Asian Management and Business Review, Volume 6 Issue 1, 2026: 103-119

The power of credibility: How influencer credibility impacts impulsive buying in live-streaming commerce

Budi Setyanta[1]*, Yosita Dwiani Suryaningtiyas[2], Maliana Puspa Arum[3], Rizal Ula Ananta Fauzi[4], Dian Citaningtyas Ari Kadi[5]

[1]Universitas Janabadra, Yogyakarta, Indonesia
[2,3]Universitas Telkom Purwokerto, Purwokerto, Indonesia
[4,5]Universitas PGRI Madiun, Madiun, Indonesia

Article History
Received : 2025-06-16
Revised : 2025-08-18
Accepted : 2025-08-23
Published : 2026-02-01

Keywords:
Impulse buying; live-streaming; credibility; uncertainty; social media influencer

***Corresponding author:**
budi@janabadra.ac.id

DOI:
10.20885/AMBR.vol6.iss1.art7

Abstract

Live-streaming commerce has grown increasingly popular in the last few years. It allows influencers to show and explain products in real-time while viewers can make purchases instantly. This study decisively examines the impact of people's trust in influencers on their propensity to make impulse purchases. The researchers collected the information through an online questionnaire from 297 participants, who were selected using convenience sampling based on their availability and ease of access. The responses were then analyzed using the PLS-SEM method. The findings indicate that trust in influencers significantly influences consumers' emotional reactions and impulsive purchasing decisions. Those who have doubts are reluctant to make purchases; those who think the influencer is trustworthy make rapid purchase decisions. A barrier, uncertainty leaves consumers to consider their options. This outcome underlines the need of companies and influencers to lower uncertainty during live-streaming events. They can fulfill this by providing honest, open information, proving the quality of the good, and quickly answering questions. By doing this, one promotes confidence and faster purchase decisions. According to this study, influencing impulse buying mostly depends on trust and clarity. Hence, organizations could boost their live-stream marketing campaigns and increase sales by utilizing these elements.

Introduction

Live-streaming commerce extends conventional social media by enabling real-time interaction during shopping through live demonstrations, instant feedback, and synchronous chat—features that can accelerate decision processes (Bawack et al., 2023; Fu & Hsu, 2023). In practice, many sessions announce product line-ups to prime viewers' attention and expectations (Cheng, 2020), further shaping how choices are made in the moment.

Impulse buying (IB) in online settings is consequential because rapid choices may occur with limited deliberation, affecting consumer outcomes and market performance (Ma et al., 2023; Rodrigues et al., 2021). At scale, unplanned purchases contribute to shifts in the online retail landscape, underscoring the managerial relevance of IB (Azad Moghddam et al., 2024).

Uncertainty is intrinsic to real-time online shopping because buyers cannot directly inspect products. Perceived quality uncertainty (PQU) involves how people expect a product to perform, last, and be overall high quality (Ma et al., 2023). On the other hand, perceived fit uncertainty (PFU) is about how well a product matches a person's needs and identity (Hewei, 2022). Ambiguity or

E ISSN 2775-202X

unforeseen information might exacerbate uncertainty and modify the probability of IB during live sessions (van der Sluis, 2025; S. Zhao, Yang, et al., 2022).

Within influencer-driven environments, influencer credibility (IC) is a central cue: audiences frequently treat credible influencers as persuasive and, at times, more trustworthy than conventional sellers, so their recommendations guide evaluations and choices in live broadcasts (Dwidienawati et al., 2020; Jamil et al., 2023). Research indicates that messages originating from expert and credible sources are more likely to persuade audiences within social media environments (Li & See-To, 2024). The effectiveness of delivering messages can significantly improve how convincing credible information is (Majerczak & Strzelecki, 2022). Consistent with attitude research, evaluative judgments—attitude towards influencers (ATI) and attitude towards products (ATP)—shape behavioral intentions and purchase outcomes, and credible information can shift these evaluations (Hagger & Hamilton, 2025; Kästner & Baczynski, 2025).

Prior social-commerce studies link IC to consumer responses (Dwidienawati et al., 2020; Jamil et al., 2023), yet the joint roles of PQU and PFU in live-streaming settings—and their associations with ATI, ATP, and IB—remain under-specified. This study advances the literature by: (i) testing how IC relates to ATI and ATP under the conditions of PQU and PFU observed in live broadcasts (Hewei, 2022; Ma et al., 2023); (ii) explaining how these variables jointly account for IB in real-time commerce (Zhao et al., 2022); and (iii) providing Indonesia-specific evidence with transparent PLS-SEM measurement and structural reporting (Azad Moghddam et al., 2024; Ma et al., 2023).

This article is organized as follows: literature and hypotheses, methods and data, results, implications, and conclusion.

Literature Review and Hypotheses Development

Live-streaming Commerce

Live-streaming commerce is a new form of e-commerce that combines real-time social interaction through live-streaming. Sellers can showcase products in live videos, allowing viewers to ask questions on-screen, providing more details about the products, and giving them a sense of presence, influencing their purchase intentions (Ming et al., 2021). Live-streaming has become a phenomenon that has altered consumer behavior and online interaction. Live-streaming shopping is the latest e-commerce trend whereby merchants or influencers live and demonstrate items to the audience. During the streaming session, viewers can ask product questions, leave comments, and make purchase decision (Lin et al., 2023). One particularly effective and increasingly preferred method to interact with and enthrall online viewers is live-streaming commerce, sometimes called live influencer marketing.

Live-streaming and influencer marketing integration have proven highly successful, showing tangible results and significant influence on consumer buying patterns. Studies indicate that live-streaming allows viewers to interact more deeply with influencers, building a more personal relationship, enhancing consumer trust, and driving impulsive decisions that ultimately affect purchase intentions (Beichert et al., 2023; Gu et al., 2023). Liu and Wang (2023) underline, as a creative business model, the great possibilities of merging influencer marketing with live-streaming commerce. In this regard, they stress the deliberate use of influencer marketing to advertise products properly. The utilization of social capital by influencers is recognized as a key factor in delivering value to followers and attracting attention during live-streaming commerce sessions (Farivar & Wang, 2022). Using influencers' social influence will help this company establish close relationships with its audience, benefiting from marketing products immediately and collaboratively in the live-streaming atmosphere (Chen & Yang, 2023).

Live-streaming has become a means of interacting among both buyers and sellers in Indonesia, drawing attention from consumers for direct shopping experiences. Findings indicate that as much as 55% of individuals participating in live shopping ultimately make purchase transactions (Annur, 2022). The potential for live-streaming commerce in Indonesia is estimated to be substantial, and it is projected to reach 450 trillion rupiah by 2025 (Septiani, 2023). This phenomenon shows a change in consumer behaviour towards digital shopping platforms, so creating new opportunities for businesses and a useful instrument for marketing products and raising customer interaction: streaming continuously. Thus, live-streaming trade in Indonesia is not just a trend but has become integral to the rapidly growing digital economy.

The Relationship between Influencer Credibility (IC) and Attitude Towards Influencers (ATI)

Within the mobile social media framework, influencers serve as favorable brand or product promoters, acting as advocates (Yan et al., 2023). Their contributions are highly significant since they are effective information sources that affect the buying alternatives of their viewers. The effectiveness of these sponsorships depends on the confidence followers have in the influencer, which transfers to the brand or product under recommendation (Joshi et al., 2023).

