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Push, Pull, and Mooring Effects on Gen Z's Switching Intention in TikTok Shop

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Abstract

This study investigates the influence of Push, Pull, and Mooring (PPM) effects on the switching intention of Generation Z users of TikTok Shop in Indonesia. The rapid growth of social commerce, combined with regulatory changes that temporarily halted TikTok Shop operations in October 2023, triggered behavioral shifts among users. Applying the PPM framework, this study analyzes the extent to which push factors (e.g., dissatisfaction, high perceived price), pull factors (e.g., attractiveness of alternatives), and mooring factors (e.g., switching costs, subjective norms) influence users' intention to switch platforms. Data were collected via a survey of 146 TikTok Shop users aged 17–27 who had used the platform prior to its closure. The data were analyzed using Structural Equation Modeling–Partial Least Squares (SEM-PLS) via SmartPLS 4.0. The results show that both push and pull effects significantly and positively influence switching intention, with the pull effect emerging as the dominant factor. However, mooring effects do not have a significant influence on switching intention and do not moderate the relationship between push/pull effects and switching intention. These findings offer insights into consumer behavior in social commerce and provide strategic implications for e-commerce platforms seeking to retain users in a competitive market.

Keywords:
Push effect; Pull effect; Mooring effect; Switching intention; Switching behavior.

1. INTRODUCTION

The rapid advancement of digital technology has significantly reshaped consumer shopping behavior, particularly among Generation Z (Bencsik & Horváth, 2016). This generation, characterized by high digital literacy and mobile-first habits, increasingly relies on online platforms for convenience, price comparisons, and social engagement (Goodstats, 2023). The rise of social commerce where social media and e-commerce are integrated has introduced new pathways for purchasing, exemplified by platforms like TikTok Shop (Mumtaha & Khoiri, 2019).

Originally launched as a short-form video content platform, TikTok has expanded into the e-commerce space with remarkable success. According to Momentum Works (2022), TikTok Shop's market share in Southeast Asia grew from 4.4% in 2022 to 13.2% in 2023, making it the only platform to increase its dominance while competitors such as Shopee, Lazada, and Tokopedia experienced declines.

In Indonesia, TikTok has the second-largest user base globally, and TikTok Shop quickly became popular – especially among Generation Z users (Sa'adah, Rosma, & Aulia, 2022). However, in October 2023, the Indonesian government enforced Minister of Trade Regulation No. 31 of 2023, which temporarily banned social media platforms from conducting e-commerce transactions (Tempo, 2023). This regulation forced the shutdown of TikTok Shop, leading to significant consumer disruption: an estimated 20% of users migrated to competing platforms, while 80% remained passive on TikTok without engaging in further purchases. Although TikTok Shop resumed operations in December 2023 through a strategic acquisition of PT GoTo, this episode highlighted the fragility of platform loyalty in social commerce environments (Databoks, 2023).

This disruption raises a critical question: what drives users, especially Gen Z, to switch between platforms when faced with platform closures or policy shifts? To address this, the present study adopts the Push, Pull, and Mooring (PPM) framework – a well – established model for explaining switching behavior. Push effects refer to negative attributes of the current platform that drive users away (e.g., dissatisfaction, high perceived prices), pull effects involve the attractiveness of alternatives (e.g., better features, social influence), and mooring effects include psychological or situational factors that influence the ease or difficulty of switching (e.g., switching costs, norms).

While prior studies have applied the PPM framework in various digital service contexts, the literature shows inconsistent results, especially regarding the influence of mooring effects and their role as moderators. Moreover, there is limited research on how these dynamics unfold within the Indonesian Gen Z social commerce segment, particularly following regulatory disruptions.

Therefore, this study aims to examine the influence of push, pull, and mooring effects on switching intention among Generation Z TikTok Shop users in Indonesia. By focusing on this unique context, the research contributes to a deeper understanding of platform-switching behavior in social commerce and offers practical insights for digital platforms navigating competitive and regulatory challenges. This study focuses on switching intention rather than actual switching behavior, as intention is widely recognized as a strong predictor of behavior in digital consumer contexts.

1.1. Push-Pull-Mooring (PPM) Framework

The Push-Pull-Mooring (PPM) framework originates from migration studies and has been widely adopted in consumer behavior research to explain switching intentions and behaviors (Chen & Keng, 2019). The framework consists of three dimensions: push factors that drive consumers away from their current provider, pull factors that attract them to alternatives, and mooring factors that facilitate or inhibit switching decisions (Kordi, 2018).

Bansal, Taylor, and James (2005) were among the first to adapt the PPM model to marketing contexts, conceptualizing consumer switching as analogous to human migration. In this context, push factors include dissatisfaction, low service quality, and high perceived costs. Pull factors refer to the attractiveness of competing services, such as better features or promotional benefits. Mooring factors include switching costs, social influence, past behavior, and personal attitudes, which may either hinder or support switching actions.

1.2. Push Effect

Push effects are negative attributes of the current service provider that encourage users to leave. Studies by Jung et al. (2017), Djusmin & Dirgahayu (2019), and Muttaqin (2022) found that dissatisfaction, low trust, low perceived value, and high prices were significant push factors in digital services. In the context of TikTok Shop, such factors may include limited product variety, poor customer service, or unfavorable price perceptions.

1.3. Pull Effect

Pull effects are positive attributes of competing platforms that entice users to switch. Prior research (Yunita & Munandar, 2023; Sugandha & Indarwati, 2021) has identified promotional offers, perceived quality, and social influence as effective pull factors. Platforms such as Shopee and Lazada often leverage these strategies to attract TikTok Shop users, especially during the platform's temporary closure.

