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Pleasure as a mediator of *economic benefit* and *online impulse buying* among Generation Z TikTok Live users in Semarang

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Abstract

Live commerce increasingly encourages impulse buying, yet the effect of *economic benefit* on *online impulse buying* remains inconsistent, while the emotional mechanism of *pleasure* requires further clarification. This study aims to examine the effect of *economic benefit* on *online impulse buying* and the mediating role of *pleasure* among Generation Z users of TikTok Live Streaming in Semarang. Using a quantitative explanatory approach, data were collected from 130 respondents selected through *purposive sampling* and analyzed using PLS-SEM with SmartPLS 4. The results show that *economic benefit* has no significant direct effect on *online impulse buying* ($\beta = 0.186$; $p = 0.072$), but significantly affects *pleasure* ($\beta = 0.562$; $p < 0.001$), which subsequently influences *online impulse buying* ($\beta = 0.400$; $p < 0.001$). The indirect effect is also significant ($\beta = 0.225$; $p < 0.001$). These findings demonstrate that *pleasure* functions as an emotional mechanism through which *economic benefit* is translated into *online impulse buying*.

Keywords: *Economic benefit*; *Pleasure*; *Online impulse buying*; TikTok Live Streaming; Generation Z.

Abstrak

Perdagangan berbasis siaran langsung semakin mendorong pembelian impulsif, tetapi pengaruh *economic benefit* terhadap *online impulse buying* belum konsisten dan mekanisme emosional *pleasure* masih perlu diperjelas. Penelitian ini bertujuan menganalisis pengaruh *economic benefit* terhadap *online impulse buying* serta menguji peran *pleasure* sebagai mediator pada Generasi Z pengguna TikTok Live Streaming di Semarang. Penelitian menggunakan pendekatan kuantitatif eksplanatori dengan 130 responden yang dipilih secara *purposive sampling* dan dianalisis menggunakan PLS-SEM melalui SmartPLS 4. Hasil menunjukkan bahwa *economic benefit* tidak berpengaruh langsung terhadap *online impulse buying* ($\beta = 0{,}186$; $p = 0{,}072$), tetapi berpengaruh positif terhadap *pleasure* ($\beta = 0{,}562$; $p < 0{,}001$), yang selanjutnya berpengaruh terhadap *online impulse buying* ($\beta = 0{,}400$; $p < 0{,}001$). Efek mediasi juga signifikan ($\beta = 0{,}225$; $p < 0{,}001$). Temuan ini menegaskan bahwa *pleasure* berfungsi sebagai mekanisme emosional yang menerjemahkan manfaat ekonomi menjadi pembelian impulsif.

Kata Kunci: *Economic benefit*; *Pleasure*; *Online impulse buying*; TikTok Live Streaming; Generasi Z.

Introduction

Digital commerce has evolved into an activity that extends beyond simply searching for and purchasing products. This transformation is evident in the growth of *live streaming commerce*, where promotion, entertainment, interaction, and transactions take place within the same real-time environment. Globally, the value of *live commerce* transactions continues to increase and is projected to exceed US$100 billion in the coming years (Salisu et al., 2025). TikTok is one of the platforms reinforcing this development through its *live streaming* feature, which enables sellers to offer products while interacting directly with potential buyers (Bai & Tan, 2024). This situation has altered consumption patterns because purchasing decisions can occur within minutes, or even seconds, after consumers encounter a product or promotion. Consequently, the boundary between planned needs and spontaneous purchases has become increasingly blurred. This phenomenon makes *online impulse buying* an important issue in the development of *live streaming*-based commerce.

The issue becomes more compelling when economic benefits constitute a central component of selling strategies. Price promotions, discounts, installment plans, *cashback*, and convenient payment options create the perception that consumers gain advantages from making a transaction. In Indonesia, the number of internet users has surpassed 200 million, while social media use has also reached a substantial proportion of the working-age population (Barata, 2019). This large user base provides considerable space for promotion strategies through digital platforms. However, economic benefits do not necessarily result in immediate purchases. Consumers may recognize that a product is cheaper without actually purchasing it. Conversely, feelings of enjoyment, excitement, satisfaction, or enthusiasm during the shopping process may make consumers more likely to follow their purchasing impulses. Thus, the issue is not merely how substantial the benefits offered are, but how these benefits shape consumers' emotional experiences.

