QUBAHAN ACADEMIC JOURNAL
VOL. 6, NO. 1, January 2026
https://doi.org/10.48161/qaj.v6n1a2092

More than a Good Deal: The Interplay of Perceived Value, Multidimensional Engagement, and Intention to Buy in Live Platform

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ABSTRACT: Live stream shopping has become popular alternative to traditional social media marketing, particularly in Indonesia. In this study, we adopted Perceived Value Theory to explore how financial, functional, individual, and social values influence three types of engagement, including affective, cognitive, and behavioral, and how these forms of engagement will shape purchase in live stream shopping environments. This research collects samples of 200 respondents via survey. Partial Least Squares Structural Equation Modeling was used to analysis the data. The output revealed that financial value strongly drives affective and cognitive engagement. Another finding is that functional value significantly influences cognitive and behavioral engagement, while individual and social values enhance users' emotional connections, that translate into direct purchasing behavior. Interestingly, the results suggest that functional benefits may not be sufficient to drive deep engagement or prompt purchasing action. The findings emphasize the need for a balanced value strategy one that effectively addresses both the emotional and practical needs of live stream audiences to foster meaningful engagement and influence purchase intention. Live streamers could emphasize financial and individual values in their contents to gain direct purchase intention. Furthermore, they need to highlight the financial, individual, and social values that could trigger emotional engagement in order to improve the purchase intention for longer term benefit.

Keywords: social media marketing, perceived value, affective engagement, cognitive engagement, behavioral engagement, live stream shopping, purchase intention.

I. INTRODUCTION

In social media, live stream shopping is an interesting phenomenon. It has arisen as a viable alternative to traditional online marketing methods. Its roots can be traced to practices in traditional markets, where sellers attract attention by performing live demonstrations and engaging directly with potential customers. These traders rely on persuasive language and real-time product displays to capture interest and encourage on-the-spot purchasing. Often, purchases are made impulsively, triggered by the immediate and tangible nature of the demonstration. This effect is further amplified by promotional strategies such as time-limited discounts or special offers, which trigger a sense of urgency and motivate viewers to buy during the live session [1].

Nowadays, that traditional live stream shopping has been adapted to online platforms using various social media channels, giving rise to what is now widely referred to as social commerce a subset of e-commerce [1]. Similar to traditional marketing practices, this approach represents a form of online social commerce that seeks to attract customers by combining entertainment with the opportunity to make real-time purchases [2]. Unlike conventional social commerce, where consumers rely solely on static images and written descriptions, live stream shopping enhances the experience through direct interactions with streamers who present detailed information about the products and demonstrate them in real time [3]. This dynamic format allows marketers to engage with customers more effectively by showcasing products, responding to questions instantly, and fostering a sense of community during the living session [4, 5]. Collectively, the interactive nature of live stream shopping increases the likelihood of online purchases, as it encourages viewers to return for future broadcasts that they find engaging or entertaining. In fact, online purchasing behavior is often influenced by the level of user engagement, with returning visitors showing a stronger tendency to make purchases compared to first-time viewers [6]. Live stream shopping is an interesting phenomenon for researcher due to its strong growth. A recent report indicates that 69% of online consumers in South-East Asia have accessed live streaming content, and 66% have made purchases through this format. The Indonesian market reflects a similar trend, as online consumers who are aware of live stream shopping account for nearly 80%, with 71% having accessed it and 56% having made purchases through the platform [7]. Seller behavior in Indonesia has also shifted toward live stream-based promotion.

Platforms like Shopee Live and TikTok Live have become the most commonly used channels for live shopping. As of 2024, 57% of online sellers report promoting their products on Shopee Live, while 49% use TikTok Live [8]. From the consumer side, survey results show that 48.7% of respondents use live shopping platforms several times per month. In terms of platform preference, the same survey found that TikTok Shop (now Tokopedia Shop) is the leading live stream shopping platform, regularly used by 56% of respondents, followed by Shopee at 33% [9]. This data showed that research in Tiktok Platform is important since is currently the leading platform for live stream shopping in Indonesia. Indonesia itself represents one of the largest and fastest-growing digital economies in Southeast Asia. This context provides a theoretically meaningful setting to investigate how perceived value and multidimensional engagement influence purchase intention. While this study focuses on TikTok users in Indonesia, the conceptual framework is transferable and can guide future research across other live commerce platforms and cultural contexts.