1.4. Mooring Effect

Mooring effects are personal, social, or situational barriers to switching. These include subjective norms, switching costs, and habitual usage. While some studies (Adjie et al., 2023; Wu et al., 2017) found mooring factors to be significant moderators, others (Jung et al., 2017; Sugandha & Indarwati, 2021) reported weak or nonsignificant influence on switching intention. This inconsistency in findings suggests the need for further examination, especially among Generation Z consumers who are considered less brand-loyal and more adaptable to change.

1.5. Switching Intention

Switching intention is defined as the likelihood or willingness of a consumer to move from one service provider to another (Bansal et al., 2005), often driven by unmet needs, dissatisfaction, or value expectations in a competitive market (Kotler & Armstrong, 2018). In digital commerce contexts, this reflects a user’s planned behavior in response to dissatisfaction, attractive alternatives, or external disruptions. While switching intention often precedes actual behavioral change, the two do not always align due to psychological or contextual constraints such as habits, loyalty, or lack of alternatives. Prior studies, including Astuti and Eliana (2019) and Djusmin and Dirgahayu (2019), have confirmed that strong switching intention is a key predictor of consumer movement across platforms in online shopping and digital services.

1.6. Research Gap

Although the Push, Pull, and Mooring (PPM) framework has been widely used to study platform switching, there is limited research focusing specifically on Generation Z within the social commerce context in Indonesia. Moreover, the existing literature shows inconsistent findings regarding the role of mooring effects—both as direct predictors and as moderators—in influencing switching intention. Few studies examine these dynamics in response to regulatory disruptions, such as platform bans or policy shifts (Marseto et al., 2019). This study addresses that gap by empirically testing the direct and moderating effects of push, pull, and mooring variables on switching intention among TikTok Shop users in Indonesia, with a focus on Generation Z.

2. RESEARCH METHOD

This study employed a quantitative causal research design to investigate the influence of push, pull, and mooring effects on switching intention and switching behavior of Generation Z TikTok Shop users in Indonesia. The Push-Pull-Mooring (PPM) framework (Bansal et al., 2005) served as the theoretical foundation, as it is widely applied in studies of consumer switching behavior and digital platform migration.

2.1. Conceptual Framework

The proposed model investigates direct relationships between push, pull, and mooring effects on switching intention, and subsequently, switching intention on switching behavior. Additionally, it examines the moderating role of mooring effect on the relationship between push/pull effects and switching intention.

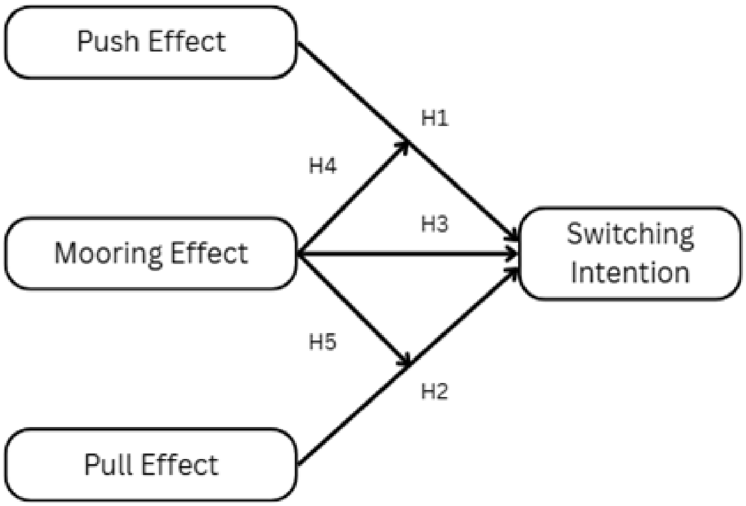

Figure 1. Conceptual Framework

Based on the Push-Pull-Mooring (PPM) framework, this study proposes five hypotheses. First, it is hypothesized that the push effect—which includes negative factors such as dissatisfaction, low trust, or poor service quality—positively influences the switching intention of Generation Z users from TikTok Shop to alternative platforms (H1). Second, the pull effect, representing the attractiveness of alternative platforms, is expected to positively influence switching intention (H2). Third, the mooring effect, which includes psychological or situational constraints such as subjective norms, perceived switching costs, and habitual behavior, is hypothesized to negatively influence switching intention (H3). Furthermore, the mooring effect is also proposed to play a moderating role, weakening or strengthening the relationship between push and pull effects and switching intention. Thus, it is hypothesized that the mooring effect moderates the relationship between push effect and switching intention (H4), and moderates the relationship between pull effect and switching intention (H5).

2.2. Variable Definition and Operationalization

The variables used in this research are defined as follows:

a. Push Effect: Negative experiences with the current service provider, such as low quality, dissatisfaction, low trust, and high price perception.
b. Pull Effect: The appeal or attractiveness of competing platforms (e.g., Shopee, Tokopedia).
c. Mooring Effect: Psychological or situational factors that hinder or support switching, including switching cost, social norms, past experience, and attitudes toward switching.
d. Switching Intention: The respondent’s desire, plan, or intention to shift platforms.