This condition is particularly relevant to Generation Z, which has grown up in a digital environment and is accustomed to using social media as part of everyday life. In Indonesia, younger people constitute one of the most active groups of internet and social media users, making them a potential segment for the development of *live commerce*. TikTok itself has more than 100 million users in Indonesia, making the country one of the platform's largest markets globally (Budiman et al., 2024). This large user base creates opportunities for commerce that simultaneously integrates content and transactions. In this context, *economic benefit* can serve as an initial stimulus that attracts consumers' attention (Khachatryan et al., 2018), while *pleasure* can function as an internal state that determines how the stimulus is translated into action (Werner et al., 2023). Thus, impulse buying cannot be adequately explained by economic factors alone but needs to be examined through the emotional processes occurring throughout the *live shopping* experience.

Research on *online impulse buying* in digital environments has produced findings that are not entirely consistent. Research by Zhao et al. (2022) shows that economic benefits, promotions, and characteristics of digital environments can increase the tendency toward impulse buying. However, Hüttel et al. (2018) found that economic benefits do not necessarily have a direct effect on spontaneous purchasing decisions. From an emotional perspective, research by Shahpasandi et al. (2020) on *live streaming commerce* shows that enjoyment and positive experiences can increase consumers' tendency to engage in impulse buying. Nevertheless, the relationship between *economic benefit* and *pleasure* has also produced inconsistent patterns across different platform contexts. These differences reveal an unresolved issue: do economic benefits actually drive impulse buying directly, or does their influence first operate through consumers' emotional experiences? This question becomes increasingly important when the research focuses on Generation Z users of TikTok Live Streaming.

This study aims to examine the effect of *economic benefit* on *online impulse buying*, the effect of *economic benefit* on *pleasure*, the effect of *pleasure* on *online impulse buying*, and the mediating role of *pleasure* in these relationships among Generation Z users of TikTok Live Streaming in Semarang. This focus is important because the study seeks to identify not only what influences impulse buying, but also why and how such an influence occurs. Specifically, the study examines whether economic benefits can transform the shopping experience into feelings of pleasure that subsequently encourage spontaneous purchases. Its urgency lies in the increasingly strong integration of entertainment and transactions in digital commerce, while understanding of the emotional mechanisms underlying purchasing behavior remains limited. Accordingly, this study is expected to clarify the position of *pleasure* as a psychological mechanism linking economic benefits to *online impulse buying* behavior.

Method

This study employed a quantitative approach with an explanatory design to analyze the relationships among *economic benefit*, *pleasure*, and *online impulse buying* among Generation Z users of TikTok Live Streaming in Semarang City (Creswell & Poth, 2016). Respondents were selected using *purposive sampling* based on the characteristics of the research population, namely Generation Z individuals residing in Semarang who had experience making purchases through TikTok Live Streaming. The sample size was determined based on Hair et al.'s recommendation of 5–10 times the number of indicators used in PLS-SEM analysis. With 13 indicators consisting of five indicators for *economic benefit*, four for *pleasure*, and four for *online impulse buying*, the minimum sample size was set at 130 respondents. Data were collected through a questionnaire as primary data. The *economic benefit* construct was measured using five indicators

(X1–X5), *pleasure* using four indicators (Z1–Z4), and *online impulse buying* using four indicators (Y1–Y4), resulting in a total of 13 indicators.

The data were analyzed using Partial Least Squares–Structural Equation Modeling (PLS-SEM) with the assistance of SmartPLS 4. The analysis involved the evaluation of the measurement model and the structural model. The measurement model was evaluated using *outer loadings* to assess *convergent validity*, the Fornell–Larcker Criterion to assess *discriminant validity*, and Cronbach's Alpha, Composite Reliability, and Average Variance Extracted (AVE) to evaluate construct reliability and quality. Subsequently, the structural model was evaluated using R-Square and Q^2 Predict to assess the model's explanatory power and predictive relevance. Direct relationships were tested by examining path coefficients, *t*-statistics, and *p*-values through the *bootstrapping* procedure. Indirect effects were also examined to determine whether *pleasure* mediated the relationship between *economic benefit* and *online impulse buying*. Through this procedure, the study simultaneously tested the direct effect of *economic benefit* on *online impulse buying*, the effect of *economic benefit* on *pleasure*, the effect of *pleasure* on *online impulse buying*, and the mediating effect of *pleasure*. The results showed that all indicators had *outer loadings* that met the validity criteria and that all three constructs demonstrated adequate reliability.