This trust transfer shows how much consumers depend on a media personality. Their faith in that personality can boost their confidence in the products or brands they support (Abdul Aziz et al., 2023; Hu et al., 2019). Previous research indicates that when influencers, especially entertainers, endorse products, they get more audience engagement in views, likes, and comments than other influencers. This finding highlights that entertainers have a unique and practical ability to grab and interact with audiences in influencer marketing (Ren et al., 2023).

Often, social media users view influencers as more in keeping than conventional celebrities. Live-streaming consumers think influencers are more honest and informed in supporting than conventional famous people who occasionally seem contractually fulfilled. Improving confidence in influences and increasing the impact of their assistance depend on this conviction in authenticity (Belanche et al., 2021).

An influencer's ability to convince others depends on how genuine they are. Studies show that being unique and consistent makes influencers more authentic. This authenticity strongly affects how consumers behave. Influencers, seen as opinion leaders, build trust by showcasing their expertise, which creates a more effective and trustworthy connection than traditional ads integrated into their daily stories (Zniva et al., 2023).

Many studies support the idea that consumers generally have a more positive view of influencers who are seen as highly credible. The research suggests that when influencers are credible, and followers have a positive attitude toward them, it directly leads to positive responses from the audience (Handranata & Kalila, 2025). Being authentic, which involves honesty, is a key factor that strongly influences the connection between influencers and their followers (Liu & Zheng, 2024).

H_{1a}: There is a positive connection between IC and ATI.

The Relationship between Influencer Credibility (IC) and Attitude Towards Products (ATP)

Credible influencers make product claims feel clear and diagnostic, which lifts evaluations of the endorsed item (Belanche et al., 2021; Saini, 2024). Classic source-credibility work explains why perceived expertise and trustworthiness shape how audiences respond to a communicator (Ohanian, 1990). In live-stream settings, this confidence can transfer from the messenger to the product, elevating attitudes toward the item itself (Hu et al., 2019).

The strength of this link depends on several conditions. When endorser–product fit is evident, viewers more readily map the influencer's credibility onto the focal product; a recent meta-analysis shows that influencer–brand fit boosts source credibility and, through it, consumer attitudes, with stronger effects for experience-type products typical of live demonstrations (Pan et al., 2025). Perceived authenticity—consistency and candor across sessions—further reduces skepticism toward product claims (Belanche et al., 2021; Liu & Zheng, 2024). Similarity in values or style between audiences and the endorser also eases acceptance of product messages (Dhun & Dangi, 2023). Although celebrity status can raise baseline trust, congruence remains the decisive lever for favorable product attitudes in live commerce (Nugroho et al., 2022; Pan et al., 2025).

H_{1b}: There is a positive connection between IC and ATP.

The Relationship between Attitude Towards Influencers (ATI) and Impulse Buying (IB)

Consumer behaviour and marketing have paid close attention to the effect of people's opinions about influencers on impromptu purchases (Joshi et al., 2023). Studies show that influencers can significantly affect the inclination of their followers towards impulsive purchase (Ooi et al., 2023). This influence typically results from a mix of factors, such as the influencer's perceived expertise, trustworthiness, similarity, and attractiveness, along with the emotional responses and social comparisons they evoke in consumers (Dwidienawati et al., 2020; Johnson & Sandström, 2023; Melnychuk et al., 2024; Ooi et al., 2023).

The perceived trustworthiness of information influencers provide in video content is positively associated with consumers' attitudes toward the endorsed brand or product. In our terms, higher influencer credibility (IC) leads to a more favorable attitude toward products (ATP) because credible claims are processed as more diagnostic and reliable (Liu, 2022). Consistent with the theory of reasoned action, more favorable product attitudes translate into stronger purchase intentions, clarifying how credibility-driven ATP can move downstream toward behavior in live commerce (Yan et al., 2023).

Research indicates that people who enjoy influencer advertisements are more inclined to alter their purchasing choices. The consequence of social media influencers on consumer buying patterns relies on whether individuals perceive them positively or negatively (Singh, 2021). People with favorable opinions about social media influencers are more likely to buy products they endorse.

On the other hand, if people have bad opinions about influencers, they are usually less likely to buy, choosing to abstain from purchases completely. Attitude towards influencer marketing is consumers' general reaction to these kinds of ads—positive or negative. It emphasizes that a person's actions are guided by their motivation to engage in a behavior, which is influenced by their attitude (Ilieva et al., 2024).

The inclination of customers to buy a product spontaneously can be affected by different factors, such as their favorable perception of the product and the perceived value it holds for them. Studies indicate that consumers who hold positive views of social media influencers are more inclined to make purchases based on the influencers' endorsements (Belanche et al., 2021; Singh, 2021). How much someone trusts an influencer in their ads can affect how likely they are to buy something without thinking much about it. This impulsive buying behavior happens when someone suddenly decides to buy something. If someone believes in, respects, and likes the influencer, they are more likely to see the ad positively and then buy something impulsively (Liu, 2022).

H_2: There is a positive connection between ATI and IB.

The Relationship between Attitude Towards Products (ATP) and Impulse Buying (IB)

Attitude toward products (ATP) captures consumers' evaluative beliefs and feelings about a focal item. More favorable ATP heightens approach motivation and anticipated gratification, lowering the threshold for an unplanned choice (Nyrhinen et al., 2024). Under affective arousal, people rely less on slow, attribute-by-attribute comparisons and are more willing to act quickly, a pattern linked to impulsive purchase tendencies (Rodrigues et al., 2021).

In live shopping contexts, presentation cues can intensify this translation from attitude to action. Vivid, emotionally engaging demonstrations and appealing product displays raise arousal and compress decision windows, which makes a spontaneous purchase more likely (Zhang & Shi, 2022; Leung et al., 2022). The link is also shaped by product characteristics: attitudes are more readily converted into impulse for low-involvement or hedonic items, and less so for higher-risk, utilitarian goods that invite additional checking before purchase (S. C. Lin et al., 2023; Ngo et al., 2024).

Practical triggers further facilitate enactment. Attractive pricing and immediate availability reduce perceived effort and elevate the expected payoff of acting now rather than later, thereby increasing the likelihood of an impulsive choice when ATP is already positive (Reza et al., 2024).

H_3: There is a positive connection between ATP and IB.

The Relationship between Perceived Quality Uncertainty (PQU) and Impulse Buying (IB)

Perceived quality uncertainty (PQU) is the consumer's doubt about a product's expected performance, durability, and overall excellence during choice, and it tends to rise when online information is incomplete or ambiguous (Chung, 2020; Ma et al., 2023). Under uncertainty, people shift away from fast, affect-driven responses toward slower, deliberative processing and information search, suppressing spur-of-the-moment purchases (Leung et al., 2022; Zhao et al., 2022).

In live-stream commerce, the absence of physical inspection and the asymmetry of seller–buyer information intensify perceived risk right at the decision window (Ma et al., 2023; Bawack et al., 2023). Anticipated regret about buying a low-quality item encourages caution or delay, rather than immediate enactment (Zhang et al., 2022). Conversely, when diagnostic product detail is credible and reduces perceived risk, viewers become more willing to act quickly (Al-Adwan & Yaseen, 2023). Higher PQU should lower the likelihood of an unplanned purchase by triggering risk management and deferral instead of impulse.

H_4: Perceived quality uncertainty (PQU) is negatively associated with impulse buying (IB).

