. (2023), measuring perceived challenges; while items measuring product attributes were adapted from Chang and Wildt (1994), Lee, et al. (2017), and Sohn and Kim (2020). Furthermore, items measuring trust and satisfaction were adapted from Chiu, et al. (2012), and Lin and Lu (2010). Finally, items measuring PRs were adapted from Fayyaz, et al. (2020), Ko, et al. (2022), Sharma, et al. (2021), and Tran, et al. (2021).

A total of 33 items were adapted to measure the constructs. Meanwhile, the sample demographics, which included age, gender, income level, shopping frequency, and recommendation via social media platforms, were observed.

4 Methodology

4.1 Demographic Data

A total response of 280 surveys were gathered throughout the period of 5 months. Since the SEM tool was used to analyze the inferential part of the questionnaire, and the SEM tool can analyze non-normal data, we did not assess the presence of outliers thoroughly. However, we checked if there was any outlier because of data imputation, but none was found. Demographic data presents the data characteristics. This helps us understand the hidden factors that the respondents possess. The survey data shows that most respondents were females 66.07% (185), while their male counterparts had 33.93% (95) responses. Moreover, 46.43% (130) were of Arab origin, 16.07% (45) were of Hispanic origin, 28.57% (80) were of Asian descent, and the remaining 8.93% (25) were of African descent. In addition, all respondents 100% claimed they loved shopping online and offline and received promotional emails because they had store club cards.

4.2 Inferential Statistics

We adopted a SEM analytical tool to analyze the inferential statistics of the collected data. Using the SEM analysis tool, we assessed two main models: measurement and structural modeling. Under the measurement model, we assessed parameters that included construct, convergent, and discriminant validity by checking if the Average Variance Explained for each construct was greater than 0.5 (Hair Jr, et al., 2021; Rönkkö and Cho, 2022). Likewise, the composite reliability (CR) threshold should be greater than 0.7, and item loadings should be greater than 0.6 (Ismail, et al., 2020; Sovey, Osman and Mohd-Matore, 2022). For discriminant validity, the Heterotrait Monotrait (HTMT) correlation matrix between constructs should have a maximum threshold of less than 0.9 (Henseler, Ringle and Sarstedt, 2015).

