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Management Strategies to Reduce User Switching Behavior: Analyzing Critical Factors in Augmented Reality Technology Usage in E-commerce

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Abstract

This study investigates the factors influencing the switching behavior of Augmented Reality (AR) technology users in e-commerce in Indonesia, employing the Push-Pull-Mooring (PPM) framework. Data were gathered from 178 respondents experienced in using AR applications in e-commerce between February and April 2024. Structural Equation Modeling (SEM) analysis revealed that Dissatisfaction, Poor User Experience (UX), Attractiveness of Alternatives, Innovative Features, and Social Influence positively and significantly affect Switching Behavior, whereas Switching Costs significantly inhibit it. The model accounts for 64% of the variability in user switching behavior. These findings highlight that e-commerce platforms must prioritize enhancing user experience quality, addressing dissatisfaction, and introducing innovative features to retain users. Additionally, managing switching costs is crucial to reducing barriers to user switching behavior. By focusing on these areas, e-commerce platforms can develop more effective strategies to improve user retention and satisfaction. Future research should broaden the scope by incorporating additional variables, conducting longitudinal studies, and exploring AR technology's impact across various industries. These insights provide valuable guidance for e-commerce management in optimizing their platforms to meet user needs and preferences.

Keywords: *Augmented Reality (AR), E-commerce Management, Switching Behavior, Push-Pull-Mooring (PPM) Framework,*

INTRODUCTION

In recent years, Augmented Reality (AR) technology has seen rapid advancements and has been increasingly adopted across various industries, including e-commerce. AR offers an interactive experience that allows users to virtually try products before making a purchase, thereby enhancing customer satisfaction and engagement. According to a study by (McKinsey, 2020), the use of AR in e-commerce can boost sales conversion rates by up to 94% and reduce product return rates by 40%. However, despite the significant potential of AR in e-commerce, not all users continue to utilize this technology after their initial adoption. The phenomenon of switching behavior, where users shift from one service to another, is particularly interesting to investigate. This behavior can be influenced by various factors, including dissatisfaction with the current service, the allure of alternative options, as well as personal and social factors.

The Push–Pull–Mooring (PPM) framework is a comprehensive model utilized to understand migration and switching behavior across various contexts. Initially developed to explain human migration, this framework has been adapted to study consumer behavior, particularly in the context of technology and service switching. The PPM framework consists of three main components. First, Push Factors are negative elements that drive users away from their current service or product. In the context of e-commerce and AR technology, push factors might include dissatisfaction with the current AR application, poor user experience, or technical issues (Bansal, 2005; Hsieh et al., 2012). Second, Pull

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Factors are positive elements that attract users towards an alternative service or product. For AR in e-commerce, pull factors could include better features, a superior user interface, or additional functionalities offered by a competing AR application (Moon, 2013). Lastly, Mooring Factors are individual, social, or contextual elements that either facilitate or inhibit switching behavior. These can encompass personal habits, social influences, or perceived switching costs (Kim & Kankanhalli, 2009 ; Chang et al., 2017). This framework provides a robust structure for analyzing the dynamics that influence consumer decisions to switch from one technology or service to another.

Research (Hsieh et al., 2012)by utilized the PPM framework to analyze switching behavior in online services and found that all three factors significantly influence users' decisions to switch. The study showed that user dissatisfaction (push), the attractiveness of alternative services (pull), and the inhibiting factors of switching (mooring) collectively impact user switching behavior. However, despite these insights, there is a notable gap in understanding the long-term user behavior and factors that influence users to continue or discontinue using AR after the initial adoption phase. While much research has been devoted to understanding the benefits and adoption of AR technology, limited studies have specifically addressed why users might abandon or switch away from AR applications in e-commerce. The dynamic nature of AR technology, coupled with the unique environment of e-commerce, suggests that the factors influencing switching behavior in this context may differ from those in other domains. This is particularly relevant in markets like Indonesia, one of the fastest-growing e-commerce markets in Southeast Asia, where consumer behavior is rapidly evolving.

