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ALGORITHMIC CURATION'S INFLUENCE ON IMPULSIVE BUYING: MEDIATING ROLE OF URGE IN TIKTOK

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ABSTRACT

The rapid growth of TikTok Live commerce has revolutionized online shopping. This study examines the role of perceived algorithmic curation intensity in driving impulsive buying in TikTok Live commerce, with urge to buy as a mediating variable. The objective of this research is to understand how algorithmic curation impacts consumer impluse buying in a live-streaming shopping context. The survey involved 100 TikTok users from Samarinda and Balikpapan, who had previously engaged in product purchases during TikTok Live sessions. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results reveal that perceived algorithmic curation intensity positively influences urge to buy, which in turn significantly drives impulsive buying. The analysis revealed that perceived algorithmic curation intensity positively influences urge to buy (path coefficient = 0.502), which in turn strongly affects Impulsive Buying (path coefficient = 0.785). The model explained 61.6% of the variance in impulsive buying behavior, highlighting the significant role of emotional triggers in driving consumer purchases.

Keywords: *Algorithmic Curation; Impulsive Buying; Urge to Buy*

A. INTRODUCTION

Exposure to algorithm-based shopping content has become one of the major drivers of consumer behavior changes in the live commerce ecosystem (Song, 2023). On platforms like TikTok, consumers no longer actively search for products, but are continuously exposed to live streams that are curated and intensely recommended by algorithmic systems (Peng et al., 2025). This curation intensity creates a strong and repetitive digital stimulus environment that potentially triggers spontaneous emotional urges to purchase, resulting in impulsive buying.

Conceptually, this phenomenon differs from traditional personalization.

Algorithmic curation intensity refers to the extent to which a platform actively filters, ranks, and repeatedly presents specific content to users based on their behavioral data and preferences, thus enhancing the visibility and salience of that content (Thurman et al., 2019; Flew et al., 2021). In live commerce contexts, algorithmic curation not only determines what consumers see but also how often and in what order live content appears, reinforcing exposure and its potential psychological effects.

Various studies indicate that algorithmic personalization and recommendations can increase engagement, exposure duration, and purchase probability (Tam & Ho, 2006; Bleier & Eisenbeiss, 2015). However, much of the research focuses on cognitive and utilitarian outcomes, such as perceived usefulness, decision efficiency, or purchase intention. In environments rich in visual, social, and temporal stimuli like live commerce, this approach is limited, as affective mechanisms play a more dominant role in driving consumption behavior. One of the key affective mechanisms identified in consumer behavior literature is urge to buy, defined as a strong, spontaneous, and uncontrollable emotional drive to make a purchase (Beatty & Ferrell, 1998). Urge to buy is seen as an internal response triggered by intense environmental stimuli, particularly in unplanned shopping situations rich in emotional triggers. Empirical studies show that interactive, real-time, and time-pressured online contexts significantly increase urge to buy, which in turn drives impulsive buying (Verhagen & van Dolen, 2011; Xu et al., 2020). Impulsive buying itself is defined as an unplanned purchase decision, driven by a momentary emotional urge (Rook, 1987; Verplanken & Herabadi, 2001). In live commerce contexts, characteristics such as real-time broadcasting, direct interaction with hosts, social cues from other viewers, and limited-time promotions further reinforce this impulsive tendency. Several studies show that live streaming commerce significantly increases impulsive buying compared to conventional e-commerce formats (Sun et al., 2019; Wongkitrungrueng & Assarut, 2020).

The urgency of this study becomes more pronounced when contextualized in Samarinda, a city in East Kalimantan with high internet penetration and social media adoption. According to the Indonesian Internet Service Providers Association (APJII), internet penetration in East Kalimantan exceeds the national average, reflecting high digital content consumption. Additionally, TikTok is one of the most widely used social media platforms in Indonesia, especially among the productive age group, which forms the core segment of live commerce consumers (APJII, 2024). This makes consumers in Samarinda particularly vulnerable to algorithmically curated live content that is repeatedly shown in their personal feeds.