Results and Discussion

Respondent characteristics and measurement model evaluation

The composition of the respondents provides an initial overview of the characteristics of the users who form the basis for the subsequent analysis. A total of 130 respondents who met the research criteria were included. Respondent characteristics covered gender, age, and purchase frequency through TikTok Live Streaming. As shown in Table 1, the 21–24 age group represented the largest group, with 78 respondents or 60%, followed by the 17–20 age group with 42 respondents or 32%, and the 25–28 age group with 10 respondents or 8%. In terms of purchase frequency, 58 respondents or 44.7% had made more than seven purchases, 44 respondents or 33.8% had made one to three purchases, while 28 respondents or 21.5% had made four to six purchases. This composition indicates that the respondents were predominantly young adults aged 21–24, with relatively diverse levels of purchasing experience through TikTok Live Streaming.

Table 1. Respondent characteristics

Characteristic	Category	Frequency	Percentage
Gender	Male	26	20%
	Female	104	80%
Age	17–20 years	42	32%

	21–24 years	78	60%
	25–28 years	10	8%
Purchase frequency	1–3 times	44	33.8%
	4–6 times	28	21.5%
	More than 7 times	58	44.7%
Total		130	100%

Source: Primary data processed (2026).

The quality of the indicators needs to be established before relationships among the variables are analyzed. Convergent validity was evaluated to determine the extent to which the indicators adequately represented their respective constructs. Hair et al. (2022) explain that *outer loading* is an important measure for evaluating indicator validity in PLS-SEM. The results presented in Table 2 show that the five *economic benefit* indicators had *outer loading* values ranging from 0.688 to 0.874. The four *pleasure* indicators ranged from 0.739 to 0.871, while the four *online impulse buying* indicators ranged from 0.808 to 0.839. All indicators were considered valid based on the criteria applied. Thus, each indicator demonstrated adequate ability to represent its respective construct and could be retained for the subsequent analysis. These results also indicate that no indicators needed to be eliminated from the measurement model.

Table 2. Convergent validity test results

Variable	**Indicator**	***Outer loading***	**Description**
Economic benefit	X1	0.705	Valid
	X2	0.768	Valid
	X3	0.688	Valid
	X4	0.742	Valid
	X5	0.874	Valid
Pleasure	Z1	0.871	Valid
	Z2	0.845	Valid
	Z3	0.815	Valid
	Z4	0.739	Valid
Online impulse buying	Y1	0.824	Valid
	Y2	0.839	Valid
	Y3	0.815	Valid
	Y4	0.808	Valid

Source: Primary data processed using SmartPLS 4 (2026).

The distinction among constructs also needs to be examined to ensure that the variables represent genuinely different concepts. Fornell and Larcker (1981) developed the *discriminant validity* criterion by comparing the square root of the AVE for each construct with the correlations among constructs. As shown in Table 3, the square roots of the AVE for *economic benefit*, *online impulse buying*, and *pleasure* were 0.680, 0.822, and 0.819, respectively. These values were higher than the correlations between the respective constructs and the other constructs. Thus, all three constructs met the *discriminant validity* criterion based on the Fornell–Larcker approach. Henseler et al. (2015) emphasize that discriminant validity is important for ensuring that constructs in an empirical model are distinct and do not excessively overlap. These results indicate that *economic benefit*, *pleasure*, and *online impulse buying* can be treated as distinct constructs in the structural model analysis.

Table 3. Discriminant validity test results based on the Fornell–Larcker criterion

Variable	***Economic benefit***	***Online impulse buying***	***Pleasure***
Economic benefit	0.680		
Online impulse buying	0.410	0.822	
Pleasure	0.562	0.504	0.819

Source: Primary data processed using SmartPLS 4 (2026).

