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THE EFFECT OF PERSONALIZED ARTIFICIAL INTELLIGENCE INTERACTION QUALITY ON IMPULSIVE STREAMING INTENTIONS MEDIATED BY AFFECTIVE RESPONSES

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ABSTRACT

This study aims to analyse the effect of artificial intelligence–based interaction quality and personalisation on impulsive streaming in social commerce live streaming, with affective aspects as a mediating variable. A quantitative approach was employed using Partial Least Squares–Structural Equation Modelling (PLS-SEM), involving 105 respondents who were students of Surabaya State University. The results indicate that interaction quality and artificial intelligence–based personalisation have a positive effect on affective aspects, which subsequently increase impulsive streaming in social commerce live streaming. In addition, both independent variables also have a direct positive effect on impulsive streaming, while affective aspects function as a mediator that strengthens these relationships. This study is limited to the TikTok platform and student respondents; therefore, future research is recommended to expand the research context and population coverage. A total of five hypotheses were tested in this study, and all were accepted based on the PLS-SEM.

Keywords: *Interaction Quality, Artificial Intelligence Personalisation, Affective Aspects, Impulsive Purchase Intentions, Social Commerce Live Streaming.*

INTRODUCTION

In today's digital era, social commerce has become one of the fastest-growing industries (Wardhana, 2024) . Technological advances have driven various innovations in the world of social commerce, one of which is the live streaming feature. Consumers are drawn to this feature because it offers a more interactive and real-time shopping experience. Through live streaming, social commerce creates a shopping atmosphere that closely resembles in-person shopping. This enhances consumer engagement and attracts more users to make direct purchases (Shang *et* al., 2023) .

According to , sales activities through live streaming have proven to increase turnover by 73%, expand market reach by 68%, reduce promotional costs by 64%, facilitate real-time interaction with customers by 60%, increase customer trust by 59%, provide a sense of security in transactions by 49%, and create a competitive advantage by 37%.

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Table 1.1 Data on platforms used by Southeast Asian consumers in 2022

Platform	Percentage
Social media	83
E-commerce	64
Live streaming only	11

Source: SEA Ahead Wave 5 (2022)

Based on the results of the SEA Ahead Wave 5 survey in (Ipsos, 2022) , it shows that most consumers in Southeast Asia access live streaming through social media platforms (83%) such as Facebook, Instagram Live, and YouTube Live; e-commerce platforms (64%) such as Shopee, Tokopedia, TikTok Shop, and Lazada; and dedicated live streaming applications (11%) such as Twitch and Periscope. In Indonesia, 78% of consumers are aware of the alternative of shopping via live streaming, 71% of whom have accessed it, and 56% admit to having purchased products via live streaming.

Table 1.*2* Average monthly expenditure on online shopping

Expenditure	Percentage
>Rp 1,000,000	19
Rp 400,001 – Rp 600,000	15
IDR 200,001 – IDR 400,000	27
<Rp 200,000	19

Source: (DataIndonesia.id, 2024)

The average expenditure per person for online shopping is mostly between Rp 200,001 and Rp 400,000, accounting for 27%. The development of Social Commerce live streaming is supported by artificial intelligence (AI), which enables personalisation of the user experience and improved interaction quality through data analytics and preference-based recommendations (Dangi et al., 2023) . AI-based personalisation plays a significant role in driving impulsive purchasing intentions. Based on previous shopping behaviour, AI is able to understand consumer preferences and present relevant live streams on the main page, thereby creating a more engaging shopping experience. In the context of live streaming social commerce, this personalisation makes shopping sessions more focused on individual needs and indirectly triggers faster purchase intent because consumers feel that the products displayed match their desires (Kusuma *et al*., 2023).

However, there are challenges in maintaining consumer attention and interest to keep them engaged in live streaming sessions and attract more viewers (Ika *et al*., 2024) . Streamers are not always successful in building strong purchasing intent through their interactions. Some consumers feel less confident about product recommendations when product presentations appear inauthentic or excessive, resulting in low conversion and consumer engagement (Dwipradhana, 2023) .

Based on previous research conducted by (Dharmawan *et* al., 2024) , the quality of interactions in social commerce live streaming often reveals several weaknesses, particularly a lack of focus on the overall user experience. In addition, research on social commerce live streaming is still relatively scarce (Xu *et* al., 2019) . Previous studies have examined impulsive

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purchase intentions in live streaming using the SOR (Stimulus-Organism-Response) theory (Festyan *et al*., 2023; Lee & Chen, 2021; G. Li *et al*., 2022; Masitoh *et al*.., 2024) , but they did not include artificial intelligence-based personalisation as a factor influencing impulsive purchase intentions. However, AI-based personalisation can create a more relevant and engaging shopping experience for consumers (Wardhana, 2024) .