The Relationship between Perceived Fit Uncertainty (PQU) and Impulse Buying (IB)

Perceived fit uncertainty (PFU) is doubt about whether the product suits one's needs, preferences, or identity—even when overall quality may be acceptable (Hong & Pavlou, 2014; Sun & Tyagi, 2020). When suitability is unclear, decision conflict arises, and consumers prefer to seek clarity rather than commit immediately, a pattern that weakens impulsive action (He & Rucker, 2023; Zhao et al., 2022). The inability to try or tailor products in online live-streams keeps fit questions unresolved despite demonstrations, widening the gap between presentation and expected use (Chen et al., 2022; Ma et al., 2023). Visible mismatches between how an item is shown and what viewers expect heighten skepticism about fit in the moment (Islam & Hussain, 2023).

Prior work also indicates that reducing fit ambiguity—through richer, diagnostic previews—improves evaluations and purchase outcomes, underscoring fit as a distinct brake on immediate conversion (Matt & Hess, 2016; Sun et al., 2022). Because impulsive buying is more likely when perceived risk is low, unresolved PFU should push viewers to defer rather than buy on the spot (Wu et al., 2020).

H_5: Perceived fit uncertainty (PFU) is negatively associated with impulse buying (IB).

Research Methods

Research Design and Data Collection

An online survey of individuals who had previously shopped via live-streaming was run by sharing a Google Forms link in WhatsApp groups. This way of finding participants is quick and inexpensive and helps reach people in many places (Ponchio et al., 2021); in survey methods, it is known as "river" recruitment, where individuals join by clicking a link (Lehdonvirta et al., 2020). Because participation is voluntary and the chance of being invited or responding is unknown, the results cannot be generalized to the whole population (Bethlehem, 2010). For transparency, the findings are treated as associations within this sample, and—when reliable external totals are available (e.g., by age or gender)—post-survey weighting can bring the sample closer to those totals, which may reduce but not remove selection bias (Penn et al., 2023).

To determine the sample size for this research, the authors followed the guidelines established by Bentler and Chou (1987) and Osborne and Costello (2004). Bentler and Chou suggest having 5 to 10 observations per estimated parameter, while Osborne and Costello recommend a sample-to-item ratio of 20 to 1. Since this research have 25 parameter items, a sample size ranging from 125 to 250 is considered acceptable. Authors may also expand our sample size to 500 participants if needed.

A recent study on consumer behavior involved 297 participants. Most respondents were female (65%), while males comprised 35%. Most were young, with 62.6% belonging to Generation Z (ages 17–27), followed by 26.6% from Generation Y (ages 28–43), and 10.8% from Generation

X (ages 44–59). Regarding education, 64% had completed high school or less, 28% held a bachelor's degree, and only 8% had a master's degree or higher. Income levels skewed low, with 70.4% earning under Rp 3,500,000 monthly. The most common occupation was a student (36.7%), followed by a team member (31.3%), then business owners, homemakers, and others. Geographically, most respondents (68.4%) lived on the island of Java, while 31.6% were from other regions. The data shows that respondents were predominantly young female students with modest incomes and education levels who mainly resided in Java.

Table 1. Profile of Respondents

Characteristics of Respondents	Frequency	Percentage
Gender		
Male	104	35.0%
Female	193	65.0%
Age		
17 – 27 years old (Gen Z)	186	62.6%
28 – 43 years old (Gen Y)	79	26.6%
44 – 59 years old (Gen X)	32	10.8%
Education		
High school or below	193	64%
Bachelor	82	28%
Master or above	22	8%
Income (IDR)		
Less than Rp 3,500,000	209	70.4%
Rp 3,500,001 - Rp 7,000,000	47	15.8%
Rp 7,500,001 - Rp 10,500,000	28	9.4%
Rp 10,500,001 and above	13	4.4%
Occupation		
Student	109	36.7%
Employee	93	31.3%
Business person	38	12.8%
Housewife	38	12.8%
Others	19	6.4%
Recidential		
Java island	203	68.4%
Outside Java island	94	31.6%

Source: Data processing, 2025

Measurement

All constructs were measured with previously validated scales and adapted to the live-stream shopping context. Impulse buying (4 items) was adapted from Ma et al. (2023); attitude toward influencers (3 items) from Chetioui et al. (2020); attitude toward products/services (4 items) from Belanche et al. (2021); perceived quality uncertainty (2 items) and perceived fit uncertainty (4 items) from Chen et al. (2023); and influencer credibility (5 items) from Crnjak-Karanović et al. (2023). The questionnaire was translated from English into Indonesian to ensure comprehension while preserving meaning. All items used a five-point Likert scale (1 = strongly disagree; 5 = strongly agree).

Results and Discussion

Validity, Reliability, and Model Fit

This study employs PLS-SEM to assess our model since it is more robust statistically than CB-SEM and has no sample size limits. Additionally, it is adept at managing numerous kinds of data. PLS-SEM is excellent for both exploring new ideas and confirming current ones. It supplies the authors with beneficial consequences in different instances.

Table 2. Evaluation of Reliability and Convergent Validity

Construct	Indicator	Loading Factors	CA	CR	AVE	VIF
Attitude Towards Influencers (ATI)	ATI1	0.778	0.803	0.806	0.720	1.413
	ATI2	0.891				2.349
	ATI3	0.872				2.202
Attitude Towards Products (ATP)	ATP1	0.868	0.849	0.857	0.687	2.304
	ATP2	0.815				1.992
	ATP3	0.819				1.917
	ATP4	0.813				1.636
Impulse Buying (IB)	IB1	0.823	0.890	0.897	0.752	2.448
	IB2	0.902				3.510
	IB3	0.848				2.108
	IB4	0.893				2.813
Influencer Credibility (IC)	IC1	0.816	0.838	0.855	0.606	1.719
	IC2	0.803				1.940
	IC3	0.709				1.535
	IC4	0.818				1.925
	IC5	0.739				1.555
Perceived Fit Uncertainty (PFU)	PFU1	0.840	0.821	0.844	0.648	1.670
	PFU2	0.811				1.821
	PFU3	0.797				1.858
	PFU4	0.769				1.595
Perceived Quality Uncertainty (PQU)	PQU1	0.916	0.786	0.790	0.823	1.720
	PQU2	0.899				1.720

Source: Data processing, 2025

Abbreviations: CA = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted; VIF = variance inflation factor.

Internal consistency was assessed using Cronbach's alpha (α) and composite reliability (CR); item reliability using standardized loadings; convergent validity using average variance extracted (AVE); and collinearity using variance inflation factors (VIF). For reflective indicators, loadings of ≥ .70 are typically considered adequate (Hair et al., 2019). Acceptable internal consistency is indicated by CA ≥ .70 and CR ≥ .70 (Fornell & Larcker, 1981). Convergent validity is supported when AVE ≥ .50 (Fornell & Larcker, 1981). In PLS-SEM, VIF < 5 is commonly used to indicate the absence of problematic collinearity (Hair et al., 2019).

As reported in Table 2, all item loadings meet the .70 guideline (range = .709–.916), consistent with recommended thresholds for reflective measures (Hair et al., 2019). Cronbach's alpha spans .786–.890 and CR spans .790–.897, both exceeding the .70 benchmark for internal consistency. AVE values range from .606 to .823, surpassing the .50 criterion for convergent validity (Fornell & Larcker, 1981). VIF values lie between 1.413 and 3.510, remaining below the <5 rule of thumb for acceptable collinearity (Hair et al., 2019).