The internal consistency of the constructs was subsequently evaluated using Cronbach's Alpha, Composite Reliability, and Average Variance Extracted (AVE). Sarstedt et al. (2021) explain that reliability assessment is an important part of ensuring construct quality in PLS-SEM analysis. As shown in Table 4, *economic benefit* had a Cronbach's Alpha of 0.716, Composite Reliability of 0.809, and AVE of 0.562. The *pleasure* construct obtained values of 0.837, 0.891, and 0.671, respectively, while *online impulse buying* obtained values of 0.840, 0.893, and 0.675. All constructs met the reliability criteria applied. Ringle et al. (2015) also identify reliability assessment as an important component of model evaluation using SmartPLS. These results indicate that the indicators within each construct demonstrated adequate internal consistency. Therefore, all constructs could be used in the subsequent structural model analysis.

Table 4. Construct reliability test results

Variable	**Cronbach's Alpha**	**Composite Reliability**	**AVE**	**Description**
Economic benefit	0.716	0.809	0.562	Reliable
Pleasure	0.837	0.891	0.671	Reliable
Online impulse buying	0.840	0.893	0.675	Reliable

Source: Primary data processed using SmartPLS 4 (2026).

Overall, the measurement model evaluation results indicate that the instrument met the requirements for proceeding with PLS-SEM analysis. Chin (1998) identifies measurement model evaluation as an important stage before structural relationships among constructs are tested. The results in Table 2 show that all indicators met the requirements for convergent validity, while Table 3 demonstrates that discriminant validity was established among the constructs. Furthermore, Table 4 shows that all constructs had adequate internal reliability based on Cronbach's Alpha and Composite Reliability. Taken together, these results provide a basis for concluding that the measurement instrument was capable of producing data suitable for subsequent analysis. With validity and reliability established, the analysis can proceed to the evaluation of the structural model, including the explanatory capacity of the endogenous constructs and the testing of direct and indirect relationships among the variables.

Structural model evaluation and hypothesis testing

The model's ability to explain the endogenous variables can be assessed through the R-Square values. Falk and Miller (1992) explain that R-Square is used to determine the proportion of variance in an endogenous construct that can be explained by the exogenous constructs in the model. As presented in Table 5, the R-Square value for *pleasure* is 0.316, with an adjusted R-Square of 0.311. Meanwhile, *online impulse buying* has an R-Square value of 0.278 and an adjusted R-Square of 0.268. These results indicate that the model explains 31.6% of the variance in *pleasure* and 27.8% of the variance in *online impulse buying*. Cohen (1988) emphasizes that the interpretation of model strength should consider the research context and the complexity of the relationships being examined. Thus, both endogenous constructs demonstrate an explanatory capacity that provides a basis for proceeding with the structural model evaluation.

Table 5. R-Square test results

Endogenous variable	**R-Square**	**Adjusted R-Square**
Pleasure	0.316	0.311
Online impulse buying	0.278	0.268

Source: Primary data processed using SmartPLS 4 (2026).

The model's predictive capability was subsequently assessed using Q^2 Predict values. Stone (1974) introduced the *cross-validatory* approach to assess a model's predictive capability, while Geisser (1974) developed a predictive approach that provided the basis for the use of the Q^2 measure. The results presented in Table 6 show that the Q^2 Predict values for the *pleasure* indicators range from 0.110 to 0.243. For the *online impulse buying* indicators, the Q^2 Predict values range from 0.029 to 0.156. All values are positive, indicating that the model demonstrates predictive relevance for the endogenous constructs examined. The highest Q^2 Predict value is found for indicator Z1 at 0.243, whereas the lowest value is found for indicator Y3 at 0.029. These results indicate that the model has predictive capability across all evaluated indicators and can therefore proceed to the testing of relationships among the variables.

Table 6. Predictive relevance test results (Q^2 Predict)

Variable	**Indicator**	**Q^2 Predict**	**PLS-SEM RMSE**	**LM RMSE**
Pleasure	Z1	0.243	0.754	0.761
	Z2	0.193	0.694	0.706
	Z3	0.232	0.652	0.668
	Z4	0.110	0.723	0.745
Online impulse buying	Y1	0.156	1.051	1.036
	Y2	0.054	1.202	1.154
	Y3	0.029	1.079	1.035
	Y4	0.123	1.211	1.182

Source: Primary data processed using SmartPLS 4 (2026).