Previous studies have begun to explore this mechanism but leave specific gaps. Research on algorithmic recommendations often stops at purchase intention or satisfaction (Bleier & Eisenbeiss, 2015; Shin & Park, 2019), while studies on urge to buy are more often placed in conventional retail or static e-commerce contexts, rather than in the intensely curated live commerce environment (Beatty & Ferrell, 1998; Verhagen & van Dolen, 2011). Thus, the integration of perceived algorithmic curation intensity, urge to buy, and impulsive buying into a coherent model is still relatively limited, particularly in the context of emerging cities outside major metropolitan areas.

There is still significant room for further research on algorithmic personalization and impulsive buying in e-commerce contexts. Previous studies have indeed examined the impact of AI-based personalization cues such as accuracy, relevance, timeliness, and diversity of recommendations on impulsive buying and have positioned urge to buy as an affective mediator (Chen et al., 2019; Rai et al., 2025). However, most of these studies view personalization as relatively static cues in non-real-time shopping environments with minimal social pressure. The intensely curated live commerce context, like TikTok Live, presents fundamentally different characteristics, namely persistent exposure, attention-based content curation, and the simultaneous integration of visual, social, and temporal stimuli. Therefore, while conceptually similar to previous research, the psychological mechanisms at work in live commerce environments are potentially more complex and remain underexplored. In particular, earlier studies have not explicitly captured perceived algorithmic curation intensity as a primary stimulus, leaving an empirical gap in understanding how perceived algorithmic curation intensity triggers urge to buy, which ultimately drives impulsive buying in algorithm-based live commerce ecosystems.

Despite these gaps, conceptual and empirical spaces remain open. First, most live commerce studies still treat personalization or recommendations as static constructs, without explicitly capturing the intensity of algorithmic curation as a form of repeated and selective stimulus exposure. Second, the relationship between algorithmic curation and impulsive buying is often tested directly, without addressing the internal affective mechanisms mediating this influence. The Stimulus–Organism–Response (SOR) framework asserts that environmental stimuli affect behavior through individuals' internal affective and psychological conditions (Mehrabian & Russell, 1974). Based on these gaps, this study aims to examine how perceived algorithmic curation intensity in the context of TikTok Live serves as an environmental stimulus triggering urge to buy as an internal affective response, which then drives impulsive buying as a behavioral response. By adopting the SOR framework, this study aims to provide a deeper understanding of the psychological mechanisms underlying impulsive buying behavior in algorithm-based live commerce environments, while also enriching the digital consumer behavior literature with empirical insights from Samarinda.

B. LITERATURE REVIEW

Perceived Algorithmic Curation Intensity

Algorithmic curation refers to the role of algorithms as gatekeepers that select, organize, and prioritize content displayed to users, thus shaping the exposure of information and consumption experiences indirectly (Braun & Gillespie, 2011). In the context of digital platforms, this mechanism works by amplifying certain content through behavioral data filtering, potentially limiting the diversity of information while increasing the intensity of exposure to relevant content (Pariser, 2011). Rader and Gray (2015) emphasize that algorithmic curation not only determines the type of content that appears but also its frequency and order, collectively shaping the user's perception of how the system "organizes" their experience. This perspective is expanded by Shin (2020), who views algorithms as persuasive agents, where data-driven recommendations and personalization actively guide users' attention and evaluation. Within the framework of platformized consumption culture, algorithms are also understood as repetitive and ongoing mechanisms designed to capture attention and shape user consumption patterns (Caliani et al., 2023).

Conceptually, Perceived Algorithmic Curation Intensity is defined as users' perception of the extent to which platforms actively filter, rank, repeat, and tailor content displayed to them based on their behavioral data, thereby increasing the exposure, visibility, and salience of certain content. This construct is perceptual, aligning with personalization literature that asserts user responses are determined by perceptions of relevance and content suitability, rather than the system's objectivity (Tam & Ho, 2005; Xu, 2011; Bleier & Eisenbeiss, 2015).