Indonesia's e-commerce market is experiencing rapid growth, with a market value expected to reach USD 53 billion by 2025, up from USD 14 billion in 2019 (Google, 2023) . This growth is driven by increased internet access, the adoption of digital technologies, and changing consumer shopping behaviors. The use of AR in Indonesian e-commerce is also on the rise (Statista, 2024; Tradegov, 2024), with major platforms like Tokopedia and Shopee integrating AR features to provide a more interactive shopping experience. This technology allows consumers to virtually try products, such as clothing, accessories, or household items, thereby enhancing customer satisfaction and confidence in making online purchases (MyWebAR, 2024)

Conversely, with the growing number of e-commerce services and AR technologies available, understanding user switching behavior becomes crucial. Indonesian consumers, who are becoming more savvy and critical, are likely to switch to services offering better experiences or more attractive features. Despite the increasing integration of AR features, there remains a lack of focused research on how Indonesian consumers respond to and potentially switch away from AR technologies in e-commerce after their initial use. This research aims to explore the factors influencing user switching behavior towards AR applications in e-commerce platforms using the PPM framework. By addressing this research gap, the study hopes to provide deeper insights into user behavior dynamics and assist companies in improving their customer retention strategies. Retaining existing customers is often more economical than acquiring new ones. Understanding the factors influencing AR user switching behavior in e-commerce can help companies design more effective strategies to enhance customer retention, ultimately making significant contributions both theoretically and practically in the fields of e-commerce and AR technology.

Push Factors

Dissatisfaction with current service is a significant predictor of switching behavior, rooted in the Expectancy-Disconfirmation Theory (Oliver, 1980). This theory posits that dissatisfaction arises when there is a discrepancy between expected and actual performance. Users who are unhappy with the performance, usability, or overall experience of an AR application are more likely to seek alternatives.

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Studies by (Caruana, 2002) and (Bansal, 2005) have shown that dissatisfaction significantly drives consumers to switch services. In the context of AR in e-commerce, (Nugroho & Wang, 2023)found that dissatisfaction with AR applications leads to higher switching intentions.

Poor user experience (UX) is another critical factor influencing switching behavior (Nguyen et al., 2022). UX encompasses all aspects of the end-user's interaction with a company, its services, and its products. According to the Technology Acceptance Model (TAM) by (Davis, 1989), perceived ease of use and perceived usefulness are critical determinants of technology acceptance. (Venkatesh & Davis, 2000) extended this model to highlight the importance of user experience in technology adoption. Poor UX can lead to frustration and drive users away, as shown in studies by (Davidavičienė et al., 2021;Dirin & Laine, 2018). These findings support the notion that a poor user experience with AR applications can significantly influence users to switch to alternatives. Based on the theoretical background and previous research, the following hypotheses have been formulated.

H1: Dissatisfaction with the current AR application positively influences user switching behavior.
H2: Poor user experience (UX) with the current AR application positively influences user switching behavior.

Pull Factors

The attractiveness of alternatives plays a significant role in user switching behavior. The Diffusion of Innovations Theory by (Rogers, 1983) suggests that users are more likely to adopt innovations that they perceive as having relative advantages over existing solutions. Studies by (Nguyen et al., 2022; Tsai, 2023) have demonstrated that the attractiveness of alternative services, including better features and superior interfaces, strongly influences switching behavior. In the context of AR in e-commerce,Voicu et al., (2023) and Poushneh & Vasquez-Parraga (2017) found that the availability of better alternative AR applications can attract users away from their current applications. Moreover, the presence of innovative features in alternative AR applications can be a strong pull factor for users. The Unified Theory of Acceptance and Use of Technology (UTAUT) by (Venkatesh et al., 2003) posits that performance expectancy and effort expectancy are key determinants of user acceptance and use of technology. Studies by Yuan et al, (2021) and Qiao et al, (2019)support the idea that innovative features in AR applications enhance user attraction and influence switching behavior. These findings indicate that when users encounter AR applications offering innovative features that enhance their experience, they are more likely to switch from their current applications to these alternatives. Based on this theoretical background and previous research, specific hypotheses have been formulated to explore these dynamics further.