The direct effects were tested to assess empirical support for the relationships formulated in the hypotheses. As shown in Table 7, the relationship between *economic benefit* and *online impulse buying* produced a path coefficient of 0.186, a *t*-statistic of 1.801, and a *p*-value of 0.072, leading to the rejection of H1. In contrast, the relationship between *economic benefit* and *pleasure* produced a coefficient of 0.562, a *t*-statistic of 8.770, and a *p*-value of <0.001, supporting H2. The relationship between *pleasure* and *online impulse buying* was also significant, with a coefficient of 0.400, a *t*-statistic of 4.485, and a *p*-value of <0.001, supporting H3. Cohen (1988) explains that relationship testing should consider both path coefficients and their significance levels. These results show that two of the three direct relationships received empirical support, whereas one relationship did not reach the established level of significance.

Table 7. Direct effect and hypothesis testing results

Hypothesis	**Relationship**	**Path coefficient**	***t*-statistic**	***p*-value**	**Decision**
H1	*Economic benefit → Online impulse buying*	0.186	1.801	0.072	Rejected
H2	*Economic benefit → Pleasure*	0.562	8.770	<0.001	Supported
H3	*Pleasure → Online impulse buying*	0.400	4.485	<0.001	Supported

Source: Primary data processed using SmartPLS 4 (2026).

The indirect effect was subsequently examined to determine whether *pleasure* mediates the relationship between *economic benefit* and *online impulse buying*. Preacher and Hayes (2008) explain that indirect effects are used to identify the influence of one variable on another through a mediator. The results presented in Table 8 show a path coefficient of 0.225, a *t*-statistic of 4.126, and a *p*-value of <0.001. Accordingly, H4 was supported because the indirect effect was statistically significant. Zhao et al. (2010) emphasize that conclusions regarding mediation should consider the patterns of both direct and indirect effects simultaneously. Nitzl et al. (2016) also demonstrate that testing indirect effects can help identify the mechanisms underlying relationships within a PLS-SEM model. These results indicate a significant indirect pathway from *economic benefit* to *online impulse buying* through *pleasure*.

Table 8. Indirect effect testing results

Hypothesis	**Relationship**	**Path coefficient**	***t*-statistic**	***p*-value**	**Decision**
H4	*Economic benefit → Pleasure → Online impulse buying*	0.225	4.126	<0.001	Supported

Source: Primary data processed using SmartPLS 4 (2026).

Overall, the structural model evaluation indicates that the model has explanatory capacity and predictive relevance for the endogenous constructs. The R-Square values show that *economic benefit* explains part of the variance in *pleasure*, while the relationships specified in the model explain part of the variance in *online impulse buying*. The hypothesis testing results indicate that *economic benefit* does not have a significant direct effect on *online impulse buying*, but it has a significant effect on *pleasure*. In turn, *pleasure* significantly affects *online impulse buying*, while the indirect pathway through *pleasure* is also significant. This pattern provides an empirical basis for further examining the role of *pleasure* in the relationship between *economic benefit* and *online impulse buying*.

The role of *pleasure* in the relationship between *economic benefit* and *online impulse buying*

Economic benefits are often considered the most rational reason for encouraging consumers to make purchases. More affordable prices, promotions, savings, and convenient payment options should make products increasingly attractive to purchase. However, this logic becomes more complex when purchases take place through *live streaming commerce*, as consumer decisions are shaped not only by benefit calculations but also by emotional experiences during the transaction process. Under such conditions, economic benefits may function as an initial stimulus but do not necessarily produce impulse buying behavior directly. Through the *Stimulus–Organism–Response* (S-O-R) perspective, Mehrabian and Russell (1974) explain that environmental stimuli first influence an individual's internal state before producing a behavioral response. This framework positions *economic benefit* as the stimulus, *pleasure* as the internal state, and *online impulse buying* as the response, making the relationships among these three constructs worthy of further analysis.