Each variable was measured using indicators adapted from Bansal et al. (2005). Responses were recorded using a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

Table 1. Variables and Operational Indicators in the PPM Framework

Variable	Indicators
Push Effect	Low quality, low satisfaction, low value, low trust, low commitment, high price perception
Pull Effect	Attractiveness of alternatives
Mooring Effect	Subjective norms, switching cost, attitudes toward switching, past behavior, low variety seeking
Switching Intention	Expectation to switch, desire to switch, plan to switch

2.3. Population and Sampling

The population of this study comprises Generation Z users in Indonesia aged 17 to 27 who had experience using TikTok Shop before its closure in October 2023 and later switched to alternative platforms. Since the exact population size was unknown, the Lemeshow formula was used to calculate the minimum required sample size at a 95% confidence level with a 10% margin of error:

$$n = \frac{Z^2 \; x \; P(1-P)}{d^2}$$

Where:
Z = 1.96 (standard score for 95% confidence)
P = 0.5 (estimated population proportion)
d = 0.1 (margin of error)

Substituting the values:

$$n = \frac{(1.96)^2 \; x \; 0.5(1-0.5)}{(0.1)^2} = 96.04$$

Thus, the minimum required sample size was 96 respondents. A total of 146 valid responses were collected through purposive sampling using the following inclusion criteria: (1) aged 17–27, (2) prior TikTok Shop users before October 2023, and (3) users who switched to another platform during the shutdown. Although the sample size may appear modest, it exceeds the minimum requirement for PLS-SEM analysis, which is suitable for small to medium samples and complex models (Hair et al., 2019).

2.4. Data Collection

Data were gathered using an online questionnaire distributed via WhatsApp and Instagram. The questionnaire comprised demographic questions and 26 items measuring the variables of interest. The responses were collected in June–July 2024. The instrument was developed and refined based on R&D design principles (Sugiyono, 2019), and pre-tested for clarity. All constructs were measured using a five-point Likert scale (Sugiyono, 2017).

2.5. Data Analysis Technique

The collected data were analyzed using Structural Equation Modeling with Partial Least Squares (SEM-PLS) through SmartPLS 4.0. SEM-PLS was chosen due to its ability to handle complex models, small to medium sample sizes, and non-normal data distributions (Rahadi, 2023). The analysis was conducted in two main stages: the measurement model evaluation and the structural model evaluation.

In the measurement model evaluation, several tests were conducted to ensure the reliability and validity of the constructs. Indicator reliability was confirmed through outer loadings, with a minimum acceptable value of 0.70 (Ghozali & Latan, 2015). Convergent validity was assessed using the Average Variance Extracted (AVE), where values above 0.50 indicate adequate convergence of indicators onto their respective constructs. Internal consistency was measured through Composite Reliability (CR) and Cronbach's Alpha, both of which must exceed 0.70 to be considered acceptable. Discriminant validity was evaluated using the Fornell-Larcker criterion, where the square root of each construct's AVE must be greater than its correlations with other constructs, confirming that the constructs are distinct from one another.

The structural model evaluation focused on testing the hypothesized relationships among variables. Path coefficients were examined to determine the strength and direction of these relationships. The model's explanatory power was assessed using the coefficient of determination (R^2), which indicates the proportion of variance in the dependent variable explained by the independent variables. Additionally, the effect size (f^2) was used to assess the impact of individual predictor variables, with thresholds of 0.02 (small), 0.15

(medium), and 0.35 (large). Model fit was evaluated using the Standardized Root Mean Square Residual (SRMR), where values below 0.08 indicate a good fit, and the Normed Fit Index (NFI), with values closer to 1 suggesting a better-fitting model.

Finally, the moderating effects of the mooring variable were tested by including interaction terms between the mooring effect and both the push and pull effects. This allowed for examination of whether mooring conditions significantly influenced the strength of the relationships between push/pull factors and switching intention.

This comprehensive methodology ensures both the reliability and validity of the measurement tools as well as the robustness of the analytical framework in explaining switching behavior among Gen Z TikTok Shop users.

3. RESULTS AND DISCUSSION

3.1. Results

This study analyzed data collected from 146 respondents who met three criteria: aged between 17 and 27 years, had used TikTok Shop prior to its shutdown in October 2023, and had since switched to another e-commerce platform such as Shopee, Tokopedia, or Lazada. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4.0. The analysis process involved evaluating both the measurement model and the structural model, including testing for moderation effects and assessing overall model fit.

3.1.1. Measurement Model Evaluation

The measurement model was first evaluated to assess the reliability and validity of the constructs. Outer loadings were examined to determine indicator reliability. As shown in Table 1, the majority of indicators demonstrated acceptable outer loadings above the threshold of 0.70. However, two indicators under the construct Attitude Toward Switching (ATS1 = 0.441 and ATS2 = 0.490) were removed from the model due to their insufficient loading values.

Two remaining indicators for this construct, ATS3 (0.606) and ATS4 (0.522), were retained despite falling below the standard 0.70 threshold. Their retention was theoretically justified to preserve the conceptual integrity of the construct. According to Hair et al. (2019), indicators with loadings between 0.50 and 0.70 may be retained when their removal would reduce the content validity of the construct, particularly in exploratory or theory-driven studies. Similarly, the three indicators for the Low Commitment variable (LC1–LC3) showed loadings ranging from 0.587 to 0.685, and were also retained for theoretical completeness.

Although several indicators exhibited loadings below the recommended 0.70 threshold, they were retained based on theoretical relevance and content validity considerations. In exploratory studies, indicators with loadings between 0.50–0.70 may be acceptable when they contribute meaningfully to construct representation and do not adversely affect composite reliability (Hair et al., 2019). Furthermore, the retention of these indicators did not significantly reduce the composite reliability and AVE values, which remained within acceptable thresholds.