The swift evolution of live stream shopping demands research into the elements affecting consumer interest and online purchasing behavior in this burgeoning marketing channel [2]. Despite its popularity, a research gap persists in comprehending the motivational differences that underlie various forms of engagement namely, affective, cognitive, and behavioral engagement. Current research has not adequately elucidated the reasons behind the varied consumer engagement with live stream shopping content. This study investigates the dimensions of perceived value that affect different types of engagement [10]. The novelty of this study is to find out the factors that drive each form of engagement. Perceived Value Theory (PVT) is a good candidate to fill the gap since it's comprehensive and accounts for both utilitarian and hedonic/social values. This breadth is essential for live stream shopping, which blends entertainment, social interaction, and transactional utility. Therefore, to address the gap, this study applies PVT to link financial, functional, individual, and social values with multidimensional engagement (emotional, mental, and action-based) and purchase intention. We believe that this choice is suitable to extend theoretical understanding and offer practical insights.

This study evaluates the role of viewer's value in live streaming. We examine how this perception affects engagement and purchase intention within that environment. Specifically, it addresses two key research questions: (1) How do perceived values namely financial, functional, individual, and social affect user engagement, including affective, cognitive, behavioral dimensions, and purchase intention? and (2) How does user engagement influence purchase intention in live stream shopping environments?

This research has both theoretical and practical ramifications for the domain of social commerce [11]. It theoretically enhances comprehension of customer behavior on digital platforms by incorporating essential concepts like perceived value, user engagement, and purchase intention. The findings offer practical insights for marketers, platform developers, and live stream merchants to improve user experience, customize engagement techniques, and ultimately increase revenues in social commerce settings. By integrating perceived value theory, this research provides a holistic view on the antecedents of user engagement and their role in driving purchase decisions. Moreover, it deepens the understanding of how online brand communities' function and how marketers can foster meaningful engagement among users [12]. On a practical level, the findings may help platform operators and sellers prioritize strategies that effectively engage consumers and drive purchase and increase brand through various engagement activities such as encouraging electronic word-of-mouth [12-17].

II. RELATED WORK

As a relatively new approach in online marketing, research and literature on live stream shopping remain limited. Several existing studies have primarily focused on factors that increase audience interest in watching live broadcasts [18, 19] as well as the motivations of streamers to create such content [18]. Current research tends to examine factors influencing consumer purchase interest, such as visibility of product [20], purchasing capability during live streams [21], and the alignment among products, streamers, content, and user identity [22]. The literature on live stream shopping tends to investigate on a range of theoretical perspectives, including social presence theory (SPT), social support theory (SST), and perceived value theory (PVT) [2, 3, 5, 23-26], alongside broader frameworks e.g. the popular Theory of Planned Behavior (TPB) [27].