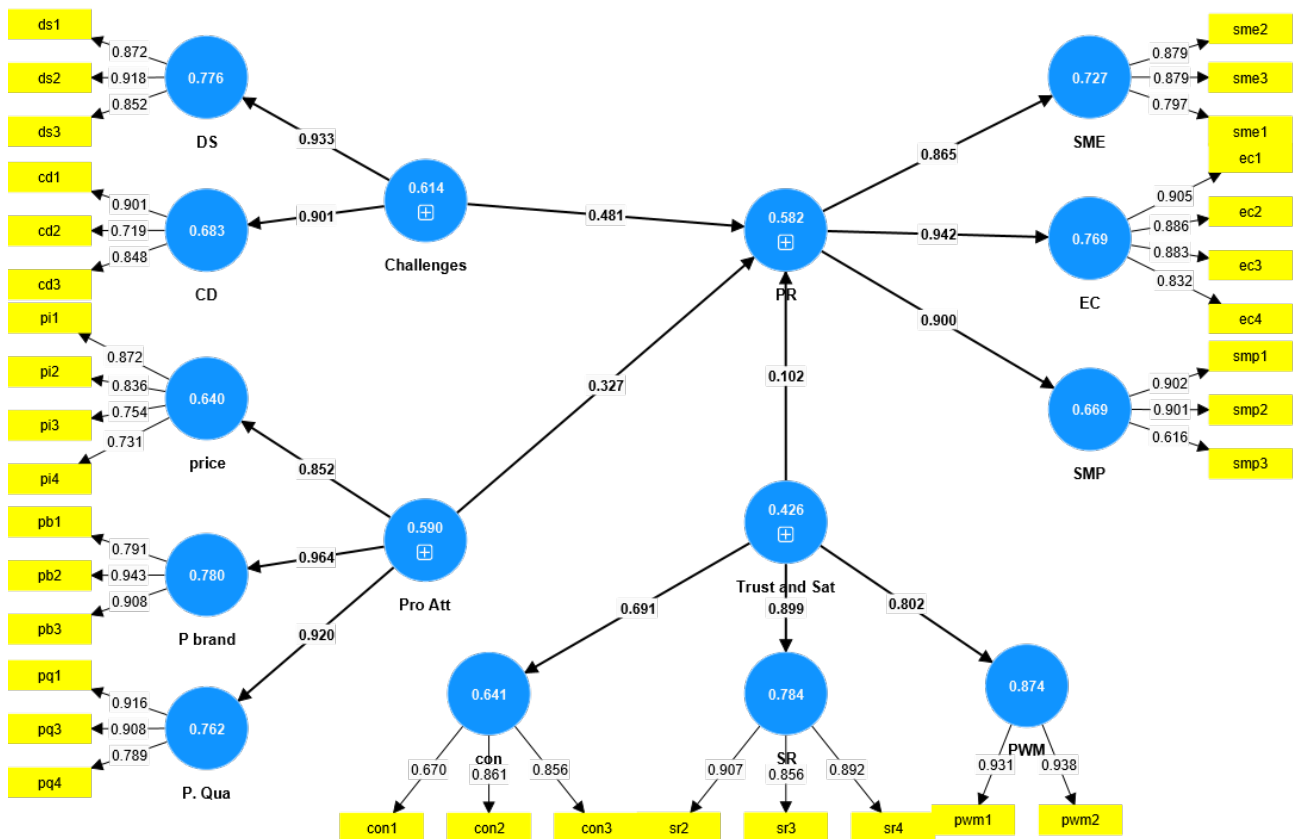


Figure 3. Measurement model
(Source: Authors' own research)

Table 1. Planned costs for the production department for 2022 AD
(Source: Authors' own research)

Construct	Items	Item loadings	CR	AVE	Discriminant validity
DS.	ds1	0.872	0.859	0.776	Yes
-	ds2	0.918	-	-	-
-	ds3	0.852	-	-	-
CD	cd1	0.901	0.77	0.683	Yes
-	cd2	0.719	-	-	-
-	cd3	0.848	-	-	-
Price	pi1	0.872	0.828	0.640	Yes
-	pi2	0.836	-	-	-
-	pi3	0.754	-	-	-
-	pi4	0.731	-	-	-
P brand	pb1	0.791	0.866	0.78	Yes
-	pb2	0.943	-	-	-
-	pb3	0.908	-	-	-
P. Qua	pq1	0.916	0.822	0.762	Yes
-	pq3	0.908	-	-	-
-	pq4	0.789	-	-	-
Con	con1	0.670	0.73	0.643	Yes
-	con2	0.861	-	-	-
-	con3	0.856	-	-	-

Construct	Items	Item loadings	CR	AVE	Discriminant validity
SR	sr2	0.907	0.783	0.603	Yes
-	sr3	0.856	-	-	-
-	sr4	0.892	-	-	-
-	-	-	-	-	-
PWM	pwm1	0.931	0.851	0.59	Yes
-	pwm2	0.938	-	-	-
SME	sme1	0.797	0.829	0.727	Yes
-	sme2	0.879	-	-	-
-	sme3	0.879	-	-	-
EC	ec1	0.905	0.901	0.769	Yes
-	ec2	0.886	-	-	-
-	ec3	0.883	-	-	-
-	ec4	0.832	-	-	-
SMP	smp1	0.902	0.81	0.669	Yes
-	smp2	0.901	-	-	-
-	smp3	0.616	-	-	-

Table 2. HTMT correlation matrix
(Source: Authors' own research)