Table 2. Indicator Outer Loadings for Each Construct

Mooring Effect		Pull Effect		Push Effect	
ATS1	0.441	AA1	0.818	HPP1	0.778
ATS2	0.490	AA2	0.822	HPP2	0.777
ATS3	0.606	AA3	0.859	LC1	0.685
ATS4	0.522	AA4	0.885	LC2	0.615
		AA5	0.873	LC3	0.587
		AA6	0.811	LS1	0.823
				LS2	0.801
				LS3	0.839

Source: SmartPLS 4.0 Output (processed, 2024)
Note: Outer loadings ≥ 0.70 indicate acceptable indicator reliability. Indicators with loadings between 0.50 and 0.70 may be retained for theoretical justification (Hair et al., 2019)

3.1.2. Convergent Validity and Internal Consistency

Convergent validity was assessed using Average Variance Extracted (AVE), while internal consistency was tested through Composite Reliability (CR) and Cronbach's Alpha. As shown in Table 2, all constructs achieved CR and Alpha values above the recommended minimum of 0.70, indicating acceptable internal consistency. Although the AVE values for some constructs, such as Low Commitment and Attitude Toward Switching, were slightly below 0.50, the values remained within acceptable limits given the exploratory nature of the research and the theoretical justification for retaining certain lower-loading indicators.

Table 3. Reliability and Convergent Validity of Constructs

	Cronbach's Alpha (α)	Composite Reliability (ρ_a)	Composite Reliability (ρ_c)	Average Variance Extracted (AVE)
Mooring Effect	0.973	0.900	0.959	0.648
Pull Effect	0.920	0.921	0.937	0.714
Push Effect	0.969	0.972	0.972	0.644
Switching Intention	0.830	0.831	0.898	0.746

Source: SmartPLS 4.0 Output (processed, 2024)
Note: All values meet the recommended thresholds of $\alpha \geq 0.70$, $\rho_a \geq 0.70$, $\rho c \geq 0.70$, and AVE ≥ 0.50, indicating good reliability and convergent validity (Hair et al., 2019)

3.1.3. Discriminant Validity

Discriminant validity was evaluated using the Fornell-Larcker criterion. As shown in Table 4, the square root of each construct's AVE was greater than its correlation with other constructs, confirming that each construct was empirically distinct from the others in the model.

Table 4. Fornell–Larcker Criterion for Discriminant Validity

	Mooring Effect	Pull Effect	Push Effect	Switching Intention
Mooring Effect	0.805			
Pull Effect	-0.099	0.845		
Push Effect	-0.178	0.790	0.803	
Switching Intention	-0.130	0.796	0.731	0.864

Source: SmartPLS 4.0 Output (processed, 2024)
Note: Discriminant validity is established when the square root of AVE (diagonal) is greater than the inter-construct correlations (off-diagonal).

3.1.4. Structural Model Evaluation

After confirming the measurement model's adequacy, the structural model was assessed to test the hypothesized relationships among variables. The final structural model, including path coefficients and explained variance (R^2), is presented in Figure 1. As shown in the figure and summarized in Table 5, both the Push Effect ($\beta = 0.304$, $p = 0.007$) and Pull Effect ($\beta = 0.539$, $p = 0.000$) had positive and statistically significant effects on Switching Intention, with the Pull Effect showing the stronger influence. This indicates that the attractiveness of alternative platforms such as Shopee or Tokopedia was a more dominant driver of switching than dissatisfaction with TikTok Shop.

The Mooring Effect did not significantly affect Switching Intention ($\beta = –0.008$, $p = 0.930$), suggesting that social or psychological factors such as habits and perceived switching costs did not play a significant role in influencing intention in this context.

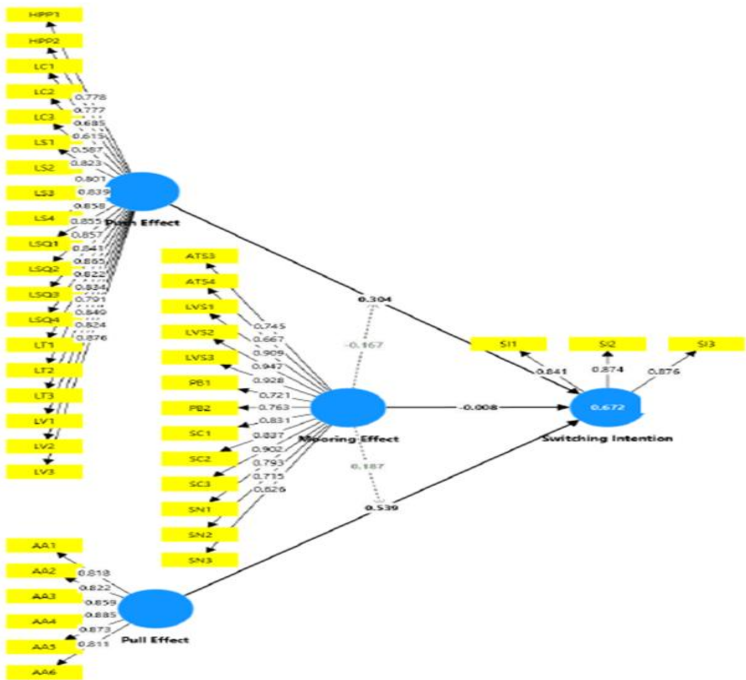

Figure 2. Final Structural Model with Path Coefficients and R² Values

Table 5. Structural Path Coefficients and Hypothesis Testing Results

	Original Sample	Sample Mean	Standard Deviation	T statistics	P values
Push Effect → Switching Intention	0.304	0.323	0.113	2.696	0.007
Pull Effect → Switching Intention	0.539	0.506	0.114	4.728	0.000
Mooring Effect → Switching Intention	-0.008	0.02	0.096	0.087	0.930
Mooring Effect + Push Effect → Switching Intention	-0.167	-0.149	0.154	1.089	0.276
Mooring Effect + Pull Effect → Switching Intention	0.187	0.137	0.148	1.262	0.207

Source: SmartPLS 4.0 Output (processed, 2024)
Note: A relationship is considered statistically significant if $p < 0.05$. β = standardized path coefficient. This table includes both direct and moderation effects (H1–H5)

3.1.5. Coefficient of Determination and Model Fit

The coefficient of determination (R^2) for Switching Intention was 0.672, indicating that the Push, Pull, and Mooring effects collectively explained 67.2% of the variance in users' intention to switch platforms.