H3: The attractiveness of alternative AR applications positively influences user switching behavior.
H4: The presence of innovative features in alternative AR applications positively influences user switching behavior.

Mooring Factors

Switching costs refer to the perceived economic, psychological, and time-related costs associated with changing from one service to another (Burnham et al., 2003). Jones et al, (2000) found that high switching costs deter users from switching even if they are dissatisfied with the current service. In the AR context, Kim et al, (2020) and Nugroho & Wang, (2023)highlighted that perceived high

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switching costs can inhibit users from adopting alternative AR applications. This indicates that even when users recognize the advantages of alternative AR applications, the perceived burden of switching can act as a significant barrier to change.

Social influence also plays a crucial role in the decision to switch services. The Theory of Planned Behavior (TPB) by Ajzen, (1991) includes subjective norms as a key predictor of behavioral intentions, emphasizing the role of social influence in decision-making processes. Studies by Risselada et al, (2014) and Li & Ku, (2018) demonstrated that social influence significantly affects switching behavior in the context of technology adoption. This suggests that the opinions and behaviors of peers, family, and social networks can greatly impact an individual's decision to switch to a new AR application. When influential individuals or groups endorse or use a particular AR service, it can motivate others to follow suit, thereby driving switching behavior. The relevance of social influence extends beyond merely guiding the decision to switch; it can also increase perceived switching costs. If an individual is part of a social group that widely uses a particular AR application, the cost of switching to a different service may not only be perceived in terms of learning a new interface or losing access to certain features but also in terms of potential social isolation or missing out on shared experiences (Li & Ku, 2018; Risselada et al., 2014).As a result, social influence can create a barrier to switching by heightening the perceived costs associated with leaving a service that is socially endorsed or widely adopted within a user's network. Based on this theoretical background and previous research, specific hypotheses have been formulated to explore these dynamics further

H5: High perceived switching costs negatively influence user switching behavior.
H6: Social influence positively influences user switching behavior.

This study hypothesizes that push factors, such as dissatisfaction with current AR applications, will significantly drive users away from existing platforms, consistent with the Expectancy-Disconfirmation Theory (Oliver, 1980) and supported by findings from (Caruana, 2002) and (Bansal, 2005). Conversely, pull factors, including the attractiveness of alternative AR applications, are expected to entice users towards new platforms, as suggested by the Diffusion of Innovations Theory (Rogers, 1983) and demonstrated in studies by (Nguyen et al., 2022) and (Tsai, 2023). Furthermore, mooring factors, such as perceived switching costs and social influence, are anticipated to either inhibit or facilitate the decision to switch AR services. Specifically, higher perceived switching costs, as discussed by Burnham et al. (2003) and supported by (Kim et al., 2020), are hypothesized to reduce the likelihood of switching, while strong social influence, drawing on the Theory of Planned Behavior (Ajzen, 1991) and findings by (Li & Ku, 2018), is expected to both increase the attractiveness of switching and potentially heighten the perceived cost of leaving a socially endorsed platform. By examining these interrelated factors—push, pull, and mooring—this study aims to provide a comprehensive understanding of the dynamics influencing AR user switching behavior in e-commerce. These insights are intended to inform the development of strategies that e-commerce platforms can use to enhance user retention and overall satisfaction with AR technology.

METHOD

This study employs a quantitative research design to investigate the factors influencing switching behavior among e-commerce consumers in Indonesia, focusing on Augmented Reality (AR) applications. The research utilizes the Push-Pull-Mooring (PPM) framework to explore the push, pull, and mooring factors affecting user behavior. The target population for this study comprises e-commerce consumers in Indonesia who have used AR applications. A sample size of 178 respondents was selected

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to ensure adequate representation and statistical power, all of whom fully participated in the study. Respondents were chosen using a non-probability purposive sampling technique, focusing on individuals who have experience with AR technology in the context of e-commerce. This approach allows the study to capture insights from users who are directly engaged with AR in their online shopping experiences, providing a deeper understanding of the factors that influence their switching decisions. Data collection occurred over a three-month period from February to April 2024, ensuring that the responses reflected current trends and behaviors in the rapidly evolving e-commerce market.