Based on these issues, this study aims to analyse the impact of interaction quality and AI-based personalisation on impulsive purchase intent in social commerce live streaming, mediated by affective aspects. To achieve this objective, this study employs a quantitative approach with data analysis using PLS-SEM. The sample consists of 105 active students from Surabaya State University, calculated using the Slovin formula and selected through purposive sampling.

LITERATURE REVIEW

Interaction Quality

Interaction quality, according to (Bao *et* al., 2016) , refers to buyers' perceptions of the level of engagement and communication between buyers and sellers.According to , interaction quality includes the ability to provide a sense of trust and security during transactions, having a good reputation, facilitating communication, creating a more personal emotional feeling, having confidence in providing personal information, being able to create a specific community, and providing confidence that promises made will be kept.Researchers conclude that interaction quality in the context of social commerce live streaming refers to how effective and satisfying communication between streamers and consumers is during live broadcasts. Quality interactions can build more personal and emotional relationships, which in turn influence consumers' impulsive purchasing decisions.

AI-Based Personalisation

According to*et* al., 2024) , AI-based personalisation is an approach that enhances the user experience by tailoring preferences based on personal data such as search history, location, and product preferences. According to (Maulida & Jaya, 2024) , AI-based personalisation is an approach where companies utilise artificial intelligence capabilities to tailor marketing activities, services, or user experiences based on individual needs, interests, and characteristics. This process involves analysing customer data to provide relevant and automatically tailored solutions, such as customising web pages or product recommendations specific to each individual. This is achieved using methods like Machine Learning (which enables systems to learn from data and experience) and Natural Language Processing (which enables interaction with human language).

Researchers conclude that the definition of artificial intelligence-based personalisation is an approach that utilises AI capabilities to enhance the user experience by customising marketing activities, services, or recommendations based on individual needs, interests, characteristics, and personal data such as search history, location, and product preferences. This process involves analysing customer data to provide relevant and automated solutions, such as customising web pages or specific product recommendations. By using methods such as Machine Learning (which enables systems to learn from data and experience) and Natural

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Language Processing (which enables interaction with human language), AI-based personalisation creates a more tailored and efficient experience for each user.

Affective Aspect

(Inaku & Paputungan, 2022) defines Affective as a person's tendency to accept or reject awareness that is considered good or bad, which has a tendency towards positive or negative attitudes. According to Affective refers to everything related to attitudes, character, behaviour, interests, emotions, and values within each individual.

Researchers conclude that the affective aspect refers to feelings, emotions, or moods that arise in response to external stimuli. In affective theory, experts emphasise the importance of the affective role in human decision-making and motivation (Inaku & Paputungan, 2022)

METHODS

This study uses a quantitative approach with an explanatory research type. The main objective of explanatory research is to analyse and describe the relationship between variables to validate the formulated hypothesis. The explanatory approach was chosen because the purpose of this study was to test the influence of independent variables (Mulyadi, 2013) , namely the quality of interaction and personalisation based on artificial intelligence, on the dependent variable, namely impulsive purchase intention in live streaming social commerce through the mediating variable, namely the affective aspect. In this study, the relationship between variables was tested to see whether the quality of interaction and personalisation based on artificial intelligence influences impulsive purchase intention and is mediated by the affective aspect. This study uses a quantitative approach, which is an approach used to study a specific population or sample. Data analysis was conducted statistically with the aim of testing the determined hypotheses (Sugiyono, 2018).

Population and Sample

Population According to , population refers to a group that includes objects and subjects with a certain number and characteristics determined by the researcher to be analysed and then concluded (Sugiyono, 2018) . In this study, the population consists of 6,203 active students at Surabaya State University (PD UNESA, 2024)

Sample. According to (Sugiyono, 2018) , a sample is a part of the population's size and characteristics. A sample can be defined as a part drawn from the population. To determine the sample size of a population, researchers use the Slovin technique. The Slovin technique is one of the concepts studied in statistics and is used to determine the minimum sample size required in a study (Agustian, 2024) .