In this study, Perceived Algorithmic Curation Intensity is summarized into four main dimensions. The first dimension is repetition and exposure intensity, reflected in the repeated appearance of similar content or products within short intervals, such as live broadcasts with the same type of product continuously reappearing even though users do not actively search for them (Pariser, 2011; Rader & Gray, 2015; Caliani et al., 2023). The second dimension is ranking and prioritization, reflected in users' perception that certain content is more frequently displayed at the top, easier to find, and more prominent than other content, thereby influencing their attention and evaluation of that content (Haubl & Trifts, 2000; Rader & Gray, 2015). The third dimension is content selection and relevance, reflected in the perception that live content and products displayed match the user's interests, needs, and preferences, thus giving the impression that the content is actively "curated" by the system for specific users (Braun & Gillespie, 2011; Tam & Ho, 2005; Shin, 2020). The fourth dimension is adaptive recommendation, reflected in changes in live content recommendations based on user interactions, such as after watching, clicking, or skipping certain streams, indicating that the system dynamically adjusts recommendations based on prior user behavior (Xiao & Benbasat, 2007; Martínez-López & López-López, 2021).

In the context of short-video-based social media and live commerce platforms like TikTok, algorithmic curation occurs in real-time and adaptively. The displayed content is continuously adjusted to the user's interaction patterns, making exposure to certain products or live broadcasts increasingly intense and targeted (Martínez-López & López-López, 2021). Therefore, the focus of analysis is no longer limited to how algorithms work technically but on how this curation intensity is perceived by users (perceived algorithmic curation intensity).

Urgue to Buy

Urge to Buy is an affective construct that has long been discussed in consumer behavior literature as a spontaneous emotional response that arises when an individual is exposed to certain shopping stimuli. Beatty and Ferrell (1998) define urge to buy as a strong and sudden internal drive to make a purchase, which emerges without prior planning and is difficult to control rationally. Unlike purchase intention, which is cognitive and deliberative, urge to buy is affective, impulsive, and often triggered by situational stimuli.

In the Stimulus–Organism–Response (S–O–R) framework, urge to buy is positioned as an internal condition (organism) that bridges the influence of environmental stimuli on behavioral responses (Mehrabian & Russell, 1974). Various studies show that shopping environments rich in visual, social, and temporal stimuli significantly enhance urge to buy, particularly in interactive online shopping contexts (Verhagen & van Dolen, 2011). Xu et al. (2020) emphasize that real-time features, time pressure, and social cues strengthen consumers' spontaneous emotional reactions, thus increasing the urge to buy immediately.

In the context of live commerce, urge to buy becomes even more relevant as consumers are exposed to a combination of intense stimuli, such as direct interaction with hosts, comments from other viewers, limited-time promotions, and dynamic product visualizations. Empirical studies suggest that urge to buy serves as a strong predictor of impulsive buying, even more dominant than cognitive factors in unplanned shopping situations (Verplanken & Sato, 2011; Xu et al., 2020). Therefore, urge to buy is understood as a key affective mechanism that explains how exposure to digital stimuli can transform into spontaneous purchasing behavior.

Impulsive Buying

Impulsive Buying is a classic concept in consumer behavior studies that refers to a spontaneous, unplanned purchase decision driven by momentary emotional urges (Rook, 1987). Rook and Fisher (1995) emphasized that impulsive buying occurs when cognitive control weakens and individuals are more influenced by affective impulses than rational considerations. Verplanken and Herabadi (2001) further developed this concept by asserting that impulsive buying has both affective and cognitive dimensions, but the affective component often dominates in shopping situations rich in stimuli.

In digital environments, impulsive buying is increasingly viewed as a consequence of system design and platform context, rather than solely an individual consumer trait. Research shows that interactive interfaces, attractive visuals, and social information can lower cognitive barriers and increase impulsive tendencies (Dholakia, 2000; Verhagen & van Dolen, 2011). In the context of live streaming commerce, characteristics such as real-time broadcasts, two-way interactions, and time-limited promotions have been shown to significantly increase impulsive buying compared to traditional e-commerce formats (Sun et al., 2019; Wongkitrungrueng & Assarut, 2020).

Several empirical studies also show that impulsive buying is often the result of an affective process triggered by environmental stimuli, where urge to buy serves as the direct trigger for purchase actions (Beatty & Ferrell, 1998; Verplanken & Sato, 2011). Therefore, impulsive buying can be understood as a behavioral response within the Stimulus–Organism–Response (S–O–R) framework, occurring after individuals experience an internal emotional urge due to exposure to intense shopping stimuli.