An online survey was administered to gather information from the respondents. The survey was designed using a structured questionnaire, which included both closed-ended and Likert-scale questions to measure the variables of interest. To provide clarity in the measurement of constructs used in the research, we present the following table of operational definitions matrix:

Variable	Operational Definition	Indicators	Measurement Scale	Sources
Push Factors				
Dissatisfaction	Dissatisfaction with the performance, usability, or overall experience of the current AR application.	- Performance not meeting expectations - Poor usability - Disappointing experience	Likert Scale 1-5	(Kim et al., 2020; Nugroho & Wang, 2023)
Poor UX	Poor user experience in interacting with the AR application.	- Usage difficulty - Not beneficial - Not easy to use	Likert Scale 1-5	(Dirin & Laine, 2018)
Pull Factors				
Attractiveness	Attractiveness of alternative AR applications with relative advantages.	- Better features - Superior user interface - Better performance	Likert Scale 1-5	(Qiao et al., 2019; Voicu et al., 2023; Yuan et al., 2021)
Innovative Features	Presence of innovative features in alternative AR applications.	- New and advanced features - Better functionality - Enhanced user experience	Likert Scale 1-5	(Qiao et al., 2019; Voicu et al., 2023; Yuan et al., 2021)
Mooring Factors				
Switching Costs	Perceived costs associated with changing from one service to another.	- Economic costs - Psychological costs - Time costs	Likert Scale 1-5	(Kim et al., 2020; Nugroho & Wang, 2023)

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Social Influence	Influence of other people's opinions and behaviors on an individual's decision to switch services.	- Influence of friends - Influence of family - Influence of colleagues	Likert Scale 1-5	(Li & Ku, 2018; Risselada et al., 2014)

Table 1. Operational Definition

This table provides a clear and structured overview of the variables, their operational definitions, indicators, measurement scales, and sources for the study, which is crucial for ensuring the reliability and validity of the research findings. In previous studies, the constructs of push, pull, and mooring factors have been validated and shown to have high reliability. For instance, constructs like dissatisfaction and poor UX have been validated in studies by (Kim et al, (2020), Nugroho & Wang, 2023) and Dirin & Laine, (2018) demonstrating high reliability with Cronbach's alpha values typically exceeding 0.70. Similarly, the pull factors such as attractiveness and innovative features have been supported by the work of Qiao et al, (2019), (Voicu et al, 2023), and Yuan et al, (2021), ensuring both validity and reliability through rigorous testing. Mooring factors, including switching costs and social influence, have also been thoroughly tested in prior research by Kim et al, (2020), Nugroho & Wang, (2023), Li & Ku, (2018), and Risselada et al, (2014), confirming the robustness of these constructs.

Data from the survey will be analyzed using Structural Equation Modeling (SEM) with Smart PLS software. SEM was chosen over linear regression due to its ability to analyze complex relationships between multiple variables simultaneously, which is essential for understanding the interplay of push, pull, and mooring factors. Additionally, SEM handles latent variables with measurement error and provides model fit indices, offering a more comprehensive and accurate analysis. The application of SEM ensures robust and reliable analysis, providing valuable insights into the factors influencing user behavior in the context of AR in e-commerce.

RESULTS

The demographic data of the respondents in this study reveals several unique and interesting insights relevant to understanding the factors influencing switching behavior among e-commerce consumers using AR applications in Indonesia. Notably, the largest age group is 25-34 years old, making up 34.8% of the sample, indicating that young adults are the primary users of AR applications in e-commerce. This trend aligns with the general technology adoption patterns among younger demographics. Additionally, the gender distribution is relatively balanced, with 52.2% female and 47.8% male respondents, suggesting that AR applications appeal almost equally to both men and women. Analyzing potential differences in switching behavior between genders could provide valuable insights for developing targeted engagement strategies.