The sample selection technique used purposive sampling, which is the selection of samples based on specific criteria (Sugiyono, 2018) . The sample taken for this study was a portion of the active students at Surabaya State University majoring in Digital Business, which totalled 1,108 active students (PD UNESA, 2024) . Since the population size was known, the sample calculation used the Slovin formula as follows:

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Formula: $n = \frac{N}{1N.e^2}$

n = sample

N = population

e = estimated error rate

Therefore, the sample size for this study is:

$n = \frac{1108}{1+1108(0,1)^2}$

n = 91.7

Note:

N =population size

N = sample size

E =percentage of margin of error due to inaccuracy (sampling error that is still tolerable is 10%).

Data Analysis Techniques

The data analysis techniques used in this study include descriptive analysis, *Structural Equation Model* (*SEM*) analysis, and hypothesis testing.

1. Descriptive Analysis

According to descriptive analysis is a data analysis method that aims to describe or illustrate the data that has been collected as it is, without the intention of drawing conclusions or making generalisations that apply broadly. The data to be described is data related to the demographics of respondents and respondent data in questionnaires on active students of the Digital Business study programme at Surabaya State University. Based on the data collected from the respondents' answers, the three box method formula (Ferdinand, 2014) was used to make classification easier.

$$Interval = \frac{\text{Skor maksimum} - \text{Skor minimum}}{3}$$

2. *Structural Equation Model Partial Least Squares* (SEM-PLS) Analysis

This study uses a data analysis method with a Structural Equation Model (SEM) approach based on Partial Least Square (PLS). PLS is a structural equation modelling (SEM) technique that focuses on components or variants. Structural Equation Model (SEM) itself is a statistical method used to test complex relationships between variables simultaneously (Sofwatillah et al., 2024) . With this approach, the influence of independent, mediating, and dependent variables can be determined. According to (Martinez-Ruiz & Montañola-Sales, 2019) , Structural Equation Modelling (SEM) is a multivariate analysis method used to describe simultaneous linear relationships between observed variables (indicators) and latent variables that cannot be measured directly. Latent variables are variables that cannot be directly observed (unobserved) or measured (unmeasured), so their measurement requires several indicators. SEM is a covariance that generally tests causality or theory, while PLS is more of a predictive model (Sofwatillah et al., 2024) . However, there are differences between covariance-based SEM and component-based PLS in the application of structural equation models, particularly

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in testing or developing theories for prediction purposes. In this study, the analysis technique used was PLS, which was carried out in two stages, namely:

1. *Measurement model* testing, which tests the validity and reliability of the constructs of each variable indicator
2. *Structural model* testing, which aims to determine whether there is an influence between variables or correlations between measured constructs, using the t-test in the PLS method.

RESULTS AND DISCUSSION

Measurement Model Test (Outer Model)

According to (Ghozali, 2021), measurement model evaluation is conducted to ensure the validity and reliability of the applied model by describing the relationship between each indicator and the latent variable it represents. Validity testing is conducted to assess the extent to which a research instrument is capable of measuring the variables that should be measured.

Average Variance Extracted (AVE)

Table 4.1Average Variance Extracted (AVE) Test

Variable	AverageVariance Extracted (AVE)	Description
Interaction Quality (X1)	0.68	Valid
Artificial Intelligence-Based Personalisation (X2)	0.707	Valid
Affective Aspect	0.749	Valid
Impulsive Purchase Intention	0.681	Valid

Source: SmartPLS 4.1.1.4 Output, Data Processing Process 2025

Based on the table above, the *Average Variance Extracted* (AVE) values for all variables exceed 0.5 , indicating that the data meets the criteria, meaning that a latent variable can explain more than half of the variance of its indicators on average.

Convergent Validity

The first step is to measure the extent to which an indicator has a positive correlation with other indicators in the same construct. This assessment can be done through data processing using the Outer Loading value. An indicator in a study can be considered valid if it has a correlation value of more than 0.7 (Ghozali, 2021)

Table 4.2 Convergent Validity Test

Item	Interaction Quality (X1)	Artificial Intelligence-Based Personalisation (X2)	Affective Aspect (Z)	Impulsive Purchase Intention (Y)	Description
X1.1	0.819				Valid
X1.2	0.867				Valid
X1.3	0.806				Valid

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Item	Interaction Quality (X1)	Artificial Intelligence-Based Personalisation (X2)	Affective Aspect (Z)	Impulsive Purchase Intention (Y)	Description
X1.4	0.799				Valid
X1.5	0.831				Valid
X1.6	0.825				Valid
X2.1		0.850			Valid
X2.2		0.801			Valid
X2.3		0.843			Valid
X2.4		0.870			Valid
Z1.1			0.860		Valid
Z1.2			0.861		Valid
Z1.3			0.853		Valid
Z1.4			0.887		Valid
Y1.1				0.818	Valid
Y1.2				0.812	Valid
Y1.3				0.792	Valid
Y1.4				0.837	Valid
Y1.5				0.863	Valid

Source: SmartPLS 4.1.1.4 Output, Data Processing Process 2025

Based on the table above, it can be seen that the results of all indicators meet the significance value requirement of > 0.70. Thus, the construct is considered valid and has met the validity requirements because it has an outer loading value above 0.70.