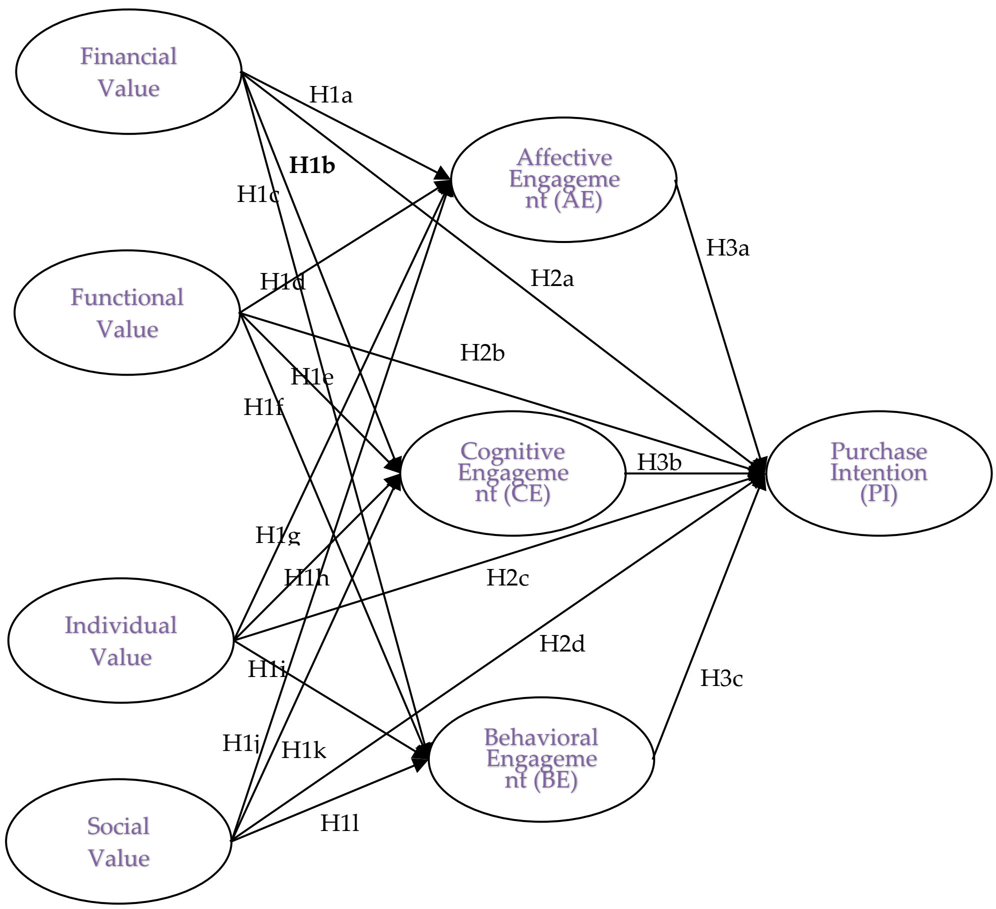
Social presence theory and social support theory highlight the relational dimensions of engagement between the host and the viewers. Social presence theory posits that an interpersonal connection and real-time interaction with the host and fellow viewers enhance the immersion and persuasiveness of the shopping experience [28]. Conversely, social support theory emphasizes the perceived accessibility of emotional and informational assistance from the community, which can bolster consumers' confidence and enhance their propensity to spend [29]. While both perspectives offer valuable insights, they often fall short in explaining the broader and more complex evaluations consumers make particularly in terms of perceived value [3]. We contend that PVT provides a more integrated view for understanding how consumers assess and balance the benefits and costs associated with their decisions to make purchases during live stream shopping experiences. This theory enables a multidimensional analysis of value, encompassing not only financial considerations but also functional, emotional, and social factors that influence consumer judgment.

Despite several studies that investigate the role of PVT in live stream shopping, there remain important gaps particularly in relation to consumer engagement within live stream environments. Research on online engagement is still considered scant [10, 12, 30, 31], largely because existing studies lack in-depth evaluations of engagement dimensions across diverse platform types [12, 32, 33]. Prior work often presents engagement without accounting for the distinct motivations and behaviors associated with affective, cognitive, and behavioral engagement [12]. Moreover, consumer perceptions vary significantly across different online platforms [34], and the interactions in it might vary significantly based on the online community engaged. These differences may result in varying levels and types of engagement across all three dimensions [32]. For instance, in product-based communities, engagement tends to be driven by functional and utilitarian values. In contrast, engagement within socially oriented communities often emphasizes social exchange, altruism, and relational bonds that go beyond product transactions [33].

Several prior studies have attempted to analyze perceived value and customer engagement. Numerous prior researches have investigated the correlation between perceived value and consumer involvement. In the realm of live stream shopping, customers may see value in symbolic (social), hedonistic, and utilitarian dimensions [2]. According to the research, utilitarian and hedonistic values influence customer loyalty. This influence is especially important when considering trust in both the product and shopping experience, while symbolic value influences loyalty both directly and indirectly through trust. All dimensions also indirectly affect customer engagement. Individual value, which reflects how consumers assess the individual benefits of using a product or service, also plays a role to shape behavior [35]. Per a recent study, is an intangible perception that can promote non-transactional behaviors, such as community interaction and content sharing [36]. In other studies, engagement is found to be positively influenced by perceived value, particularly across financial, functional, individual, and social dimensions [3]. However, while much of the existing literature treats engagement as a general outcome, several scholars emphasize the importance of investigating its distinct dimensions namely affective, cognitive, and behavioral engagement [10, 12]. From that foundation, we postulate the following hypotheses:

- H1: Perceived value (financial, functional, individual, and social) positively influences multidimensional engagement (affective, cognitive, and behavioral).

  We breakdown this hypothesis into the following hypotheses:
- H1a: Financial value affects affective engagement.
- H1b: Financial value affects cognitive engagement.
- H1c: Financial value affects behavioral engagement.
- H1d: Functional value affects affective engagement.
- H1e: Functional value affects cognitive engagement.
- H1f: Functional value affects behavioral engagement.
- H1g: Individual value affects affective engagement.
- H1h: Individual value affects cognitive engagement.
- H1i: Individual value affects behavioral engagement.
- H1j: Social value affects affective engagement.
- H1k: Social value affects cognitive engagement.
- H1l: Social value affects behavioral engagement.



source: Adapted from Previous Studies [3, 12]

FIGURE 1. Research framework.