C. RESEARCH METHOD

This study employs a quantitative approach with an explanatory design to examine the mechanism of how perceived algorithmic curation intensity influences urge to buy and impulsive buying within the Stimulus-Organism-Response (SOR) framework (Mehrabian & Russell, 1974). Perceived algorithmic curation intensity is operationalized as a multidimensional latent construct reflecting the intensity of algorithmic curation as perceived by users, while urge to buy represents the spontaneous affective response triggered by stimulus exposure, and impulsive buying represents the unplanned purchase behavior driven by emotional impulses (Beatty & Ferrell, 1998; Rook, 1987).

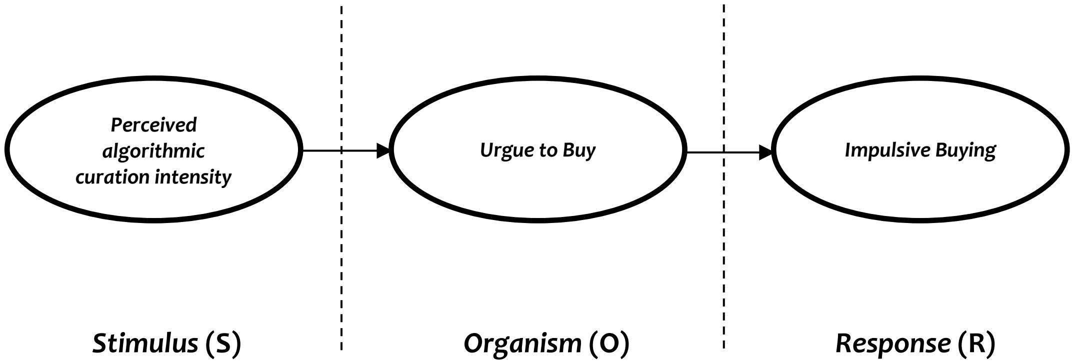

Figure 1. Research Model

Data were collected cross-sectionally through an online questionnaire survey targeted at TikTok users in Samarinda who had previously watched and purchased skincare or beauty products via TikTok Live. Given the uncertain size of the population, the study used purposive sampling with established inclusion criteria to ensure the relevance of respondents' experiences to the research context (Etikan et al., 2016). The sample size was determined based on general guidelines for SEM-based research, recommending a sample size of 5 to 10 times the number of indicators in the research instrument to ensure the stability of parameter estimates (Hair et al., 2019). The research instrument consisted of 19 indicators, so the minimum recommended sample size was approximately 95 respondents. In this study, 100 respondents were successfully collected and deemed eligible for analysis, meeting and exceeding the recommended minimum.

Data analysis was conducted using Partial Least Squares-Structural Equation Modeling (PLS-SEM). This method was chosen as it is suitable for testing causal relationships between latent constructs, mediation models, and studies aimed at explaining behavioral mechanisms in relatively new and evolving contexts (Hair et al., 2019). The model evaluation was performed by testing the measurement model to ensure the validity and reliability of the constructs, and the structural model to assess the significance of the relationships between the variables in the research model.

D. RESULT AND DISCUSSION

The respondents in this study are predominantly active TikTok users residing in Samarinda (71%) and Balikpapan (29%). All respondents had previously watched TikTok Live streams featuring product sales and made purchases through TikTok Live (See Table 1). The study shows a dominance of young respondents aged 18–24 years, making up 50% of the sample, with the majority being students (55%).

Table 1. The respondent's characteristics

Category	Option	Number of Respondents	Percentage
Gender	Female	75	75%
	Male	25	25%
Age	18–24 years	50	50%
	25–34 years	25	25%
Occupation	Student	55	55%
	Private Employee	20	20%
	Government Employee	15	15%
	Freelancer	10	10%
Location	Samarinda	71	71%
	Balikpapan	29	29%
Active TikTok User	Yes	100	100%
TikTok Usage Duration per Day	1–2 hours	20	20%
	2–4 hours	25	25%
	> 4 hours	55	55%
Watched TikTok Live (Product Sales)	Yes	100	100%
Purchased Products via TikTok Live	Yes	100	100%

Source: Analysis, 2026

The demographic characteristics of the respondents in this study indicate that TikTok is a highly popular platform among the younger generation, who tend to be more open to social media-based e-commerce trends. The majority of respondents (55%) use TikTok for more than 4 hours per day, reflecting a high level of engagement. This is relevant to the influence of algorithmic curation on impulsive buying decisions. Based on the demographic characteristics of the respondents, it is evident that TikTok Live is particularly relevant for the younger age group, who are highly engaged with the platform. Therefore, this study provides valuable insights into how TikTok's algorithms can trigger purchase urges and drive impulsive buying behavior in live-streaming-based e-commerce.