Table 3. Fornell-Larcker Criteria, R-Square, SRMR

	ATI	ATP	IB	IC	PFU	PQU	R-Square	SRMR
ATI	0.848						0.384	0.084
ATP	0.334	0.829					0.104	
IB	0.678	0.288	0.867				0.477	
IC	0.621	0.328	0.341	0.778				
PFU	0.578	0.335	0.314	0.899	0.805			
PQU	0.001	0.034	-0.087	-0.006	-0.021	0.907		

Source: Data processing, 2025

Note. ATI=attitude toward influencers, ATP=attitude towards products, IB=impluse buying, IC=influencer credibility, PFU=perceived fit uncertainty, PQU=perceived quality uncertainty.

In Table 3, using the Fornell-Larcker criterion, we confirm discriminant validity. This finding ensures that the square root of a construct's AVE appears on the diagonal. It is greater than the correlations with other constructs represented by the off-diagonal values (Hair et al., 2019). In this table, all constructs meet that requirement, such as the square root of AVE for ATI, which is 0.848, higher than its correlation with any other construct, such as IB (0.678) or PFU (0.578). Similarly, all other constructs—including ATP, IB, IC, PFU, and PQU—have diagonal values greater than their respective correlations with other variables. PQU demonstrates minimal or even negative associations with other variables, although its AVE square root is significantly high at 0.907. The findings indicate that each concept is distinct, confirming strong discriminant validity across the model.

The R-squared values for attitude towards influencers (ATI), attitude towards products (ATP), and impulse buying (IB) are 0.384, 0.104, and 0.477, respectively, in the social science context, these values indicate that the proportion of the independent variables explaining the dependent variable in social science is acceptable, as they fall within the range of 0.1 to 0.5 (Ozili, 2023).

Additionally, SRMR = 0.084 is marginal concerning the 0.08 cutoff frequently (Hu & Bentler, 1999); in PLS-SEM applications, some guidance considers values < 0.10 acceptable (Ringle et al., 2024), fit is interpreted as marginally acceptable.

Structural Model Assessment

Table 4 depicts the results of the structural model test. Based on the structural model analysis, all hypotheses in this study are supported, as shown by significant results with p-values below 0.05 and t-statistics above 1.96.

Table 4. Results of Hypotheses Testing

Hypothesis	Path	Original sample (O)	T-statistics	P-values	Result
H1a	IC → ATI	0.621	14.029	0.000	Supported
H1b	IC → ATP	0.328	4.963	0.000	Supported
H2	ATI → IB	0.727	15.632	0.000	Supported
H3	ATP → IB	0.096	2.098	0.036	Supported
H4	PQU → IB	-0.094	2.011	0.044	Supported
H5	PFU → IB	-0.141	2.741	0.006	Supported

Source: Data processing, 2025

Note. ATI=attitude toward influencers, ATP=attitude towards products, IB=impluse buying, IC=influencer credibility, PFU=perceived fit uncertainty, PQU=perceived quality uncertainty.

Influencer credibility and attitudes toward influencers (H1a)

Consistent with Table 4 ($\beta = 0.621$, $p < .001$), live-stream credibility cues appear highly diagnostic. In live-stream settings, real-time demonstrations and two-way chat make cues of expertise and honesty highly visible, which raises viewers' evaluations of the communicator (Belanche et al., 2021). Classic source-credibility work shows that perceived expertise, trustworthiness, and attractiveness jointly shape attitudes toward endorsers (Ohanian, 1990).

Interactive formats draw attention to the presenter and intensify message reception during the decision window (Ren et al., 2023). Confidence formed while watching the endorsement stabilizes judgments about the messenger beyond a single pitch (Hu et al., 2019). Perceived authenticity—signaled by consistency and candor—pushes impressions upward, especially when the influencer appears sincere and distinctive rather than purely transactional (Liu & Zheng, 2024).

These mechanisms build on source-credibility models by showing that in live commerce, especially during real-time and engaging interactions, credibility quickly shapes attitudes toward the toward the communicator. This pattern refines prior accounts by identifying authenticity and the intensity of interaction as key factors (Singh, 2021). The association is likely to be stronger when real-time demonstrations highlight expertise and honesty. Conversely, it tends to be weaker when cues of authenticity are unclear or when interactions are limited.

Influencer credibility and attitudes toward products (H1b)

Consistent with Table 4, influencer credibility (IC) enhances attitudes toward the endorsed product (ATP) by reducing evaluative ambiguity and increasing the diagnosticity of claims (Ohanian, 1990; Saini, 2024). Confidence in the communicator can transfer to the item itself, elevating product evaluations (Hu et al., 2019).

The association strengthens when endorser–product fit is salient and the message is appropriate and informative (Saini & Bansal, 2023), and when audiences perceive value or style similarity with the endorser (Dhun & Dangi, 2023). Celebrity status can raise baseline credibility, but congruence remains the decisive lever for favorable product attitudes (Nugroho et al., 2022).

Clear linkage between the influencer's persona and the product further consolidates positive appraisals of the item (Pan et al., 2025). Taken together, these mechanisms extend source-credibility accounts by specifying how, in real time, credibility functions as a low-effort cue that converts into product attitudes, and they refine trust-transfer logic by identifying fit and message appropriateness as boundary conditions (Hu et al., 2019; Ohanian, 1990).

Attitudes toward influencers and impulse buying (H2)

Model estimates indicate a significant positive association between ATI and IB ($\beta = 0.727$, $p < .001$; Table 4). In live-streams, favorable evaluations of the messenger act as a fast decision heuristic, shortening deliberation and raising the likelihood of spontaneous purchase (Belanche et al., 2021). This mechanism works with the idea that when individuals have a positive attitude toward a communicator, they are more likely to take immediate action, especially under time pressure (Yan et al., 2023).

Perceived trust further reduces the need for attribute-by-attribute scrutiny, accelerating movement from interest to choices (Liu, 2022). Core evaluation cues—expertise, trustworthiness, similarity, and attractiveness—supply affective and cognitive signals that tip decisions at the moment (Singh, 2021). Emotional appraisals of influencer content then nudge borderline viewers over the threshold to buy (Ilieva et al., 2024).

Evidence from social commerce likewise shows that unplanned purchases are shifted primarily by credibility and liking rather than extended product evaluation (Ooi et al., 2023). Theoretically, this pattern refines persuasion accounts by identifying a messenger-centric last-mile route to impulsive behavior in synchronous, high-presence streams. The association should be stronger when time pressure (Sun et al., 2023) and low-friction checkout are salient (Han, 2023), and weaker when verification prompts or safeguards introduce deliberative pauses (He & Rucker, 2023).

Attitudes toward products and impulse buying (H3)

The standardized path is small but positive ($\beta = 0.096$, $p = .036$; Table 4), consistent with live-stream settings where person-centric cues dominate the last mile while product attitudes still add marginal pull (Saini, 2024). Favorable product evaluations heighten desire and anticipated gratification, making quick action more likely when the opportunity is salient (Nyrhinen et al., 2024). Under time pressure, such affect can override slower attribute-by-attribute appraisal, allowing modestly positive attitudes to translate into spontaneous purchases (Rodrigues et al., 2021).