Model fit was assessed using the Standardized Root Mean Square Residual (SRMR) and the Normed Fit Index (NFI). As shown in Table 7, the SRMR value was 0.074, which is below the recommended threshold of 0.08, indicating good model fit. The NFI was 0.721, which is slightly below the commonly accepted threshold of 0.80, but still considered acceptable for complex models in PLS-SEM.

Table 6. Coefficient of Determination (R^2) for Switching Intention

Construct	R^2	Adjusted R^2
Switching Intention	0.672	0.659

Source: SmartPLS 4.0 Output (processed, 2024)
Note: R^2 values represent the proportion of variance in the dependent variable explained by the independent constructs.

Table 7. Model Fit Indices (SRMR and NFI)

Fit Index	Value
Standardized Root Mean Square Residual (SRMR)	0.074
Normed Fit Index (NFI)	0.721

Source: SmartPLS 4.0 Output (processed, 2024)
Note: SRMR < 0.08 indicates acceptable model fit; NFI ≥ 0.70 is considered acceptable in exploratory PLS-SEM studies.

3.1.6. Moderation Test Results

Moderation analysis was conducted to examine whether the Mooring Effect moderated the relationship between the Push and Pull Effects on Switching Intention. As shown in Table 5 before, the results indicate that neither interaction term was statistically significant. The interaction between Mooring Effect and Push Effect ($\beta = -0.167$, $p = 0.276$) and the interaction between Mooring Effect and Pull Effect ($\beta = 0.187$, $p = 0.207$) did not meet the significance threshold ($p < 0.05$). This suggests that mooring conditions—such as social norms or behavioral inertia—did not meaningfully alter the influence of push or pull factors on switching intention in this context.

3.1.7. Effect Size (f^2)

Beyond statistical significance, the strength of each predictor's impact on the dependent variable was assessed using Cohen's f^2 effect size. As shown in Table 7, the Pull Effect had a large effect on Switching Intention ($f^2 = 0.310$), while the Push Effect had a small effect ($f^2 = 0.095$). The Mooring Effect, as well as the interaction terms (moderating effects), had negligible or no effect, as their f^2 values were below the 0.02 threshold. These results reinforce that the Pull Effect (e.g., attractiveness of alternatives) was the most influential driver of switching intention in this context.

Table 8. Effect Size (f²) for Predictor Variables on Switching Intention

Predictor Variable	f²	Effect Size Interpretation
Mooring Effect	0.000	None
Pull Effect	0.310	Large
Push Effect	0.095	Small
Mooring Effect + Push Effect	0.021	Very Small
Mooring Effect + Pull Effect	0.033	Small

Source: SmartPLS 4.0 Output (processed, 2024)
Note: According to Cohen (1988), f² values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively.

3.2. Discussion

This study aimed to analyze the effects of Push, Pull, and Mooring (PPM) variables on the switching intention of Generation Z users in the context of TikTok Shop's temporary closure in Indonesia. The structural model results revealed several key findings. Both push and pull effects had significant positive impacts on switching intention, with the pull effect showing a stronger influence. Conversely, the mooring effect neither directly affected switching intention nor significantly moderated the relationship between push/pull effects and switching intention. These findings offer several theoretical and practical implications.

The significant impact of the push effect on switching intention aligns with the core assumption of the PPM framework—that dissatisfaction or negative experiences can motivate users to consider alternatives. In this study, push indicators such as low satisfaction, high perceived price, and declining trust were linked to user intention to migrate from TikTok Shop to competing platforms such as Shopee or Tokopedia. The closure of TikTok Shop, driven by regulatory action (Minister of Trade Regulation No. 31 of 2023), likely intensified user dissatisfaction, reinforcing push-based migration. This is consistent with the findings of Bansal et al. (2005) and Thahirah (2015), who demonstrated that service-related problems often trigger consideration of switching alternatives.

This finding is further supported by studies in digital commerce and service switching. For instance, Djusmin and Dirgahayu (2019) found that low service quality and poor customer experience were primary push triggers for platform switching in Indonesian e-commerce. Similarly, Astuti and Eliana (2019) emphasized that trust and satisfaction levels play a critical role in consumers' decisions to remain loyal or switch. In the case of TikTok Shop, trust may have been compromised not only by service features but also by the sudden unavailability of the platform, which had previously contributed to strong purchase decisions on TikTok Shop (Wijaya, 2023), creating a perceived instability among users.

However, the push effect in this study demonstrated a relatively small effect size ($f^2 = 0.095$), indicating that while it was statistically significant, it was not the dominant driver of switching behavior. This supports prior observations that dissatisfaction alone is often insufficient to trigger switching unless paired with attractive alternatives—highlighting the importance of the pull effect.