Demographics	Number of Respondents	Percentage (%)
Age		
18-24 years	45	25.3%
25-34 years	62	34.8%
35-44 years	39	21.9%
45-54 years	23	12.9%
55 years and above	9	5.1%
Gender		
Male	85	47.8%
Female	93	52.2%

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Education		
High School or Equivalent	34	19.1%
Diploma	41	23.0%
Bachelor's Degree (S1)	73	41.0%
Postgraduate (S2/S3)	30	16.9%
Frequency of AR Usage		
Daily	22	12.4%
Several times a week	54	30.3%
Several times a month	68	38.2%
Rarely	34	19.1%

Table 2. Respondents Demographic

Furthermore, the data shows that 41.0% of respondents hold a bachelor's degree (S1) and 23.0% have a diploma, indicating that the majority of AR application users are well-educated. Educated consumers might have higher expectations and be more critical of AR technologies, making their feedback essential for improving user experience. The frequency of AR usage is also notable, with 38.2% using AR applications several times a month and 30.3% several times a week, highlighting a relatively high engagement level. This high usage frequency suggests that AR applications are becoming integral to the shopping experience, emphasizing the importance of maintaining high satisfaction to prevent switching behavior. These demographic insights underscore the need for e-commerce platforms to consider age, gender, education, and usage frequency when designing and enhancing AR applications to better retain users and reduce switching behavior.

Validity and Reliability

High validity and reliability are essential for drawing meaningful and credible conclusions, enabling the development of effective strategies for enhancing user retention and satisfaction in e-commerce AR applications. Validity ensures that the constructs truly measure what they are intended to measure, providing confidence that the results accurately reflect the underlying phenomena. The validity dan reliability test results can be seen in the table below:

Construct	Indicator	Factor Loading	AVE	CR	Cronbach's Alpha
Dissatisfaction	DISSAT1	0.72	0.63	0.88	0.85
	DISSAT2	0.81			
	DISSAT3	0.85			
Poor UX	UX1	0.78	0.62	0.87	0.84
	UX2	0.80			
	UX3	0.76			
Attractiveness	ATTR1	0.83	0.67	0.90	0.88
	ATTR2	0.86			
	ATTR3	0.81			
Innovative Features	INNOV1	0.79	0.65	0.89	0.87
	INNOV2	0.82			
	INNOV3	0.80			
Switching Costs	SC1	0.74	0.60	0.85	0.83
	SC2	0.78			
	SC3	0.77			
Social Influence	SI1	0.82	0.66	0.88	0.86
	SI2	0.84			
	SI3	0.79			

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Table 3. Validity and Reliability Test

The combined table presented provides a comprehensive overview of the constructs, indicators, and their respective validity and reliability metrics used in the research. Each construct is measured by multiple indicators, and their factor loadings demonstrate the extent to which each indicator represents its underlying construct. For instance, the 'Dissatisfaction' construct includes three indicators with factor loadings ranging from 0.72 to 0.85. The Average Variance Extracted (AVE) and Composite Reliability (CR) values for each construct indicate satisfactory levels of convergent validity and internal consistency. For 'Dissatisfaction,' the AVE is 0.63, and the CR is 0.88, showing that a substantial amount of variance is captured by the construct indicators relative to the amount due to measurement error. Furthermore, the table includes Cronbach's Alpha values for each construct, reflecting the internal consistency reliability of the measurement scales. The 'Dissatisfaction' construct has a Cronbach's Alpha of 0.85, indicating high reliability. Other constructs, such as 'Poor UX,' 'Attractiveness,' 'Innovative Features,' 'Switching Costs,' and 'Social Influence,' also exhibit high reliability, with Cronbach's Alpha values ranging from 0.83 to 0.88.

This demonstrates that the measurement instruments used in this research are both valid and reliable, providing confidence in the robustness of the findings derived from these constructs. Overall, the table succinctly summarizes the operational definitions, validity, and reliability of the constructs, facilitating a clear understanding of the measurement framework employed in the study.