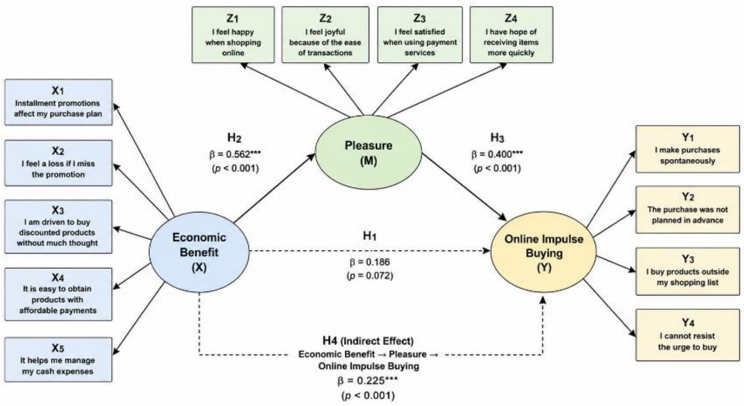

Figure 1. Empirical Model of the Relationships among Economic Benefit, Pleasure, and Online Impulse Buying

Source: Author's elaboration based on the research findings (2026).

Figure 1 is used to illustrate the overall empirical structure of the relationships while clarifying the position of *pleasure* within the mechanism linking the variables. The model consists of three constructs: *economic benefit*, measured by five indicators; *pleasure*, measured by four indicators; and *online impulse buying*, measured by four indicators. At the structural level, *economic benefit* has two pathways toward *online impulse buying*: a direct pathway and an indirect pathway through *pleasure*. The first branch represents H1, while the second forms the sequence of H2 and H3, which also provides the basis for testing H4 as a mediation effect. This structure demonstrates that economic benefits are not only positioned as a factor associated with purchasing behavior but also as a stimulus capable of shaping consumers' emotional experiences. This pattern is consistent with the S-O-R logic of Mehrabian and Russell (1974), which positions the internal state as a link between environmental stimuli and behavioral responses.

The first branch in Figure 1 illustrates the direct relationship between *economic benefit* and *online impulse buying*, but this pathway did not receive statistical support. A coefficient of 0.186 with a *p*-value of 0.072 indicates that perceived economic benefits were not sufficiently strong to directly encourage impulse buying. This condition is understandable because economic benefits primarily provide functional reasons for considering a transaction, whereas impulse buying involves spontaneous urges and a tendency to act without prior planning. Rook (1987) conceptualizes impulse buying as a strong and spontaneous purchasing urge, while Beatty and Ferrell (1998) demonstrate that impulse buying is influenced by situational conditions and consumers' internal states. Verhagen and van Dolen (2011) likewise position characteristics of the online environment as an important factor in the formation of impulse buying. In contrast to Lamis et al. (2022), who found a direct effect of *economic benefit* on *online impulse buying*, the present findings indicate that economic benefits do not automatically transform rational considerations into spontaneous purchasing actions.

The second branch reveals a stronger relationship when *economic benefit* is directed toward *pleasure*. A coefficient of 0.562 with a *p*-value of <0.001 indicates that economic benefits can generate positive emotional experiences. In other words, promotions, affordable prices, and opportunities to save money do not remain merely functional advantages but can also make the shopping process more enjoyable. Within the S-O-R framework, this condition represents the transformation of an external stimulus into an internal state. Mehrabian and Russell (1974) explain that environmental stimuli can generate affective responses that subsequently influence behavior. This explanation is reinforced by Koufaris (2002), who demonstrates the importance of *enjoyment* in online consumer experiences. Consistent with Camacho-Otero et al. (2018), economic benefits have also been found to be associated with positive consumer experiences. This finding strengthens the view that economic value gains psychological significance when consumers not only perceive savings but also experience the transaction as beneficial and enjoyable.

Once economic benefits generate an emotional experience, the position of *pleasure* becomes increasingly important in explaining the emergence of impulse buying. The relationship between *pleasure* and *online impulse buying* produces a coefficient of 0.400 with a *p*-value of <0.001, indicating that a pleasurable experience is associated with a greater tendency to make spontaneous purchases. This condition suggests that consumers who feel happy, excited, satisfied, or positively expectant during the shopping process are more likely to respond to purchasing impulses that emerge situationally. Verplanken and Herabadi (2001) explain that impulse buying consists of affective and cognitive components, making emotional aspects inseparable from the tendency to engage in impulsive purchases. In the context of *live-streaming e-commerce*, Li et al. (2022) likewise found a relationship between *pleasure* and impulse buying through the S-O-R framework. This finding reinforces the present results while demonstrating that emotional experiences occupy an important position in digital purchasing behavior. Thus, *pleasure* is not merely a consequence of shopping activity but can function as a psychological state that increases the likelihood of consumers following spontaneous purchasing urges.