Discriminant Validity

Discriminant validity can be evaluated through cross loading values. An indicator is considered valid if it has a higher correlation coefficient with its own construct than with other constructs. The discriminant validity test aims to ensure that a construct is truly different from other constructs. The results of the cross loading test with SmartPLS in this study are presented as follows .

Table 4.3. Discriminant Validity

Item	Interaction Quality	Artificial Intelligence-Based Personalisation	Impulsive Purchase Intention	Affective Aspect
X1.1	**0.819**	0.788	0.778	0.786
X1.2	**0.867**	0.831	0.834	0.813
X1.3	**0.806**	0.703	0.727	0.742
X1.4	**0.799**	0.687	0.686	0.710
X1.5	**0.831**	0.781	0.733	0.731
X1.6	**0.825**	0.751	0.740	0.762
X2.1	0.768	**0.850**	0.756	0.739

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Item	Interaction Quality	Artificial Intelligence-Based Personalisation	Impulsive Purchase Intention	Affective Aspect
X2.2	0.738	**0.801**	0.730	0.706
X2.3	0.790	**0.843**	0.782	0.837
X2.4	0.795	**0.870**	0.844	0.800
Y1.1	0.773	0.775	**0.818**	0.784
Y1.2	0.704	0.754	**0.812**	0.745
Y1.3	0.756	0.747	**0.792**	0.737
Y1.4	0.763	0.766	**0.837**	0.759
Y1.5	0.762	0.780	**0.863**	0.790
Z1.1	0.772	0.778	0.815	**0.860**
Z1.2	0.779	0.780	0.807	**0.861**
Z1.3	0.805	0.823	0.804	**0.853**
Z1.4	0.824	0.795	0.775	**0.887**

Source: SmartPLS 4.1.1.4 Output, Data Processing Process, 2025

Based on the table above, it can be seen that the cross-loading results should show that each indicator in a construct has a higher value than the indicators in other constructs, so that the indicators can be considered valid.

Composite Reliability

Reliability testing is used to assess questionnaires that function as indicators of a variable. An instrument or measuring tool is considered reliable if it is able to produce consistent and stable measurements. According to (Ghozali, 2021) , the *composite reliability* and *Cronbach's alpha* values must be > 0.70 to be considered reliable.

Table 4.4. Composite Reliability

Variable	*Cronbach's Alpha*	Composite Reliability
Interaction Quality (X1)	0.906	0.908
Artificial Intelligence-Based Personalisation (X2)	0.862	0.865
Affective Aspect (Z)	0.888	0.888
Impulsive Purchase Intention (Y)	0.882	0.883

Source: SmartPLS 4.1.1.4 Output, Data Processing 2025

Based on the table above, the results of *Cronbach's Alpha* and *Composite Reliability* have values greater than 0.70. This indicates that the variables in this research model can be considered reliable.

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Structural Model Test (Inner Model)

According to The structural model test aims to assess the relationship between latent variables in the study. The testing conducted on the inner model begins by looking at the R-Square value for each endogenous latent variable.

R-Square

The *R-Square* value is the coefficient of determination for the endogenous construct. The criteria for *R-Square* values are 0 - 0.24 (very weak), 0.25 - 0.49 (weak), 0.50 - 0.74 (moderate), > 0.75 (strong) (Ghozali, 2021)

Table 4.5 R-Square Test

	R-Square
Affective Aspect	0.880
Impulsive Purchase Intentions	0.899

Source: SmartPLS 4.1.1.4 Output, Data Processing 2025

Based on the table above, it is known that the *R-Square* value of the affective aspect variable is 0.880 (strong category). This result indicates that 88% of the affective aspect variable can be influenced by the variables of interaction quality and artificial intelligence-based personalisation, and the impulsive purchase intention variable is 0.899 (strong category). This result indicates that 89.9% of the impulsive purchase intention variable can be influenced by the affective aspect variable.