The literature indicates that purchase intention in live stream is affected by perceived value, which includes financial, functional, individual, and social dimensions [3]. Financial value, in this context, refers to consumers' perceptions of the economic benefits gained through purchasing products or services during live stream sessions. These sessions often feature exclusive deals that enhance the perception of financial value, especially if combined with time-limit offers. Consumers who perceive high financial value in live stream shopping are found to develop a stronger purchase intention [5]. Additionally, the availability of product supply is a critical aspect in meeting consumer demand, thereby influencing purchase intention [37].

Live streaming also makes sellers have some features. They can show live product functionality, respond to consumer questions, and highlight product benefits. This interactive format enhances the perceived functional value, which is closely linked to utilitarian motivations, such as fulfilling specific purchasing goals [38]. Individual value captures the emotional and psychological benefits consumers derive from the live stream shopping experience. This includes feelings of enjoyment, satisfaction, or self-expression, which can significantly contribute to purchase intention. Moreover, live streaming platforms often include interactive features. Streamers can utilize live chat, comments, and virtual gifts, allowing consumers to engage with both hosts and other viewers [39]. These interactions elevate the perceived social value by facilitating a sense of connection and community. As consumers increasingly prioritize social objectives such as knowledge sharing, emotional expression, and real-time interaction a strong sense of social presence emerges [40]. When consumers perceive that live stream shopping enhances their social presence or strengthens their sense of community, they are more inclined to develop favorable purchase intentions. Thus, we predict that:

- H2: Perceived value (financial, functional, individual, and social) positively influences purchase intention.

We breakdown this main hypothesis into the following hypotheses:

- H2a: Financial value affects purchase intention.
- H2b: Functional value affects purchase intention.
- H2c: Individual value affects purchase intention.
- H2d: Social value affects purchase intention.

A study revealed that consumer engagement in social commerce can affect purchasing intentions [41]. Their research suggests that consumers that are actively involved in an online community tend to have better purchase. In live stream shopping, this relationship becomes even more pronounced, since interaction between viewers and streamers fosters emotional resonance and deeper engagement, and ultimately strengthens purchase intention especially in real time context [3]. Live streaming also provides immediate access to product information, which helps reduce uncertainty and enhances the shopping experience, and better buying opportunity [21]. Building on these insights, and supported by previous research emphasizing the multidimensional nature of engagement [10, 12], we suggest the following hypotheses for each engagement dimension:

- H3: Multidimensional engagement (affective, cognitive, and behavioral) positively influences purchase intention.

with the following breakdown hypotheses:

- H3a: Affective engagement affects purchase intention.
- H3b: Cognitive engagement affects purchase intention.
- H3c: Behavioral engagement affects purchase intention.

The relationship between those hypotheses is shown in Figure 1 framework and Table 1.

Table 1. Hypothesis summary.

Consolidated Hypothesis	Hypothesis	Hypothesis
H1: Perceived value (financial, functional, individual, and social) positively influences multidimensional engagement (affective, cognitive, and behavioral).	H1a	Financial value affects affective engagement.
	H1b	Financial value affects cognitive engagement.
	H1c	Financial value affects behavioral engagement.
	H1d	Functional value affects affective engagement.
	H1e	Functional value affects cognitive engagement.
	H1f	Functional value affects behavioral engagement.

	H1g	Individual value affects affective engagement.
	H1h	Individual value affects cognitive engagement.
	H1i	Individual value affects behavioral engagement.
	H1j	Social value affects affective engagement.
	H1k	Social value affects cognitive engagement.
	H1l	Social value affects behavioral engagement.
H2: Perceived value (financial, functional, individual, and social) positively influences purchase intention	H2a	Financial value affects purchase intention.
	H2b	Functional value affects purchase intention.
	H2c	Individual value affects purchase intention.
	H2d	Social value affects purchase intention.
H3: Multidimensional engagement (affective, cognitive, and behavioral) positively influences purchase intention.	H3a	Affective engagement affects purchase intention.
	H3b	Cognitive engagement affects purchase intention.
	H3c	Behavioral engagement affects purchase intention.