The pull effect emerged as the most influential factor in driving switching intention ($\beta = 0.539$, $f^2 = 0.310$), suggesting that users were more motivated by the perceived advantages of other platforms than by dissatisfaction with TikTok Shop. This result is consistent with Bansal et al. (2005), who argued that the attractiveness of alternatives—such as better service quality, promotional offers, product variety, and a stronger ecosystem—can serve as powerful pull forces in consumer decision-making. Recent findings in the context of e-commerce live streaming also support this pattern, showing pull effects as the dominant influence on switching decisions (Ye et al., 2022). The dominance of pull factors may also be attributed to TikTok Shop's competitors being well-established players with high market trust and logistical maturity.

Social commerce users in Generation Z are typically more flexible, trend-oriented, and responsive to social influence (Firamadhina & Krisnani, 2021), which likely amplifies the pull effect. Generation Z values convenience, speed, personalization, and peer recommendations (Francis & Hoefel, 2018)—all factors offered more robustly by established platforms (Christian & Ikasari, 2020). This aligns with Setyaningrum et al. (2022), who found that Indonesian Gen Z consumers were highly influenced by perceived usefulness, ease of use, and peer influence when switching platforms. The strong impact of the pull effect underscores the importance for platforms to continuously innovate and enhance value propositions, not just to attract new users but to prevent existing users from leaving.

Interestingly, the mooring effect was not found to have a significant direct impact on switching intention ($\beta = -0.008$, $p = 0.930$), nor did it significantly moderate the relationship between either push or pull effects and switching intention. This finding contrasts with prior research where mooring factors such as switching cost, subjective norms, or behavioral inertia were found to dampen switching intention. For example, Bansal et al. (2005) identified mooring effects as a significant stabilizing force, especially when emotional attachment or effortful switching was involved. Similarly, Luu and Ngo (2022) observed that switching cost moderated switching behavior in Vietnamese mobile users.

However, in this study, the mooring effect appears to have played a minimal role. One possible explanation is the behavioral characteristics of Generation Z users. Compared to older generations, Gen Z is more digitally literate, less brand loyal, and more willing to experiment with platforms. Studies such as

Kurniawati et al. (2023) have shown that Gen Z users in Indonesia exhibit a lower degree of platform loyalty and are more driven by short-term gratification and trending user experiences. As such, constructs like switching cost or behavioral inertia may be less relevant for this demographic, reducing the mooring effect's overall impact.

The low f^2 effect sizes for mooring and its interaction terms ($f^2 = 0.000$ for direct, 0.021 and 0.033 for moderation) further validate this conclusion. Users did not appear to experience substantial friction in switching platforms, either socially or technically. The low stickiness observed may also reflect the nature of social commerce platforms like TikTok Shop, which operate with relatively low switching barriers compared to banking, telecommunications, or insurance services where mooring tends to be more prominent.

Another possible explanation lies in the operationalization of the mooring construct in this study. Mooring factors were measured using a broad set of indicators, including switching cost, subjective norms, and attitudes toward switching. However, these dimensions may not fully capture the more nuanced psychological attachment or ecosystem dependency that characterizes user retention in digital platforms. Future studies may benefit from incorporating more specific constructs such as emotional attachment, platform embeddedness, or perceived ecosystem lock-in to better represent mooring effects in social commerce contexts.

The insignificant moderation results also suggest that mooring factors did not weaken or enhance the relationship between dissatisfaction or alternative appeal and switching intention. This further implies that switching decisions in this context were largely independent of subjective norms or habitual behavior. For platform providers, this highlights a significant vulnerability: when mooring is weak, user migration can occur rapidly, especially in response to regulatory disruption or competitor improvements.

In summary, the findings of this study demonstrate that switching intention among Generation Z users of TikTok Shop is driven more by the appeal of alternative platforms than by dissatisfaction alone. Furthermore, the limited influence of mooring factors suggests that traditional barriers to switching, such as perceived effort or social norms, may be weakening in fast-moving digital commerce environments—especially among younger users. These insights reinforce the need to revisit existing theoretical assumptions when applying the PPM framework to newer generations and digital-first platforms.

4. CONCLUSION

This study investigated the influence of push, pull, and mooring effects on switching intention among Generation Z users of TikTok Shop in Indonesia, using the Push–Pull–Mooring (PPM) framework. The research was conducted in the context of the platform's temporary closure in late 2023 due to regulatory restrictions, providing a unique opportunity to observe user switching behavior in real-time.

The findings indicate that both push and pull effects significantly influence switching intention, confirming the first two hypotheses of this study. Among the two, the pull effect demonstrated the strongest impact, indicating that Generation Z users were primarily driven to switch platforms by the perceived attractiveness of alternatives. In contrast, the mooring effect did not have a significant direct influence on switching intention, nor did it moderate the relationship between push or pull effects and switching intention. These results lead to the rejection of the final three hypotheses, suggesting that mooring factors such as switching costs or subjective norms did not meaningfully affect switching decisions in this context.

Theoretically, this study contributes to the growing body of research on digital consumer behavior by validating the PPM framework within the emerging domain of social commerce in Southeast Asia. While PPM has been widely applied in mobile app switching and e-services, its use in the context of social media–commerce integration remains limited. By focusing on a real-world regulatory event and its behavioral consequences, this study extends the applicability of PPM and underscores the need to revisit the role of mooring variables in young, digital-native user populations.

Practically, the results offer several important implications for platform managers. Enhancing pull factors—such as superior features, user experience, and trust—can serve as a more effective retention strategy than merely reducing dissatisfaction. Additionally, the weak role of mooring effects signals a vulnerability: platforms must invest in building emotional attachment and ecosystem stickiness if they wish to reduce switching rates. For policymakers, this study provides insights into how sudden regulatory actions may unintentionally accelerate user migration across platforms.