F-Square

According to, to estimate the magnitude of the influence of one variable on another in the model structure, the value limits used are around 0.02 for the small influence category, 0.15 for moderate influence, and 0.35 for large influence.

Indicator	***f-Square***	**Category**
Interaction Quality – Affective Aspect	0.305	**Moderate**
Artificial Intelligence-based Personalisation – Affective Aspects	0.285	**Moderate**
Affective Aspects – Impulsive Purchase Intentions	0.169	**Moderate**
Interaction Quality – Impulsive Purchase Intention	0.046	**Low**
Artificial Intelligence-Based Personalisation – Impulsive Purchase Intentions	0.187	**Medium**

Source: SmartPLS 4.1.1.4 Output, Data Processing 2025

Based on the results of the table, the following conclusions can be drawn:

1. The quality of interaction on the affective aspect has an f Squar value of 0.305, which is in the moderate category, so this variable contributes significantly to the improvement of the affective aspect.

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2. Artificial Intelligence-based Personalisation on Affective Aspects yields a value of 0.285, which is also in the moderate category, indicating that its influence on Affective Aspects is moderately significant.
3. The Affective Aspect on Impulsive Purchase Intention has a value of 0.169, which is in the moderate category, indicating that the affective aspect has a fairly significant influence on the formation of impulsive purchase intention.
4. Interaction Quality on Impulsive Purchase Intention obtained a value of 0.046, which is in the small category, so that the contribution of this variable to impulsive purchase intention is relatively low.
5. Artificial Intelligence-based Personalisation on Impulsive Purchase Intention has a value of 0.187, which is in the moderate category, so this variable has a moderate influence on increasing impulsive purchase intention.

Hypothesis Testing

***Path Coefficient* (Direct Effect)**

Table 4.6. Path Coefficient Test (Direct Effect)

	Original Sample (o)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics	P Values	Description
Interaction Quality > Affective Aspect	0.487	0.486	0.100	4.067	0.000	**Accepted**
Artificial Intelligence-Based Personalisation >Affective Aspects	0.471	0.470	0.099	4.747	0.000	**Accepted**
Affective Aspect > Impulsive Purchase Intention	0.378	0.375	0.093	4.067	0	**Accepted**
Interaction Quality > Impulsive Purchase Intent	0.199	0.200	0.09	2.203	0.028	**Accepted**
Artificial Intelligence-Based Personalisation > Impulsive Purchase Intent	0.397	0.397	0.078	5.100	0.00	**Accepted**

Source: SmartPLS 4.1.1.4 Output, Data Processing Process 2025

From the table above, the hypothesis can be concluded as follows:

Hypothesis Testing H1 (Interaction Quality > Affective Aspect)

Based on the test results, the original sample value is 0.487, the T-statistics value is 4.067, and the p-value is 0.000. With a significance level of 5% ($\alpha = 0.05$), the test criteria are that if the t-count ≥ t-table (1.96) or p-value < 0.05, then the hypothesis is accepted. Since the T-statistics value (4.067) ≥ 1.96 and the p-value (0.000) < 0.05, hypothesis H1 is accepted. This indicates that interaction quality has a positive and significant effect on the affective aspect.

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Testing Hypothesis H2 (Artificial Intelligence-Based Personalisation > Affective Aspect)

Based on the test results, the original sample value was 0.471, the T-statistics was 4.747, and the p-value was 0.000. With the same test criteria (calculated t ≥ 1.96 and p- -value < 0.05), the results showed that hypothesis H2 was also accepted. This means that artificial intelligence-based personalisation has a positive and significant effect on the affective aspect.

Testing Hypothesis H3 (Affective Aspect > Impulsive Purchase Intention)

Based on the test results, the original sample value was 0.378, the T-statistics was 4.067, and the p-value was 0.000. With a significance level of 5% (α = 0.05), it was found that the T-statistics (4.067) ≥ 1.96 and the p-value (0.000) < 0.05. Therefore, hypothesis H3 was accepted. This means that the affective aspect has a positive and significant effect on impulsive buying intention.

Testing Hypothesis H4 (Interaction Quality > Impulsive Purchase Intention)

Based on the test results, the original sample value was 0.199, the T-statistic was 2.203, and the p-value was 0.028. Because the T-statistic (2.203) ≥ 1.96 and the p-value (0.028) < 0.05, hypothesis H4 is accepted. This indicates that interaction quality has a positive and significant effect on impulsive purchase intention.