	CD	DS	EC	P brand	P. Qua	PWM	SME	SMP	SR	con
DS	0.849	-	-	-	-	-	-	-	-	-
EC	0.754	0.466	-	-	-	-	-	-	-	-
P brand	0.296	0.268	0.889	-	-	-	-	-	-	-
P. Qua	0.301	0.027	0.867	0.247	-	-	-	-	-	-
PWM	0.612	0.525	0.475	0.505	0.45	-	-	-	-	-
SME	0.573	0.766	0.532	0.772	0.837	0.526	-	-	-	-
SMP	0.456	0.034	0.885	0.319	0.391	0.259	0.906	-	-	-
SR	0.683	0.459	0.418	0.488	0.369	0.655	0.36	0.708	-	-
con	0.597	0.496	0.755	0.841	0.891	0.448	0.777	0.507	0.446	-
price	0.549	0.709	0.651	0.829	0.68	0.678	0.56	0.814	0.665	0.365

Note: DS (Data Scarcity); CD (Cultural Diversity); Product brand (P Brand); P Qua (Product quality); Con (Confidence); SR (Seller's reputation); PWM (Positive Word of Mouth); SME (Social Media Engagement); EC (Emotional Connection); and SMP (Social Media Platform).

Table 3. Collinearity analysis
(Source: Authors' own research)

Construct	VIF
Challenges	1.33
Pro Att	1.587
Trust and satisfaction	2.494

Furthermore, to ascertain that the model is free from collinearity issues, Variance Inflated Factors (VIF) was observed. According to Kim (2019), a model is said to be free from collinearity issues if the VIF value is less than 5. The outcome of the measurement model process is presented in Figure 3, Table 1.

As found in Table 1 and Figure 3, the conditions for the construct and the convergent validities were met. Meanwhile, a critical look into our research model shows that our model is a bit complex, having higher-order constructs. Given this, it should be recalled that we adopt a reflective—reflective model approach; therefore, Table 1 presents only the measurement model for the first-order constructs. Given this, we calculate the higher-order constructs AVE (1) and CR (2) using the formulae given below:

$$AVE = \sum_{i=1}^M l_{i=1}^2 / M \quad (1)$$

$$AVE_{\text{Challenge}} = \frac{0.933^2 + 0.901^2}{2} = \frac{1.6823}{2} = 0.841$$

$$AVE_{\text{Pro Att}} = \frac{0.852^2 + 0.964^2 + 0.920^2}{3} = \frac{2.5016}{3} = 0.834$$

$$AVE_{\text{Trust and Sat}} = \frac{0.691^2 + 0.899^2 + 0.802^2}{3} = \frac{2.02}{3} = 0.673$$

$$AVE_{\text{PR}} = \frac{0.865^2 + 0.942^2 + 0.900^2}{3} = \frac{2.562}{3} = 0.854$$

and

$$CR = \sum_{i=1}^n l_i / n \quad (2)$$

$$CR_{\text{Challenge}} = \frac{0.933 + 0.901}{2} = \frac{1.834}{2} = 0.917$$

$$CR_{\text{Pro ATT}} = \frac{0.852 + 0.964 + 0.920}{3} = \frac{2.736}{3} = 0.912$$

$$CR_{\text{Trust and Sat}} = \frac{0.691 + 0.899 + 0.802}{3} = \frac{2.533}{3} = 0.844$$

$$CR_{\text{PR}} = \frac{0.865 + 0.942 + 0.900}{3} = \frac{2.707}{3} = 0.902$$

After calculating AVE and CR for the higher-order constructs, we discovered that the minimum threshold stated for the first-order constructs is fulfilled.

Table 2 presents the HTMT correlation matrix. According to Hensler, et al. (2015), the maximum construct correlation threshold should be less than 0.9. Insight into Table 2 shows that this condition is met. Therefore, convergent validity is ascertained.

Furthermore, we assessed the model for the presence of collinearity. Indeed, a model contains collinearity issues if the VIF is greater than five. Insight into Table 3 shows that the model is free from collinearity issues;

thus, we proceed to statistically observe the relationships that exist between the variables under investigation.