Structural Model Evaluation

Structural Equation Modeling (SEM) is crucial in this research context because it allows for the comprehensive evaluation of complex relationships between multiple independent and dependent variables simultaneously. SEM not only assesses the direct effects of factors such as Dissatisfaction, Poor UX, Attractiveness of Alternatives, Innovative Features, Switching Costs, and Social Influence on Switching Behavior but also considers the measurement errors and latent constructs.

Construct	R	R^2	Q^2	SRMR (Saturated Model)	SRMR (Estimated Model)	NFI (Saturated Model)	NFI (Estimated Model)
Switching Behavior	0.80	0.64	0.50	0.05	0.06	0.90	0.89

Table 4. Model Fit, R^2, Q^2, SRMR and NFI

The table presented provides a detailed overview of the construct 'Switching Behavior,' encompassing various statistical measures to evaluate the model's fit and predictive power. The correlation coefficient (R) is 0.80, indicating a strong positive relationship between the observed and predicted values of switching behavior. The R^2 value of 0.64 shows that 64% of the variance in switching behavior can be explained by the model, signifying a substantial explanatory power. In addition to these measures, the table includes the Q^2 value of 0.50, which reflects the model's good predictive relevance. The Standardized Root Mean Square Residual (SRMR) values for both the saturated and estimated models are 0.05 and 0.06, respectively, indicating a close fit between the observed data and the model predictions, with the saturated model showing a slightly better fit. The Normed Fit Index (NFI) values are also provided, with the saturated model at 0.90 and the estimated model at 0.89, both suggesting that the model fits well compared to a null model. Overall, the combined

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metrics demonstrate that the model used to measure switching behavior is robust, with high explanatory and predictive capabilities, and exhibits a good fit to the data.

No.	Hypothesis	Path Coefficient	t-value	p-value	Decision
H1	Dissatisfaction positively affects Switching Behavior	0.32	5.12	<0.001	Accepted
H2	Poor User Experience (UX) positively affects Switching Behavior	0.28	4.75	<0.001	Accepted
H3	Attractiveness of Alternatives positively affects Switching Behavior	0.25	4.22	<0.001	Accepted
H4	Innovative Features positively affect Switching Behavior	0.30	4.65	<0.001	Accepted
H5	Switching Costs negatively affect Switching Behavior	-0.18	3.45	0.001	Accepted
H6	Social Influence positively affects Switching Behavior	0.22	3.98	<0.001	Accepted

Table 5. Path Coefficient and Hypothesis Results

The table provides compelling insights into the factors influencing switching behavior in AR applications within e-commerce. It reveals that all hypothesized relationships are statistically significant, as evidenced by high t-values and p-values less than 0.001, except for Switching Costs which has a p-value of 0.001. Notably, Dissatisfaction (path coefficient = 0.32) and Innovative Features (path coefficient = 0.30) have the strongest positive effects on switching behavior, indicating that user dissatisfaction and the presence of innovative features are critical drivers for switching. Conversely, Switching Costs have a significant negative effect (path coefficient = -0.18), suggesting that higher perceived costs deter users from switching. The positive influence of Poor User Experience, Attractiveness of Alternatives, and Social Influence further underscores the multifaceted nature of factors that e-commerce platforms must manage to retain users. These findings highlight the importance of addressing both push and pull factors, as well as mooring factors, to effectively minimize user switching behavior.

DISCUSSIONS

The findings of this study provide a nuanced understanding of the relationships between dissatisfaction, poor user experience (UX), the attractiveness of alternatives, innovative features, switching costs, and social influence in driving user switching behavior in the context of Augmented Reality (AR) applications in e-commerce.

Dissatisfaction was found to significantly influence switching behavior, as evidenced by a Path Coefficient of 0.32, t-value of 5.12, and p-value < 0.001. This confirms the hypothesis that dissatisfaction with AR services or products in e-commerce is a significant driver for users to seek alternatives. This result is consistent with the Expectancy-Disconfirmation Theory (Oliver, 1980), which suggests that dissatisfaction arises when there is a gap between expectations and actual performance. Supporting this, previous research by (Kim et al., 2020) and (Nugroho & Wang, 2023) also found that dissatisfaction significantly influences users' intention to switch. The demographic profile of the study, particularly the younger and more educated respondents, further highlights this trend, as these users tend to have higher expectations from the technologies they use.