Testing Hypothesis H5 (Artificial Intelligence-Based Personalisation > Impulsive Purchase Intention)

Based on the test results, the original sample value is 0.397, the T-statistics is 5.100, and the p-value is 0.000. Since the T-statistics (5.100) ≥ 1.96 and the p-value (0.000) < 0.05, hypothesis H5 is accepted. This means that artificial intelligence-based personalisation has a positive and significant effect on impulsive purchase intention.

Path Coefficient (Indirect Effect)

Table 4.7. Path Coefficient Test (Indirect Effect)

	Original Sample (o)	**Sample Mean (M)**	**Standard Deviation (STDEV)**	**T Statistics**	**P Values**	**Description**
Interaction Quality > Affective Aspect > Impulsive Purchase Intention	0.184	0.181	0.056	3.284	0.001	**Accepted**
Artificial Intelligence-Based Personalisation > Affective Aspects > Impulsive Purchase Intentions	0.178	0.178	0.063	2.840	0.005	**Accepted**

Source: SmartPLS 4.1.1.4 Output, Data Processing Process 2025

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From the results of the table above, the following conclusions can be drawn:

Interaction Quality > Affective Aspect > Impulsive Purchase Intention

The test results show an original sample value of 0.184, a T-statistic of 3.284, and a p-value of 0.001. With a significance level of 5% ($\alpha = 0.05$), the testing criteria are that the hypothesis is accepted if the T-statistics ≥ 1.96 and the p-value < 0.05. Since the T-statistics (3.284) ≥ 1.96 and the p-value (0.001) < 0.05, the results are accepted. This means that the affective aspect significantly mediates the influence of interaction quality on impulsive purchase intention ( ). In other words, the better the quality of interaction perceived by users, the more it will increase the affective aspect, which ultimately encourages impulsive purchase intention.

Artificial Intelligence-Based Personalisation > Affective Aspect > Impulsive Purchase Intention

The test results show an original sample value of 0.178, T-statistics of 2.840, and a p-value of 0.005. Because the T-statistics (2.840) ≥ 1.96 and the p-value (0.005) < 0.05, the result is accepted. This means that the affective aspect also mediates the effect of artificial intelligence-based personalisation on impulsive purchase intention. This indicates that the more relevant the level of artificial intelligence-based personalisation provided, the more the affective aspect of consumers increases, which ultimately encourages them to make impulsive purchases.

CONCLUSION

The results of the study indicate that interaction quality has a positive and significant effect on the affective aspect. Communicative, informative, and responsive interactions between streamers and consumers can evoke positive emotions such as comfort and trust during live streaming sessions. The clarity of product information is an important element in shaping the emotional experience of consumers, in line with the findings of and (Masitoh et al., 2024) which state that the quality of interaction can increase the affective response of the audience in the context of live streaming commerce.

Furthermore, artificial intelligence-based personalisation has been proven to have a positive and significant effect on affective aspects. Product recommendations that are relevant to consumers' needs and preferences can increase comfort and positive feelings when watching live streaming. These findings support the research (G. Li et al., 2022) and (Bernard et al., 2024) which states that AI-based personalisation not only enhances the shopping experience but also strengthens consumers' emotional attachment to the products offered.

The affective aspect has also been proven to have a positive and significant impact on impulsive purchase intent. Emotional stimuli in the form of pleasure and arousal that arise during live streaming, especially when there are promotions, encourage consumers to make spontaneous purchases. These results are in line with the research (Verplanken & Herabadi, 2001) and (Frianka Anindea et al., 2023) which confirm that emotional aspects are the main predictors of impulsive purchasing behaviour in consumers.

The quality of interaction and artificial intelligence-based personalisation have a direct, positive, and significant influence on impulsive purchase intent. Good interaction between streamers and consumers can increase trust and interest, while AI-based personalisation creates emotional urgency through relevant product recommendations. These findings support the research (Harahap & Wahyuni, 2024) , (Liu & Xiao, 2018) , and (Bernard et al., 2024) which

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states that interaction and personalisation are important factors in driving impulsive purchasing in a digital context.

Furthermore, the affective aspect was found to mediate the influence of interaction quality and artificial intelligence-based personalisation on impulsive purchase intent. Clear interactions and relevant personalisation can evoke positive emotions in consumers, which in turn strengthen the urge to make impulsive purchases. These results are consistent with the research (G. Li et al., 2022) , (Masitoh et al., 2024) , and (Bernard et al., 2024) which confirm the role of the affective aspect as an important mediator in the relationship between marketing stimuli and consumer behavioural responses.

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