Stream design intensifies this translation: vivid on-screen presentation and low-friction purchase flows shorten decision time (Zhang & Shi, 2022)., while practical levers like attractive pricing and immediate availability reduce effort costs (Huo et al., 2023). Social proof further eases residual doubts so existing product attitudes can convert into action (Ullah et al., 2023). Theoretically, this pattern refines product-attitude accounts by showing that, in synchronous streams, attitudes work alongside situational and affective triggers rather than acting alone (Iyer et al., 2020). The link should strengthen for low-involvement/hedonic items and weaken for higher-risk, utilitarian purchases that prompt extra checking (Ngo et al., 2024).

Product quality uncertainty and impulse buying (H4)

The standardized path is small and negative ($\beta = -0.094$, $p = .044$; Table 4). Perceived quality uncertainty (PQU) raises doubt about performance and durability, which increases perceived downside risk at the moment of choice (Chung, 2020). The lack of physical inspection amplifies that doubt in live-streams because viewers must infer quality from demonstrations and claims alone (Ma et al., 2023).

Under uncertainty, consumers focus on diagnostic reviews, especially negative comments, which shape purchase judgments (Chen et al., 2024). They also seek clarifying information rather than act on momentary affect (He & Rucker, 2023), and such review-focused processing improves decision accuracy (Chen et al., 2024).

Credible reviews on trusted platforms reduce perceived product uncertainty by supplying usable detail and social proof, making rapid decisions more acceptable when quality seems clearer (Sung et al., 2023). Conversely, when perceived transaction risk is low, the likelihood of an impulsive purchase rises in real time (Wu et al., 2020).

When outcomes feel hard to judge, individuals shift into information search and postpone action rather than act on momentary affect (Zhao et al., 2023). Anticipated regret about a poor-quality outcome encourages caution, especially near checkout (Zhang et al., 2022). Individuals with stronger uncertainty-avoidance tendencies are particularly likely to delay or reschedule purchases under these conditions (Chen et al., 2023). Credible reviews and user feedback can lower PQU by supplying diagnostic detail, which makes rapid decisions more acceptable (Al-Adwan & Yaseen, 2023).

Theoretically, these patterns refine impulse-buying accounts by positioning quality uncertainty as a brake that shifts viewers from affective impulse to risk management in synchronous streams (Chung, 2020). The association is expected to be stronger for harder-to-assess categories and weaker when streams provide credible, concrete diagnostics that reduce PQU (Ma et al., 2023).

Product fit uncertainty and impulse buying (H5)

The standardized path is moderate and negative ($\beta = -0.141$, $p = .006$; Table 4). Perceived fit uncertainty (PFU) is doubt about whether a product matches a consumer's needs or preferences (Hong & Pavlou, 2014; Matt & Hess, 2016). This uncertainty creates tension between the immediate urge to buy and the desire for a confident decision, thereby weakening impulsive action (Sun & Tyagi, 2020; Zhao et al., 2022). In such a conflict, viewers defer purchasing to seek clarity rather than commit to the spot (He & Rucker, 2023).

Online information asymmetry widens this fit-confidence gap because suitability must be inferred from limited cues without trial (Chen et al., 2022). Visible gaps between how an item is presented and what viewers expect further heighten skepticism about fit in the moment (Islam & Hussain, 2023). As perceived mismatch risk rises, expected value falls, and the appeal of an immediate purchase diminishes (Sun & Tyagi, 2020). Contrastingly, impulse buying is more likely when perceived risk is low and suitability feels assured (Wu et al., 2020).

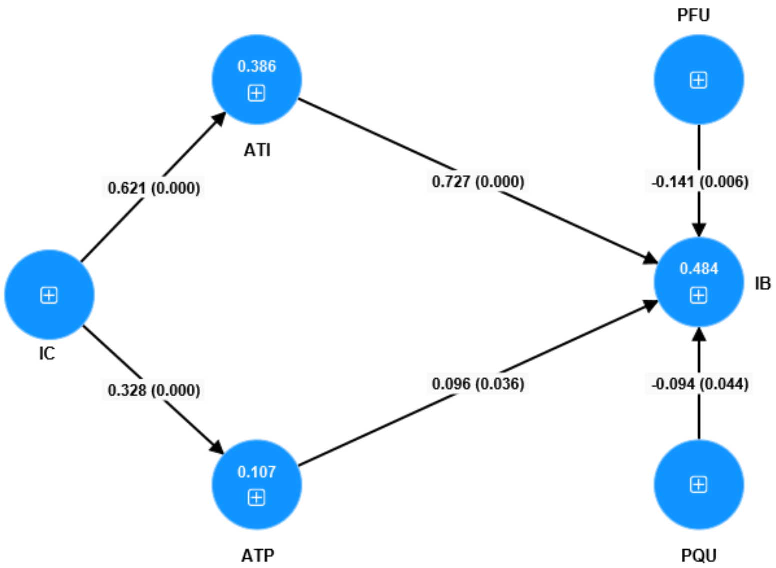

Figure 1. Structural Model: Path Coefficients, P-values, and R^2

Theoretically, these results extend uncertainty frameworks by identifying fit as a distinct channel—separate from quality—through which doubt suppresses impulsive action in live-stream settings (Hong & Pavlou, 2014). The association should be stronger in categories where fit is idiosyncratic and weaker when streams provide sizing guidance, use-case demonstrations, or rapid Q&A that reduce PFU (Ma et al., 2023).

Conclusion and Implication

This study advances theory on influencer-driven live commerce in three ways. First, it clarifies how source credibility works in synchronous streams: credibility operates as a fast, diagnostic cue that shapes attitudes toward the communicator and can transfer trust to product evaluations (Belanche et al., 2021; Hu et al., 2019; Ohanian, 1990). Second, it qualifies attitude effects in real time: favorable attitudes toward influencers and products translate more quickly into action when expertise and authenticity are salient, while safeguards or verification steps introduce deliberative pauses (He & Rucker, 2023; Liu, 2022). Third, it distinguishes two uncertainty brakes, namely perceived quality uncertainty (PQU) and perceived fit uncertainty (PFU), which shift viewers from affective impulse toward information search and deferral; these brakes are stronger for harder-to-assess goods and weaker when streams provide credible diagnostics such as demonstrations, specifications, or sizing and use-case guidance (Hong & Pavlou, 2014; Ma et al., 2023; Matt & Hess, 2016).

For managers and platforms, several levers follow. Provide diagnostic product information in-stream, including precise specifications, close-up demonstrations, and real-time Q&A, to lower PQU and PFU at the moment of choice (Sun & Tyagi, 2020). Elevate visible credibility cues by highlighting influencer expertise and honesty and fostering perceived authenticity across sessions (Belanche et al., 2021; Liu, 2022). Use low-friction purchase flows judiciously: streamlined checkout can speed enactment, yet its impact is context dependent and may require strong brand and social cues to be effective (Han, 2023). Surface trustworthy reviews and fit-relevant feedback, for example, sizing and compatibility notes, to help viewers close remaining informational gaps before purchase (Sung et al., 2023).

This study faced several practical constraints. The sample was recruited via WhatsApp using non-probability convenience methods, so inclusion probabilities are unknown, and self-selection is likely; external validity is therefore limited, and estimates are interpreted as sample-level associations rather than population parameters. The study relies on self-reported survey responses, which are susceptible to recall error and social desirability bias. The design does not control for platform-specific features that may shape impulse propensity in live-streams (e.g., interactivity, time pressure, checkout frictions) and does not account for product-category differences (e.g., hedonic vs. utilitarian goods). Finally, the analysis does not examine demographic subgroups.