III. MATERIAL AND METHOD

1. MEASUREMENT

This study specifically targeting Indonesian individuals who participate in live stream shopping on the TikTok platform. TikTok was selected due to its significant popularity as a live stream shopping platform in Indonesia, making it a suitable and representative choice for examining live stream user behavior more broadly [42]. A quantitative technique was utilized to achieve the research aims, enabling the collecting and analysis of numerical data to identify statistically significant patterns and correlations among the analyzed variables. We utilized a quantitative methodology to gather and analyze numerical data, aiming to discern statistically significant patterns and relationships among the examined variables. The principal data gathering tool was a structured questionnaire, modified from previously validated measures, ensuring content validity and relevance to the research context. All constructs were measured using a 7-point Likert scale ranging from 1 = strongly disagree to 7 = strongly agree. Items were adapted from validated scales [3,12] with wording adjustments to fit the TikTok Live Stream Shopping context.

2. SAMPLE SIZE

Determining a proper sample size is a crucial aspect in quantitative research. A calculation of samples is done using G*Power 3.1 software, as advised by Hair et al., to ascertain the minimal necessary sample size for this investigation [43]. The investigation utilized a linear multiple regression model, incorporating a maximum of seven structural routes oriented towards a single endogenous construct inside the suggested PLS-SEM model. Assuming a medium effect size ($f^2 = 0.15$) and a significance level of 0.05 the calculation determined that at least 153 respondents are necessary to identify significant effects in the model, considering a statistical power of 0.95. This study successfully collected 200 samples, significantly surpassing the minimum required sample size, hence ensuring sufficient statistical power to rigorously evaluate the research model with excellent validity and reliability. After data collection is complete, the collected data processed using the PLS-SEM data analysis technique.

3. DATA COLLECTION

The questionnaire was distributed using a paid online survey agency, Populix, which is widely used in Indonesia for academic and market research. Populix maintains a large respondent panel with verified demographic profiles, enabling targeted recruitment. The questionnaire was distributed electronically through the Populix platform to respondents who had prior experience using TikTok Live Shopping. To ensure alignment with the study's objectives, screening questions were applied to confirm that participants fall into the following criteria: respondents were required to be Indonesian residents, hold a TikTok account, and have prior experience watching live stream shopping on the platform.

To further minimize sampling bias, anonymity and confidentiality were guaranteed, and participation was voluntary. Respondents received modest incentives provided by Populix, which encouraged completion while reducing nonresponse bias. These procedures strengthen the representativeness and reliability of the sample, offering greater confidence in the generalizability of the findings within the Indonesian TikTok Live Shopping context.

4. ANALYSIS TECHNIQUE

The PLS-SEM data analysis technique was chosen because of its ability to handle models with high complexity and test causal relationships between latent variables simultaneously, where WarpPLS software is used as a tool to process data and produce accurate model parameter estimates. This study employed WarpPLS 8.0 for data analysis. WarpPLS was selected over other PLS-SEM software due to its ability to model both linear and nonlinear relationships, provide advanced diagnostics for multicollinearity and common method bias [44]. These features are particularly relevant to this study, which examines complex behavioral relationships with potential nonlinear effects and requires rigorous assessment of method bias.

Validity analysis is conducted to confirm that the measurement instrument accurately assesses the intended concept, encompassing discriminant and convergent validity. The assessment of convergent validity involves examining the loading factor value and the average variance extracted. A high loading factor value, typically exceeding 0.70, along with an AVE value greater than 0.50, suggests that the indicators within a construct reliably measure that construct. [44]. Discriminant validity is assessed using indicators such as cross-loading analysis and the Heterotrait-Monotrait (HTMT) Ratio to ensure that distinct constructs are empirically differentiated. Reliability testing is conducted using Cronbach's alpha and composite reliability, with the criterion being that both values must be ≥ 0.7 [44]. A significance test was used with a significance level of 0.05 to determine whether a hypothesis is supported.

IV. DATA ANALYSIS

The evaluation of the measurement model's integrity is important in ensuring the credibility and robustness of the next structural equation modeling analyses. The assessment to the indicator reveals that the chosen indicators showed satisfactory levels of validity and reliability. These results confirm their suitability for measuring the intended latent variables [45, 46]. The fulfillment of these criteria underscores the indicators' ability to accurately and consistently capture the underlying constructs, bolstering confidence in the study's findings.

An important aspect of validity assessment is the examination of discriminant validity, which confirms that each indicator demonstrates a stronger association with its hypothesized latent variable than with other constructs in the model [37]. The final indicators used after considering validity is shown in Table 2. These results show the establishment of discriminant validity, which is supported by the observation that all indicators exhibit their highest loading values on their respective target latent variables, surpassing their cross-loadings [47]. This indicates that the indicators uniquely represent their intended constructs, minimizing overlap and ambiguity in their measurement. Furthermore, convergent validity is confirmed as majority of outer measurement models exceeded the threshold of 0.50, suggesting the indicators are well representative of the constructs [44].