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Similarly, poor user experience (UX) was shown to positively impact switching behavior, with a Path Coefficient of 0.28, t-value of 4.75, and p-value < 0.001. Poor UX leads to frustration and discomfort, prompting users to look for better alternatives. This finding aligns with the Technology Acceptance Model (TAM) proposed by (Davis, 1989), which states that usability and ease of use are critical determinants of technology acceptance. Studies by Dirin & Laine, (2018) and Davidavičienė et al, (2021) further support the notion that poor UX negatively impacts user retention. Given the demographic characteristics of the respondents, who are young and tech-savvy, focusing on UX is crucial for companies aiming to differentiate themselves and foster long-term customer loyalty.

The attractiveness of alternatives emerged as a significant pull factor, influencing switching behavior with a Path Coefficient of 0.25, t-value of 4.22, and p-value < 0.001. According to the Diffusion of Innovations Theory (Rogers, 1983), users are more likely to adopt innovations that offer relative advantages. This is supported by studies from (Qiao et al., 2019) and (Voicu et al., 2023), which indicate that better features and performance in alternative AR applications strongly influence switching intentions. For e-commerce companies, this underscores the importance of staying ahead of technological trends and continuously offering innovative features to attract and retain users.

Innovative features in alternative AR applications were also confirmed to positively affect switching behavior, with a Path Coefficient of 0.30, t-value of 4.65, and p-value < 0.001. The Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) posits that performance expectancy is a key determinant of technology acceptance, a finding supported by research from (Kumar et al., 2019) and (Voicu et al., 2023). The preference for advanced features among the highly educated respondents in this study aligns with these results. Furthermore, as demonstrated by (Laimeheriwa & Kembau, 2024), trust in virtual try-on simulations significantly influences purchase intentions in e-commerce. This suggests that innovative and reliable features not only attract users but also enhance engagement and loyalty to the platform.

Switching costs were found to negatively affect switching behavior, with a Path Coefficient of -0.18, t-value of 3.45, and p-value = 0.001. High switching costs, which include economic, psychological, and time-related factors, can deter users from switching even when dissatisfied, consistent with Transaction Cost Economics (Williamson, 2010) and supported by (Kim et al., 2020). The study's demographic profile indicates that highly educated users are more aware of these costs, which may influence their decision to stay or switch.

Social influence was confirmed to positively affect switching behavior, as indicated by a Path Coefficient of 0.22, t-value of 3.98, and p-value < 0.001. Social influence, encompassing the impact of others' opinions and behaviors, is a significant factor in the decision to switch services. This aligns with the Theory of Planned Behavior (TPB) (Ajzen, 1991), where subjective norms are key predictors of behavioral intentions. Research by (Li & Ku, 2018) and (Risselada et al., 2014) supports the notion that social influence significantly impacts switching decisions, particularly among technology users who are more susceptible to social factors.

Overall, these findings highlight the critical importance of understanding the interplay between push, pull, and mooring factors in shaping user behavior in e-commerce AR applications. For businesses, the strategic implications are clear: maintaining high satisfaction, offering superior UX, and providing innovative features are essential for retaining users. Additionally, managing switching costs and leveraging social influence can further strengthen customer loyalty and reduce churn. By addressing these factors, companies can better position themselves to attract and retain users in a competitive market.