In conclusion, platform loyalty among Generation Z users is driven more by perceived value than by inertia or resistance to change. Future research should examine switching behavior longitudinally and across different demographic groups or platform categories to provide a more comprehensive view of digital consumer behavior. These findings also suggest that the traditional role of mooring factors in the PPM framework may need to be reconsidered when applied to digitally native generations in low-switching-barrier environments.

This study has several limitations that should be acknowledged. First, the research focused solely on Generation Z users in Indonesia who had used TikTok Shop and experienced a platform switch after its temporary closure. As a result, the findings may not be generalizable to other age groups, countries, or users who have not experienced such a disruption. The cultural, regulatory, and technological context of Indonesia during this specific event may also have influenced user behavior in ways not fully captured by the PPM model.

Second, the study employed a cross-sectional survey design, which limits the ability to observe switching behavior over time. Since user decisions are dynamic and often evolve in response to changing platform features or market conditions, a longitudinal approach would provide a more comprehensive understanding of switching patterns, especially in fast-paced digital environments like social commerce.

Third, while the PPM framework remains a strong theoretical foundation, the operationalization of mooring effects in this study may not have captured the full spectrum of psychological, emotional, or contextual barriers to switching. Future studies might explore alternative or expanded indicators, such as emotional attachment, brand community involvement, or legal concerns, to enrich the mooring dimension.

Additionally, the use of purposive sampling through online platforms such as WhatsApp and Instagram may introduce self-selection bias, as respondents who are more active digitally are more likely to participate. The cross-sectional nature of the data limits causal inference and does not capture post-resumption behavioral adjustments following TikTok Shop's reopening in December 2023.

Despite these limitations, the study offers practical implications for platform managers, marketers, and policymakers. Platform developers should focus on strengthening pull factors—such as usability, product variety, trustworthiness, and community engagement—since these are the most influential in retaining Generation Z users. Push factors should also be carefully monitored, particularly service quality and transparency, to avoid triggering dissatisfaction-driven switching.

In addition, given the weak influence of mooring effects in this context, platforms should not assume that users will remain loyal out of habit or perceived switching cost. Strategies to increase switching barriers—such as loyalty programs, personalized experiences, or ecosystem lock-in—may help increase retention (Yusuf & Ratnasari, 2022).

For policymakers, this study highlights how abrupt regulatory changes can lead to unintended behavioral shifts. Government agencies should consider user experience and platform stability when crafting digital commerce regulations. Transparent communication, transition policies, and collaboration with platforms can help maintain consumer trust during regulatory interventions.

REFERENCES

Adjie, E. A., Calista, N., Muhtadiin, R. R., Handayani, P. W., & Larasati, P. D. (2023). User switching intention from E-marketplace to E-pharmacy: The Influence of push, pull, and mooring factors. Informatics in Medicine Unlocked, 43, 101404. https://doi.org/10.1016/j.imu.2023.101404

Astuti, Y., & Eliana, E. (2019). Perilaku Switching Behavior Pengguna Electronic Commerce (e-Ceommerce) di Kota Langsa dengan Model Migrasi Konsumen Push, Pull Mooring. SI-MEN (Akuntansi dan Manajemen) STIES, 10(1), 9-21.

Bansal, H. S., Taylor, S. F., & James, Y. S. (2005). "Migrating" to New Service Providers: Toward a Unifying Framework of Consumers' Switching Behaviors. Journal of the Academy of Marketing Science, 33(1), 96–115. https://doi.org/10.1177/0092070304267928

Bencsik, A., Juhász, T., & Horváth-Csikós, G. (2016). Y and Z Generations at Workplaces. Journal of Competitiveness, 6(3), 90–106. https://doi.org/10.7441/joc.2016.03.06

Chen, Y.-H., & Keng, C.-J. (2019). Utilizing the Push-Pull-Mooring-Habit framework to explore users' intention to switch from offline to online real-person English learning platform. Internet Research, 29(1), 167–193. https://doi.org/10.1108/IntR-09-2017-0343

Christiani, L. C., & Ikasari, P. N. (2020). Generasi Z dan pemeliharaan relasi antar generasi dalam perspektif budaya Jawa. Jurnal komunikasi dan kajian media, 4(2), 84-105. https://doi.org/10.31002/jkkm.v4i2.3326

Databoks. (2023, October 4). Sebelum Tutup di Indonesia, Pangsa Pasar TikTok Shop Diprediksi Melesat pada 2023. Katadata. https://databoks.katadata.co.id/teknologitelekomunikasi/statistik/4abcca668fab154/sebelum-tutup-di-indonesia-pangsa-pasar-tiktok-shop-diprediksi-melesat-pada-2023

Djusmin, V., & Dirgahayu, R. T. (2019). Push Pull Mooring dan Pyschological Ownership terhadap Perilaku Beralih Pengguna Instant Messaging. Indonesian Journal of Information Systems, 2(1), 1–12. https://doi.org/10.24002/ijis.v2i1.2013

Firamadhina, F. I. R., & Krisnani, H. (2021). Perilaku Generasi Z terhadap Penggunaan Media Sosial TikTok: TikTok Sebagai Media Edukasi dan Aktivisme. Share: Social Work Journal, 10(2), 199. https://doi.org/10.24198/share.v10i2.31443

Francis, T., & Hoefel, F. (2018). "True Gen": Generation Z and its implications for companies. McKinsey & Company. https://www.mckinsey.com/industries/ consumer-packaged-goods/our-insights/true-gen-generation-z-and-its- implications-for-companies

Ghozali, I., & Latan, H. (2015). Partial Least Squares: Konsep, Teknik dan Aplikasi Menggunakan Program SmartPLS 3.0. Badan Penerbit Universitas Diponegoro.