Table 2. Loading factors results (Discriminant Validity Test).

	PFi	PFU	PIV	PSV	AE	CE	BE	PI
PFi2	0.909	0.506	0.636	0.451	0.689	0.499	0.473	0.586
PFi3	0.909	0.600	0.625	0.507	0.652	0.451	0.476	0.641
PFU5	0.513	0.888	0.438	0.390	0.503	0.442	0.487	0.468
PFU6	0.569	0.888	0.534	0.488	0.557	0.400	0.460	0.482
PIV2	0.685	0.527	0.921	0.600	0.670	0.449	0.573	0.659
PIV3	0.593	0.480	0.921	0.525	0.597	0.439	0.456	0.649

PSV1	0.436	0.398	0.535	0.917	0.552	0.499	0.661	0.437
PSV2	0.532	0.509	0.585	0.917	0.651	0.564	0.646	0.520
AE4	0.688	0.543	0.647	0.612	0.949	0.586	0.590	0.646
AE5	0.713	0.590	0.659	0.633	0.949	0.588	0.609	0.662
CE1	0.539	0.507	0.492	0.561	0.607	0.894	0.635	0.418
CE3	0.419	0.349	0.404	0.485	0.512	0.905	0.624	0.308
CE5	0.462	0.431	0.414	0.527	0.560	0.915	0.648	0.369
BE4	0.480	0.499	0.480	0.675	0.583	0.572	0.853	0.419
BE5	0.436	0.475	0.490	0.578	0.539	0.608	0.848	0.390
BE7	0.426	0.397	0.466	0.579	0.502	0.625	0.869	0.292
PI2	0.636	0.472	0.716	0.546	0.717	0.420	0.462	0.917
PI3	0.603	0.508	0.587	0.410	0.547	0.320	0.324	0.917

Note: All highest indicator values are in the measured variables, confirming adequate discriminant validity.

Furthermore, variance inflation factor values as in Table 3, used to assess multicollinearity among the indicators are satisfactory. They lie below the critical threshold of 5, and also greater than 0.1 [37]. This finding suggests the indicators are relatively independent and contribute unique information to the measurement of their respective constructs.

Table 3. Variance inflation factor (VIF) values for multicollinearity assessment.

	PFi	PFU	PIV	PSV	AE	CE	BE
AE	2.294	1.750	2.171	1.840			
CE	2.304	1.751	2.330	1.775			
BE	2.265	1.749	2.252	1.852			
PI	2.773	1.909	2.520	2.536	2.425	2.157	2.633

Note: The results show that all values < 3.3, indicate no multicollinearity concern.

The observation of adequate composite reliability values in Table 4, exceeding the commonly accepted threshold of 0.70, signifies that tested indicators showed enough internal consistency and are collectively measuring the same underlying phenomenon. In addition, Cronbach's alpha surpasses recommended value of 0.70 [44, 48]. This further corroborates the reliability of the indicators and their ability to provide consistent and dependable measurements of the constructs [48]. The AVE which exceeds 0.50, also demonstrates that the indicators effectively represent their respective constructs, with a substantial proportion of variance [44].

Table 4. General results.

	PFi	PFU	PIV	PSV	AE	CE	BE	PI
R-sq.					0.669	0.411	0.562	0.727
Adjusted R-sq.					0.662	0.399	0.553	0.717
CR	0.904	0.882	0.918	0.914	0.948	0.931	0.892	0.914
Cronbach's alpha	0.789	0.732	0.822	0.812	0.89	0.889	0.818	0.812
AVE	0.825	0.789	0.849	0.842	0.901	0.818	0.734	0.842
Full collinearity. VIF	2.868	1.855	2.799	2.511	3.461	2.231	2.926	2.592
Q-squared					0.675	0.416	0.566	0.646
Min	-2.983	-4.317	-4.495	-3.942	-4.147	-2.602	8.301	-4.129
Max	0.949	0.937	0.936	0.943	0.855	1.118	1.103	0.761
Median	0.364	0.303	0.353	0.129	0.372	0.199	0.14	0.167

Mode	0.949	0.937	0.936	0.943	0.855	1.118	1.103	0.761
Skewness	4.982	-1.371	-1.155	-1.469	-1.409	-0.784	-0.912	-1.513
Exc. kurtosis	0.138	1.932	1484	2.656	1.971	-0.19	0.323	2.165