Future work should address current constraints by (i) employing probability-based or quota sampling and, where benchmarks exist, applying post-stratification to reduce self-selection; (ii) comparing multiple platforms and product categories; (iii) testing heterogeneity across demographic subgroups; (iv) linking surveys to behavioral logs to lessen self-report bias; and (v) using experiments that manipulate in-stream diagnosticity and transaction frictions to identify causal pathways from credibility and uncertainty to impulse buying.

References

Abdul Aziz, N., Othman, N. A., & Abdul Murad, S. M. Bin. (2023). The effects of social support and social media influencers' credibility on emotional brand attachment: the mediating roles of trust in multichannel. *Social Sciences and Humanities Open*, *8*(1), 100727. https://doi.org/10.1016/j.ssaho.2023.100727

Al-Adwan, A. S., & Yaseen, H. (2023). Solving the product uncertainty hurdle in social commerce: the mediating role of seller uncertainty. *International Journal of Information Management Data Insights*, *3*(1), 100169. https://doi.org/10.1016/j.jjimei.2023.100169

Annur, C. M. (2022). *Survei Jakpat: Shopee Rajai Penggunaan Live Shopping di Indonesia*. https://databoks.katadata.co.id/teknologi-telekomunikasi/statistik/1495a09cd46b53b/survei-jakpat-shopee-rajai-penggunaan-live-shopping-di-indonesia. Retrieved May 23, 2024

Azad Moghddam, H., Carlson, J., Wyllie, J., & Mahmudur Rahman, S. (2024). Scroll, stop, shop: decoding impulsive buying in social commerce. *Journal of Business Research*, *182*(June), 114776. https://doi.org/10.1016/j.jbusres.2024.114776

Bawack, R. E., Bonhoure, E., Kamdjoug, J. R. K., & Giannakis, M. (2023). How social media live streams affect online buyers: a uses and gratifications perspective. *International Journal of Information Management*, *70*(January), 102621. https://doi.org/10.1016/j.ijinfomgt.2023.102621

Beichert, M., Bayerl, A., Goldenberg, J., & Lanz, A. (2024). Revenue generation through influencer marketing. *Journal of Marketing*, *88*(4), 40-63. https://doi.org/10.1177/00222429231217471

Belanche, D., Casaló, L. V., Flavián, M., & Ibáñez-Sánchez, S. (2021). Building influencers' credibility on Instagram: effects on followers' attitudes and behavioral responses toward the influencer. *Journal of Retailing and Consumer Services*, *61*(June), 102585. https://doi.org/10.1016/j.jretconser.2021.102585

Bentler, P. M., & Chou, C. P. (1987). Practical issues in structural modeling. *Sociological Methods & Research*, *16*(1), 78–117. https://doi.org/10.1177/0049124187016001004

Bethlehem, J. (2010). Selection bias in web surveys. *International Statistical Review*, *78*(2), 161–188. https://doi.org/10.1111/j.1751-5823.2010.00112.x

Chen, N., & Yang, Y. (2023). The role of influencers in live streaming e-commerce: influencer trust, attachment, and consumer purchase intention. *Journal of Theoretical and Applied Electronic Commerce Research*, *18*(3), 1601–1618. https://doi.org/10.3390/jtaer18030081

Chen, T., Samaranayake, P., Cen, X. Y., Qi, M., & Lan, Y. C. (2022). The impact of online reviews on consumers' purchasing decisions: evidence from an eye-tracking study. *Frontiers in Psychology*, *13*(June), 865702. https://doi.org/10.3389/fpsyg.2022.865702

Chen, X., Shen, J., & Wei, S. (2023). What reduces product uncertainty in live streaming e-commerce? from a signal consistency perspective. *Journal of Retailing and Consumer Services*, *74*(June), 103441. https://doi.org/10.1016/j.jretconser.2023.103441

Chen, Y., Qin, Z., Yan, Y., & Huang, Y. (2024). The power of influencers: how does influencer marketing shape consumers' purchase intentions? *Sustainability (Switzerland)* , *16*(13), 1–18. https://doi.org/10.3390/su16135471

Cheng, H. H. (2020). The effects of product stimuli and social stimuli on online impulse buying in live streams. *ACM International Conference Proceeding Series*, 31–35. https://doi.org/10.1145/3409891.3409895

Chetioui, Y., Benlafqih, H., & Lebdaoui, H. (2020). How fashion influencers contribute to consumers' purchase intention. *Journal of Fashion Marketing and Management*, *24*(3), 361–380. https://doi.org/10.1108/JFMM-08-2019-0157

Chung, J. (2020). Effect of quality uncertainty, regulatory focus, and promotional strategies on perceived savings for sustainable marketing. *Sustainability (Switzerland)*, *12*(14). https://doi.org/10.3390/su12145653

Crnjak-Karanović, B., Kursan Milaković, I., & Elez, J. (2023). Which decision-making stages matter more? influencer's perceived credibility, sponsorship and moderating role of trust. *Young Consumers*, *24*(6), 649–668. https://doi.org/10.1108/YC-08-2022-1590

Dhun, & Dangi, H. K. (2023). Influencer marketing: role of influencer credibility and congruence on brand attitude and eWOM. *Journal of Internet Commerce*, *22*(S1), S28–S72.

https://doi.org/10.1080/15332861.2022.2125220

Dwidienawati, D., Tjahjana, D., Abdinagoro, S. B., Gandasari, D., & Munawaroh. (2020). Customer review or influencer endorsement: which one influences purchase intention more? *Heliyon*, *6*(11), e05543. https://doi.org/10.1016/j.heliyon.2020.e05543

Farivar, S., & Wang, F. (2022). Effective influencer marketing: a social identity perspective. *Journal of Retailing and Consumer Services*, *67*(May), 103026. https://doi.org/10.1016/j.jretconser.2022.103026

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39. https://doi.org/10.2307/3151312

Fu, J. R., & Hsu, C. W. (2023). Live-streaming shopping: the impacts of para-social interaction and local presence on impulse buying through shopping value. *Industrial Management and Data Systems*, *123*(7), 1861–1886. https://doi.org/10.1108/IMDS-03-2022-0171

Gu, X., Zhang, X., & Kannan, P. K. (2024). Influencer mix strategies in livestream commerce: impact on product sales. *Journal of Marketing*, *88*(4), 64-83. https://doi.org/10.1177/00222429231213581

Hagger, M. S., & Hamilton, K. (2025). Progress on theory of planned behavior research: advances in research synthesis and agenda for future research. *Journal of Behavioral Medicine*, 43–56. https://doi.org/10.1007/s10865-024-00545-8

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Han, M. C. (2023). Checkout button and online consumer impulse-buying behavior in social commerce: a trust transfer perspective. *Journal of Retailing and Consumer Services*, *74*(April), 103431. https://doi.org/10.1016/j.jretconser.2023.103431

Handranata, Y. W., & Kalila, S. (2025). Attitude toward fashion influencers and its impact on purchase behavior: the roles of brand attitude and purchase intention. *Frontiers in Communication*, *10,* 1583602. https://doi.org/10.3389/fcomm.2025.1583602

He, S., & Rucker, D. D. (2023). How uncertainty affects information search among consumers: a curvilinear perspective. *Marketing Letters*, *34*(3), 415–428. https://doi.org/10.1007/s11002-022-09657-0