Goodstats. (2023, February 6). Sensus BPS: Saat Ini Indonesia Didominasi Oleh Gen Z. Goodstats. https://data.goodstats.id/statistic/sensus-bps-saat-ini-indonesia-didominasi-oleh-gen-z-n9kqv

Hair, J. F., Babin, B. J., Anderson, R. E., & Black, W. C. (2022). Multivariate Data Analysis (8th ed.). Cengage Learning.

Jung, J., Han, H., & Oh, M. (2017). Travelers' switching behavior in the airline industry from the perspective of the push-pull-mooring framework. Tourism Management, 59, 139–153. https://doi.org/10.1016/j.tourman.2016.07.018

Kordi Ghasrodashti, E. (2018). Explaining brand switching behavior using pull–push–mooring theory and the theory of reasoned action. Journal of Brand Management, 25(4), 293–304. https://doi.org/10.1057/s41262-017-0080-2

Kotler, P., & Armstrong, G. (2018). Principles of Marketing (17th global ed.). Pearson.

Marseto, F., Handayani, P. W., & Pinem, A. A. (2019). Push, Pull, and Mooring Evaluation of User Switching Intention from Social Commerce to E-Commerce. 2019 International Conference on Information Management and Technology (ICIMTech), 575–580. https://doi.org/10.1109/ICIMTech.2019.8843841

Mumtaha, H. A., & Khoiri, H. A. (2019). Analisis Dampak Perkembangan Revolusi Industri 4.0 dan Society 5.0 Pada Perilaku Masyarakat Ekonomi (E-Commerce). JURNAL PILAR TEKNOLOGI: Jurnal Ilmiah Ilmu Ilmu Teknik, 4(2). https://doi.org/10.33319/piltek.v4i2.39

Muttaqin, F. (2022). Pengaruh Push, Pull, and Mooring Effect terhadap Switching Intention Konsumen Mobile Legends Bang Bang pada League of Legends Wild Rift. SIBATIK JOURNAL: Jurnal Ilmiah Bidang Sosial, Ekonomi, Budaya, Teknologi, Dan Pendidikan, 1(10), 2121–2132. https://doi.org/10.54443/sibatik.v1i10.311

Rahadi, D. R. (2023). Pengantar Partial Least Squares Structural Equation Model (PLS-SEM). Lentera Ilmu Madani.

Sa'adah, A. N., Rosma, A.., & Aulia, D. (2022 Persepsi generasi Z terhadap fitur Tiktok Shop pada aplikasi Tiktok. TRANSEKONOMIKA: AKUNTANSI, BISNIS DAN KEUANGAN, 2(5), 131–140. https://doi.org/10.55047/transekonomika.v2i5.176

Sugandha, A. P., & Indarwati, T. A. (2021). Pengaruh Push, Pull, dan Mooring terhadap Switching Intention pada Konsumen Pengguna Wifi di Era Pandemi Covid-19. Jurnal Ilmu Manajemen, 9(4), 1537–1548. https://doi.org/10.26740/jim.v9n4.p1537-1548

Sugiyono. (2019). Metode Penelitian dan Pengembangan: Research and Development (R&D). Alfabeta.

Tempo.co. (2023, October 10). Pasca TikTok Shop Ditutup, Teten Sebut 20 Persen Pembeli Beralih ke Tokopedia, Shopee, dkk. Tempo.Co. https://www.tempo.co/ekonomi/pasca-tiktok-shop-ditutup-teten-sebut-20-persen-pembeli-beralih-ke-tokopedia-shopee-dkk-117317

Thahirah, C. F. I. (2016). Pengaruh Faktor Push, Pull, dan Mooring Effect Terhadap Keinginan Berpindah (Switching Intention) pada Konsumen Telkom IndiHome Kota Malang. http://repository.ub.ac.id/id/eprint/108766

Wijaya, K. S. (2023). The Influence of Brand Image and Trust on Purchase Decisions in TikTok Shop. Journal Research of Social Science, Economics, and Management, 3(1), 1–13. https://doi.org/10.59141/jrssem.v3i01.516

Wu, K., Vassileva, J., & Zhao, Y. (2017). Understanding users' intention to switch personal cloud storage services: Evidence from the Chinese market. Computers in Human Behavior, 68, 300–314. https://doi.org/10.1016/j.chb.2016.11.039

Ye, D., Liu, F., Cho, D., & Jia, Z. (2022). Investigating switching intention of e-commerce live streaming users. Heliyon, 8(10), e11145. https://doi.org/10.1016/j.heliyon.2022.e11145

Yunita, E., & Munandar, J. M. (2023). The Influence of Push-Pull-Mooring Effects on E-Wallet Customer Switching in Generation Z in DKI Jakarta. The South East Asian Journal of Management, 17(1), 1–27. https://doi.org/10.21002/seam.v17i1.1177

Yusuf, H. G., & Ratnasari, A. (2022). Pengaruh Push Pull Mooring terhadap Switching Intention pada Pengguna Aplikasi Video on Demand di Masa Pandemi Covid-19. Indonesian Journal of Business Intelligence (IJUBI), 5(1), 17. https://doi.org/10.21927/ijubi.v5i1.2321