Evaluation of the Measurement and Structural Model

This study aims to evaluate the measurement and structural model in the relationship between perceived algorithmic curation intensity, urge to buy, and impulsive buying behavior on TikTok Live commerce using Structural Equation Modeling (SEM) with a Partial Least Squares (PLS) approach was used to assess the validity and reliability of the constructs, as well as to test the relationships between the variables in the model.

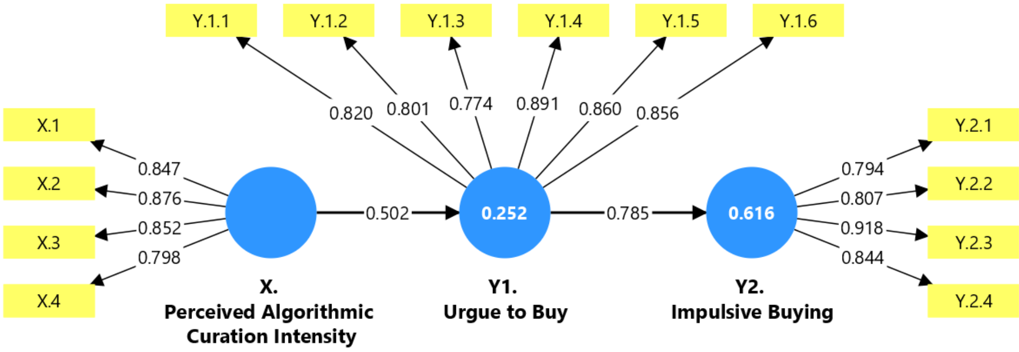

Figure 2. Path coefficients dan outer loadings
(Source: Analysis, 2026)

The evaluation of the measurement model began by testing the outer loadings for each indicator on the latent constructs. The results revealed that all outer loadings were greater than 0.7, for both Perceived Algorithmic Curation Intensity, Urge to Buy, and Impulsive Buying. This indicates that the indicators used have a strong relationship with the constructs they represent, demonstrating good measurement validity for each variable in the model. Additionally, the high values of construct reliability, including Cronbach's Alpha, Composite Reliability, and Average Variance Extracted (AVE), indicate that the constructs in this model exhibit excellent reliability and can be trusted as valid measurement tools for this study (see Table 2).

Table 2. The Result of Outer Loadings, Reliability, and Validity of Construct

Indicator	Loadings	Cronbach's Alpha (CA)	Composite Reliability (CR)	Average Variance Extracted (AVE)
Perceived Algorithmic Curation Intensity		0.864	0.908	0.712
X.1 Live content with the same type of product frequently reappears on my FYP.	0.847			
X.2 Certain live content often appears at the top of my page.	0.876			
X.3 The live content that appears aligns with my shopping needs.	0.852			
X.4 The system displays different live content after I skip a certain live session.	0.798			

Indicator	Loadings	Cronbach's Alpha (CA)	Composite Reliability (CR)	Average Variance Extracted (AVE)
Urge to Buy		0.913	0.932	0.697
Y1.1 While watching live, I feel compelled to buy products that were not in my shopping plan.	0.820			
Y1.2 I feel tempted to buy additional products while watching live, even though I had no prior intention.	0.801			
Y1.3 I find it difficult to resist the urge to buy products during the live stream.	0.774			
Y1.4 The urge to buy arises quickly when a product is displayed.	0.891			
Y1.5 Exposure to products during the live stream triggers an urge to buy, even though it was not planned.	0.860			
Y1.6 The desire to buy emerges immediately after I see a particular product in the live stream.	0.856			
Impulsive Buying		0.866	0.907	0.710
Y2.1 I purchase products during the live stream without prior planning.	0.918			
Y2.2 I make purchases without comparing them to other products.	0.794			
Y2.3 I buy products even though I had no initial intention.	0.807			
Y2.4 The purchase happens due to a	0.844			

Indicator	Loadings	Cronbach's Alpha (CA)	Composite Reliability (CR)	Average Variance Extracted (AVE)
momentary impulse.				