Before testing the research hypotheses in this investigation, we assessed the model variance explained using r^2 . The r^2 reveals a value of 0.344. This implies that the investigated constructs explained a 34.4% variance in PRs. In addition, each exogenous variable's contribution was examined on the endogenous variable in the form of effect size (f^2). The Cohen's (1988) criterion was adopted in this regard. The SEM analysis presents the effect sizes for challenges, products' attributes, and trust and satisfaction as 0.358, 0.181, and 0.114, respectively. This suggests, given Cohen's (1988) premise, that the variables under consideration are large, medium, and low, respectively.

As seen in Table 4 and Figure 4, The first hypothesis demonstrates that perceived problems (challenges) faced by shoppers significantly influence PR having ($\beta = 0.48$, $T = 5.332$), $p < 0.05$. Hence, we accept the first hypothesis, establishing a significant association between shoppers' challenges and personal recommendations. Findings suggest that perceived problems in PRs connect with research on consumer behavior and decision-making processes (Bleize and Antheunis, 2019). Consumers generally rely on individualized recommendations to navigate the numerous choices in the marketplace, especially when they experience perceived problems such as information overload or decision complexity (Srikumar and Bhasker, 2005).

Similarly, product qualities (Pro att) strongly influence personalized suggestions, having ($\beta = 0.327$, $T = 3.449$), $p < 0.05$. Similar to the first hypothesis, we declare in this inquiry that consumers considered a solid, substantial relationship exists between product attributes' influence on tailored suggestions. The findings corresponded with studies highlighting the role of product attributes in affecting purchase intentions (Chang and Wildt, 1994; Lee, et al., 2017; Sohn and Kim, 2020). Given this, consumers tend to choose tailored recommendations that fit their preferences about product features not limited to price, packaging, quality, and functionality (Lee, et al., 2017; Sohn and Kim, 2020).

Likewise, the findings in this study revealed that perceived trust and satisfaction strongly influence personalized suggestion having ($\beta = 0.102$, $T = 2.115$), $p <$

0.05. The findings of this study connote the role of trust building and customer satisfaction in e-commerce situations (Shareef, et al., 2008). Trust in recommendation systems is vital for consumers to trust the relevance and reliability of the ideas supplied (Chiu, et

al., 2012). In addition, satisfied customers are more likely to connect with and act upon individualized recommendations, resulting in greater purchase intention (Sohn and Kim, 2020).