The Heterotrait-Monotrait was implemented to further assess discriminant validity. All values observed appears to be below the stringent threshold of 0.9, thereby confirming adequate distinctiveness among constructs. This outcome, as shown in Table 5, provides strong evidence that the constructs are empirically separable, satisfying a critical prerequisite for the subsequent structural model analysis [49]. However, despite this robust satisfaction of discriminant validity, an issue emerged concerning common method bias, as indicated by a Full Collinearity Variance Inflation Factor for affective engagement exceeding the critical threshold of 3.3 [12]. This elevated VIF value signaled a potential inflation of relationships due to shared method variance, necessitating further diagnostic procedures to ensure the integrity of the research findings.

Table 5. Heterotrait–Monotrait (HTMT) ratio for discriminant validity testing.

	PFi	**PFU**	**PIV**	**PSV**	**AE**	**CE**	**BE**
PFU	0.801						
PIV	0.862	0.705					
PSV	0.659	0.641	0.747				
AE	0.881	0.739	0.804	0.771			
CE	0.625	0.588	0.564	0.682	0.695		
BE	0.650	0.689	0.681	0.874	0.741	0.824	
PI	0.844	0.693	0.869	0.642	0.810	0.475	0.526

Note: All HTMT values fall below the threshold (<0.90), demonstrating sufficient discriminant validity among constructs.

To address this methodological concern, the procedure to identify common method bias outlined by Kock through assessing full collinearity is used [50]. The application of Kock's method involved a re-evaluation of the model's collinearity diagnostics, which subsequently demonstrated that all variables, including affective engagement, now exhibited Full Collinearity VIF values below the 3.3 threshold, as meticulously showed in Table 6. This mitigation makes sure that common method bias was effectively addressed, thereby bolstering the validity and reliability of the subsequent inferential statistics [51]. This re-assessment ensures the independence of the constructs [49]. This re-assessment process thereby ensures that the observed effects are genuinely attributable to theoretical constructs rather than to methodological artifacts, enhancing the trustworthiness of the study's findings [52].

Table 6. Full collinearity VIF after procedure values for CMB assessment.

	PFi	PFU	PİV	PSV	AE	CE	BE	PI
R-sq.					0.569	0.411	0.562	0.730
Adjusted R-sq.					0.560	0.399	0.553	0.721
Full collinearity. VIF	2.779	1.842	2.782	2.466	2.629	2.231	2.926	2.592
Q-squared					0.576	0.416	0.566	0.647

Note: (values < 3.3 indicate no CMB concern).

Although variance inflation factor (VIF) values were all below the recommended threshold of 3.3, indicating that multicollinearity was not a concern, the possibility of common method bias (CMB) remains an important consideration in self-reported survey research. To mitigate this issue, several procedural remedies were employed during data collection, such as ensuring respondent anonymity and full collinearity VIFs examination and remedies was performed. Nevertheless, it is important to acknowledge that CMB cannot be fully ruled out, and its residual influence may have contributed to the insignificance of certain hypothesized relationships, particularly those that were unsupported. Recognizing this limitation enhances the methodological rigor of the study and provides a basis for future research to employ additional approaches that carefully consider the effective combination of procedural and statistical remedies to control to further minimize the risk of CMB [51].

Table 7 presents the p-value results. These results identify which hypotheses are supported and which are not, and these outcomes are further summarized in Table 8. The findings reveal that 11 out of 19 hypotheses are supported, indicating that there are a substantial portion are not supported. Furthermore, Table 9 provides the path coefficients, which not only indicates the significance but also the relative strength of each relationship. This information highlights that functional value is the main driver for affective engagement, while individual value is the main trigger for purchase intention. The results also showed that social value is the main driver for engagement. Figure 2 visually depicts the final structural model, offering a holistic view of the supported and unsupported paths. These results demonstrate that financial, social, and individual values function as stronger predictors of consumer behavior, whereas functional value exhibits weaker or non-significant effects.

Table 7. P Values Results.

	PFi	PFU	PIV	PSV	AE	CE	BE	PI
AE	<0.001	0.133	0.003	<0.001				
CE	<0.001	0.028	0.387	<0.001				
BE	0.273	0.003	0.065	<0.001				
PI	<0.001	0.389	<0.001	0.046	<0.001	0.319	0.168	

Table 8. Hypotheses testing results.