Source: Analysis, 2026

In testing discriminant validity, the results obtained show that both the Fornell-Larcker Criterion and HTMT ratio support good discriminant validity. All diagonal values for the constructs are higher than the values outside the diagonal, indicating that each construct can be clearly distinguished from the others (see Table 3). This confirms that the model has adequate discriminant validity, and there is no significant overlap between the constructs.

Table 3. The result of discriminant validity

Construct	Perceived Algorithmic Curation Intensity	Urge to Buy	Impulsive Buying
Fornell-Larcker Criterion:			
Perceived Algorithmic Curation Intensity	0.844		
Urge to Buy	0.502	0.835	
Impulsive Buying	0.477	0.785	0.842
HTMT (Heterotrait-Monotrait Ratio):			
Perceived Algorithmic Curation Intensity			
Urge to Buy	0.558		
Impulsive Buying	0.548	0.843	

Source: Analysis, 2026

The structural model evaluation was conducted by assessing the path coefficients, which measure the direct relationships between latent variables. The analysis results show that Perceived Algorithmic Curation Intensity has a positive effect on Urge to Buy with a path coefficient of 0.502. Although this relationship is considered moderate, these findings suggest that the perceived intensity of algorithmic curation can enhance consumers' desire to purchase. Furthermore, a stronger relationship was observed between Urge to Buy and Impulsive Buying, with a path coefficient of 0.785, indicating that the greater the urge to buy, the higher the likelihood of impulsive buying behavior (see Table 4).

Table 4. The structural model evaluation

	Original Sample	Sample Mean	Standard Deviation (STDEV)	F-Square
Perceived Algorithmic Curation Intensity → Urge to Buy	0.502	0.505	0.073	0.336
Urge to Buy → Impulsive Buying	0.785	0.789	0.041	1.605

Sumber: Analisis 2013

The F-square value of 0.336 for the relationship between Perceived Algorithmic Curation Intensity and Urge to Buy indicates a relatively large effect, while the F-square value of 1.605 for the relationship between Urge to Buy and Impulsive Buying suggests a very large effect. These results indicate that Urge to Buy has a very strong influence on Impulsive Buying behavior.

Table 5. The result of R-Square

	R-Square	R-Square Adjusted
Urge to Buy	0.252	0.244
Impulsive Buying	0.616	0.612

Source: Analysis, 2026

In terms of R-squared (R^2), the value obtained for Urge to Buy is 0.252, indicating that the model explains approximately 25.2% of the variance in the urge to buy. Meanwhile, the R^2 value for Impulsive Buying is 0.616, suggesting that the model explains 61.6% of the variance in impulsive buying behavior. While there is room for improvement, these results demonstrate that the model significantly contributes to understanding consumer behavior related to impulsive buying (see Table 5).

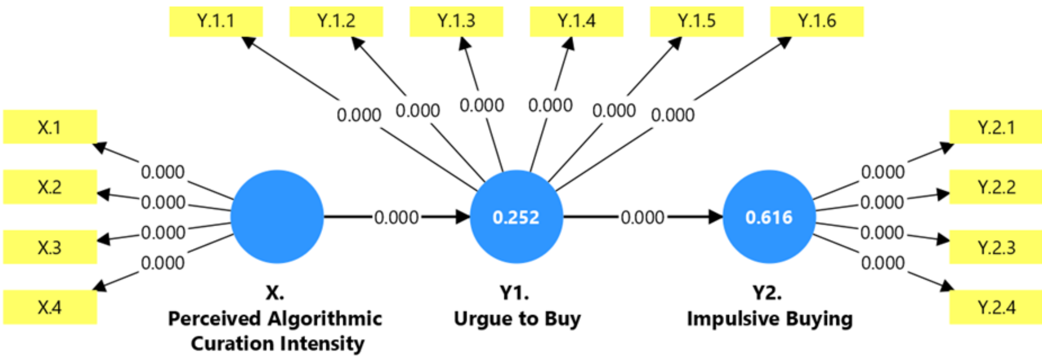

Figure 2. Structural Model (Source: Analysis, 2026)

Finally, to test the significance of the paths between the variables in the model, t-statistic testing was performed, with a very low p-value of 0.000 for both tested paths. This indicates that all paths in the model have strong statistical significance, providing strong support for the relationships between the variables proposed in the model.