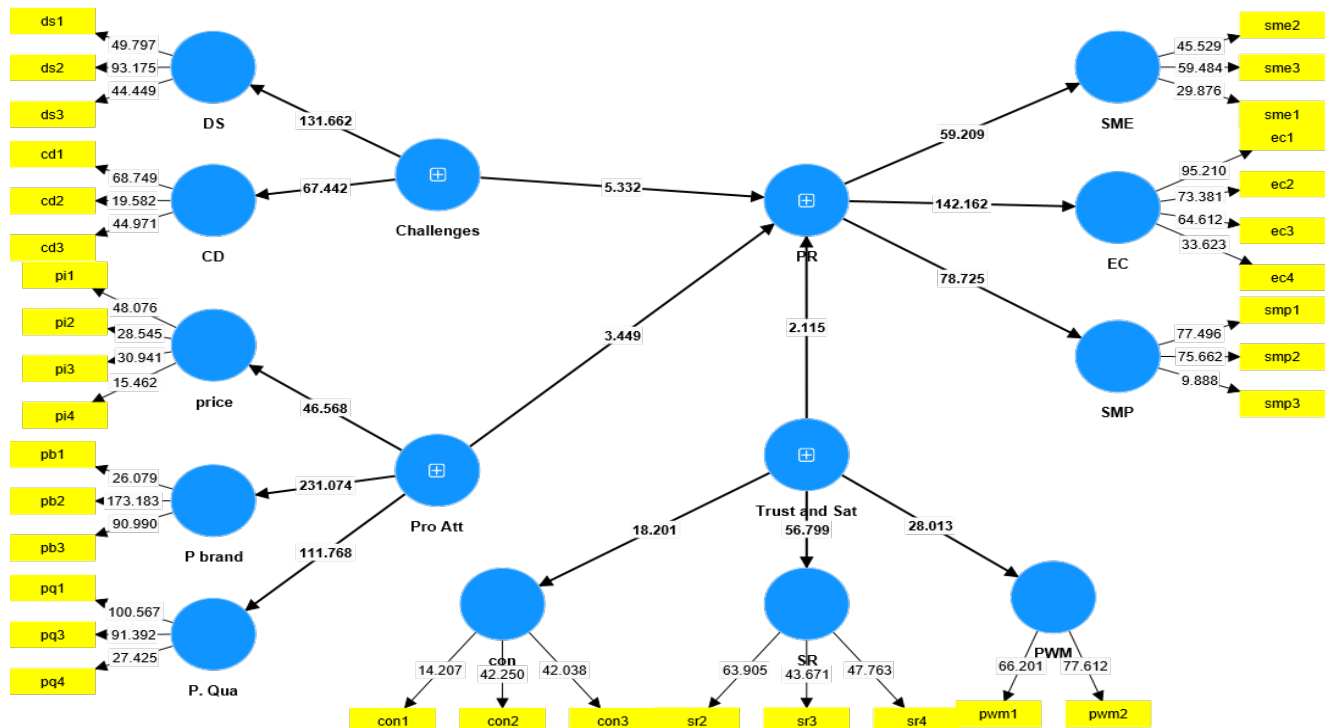


Figure 4. Structural model assessment (hypothesis testing)
(Source: Author's own research)

Table 4. Hypothesis testing
(Source: Authors' own research)

Hypotheses	Relationships	B	Standard deviation	T stat	P-values	Decision
H ₁	Challenges -> PR	0.481	0.09	5.332	0.000	Accepted
H ₂	Pro Att -> PR	0.327	0.095	3.449	0.001	Accepted
H ₃	Trust and Sat -> PR	0.102	0.048	2.115	0.034	Accepted

5 Theoretical Contribution/Implication of Findings

The study explores the elements that affect the acceptability of personalized suggestions by applying Social Exchange Theory, which suggests that individuals seek to maximize advantages and avoid negatives in social interactions. The strong relationship between buyers' perceived challenges and PRs highlights the

need to address consumer concerns in decision-making. Consumers depend on personalized suggestions to efficiently traverse the marketplace when faced with information overload or decision complexity (Srikumar and Bhasker, 2005; Bleize and Antheunis, 2019). Therefore, comprehending and addressing these problems can boost the efficiency of recommendation systems and increase the overall user experience.

Likewise, the significant impact of product qualities on PRs emphasizes the importance of product attributes

in influencing consumer preferences and purchase intentions (Chang and Wildt, 1994; Sohn and Kim, 2020). Recommendations customized to match consumers' preferences for product features, quality, and functionality are more likely to be embraced and followed, unearthing the crucial significance of including product aspects in recommendation algorithms.

Furthermore, the results highlight the importance of perceived trust and satisfaction in influencing the acceptance of PRs. Consumers' trust in recommendation systems is essential for viewing the suggestions as relevant and reliable (Shareef, et al., 2008; Chiu, et al., 2012). Satisfied customers are more likely to interact with and follow tailored recommendations, increasing their intention to purchase (Sohn and Kim, 2020). Thus, establishing trust and guaranteeing client happiness are crucial tactics for improving the efficiency of recommendation systems in e-commerce settings. This study's theoretical implications emphasize the significance of tackling consumers' challenges, evaluating product attributes, and promoting trust and pleasure in PR systems. By incorporating Social Exchange Theory ideas, academics and practitioners can create more effective recommendation algorithms tailored to individual users' tastes, improving user happiness, engagement, and purchasing behavior on online platforms.