Hewei, T. (2022). Influence of online comments on clothing impulse buying behavior in mobile short video app live broadcast. *Frontiers in Psychology*, *13*(August), 1–11. https://doi.org/10.3389/fpsyg.2022.913073

Hong, Y., & Pavlou, P. A. (2014). Product fit uncertainty in online markets: nature, effects, and antecedents. *Information Systems Research*, *25*(2), 328–344. https://doi.org/10.1287/isre.2014.0520

Hu, H., Zhang, D., & Wang, C. (2019). Impact of social media influencers' endorsement on application adoption: a trust transfer perspective. *Social Behavior and Personality*, *47*(11). https://doi.org/10.2224/sbp.8518

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives. *Structural Equation Modeling*, *6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Huo, C., Wang, X., Sadiq, M. W., & Pang, M. (2023). Exploring factors affecting consumer's impulse buying behavior in live-streaming shopping: an interactive research based upon SOR Model. *SAGE Open*, *13*(2), 1–15. https://doi.org/10.1177/21582440231172678

Ilieva, G., Yankova, T., Ruseva, M., Dzhabarova, Y., Klisarova-Belcheva, S., & Bratkov, M. (2024). Social media influencers: customer attitudes and impact on purchase behaviour. *Information (Switzerland)*, *15*(6), 15060359. https://doi.org/10.3390/info15060359

Islam, T., & Hussain, M. (2023). How consumer uncertainty intervene country of origin image and consumer purchase intention? the moderating role of brand image. *International Journal of Emerging Markets*, *18*(11), 5049–5067. https://doi.org/10.1108/IJOEM-08-2021-1194

Iyer, G. R., Blut, M., Xiao, S. H., & Grewal, D. (2020). Impulse buying: a meta-analytic review. *Journal of the Academy of Marketing Science*, *48*(3), 384–404. https://doi.org/10.1007/s11747-019-00670-w

Jamil, R. A., Qayyum, U., ul Hassan, S. R., & Khan, T. I. (2023). Impact of social media influencers on consumers' well-being and purchase intention: a TikTok perspective. *European Journal of Management and Business Economics, 33*(3), 366-385. https://doi.org/10.1108/EJMBE-08-2022-0270

Johnson, P. C., & Sandström, C. (2023). Making use of digital methods to study influencer marketing. *The Dynamics of Influencer Marketing*, *5*. https://doi.org/10.4324/9781003134176

Joshi, Y., Lim, W. M., Jagani, K., & Kumar, S. (2023). Social media influencer marketing: foundations, trends, and ways forward. *Electronic Commerce Research* (Issue 0123456789). Springer US, *25*(2), 1199. https://doi.org/10.1007/s10660-023-09719-z

Kästner, E., & Baczynski, M. (2025). Believe me, even though I'm fake: how the credibility of real and virtual influencers affects purchase intention. *Journal of Media Business Studies*, *00*(00), 1–25. https://doi.org/10.1080/16522354.2025.2475424

Lehdonvirta, V., Oksanen, A., Räsänen, P., & Blank, G. (2021). Social media, web, and panel surveys: using non-probability samples in social and policy research. *Policy & internet*, *13*(1), 134-155. https://doi.org/doi: 10.1002/poi3.238

Leung, F. F., Gu, F. F., Li, Y., Zhang, J. Z., & Palmatier, R. W. (2022). Influencer marketing effectiveness. *Journal of Marketing*, *86*(6), 93–115. https://doi.org/10.1177/00222429221102889

Li, H., & See-To, E. W. K. (2024). Source credibility plays the central route: an elaboration likelihood model exploration in social media environment with demographic profile analysis. *Journal of Electronic Business & Digital Economics*, *3*(1), 36–60. https://doi.org/10.1108/jebde-10-2022-0038

Lin, S. C., Tseng, H. T., Shirazi, F., Hajli, N., & Tsai, P. T. (2023). Exploring factors influencing impulse buying in live streaming shopping: a stimulus-organism-response (SOR) perspective. *Asia Pacific Journal of Marketing and Logistics*, *35*(6), 1383–1403. https://doi.org/10.1108/APJML-12-2021-0903

Liu, B., & Wang, W. (2023). Live commerce retailing with online influencers: two business models. *International Journal of Production Economics*, *255*(February 2022), 108715. https://doi.org/10.1016/j.ijpe.2022.108715

Liu, M. (2022). Determining the role of influencers' marketing initiatives on fast fashion industry sustainability: the mediating role of purchase intention. *Frontiers in Psychology*, *13*(June). https://doi.org/10.3389/fpsyg.2022.940649

Liu, X., & Zheng, X. (2024). The persuasive power of social media influencers in brand credibility and purchase intention. *Humanities and Social Sciences Communications*, *11*(1), 1–12. https://doi.org/10.1057/s41599-023-02512-1

Ma, X., Aw, E. C. X., & Filieri, R. (2023). From screen to cart: how influencers drive impulsive buying in livestreaming commerce?. *Journal of Research in Interactive Marketing*, *18*(6), 1034-1058. https://doi.org/10.1108/JRIM-05-2023-0142

Majerczak, P., & Strzelecki, A. (2022). Trust, media credibility, social ties, and the intention to share information verification in an age of fake news. *Behavioral Sciences*, *12*(2), 51. https://doi.org/10.3390/bs12020051

Matt, C., & Hess, T. (2016). Product fit uncertainty and its effects on vendor choice: an experimental study. *Electronic Markets*, *26*(1), 83–93. https://doi.org/10.1007/s12525-015-0199-5

Melnychuk, H. A., Arasli, H., & Nevzat, R. (2024). How to engage and attract virtual influencers' followers: a new non-human approach in the age of influencer marketing. *Marketing Intelligence and Planning*, *42*(3), 393–417. https://doi.org/10.1108/MIP-06-2023-0251

Ming, J., Jianqiu, Z., Bilal, M., Akram, U., & Fan, M. (2021). How social presence influences impulse buying behavior in live streaming commerce? the role of S-O-R theory. *International Journal of Web Information Systems*, *17*(4), 300–320. https://doi.org/10.1108/IJWIS-02-2021-0012

Ngo, T. T. A., Nguyen, H. L. T., Nguyen, H. P., Mai, H. T. A., Mai, T. H. T., & Hoang, P. L. (2024). A comprehensive study on factors influencing online impulse buying behavior: evidence from Shopee video platform. *Heliyon*, *10*(15), e35743. https://doi.org/10.1016/j.heliyon.2024.e35743

Nugroho, S. D. P., Rahayu, M., & Hapsari, R. D. V. (2022). The impacts of social media influencer's credibility attributes on gen Z purchase intention with brand image as mediation. *International Journal of Research in Business and Social Science (2147- 4478)*, *11*(5), 18–32. https://doi.org/10.20525/ijrbs.v11i5.1893

Nyrhinen, J., Sirola, A., Koskelainen, T., Munnukka, J., & Wilska, T. A. (2024). Online antecedents for young consumers' impulse buying behavior. *Computers in Human Behavior*, *153*(December 2023), 108129. https://doi.org/10.1016/j.chb.2023.108129

Ohanian, R. (1990). Construction and validation of a scale to measure celebrity endorsers' perceived expertise, trustworthiness, and attractiveness. *Journal of Advertising*, *19*(3), 39–52. https://doi.org/10.1080/00913367.1990.10673191