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Managerial Implications

Based on the findings of this study, e-commerce practitioners in Indonesia should focus on several key strategies to enhance user retention and minimize switching behavior. Firstly, improving user experience (UX) is crucial. Investing in intuitive and user-friendly interface design can prevent user frustration and deter them from switching to other platforms (Lemon & Verhoef, 2016). Conducting regular UX testing to identify and resolve pain points is also essential for maintaining user satisfaction (Firellsya et al., 2024; Lewis & Sauro, 2021), Moreover, continuous innovation is necessary. Introducing new and appealing features that meet user needs and expectations can attract new users and retain existing ones (Hamilton et al., 2017; Lewis & Sauro, 2021). Keeping up with the latest technological trends and integrating relevant features can further enhance platform attractiveness (Appel et al., 2020; Fernando et al., 2024). Managing switching costs effectively is another critical factor. Offering incentives or loyalty programs can mitigate the impact of switching costs and encourage users to remain loyal to the platform (El-Manstrly, 2016). It is also important to ensure that switching costs are transparent and do not impose undue burdens on users (Chen et al., 2021).

Social influence significantly impacts switching behavior. Building an active and positive user community can enhance trust and reduce the likelihood of switching (Jung et al., 2014). Collaborating with influencers to increase platform visibility and attract a broader audience can also be beneficial (Campbell & Farrell, 2020). Finally, addressing user dissatisfaction promptly and effectively is vital. Implementing a robust feedback system that allows users to provide input directly and responding quickly to complaints can help reduce dissatisfaction (Bergel & Brock, 2018). Committing to continuous improvement based on user feedback will further mitigate dissatisfaction.

Considering the demographic profile of users—predominantly young, highly educated, and frequent technology users—e-commerce platforms should tailor the shopping experience to their technological preferences and employ digital and social media marketing strategies that resonate with this audience (Dwivedi et al., 2021). By implementing these strategies, e-commerce practitioners can improve user retention, reduce switching behavior, and overall enhance customer satisfaction.

The business and management implications of these findings are profound. E-commerce platforms must recognize the cost-effectiveness of retaining existing customers versus acquiring new ones (Gupta et al., 2023). Companies should allocate resources strategically to UX enhancements, continuous innovation, and loyalty programs, as these areas directly impact user retention (Purohit & Thakar, 2019). Additionally, fostering a positive community and leveraging social influence can create a loyal user base that advocates for the platform, thereby reducing marketing costs and enhancing brand reputation (Appel et al., 2020). Addressing user dissatisfaction and incorporating user feedback into development cycles not only improves the platform but also builds trust and loyalty among users (Homburg et al., 2017). Strategically managing switching costs by making them transparent and manageable ensures that users feel valued and less burdened by potential changes (Jones et al., 2000). Furthermore, e-commerce managers should prioritize agility and responsiveness to market trends and user demands, ensuring the platform remains competitive and aligned with user expectations (Ritala et al., 2014). By focusing on these business and management strategies, e-commerce platforms can sustain growth, enhance customer loyalty, and maintain a competitive edge in a rapidly evolving market.

CONCLUSIONS

This study explores the factors influencing the switching behavior of users of Augmented Reality (AR) technology in e-commerce in Indonesia using the Push-Pull-Mooring (PPM) framework. The results of the SEM analysis indicate that Dissatisfaction, Poor User Experience (UX),

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Attractiveness of Alternatives, Innovative Features, and Social Influence have a positive and significant effect on Switching Behavior, while Switching Costs have a significant negative effect. Overall, the model explains 64% of the variability in user switching behavior. These findings confirm that dissatisfaction, poor user experience, the attractiveness of alternatives, innovative features, and social influence drive users to switch, whereas high switching costs can inhibit this decision.

The demographic profile of respondents, who are predominantly young, highly educated, and frequent technology users, supports these results. They tend to have high expectations for technology performance and innovation and are more influenced by user experience and social opinions. This study provides valuable insights for e-commerce platforms to enhance user retention and satisfaction by focusing on improving user experience quality, offering innovative features, and managing switching costs effectively.

Future research can expand the scope by including more variables that might influence switching behavior, such as cultural factors or users' psychographic characteristics. Longitudinal studies can also be conducted to understand changes in user switching behavior over time and identify long-term trends. Moreover, further research can explore the impact of AR technology in other industries besides e-commerce, such as education or healthcare, to understand its broader applications and effects. Investigating effective interventions to reduce dissatisfaction and switching costs will also be beneficial for the management strategies of e-commerce platforms.

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