The mediation relationship represents the most important part because it demonstrates how economic benefits can ultimately be associated with impulse buying through consumers' emotional states. The indirect effect of *economic benefit → pleasure → online impulse buying* is 0.225 with a *p*-value of <0.001, indicating that the mediation pathway is significant, whereas the direct pathway from *economic benefit* to *online impulse buying* is not significant. This pattern indicates that *pleasure* functions as a mechanism through which economic benefits are translated into behavioral impulses. Ngo et al. (2024) found a different pattern in the context of *Shopee Video*, particularly because the relationship between *economic benefit* and *pleasure* was not significant. This difference is important because the present study indicates that economic benefits may have stronger emotional consequences in the context of TikTok Live Streaming. The real-time and interactive characteristics of *live commerce* may be one possible factor distinguishing this process. However, differences between platforms cannot be positioned as a direct cause because this study did not conduct a comparative analysis across platforms.

This mediation pattern should also be situated within the context of Generation Z's behavior as a group increasingly familiar with the *live commerce* environment. Purnomo and Murhadi (2025) demonstrate that *live commerce* platforms are associated with impulse buying behavior among Generation Z in Java, making regional context and generational characteristics relevant to understanding such behavior. The present findings extend this perspective by demonstrating that impulse buying is associated not only with platform characteristics or interaction intensity but also with how consumers interpret the benefits they receive during transactions. Whereas Li et al. (2024) emphasize the role of *live commerce* characteristics in encouraging impulse buying, the present findings indicate that this process involves a more specific psychological sequence: economic benefits first generate *pleasure*, which subsequently relates to impulsive purchasing behavior. Thus, in the context of Generation Z in Semarang, emotional experience represents an important link between economic stimuli and spontaneous purchasing decisions.

Taken together, these relationships demonstrate that *online impulse buying* cannot be adequately explained solely by the extent of the economic benefits offered to consumers. Economic benefits function as a stimulus, but their influence on behavior becomes more meaningful when the stimulus generates an internal state of *pleasure*. This pattern reinforces the S-O-R perspective of Mehrabian and Russell (1974) while further emphasizing that consumer responses in digital environments depend on the psychological processes that occur after a stimulus is received. Chan et al. (2017) show that research on *online impulse buying* has increasingly considered situational and digital environmental factors, while Wang et al. (2021) highlight the importance of consumer experiences in *live commerce* environments. The present findings extend this understanding by positioning *pleasure* as a linking mechanism that explains why economic benefits are not significant directly but become significant through an indirect pathway. Practically, these results indicate that *live commerce* strategies should not rely solely on low prices or promotions but should also create enjoyable transaction experiences so that economic benefits can be translated into purchasing behavior.

Conclusion

Online impulse buying behavior among Generation Z users of TikTok Live Streaming is not shaped solely by the economic benefits associated with a transaction. The results show that *economic benefit* has no significant direct effect on *online impulse buying* (β = 0.186; p = 0.072), but has a strong effect on *pleasure* (β = 0.562; p < 0.001), while *pleasure* significantly influences *online impulse buying* (β = 0.400; p < 0.001). Furthermore, the indirect effect of *economic benefit* on *online impulse buying* through *pleasure* is significant (β = 0.225; p < 0.001). This pattern indicates that economic benefits operate through an emotional process: perceived benefits first generate a pleasurable experience, which subsequently encourages impulse buying. Thus, *pleasure* serves as an important mechanism explaining how economic stimuli are translated into behavioral responses in the TikTok Live Streaming environment.

The contribution of this study lies in explaining the emotional mechanism underlying the relationship between economic benefits and impulse buying, particularly by positioning *pleasure* as a mediator among Generation Z users of TikTok Live Streaming in Semarang. These findings extend the understanding that economic strategies such as promotions, affordable prices, and savings do not automatically generate impulse buying without an accompanying emotional response. Nevertheless, the study is limited by the use of respondents from a single geographic area and a single platform user group, which limits the generalizability of the findings to Generation Z as a whole or to other *live commerce* platforms. Future studies are encouraged to involve broader geographical areas, compare multiple *live commerce* platforms, and incorporate variables such as *social interaction*, *arousal*, *urgency*, or *trust* to provide a more comprehensive explanation of *online impulse buying* formation.

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