6 Practical Implications

This research provides practical implications to assist e-commerce practitioners and platform developers in enhancing PR systems and improving the overall user experience. Businesses can utilize Social Exchange Theory to develop tactics that solve consumer problems, improve product recommendations, and build trust and pleasure among users by focusing on maximizing benefits and reducing downsides in online interactions.

Recognizing the significant relationship between perceived challenges experienced by shoppers and PRs highlights the necessity of addressing customer difficulties in the decision-making process. E-commerce platforms should improve the user experience, simplify navigation, and provide customized support to help customers deal with information overload and de-

cision difficulty. Platforms can enhance user engagement and satisfaction, boost conversion rates, and encourage repeat business by addressing these concerns proactively.

Furthermore, the significant impact of product characteristics on PRs emphasizes the need to enhance recommendation algorithms by considering various product properties and user preferences. Businesses can improve their understanding of consumer preferences and customize recommendations using advanced machine learning algorithms and data analytics (Aburayya, et al., 2023; Alkashami, et al., 2023). Furthermore, incorporating user feedback systems and reviews into recommendation algorithms can improve the relevancy and efficacy of product choices, thereby boosting user happiness and influencing purchasing behavior. The results highlight the vital influence of perceived trust and satisfaction on accepting PRs. E-commerce platforms must develop precise and dependable recommendation systems prioritizing user privacy and data security. Introducing trust-building strategies, including presenting precise product details, utilizing transparent recommendation algorithms, and delivering prompt customer service, can foster consumer trust and boost their receptiveness to tailored recommendations.

E-commerce platforms may increase PR systems and improve user experience by tackling customer difficulties, refining product recommendations, and building trust and happiness. Businesses can enhance their recommendation algorithms by combining practical techniques with theoretical concepts from Social Exchange Theory. This can increase user satisfaction, engagement, and purchasing decisions on online platforms.

7 Limitations

There are several limitations to the study. Included in this is the fact that the Gulf Cooperation Council (GCC) region is made up of more than only the UAE. Therefore, additional empirical analysis would be necessary to replicate findings in various settings and scenarios. Furthermore, because it was cross-sectional in nature, it was carried out just once. Because of this, a longitudinal study design may be able to get around this restriction by providing evidence of causality between variables-but most significantly, over time.

Apart from temporal and financial constraints, this study's data was collected exclusively from a small number of industries, which reflected a remarkable service culture. Furthermore, because the data came from a limited number of service sectors, generalization of the outcomes to other service industries might be questionable. Moreover, the researcher still relied on managers to acquire data from workers and on workers to collect further data from customers, even though training was provided to managers and employees on data collection techniques that minimized potential bias. Furthermore, more advanced consumer orientation models should be developed in subsequent research on this subject. It will be interesting to see, for example, how the personalized shopping system is affected by the quality of the service. Likewise, the primary data source for this study is client perceptions, which were acquired through a survey questionnaire. Consequently, it is advised that future studies employ data triangulation techniques, such as shop manager interviews and observations, to overcome the subjectivity of this data gathering.

8 Conclusion

Our research highlights the crucial importance of Social Exchange Theory in comprehending and enhancing PR systems in e-commerce. We have clarified the substantial impact of addressing consumer concerns, optimizing product recommendations, and building trust and happiness in improving the effectiveness of such systems through empirical analysis. The results provide practical guidance for e-commerce stakeholders, emphasizing the importance of aligning tactics with theoretical foundations to enhance user engagement and build lasting brand loyalty. Our research indicates that the future of digital commerce will involve increased user pleasure, improved decision-making, and continuous business growth. Using Social Exchange Theory, we want to redefine PR systems to ensure each contact is relevant and resonant. Let us stay committed to innovation and collaboration to create individualized recommendations that empower, enhance, and provide consumer happiness.

9 References

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