The Relationship Between X (Perceived Algorithmic Curation Intensity) and Y1 (Urge to Buy)

The analysis results show that Perceived Algorithmic Curation Intensity (X) positively influences Urge to Buy (Y1) with a path coefficient of 0.502 and a highly significant p-value (0.000). This coefficient indicates that an increase in perceived algorithmic curation intensity enhances consumers' desire to buy. The influence is moderate, suggesting that the algorithms used on e-commerce platforms or applications can trigger consumers to feel more compelled to make purchases. These findings are consistent with previous research by Zhao et al. (2020), which demonstrated that personalized algorithm-based recommendations can increase consumers' desire to make impulsive purchases. Furthermore, Tsiros et al. (2021) revealed that algorithms that tailor shopping experiences to individual preferences tend to create an increase in purchase intention, reinforcing this study's findings that algorithmic curation influences the desire to buy.

The Relationship Between Urge to Buy and Y2 Impulsive Buying

The analysis results show that Urge to Buy (Y1) has a very strong influence on Impulsive Buying (Y2) with a path coefficient of 0.785 and a highly significant p-value (0.000). This high coefficient suggests that the greater the urge to buy, the higher the likelihood of impulsive buying occurring. This confirms that the urge to buy not only affects purchasing decisions but also plays a significant role in encouraging consumers to purchase without planning, consistent with the characteristics of impulsive buying behavior. This study supports the research by Liu et al. (2021), which shows that urges to purchase triggered by external factors (such as advertisements or product recommendations) are strongly related to impulsive buying behavior. Additionally, Kacen & Lee (2020) highlighted that emotional triggers in advertisements and digital promotions directly lead to impulsive buying decisions, aligning with the findings of this study, which emphasizes the desire that arises due to exposure to algorithmic curation.

The Mediating Role of Urge to Buy in the Relationship Between Perceived Algorithmic Curation Intensity and Impulsive Buying

Further analysis tested whether Urge to Buy (Y1) functions as a mediating variable in the relationship between Perceived Algorithmic Curation Intensity (X) and Impulsive Buying (Y2). The analysis results show that Y1 (Urge to Buy) indeed acts as a significant mediator. This can be seen from the path coefficients of 0.502 for Perceived Algorithmic Curation Intensity (X) to Urge to Buy (Y1) and 0.785 for Urge to Buy (Y1) to Impulsive Buying (Y2), both showing significant positive relationships. These findings confirm the role of Urge to Buy as a mediating variable, in line with research by Kunz et al. (2017), which found that impulsivity in purchasing is heavily influenced by cues provided through algorithm-based recommendations, which, in turn, increase the desire to buy and lead to impulsive buying. Cheung & Lee (2018) also highlighted that recommendation algorithms enhance the desire to buy by triggering emotional engagement, accelerating decisions for impulsive purchases.

E. CONCLUSION

This study successfully reveals the significant role of Perceived Algorithmic Curation Intensity in influencing Urge to Buy, which in turn drives Impulsive Buying behavior. The findings indicate that the algorithmic curation perceived by consumers can trigger the desire to purchase and strengthen impulsive buying behavior. Furthermore, this research emphasizes that Urge to Buy functions as a mediator bridging the relationship between algorithmic curation intensity and impulsive buying. This provides important insights for e-commerce platform developers and digital marketers on how algorithms can be optimized to influence consumer decisions.

Future research is recommended to test this model with other e-commerce platforms to identify differences in the impact of algorithmic curation across platforms. Additionally, further studies can involve specific product categories, such as fashion or electronics, and should explore the differing effects of algorithms based on demographic factors like age and digital literacy to understand how different consumer groups respond to algorithmic curation. Investigating the long-term effects of impulsive buying on brand loyalty and consumer satisfaction would also provide deeper insights into the lasting impact of purchases influenced by algorithms.

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