Ooi, K. B., Lee, V. H., Hew, J. J., Leong, L. Y., Tan, G. W. H., & Lim, A. F. (2023). Social media influencers: an effective marketing approach? *Journal of Business Research*, *160*(February), 113773. https://doi.org/10.1016/j.jbusres.2023.113773

Osborne, J. W., & Costello, A. B. (2004). Sample size and subject to item ratio in principal components analysis. *Practical Assessment, Research and Evaluation*, *9*(11). https://doi.org/https://doi.org/10.7275/ktzq-jq66

Ozili, P. K. (2023). The acceptable R-square in empirical modelling for social science research. In Saliya, C. A. (Ed.), *Social Research Methodology and Publishing Results: A Guide to Non-Native English Speakers* (pp. 134–143). IGI Global. https://doi.org/10.4018/978-1-6684-6859-3.ch009

Pan, M., Blut, M., Ghiassaleh, A., & Lee, Z. W. Y. (2025). Influencer marketing effectiveness: a meta-analytic review. *Journal of the Academy of Marketing Science*, *53*(1), 52–78. https://doi.org/10.1007/s11747-024-01052-7

Penn, J. M., Petrolia, D. R., & Fannin, J. M. (2023). Hypothetical bias mitigation in representative and convenience samples. *Applied Economic Perspectives and Policy*, *45*(2), 721–743. https://doi.org/10.1002/aepp.13374

Ponchio, M. C., Barth, N. L., & Zambaldi, F. (2021). Using the internet for data collection in business research. *RAUSP Management Journal*, *56*(2), 254–258. https://doi.org/10.1108/rausp-04-2021-251

Ren, S., Karimi, S., Bravo Velázquez, A., & Cai, J. (2023). Endorsement effectiveness of different social media influencers: the moderating effect of brand competence and warmth. *Journal* *of Business Research*, *156*(November 2022). https://doi.org/10.1016/j.jbusres.2022.113476

Reza, M. D. S. binti M., Tan, S. H., Chong, L. L., & Ong, H. B. (2024). Continuance usage intention of e-wallets: insights from merchants. *International Journal of Information Management Data Insights*, *4*(2), 100254. https://doi.org/10.1016/j.jjimei.2024.100254

Ringle, C. M., Wende, S., & Becker, J.-M. (2024). *SmartPLS 4. Bönningstedt: SmartPLS*. https://www.smartpls.com/documentation/algorithms-and-techniques/model-fit. Retrieved June 11, 2025

Rodrigues, R. I., Lopes, P., & Miguel Varela. (2021). Factors affecting impulse buying behavior of consumers. *Frontiers in Psychology*, *12*(697080), 1–3. https://doi.org/10.3389/fpsyg.2021.697080

Saini, S. (2024). Influencer credibility and brand image : the mediating effect of brand attitude in the premium cosmetics market. *Jindal Journal of Business Research*, *0*(0), 1–18. https://doi.org/10.1177/22786821241287610

Septiani, L. (2023). *TikTok: Potensi Bisnis Belanja Live Streaming Indonesia Rp 405 Triliun*. https://katadata.co.id/digital/e-commerce/64a51690c7d5c/tiktok-potensi-bisnis-belanja-live-streaming-indonesia-rp-405-triliun. Retrieved June 10, 2024

Singh, K. (2021). Influencer marketing from a consumer perspective: how attitude, trust, and word of mouth affect buying behavior. *European Integration Studies*, *1*(15), 231–241. https://doi.org/10.5755/j01.eis.1.15.28803

Sun, B., Zhang, Y., & Zheng, L. (2023). Relationship between time pressure and consumers' impulsive buying—role of perceived value and emotions. *Heliyon*, *9*(12), e23185. https://doi.org/10.1016/j.heliyon.2023.e23185

Sun, C., Fang, Y., Kong, M., Chen, X., & Liu, Y. (2022). Influence of augmented reality product display on consumers' product attitudes: a product uncertainty reduction perspective. *Journal of Retailing and Consumer Services*, *64*(October 2021), 102828. https://doi.org/10.1016/j.jretconser.2021.102828

Sun, M., & Tyagi, R. K. (2020). Product fit uncertainty and information provision in a distribution channel. *Production and Operations Management*, *29*(10), 2381-2402. https://doi.org/10.1111/poms.13237

Sung, E., Chung, W. Y., & Lee, D. (2023). Factors that affect consumer trust in product quality: a focus on online reviews and shopping platforms. *Humanities and Social Sciences Communications*, *10*(1), 1–10. https://doi.org/10.1057/s41599-023-02277-7

Ullah, A., Khan, K., Khan, A., & Ullah, S. (2023). Understanding quality of products from customers' attitude using advanced machine learning methods. *Computers*, *12*(3), 49. https://doi.org/10.3390/computers12030049

van der Sluis, F. (2025). Wanting information: uncertainty and its reduction through search engagement. *Information Processing and Management*, *62*(2), 103890. https://doi.org/10.1016/j.ipm.2024.103890

Wu, I. L., Chiu, M. L., & Chen, K. W. (2020). Defining the determinants of online impulse buying through a shopping process of integrating perceived risk, expectation-confirmation model, and flow theory issues. *International Journal of Information Management*, *52*(May 2019), 102099. https://doi.org/10.1016/j.ijinfomgt.2020.102099

Yan, M., Kwok, A. P. K., Chan, A. H. S., Zhuang, Y. S., Wen, K., & Zhang, K. C. (2023). An empirical investigation of the impact of influencer live-streaming ads in e-commerce platforms on consumers' buying impulse. *Internet Research*, *33*(4), 1633–1663. https://doi.org/10.1108/INTR-11-2020-0625

Zhang, M., & Shi, G. (2022). Consumers' impulsive buying behavior in online shopping.

Computational Intelligence and Neuroscience, 1–8. https://doi.org/https://doi.org/10.1155/2022/6794729

Zhang, Y., Zhou, H., & Qin, J. (2022). Research on the effect of uncertain rewards on impulsive purchase intention of blind box products. *Frontiers in Behavioral Neuroscience*, *16*(August), 1–14. https://doi.org/10.3389/fnbeh.2022.946337

Zhao, H., Yu, M., Fu, S., Cai, Z., Lim, E. T. K., & Tan, C. W. (2023). Disentangling consumers' negative reactions to impulse buying in the context of in-app purchase: insights from the affect-behavior-cognition model. *Electronic Commerce Research and Applications*, *62*(October), 101328. https://doi.org/10.1016/j.elerap.2023.101328

Zhao, S., Yang, Q., Im, H., Ye, B., Zeng, Y., Chen, Z., Liu, L., & Huang, D. (2022). The impulsive online shopper: effects of COVID-19 burnout, uncertainty, self-control, and online shopping trust. *Future Business Journal*, *8*(1), 1–15. https://doi.org/10.1186/s43093-022-00174-0

Zhao, S., Ye, B., Wang, W., & Zeng, Y. (2022). The intolerance of uncertainty and "untact" buying behavior: the mediating role of the perceived risk of COVID-19 variants and protection motivation. *Frontiers in Psychology*, *13*(January), 1–10. https://doi.org/10.3389/fpsyg.2022.807331

Zniva, R., Weitzl, W. J., & Lindmoser, C. (2023). Be constantly different! how to manage influencer authenticity. *Electronic Commerce Research*, *23*(3), 1485–1514. https://doi.org/10.1007/s10660-022-09653-6