Hypothesis	Result
H1a: Financial Value → Affective Engagement	Supported
H1b: Financial Value → Cognitive Engagement	Supported
H1c: Financial Value → Behavioral Engagement	Not Supported
H1d: Functional Value → Affective Engagement	Not Supported
H1e: Functional Value → Cognitive Engagement	Supported
H1f: Functional Value → Behavioral Engagement	Supported
H1g: Individual Value → Affective Engagement	Supported
H1h: Individual Value → Cognitive Engagement	Not Supported
H1i: Individual Value → Behavioral Engagement	Not Supported
H1j: Social Value → Affective Engagement	Supported
H1k: Social Value → Cognitive Engagement	Supported
H1l: Social Value → Behavioral Engagement	Supported
H2a: Financial Value → Purchase Intention	Supported
H2b: Functional Value → Purchase Intention	Not Supported
H2c: Individual Value → Purchase Intention	Supported
H2d: Social Value → Purchase Intention	Not Supported
H3a: Affective Engagement→ Purchase Intention	Supported
H3b: Cognitive Engagement → Purchase Intention	Not Supported
H3c: Behavioral Engagement → Purchase Intention	Not Supported

Table 9. Path coefficients for hypothesized relationships testing.

	PFi	PFU	PIV	PSV	AE	CE	BE
AE	0.377	0.078	0.192	0.238			
CE	0.223	0.132	0.020	0.381			

BE	0.042	0.187	0.105	0.526			
PI	0.224	0.020	0.364	0.117	0.269	0.033	0.067

This study's structural model assessment elucidates the links among perceived value aspects (financial, functional, individual, and social), styles of customer involvement (affective, cognitive, and behavioral), and purchase intention. The analysis robustly corroborates most of the offered hypotheses, highlighting the essential influence of perceived value on customer behavior [53]. The findings showed the importance of financial value for emotional connection and purchase intention. This indicates that consumers tend to establish emotional bonds with items or services that provide evident economic advantages, hence enhancing their propensity to purchase [54]. These results emphasize the importance of financial considerations in the decision-making process, where perceived economic value can enhance both emotional engagement and transactional behavior. Indonesian consumers are generally known for their price sensitivity. Their purchasing decisions often influenced by discounts, bundling, and flash sales that are common in live stream shopping events [55, 56]. This tendency explains why financial value emerged as a strong driver of purchase intention, as affordability and promotions strongly resonate with middle-income and value-conscious segments.

We also confirm the positive influence of functional value on cognitive and behavioral engagement. Consumers who perceive that a product or service meets their practical needs will engage in thoughtful evaluation and exhibit active involvement [57]. This finding underscores the significance of utility and problem-solving attributes in driving customer engagement, suggesting that delivering tangible functional benefits can strengthen cognitive processing and promote sustained participation.

Furthermore, individual and social values role in influencing various dimensions of customer engagement also confirmed [12]. The acceptance of hypotheses related to individual value indicates that consumers who perceive products or services as reflective of their personal identity and self-expression are more likely to experience affective engagement. A more interesting result is the acceptance of hypotheses related to social value which suggests that when consumers view products or services as enhancing their social standing or strengthening interpersonal connections, they are more likely to exhibit all affective, cognitive, and behavioral aspects of engagement [5]. Put in Indonesian context, this study proved that Indonesia's collectivist cultural orientation [58] is particularly strong. Consumers are more likely to engage with live stream shopping when they feel part of a community, or when the streamer is endorsed by social networks. Emotional involvement is heightened when shopping is perceived as a shared experience rather than an individual act. These findings highlight that both individual relevance and social context play important role to shape engagement [12].

It is also important to acknowledge the hypotheses that were not supported by the data process results. Notably, financial value did not significantly influence behavioral engagement, functional value was not a significant predictor of affective engagement or purchase intention, while individual value did not significantly predict cognitive and behavioral engagement. Additionally, cognitive and behavioral engagement did not show a significant relationship with purchase intention [12]. These outcomes suggest that while value perceptions and engagement are important, their influence may vary across different engagement dimensions and outcomes.

While financial value may foster emotional connections and influence purchase decisions, it appears insufficient to trigger extensive deliberation or information-seeking behavior. Likewise, the non-significant relationship between financial value and behavioral engagement indicates that economic incentives alone do not guarantee active consumer participation. This implies that while attractive pricing or promotions may draw attention, they may not encourage deeper involvement or community-building behaviors around a product or service.

Similarly, significant link between functional value and affective engagement is absent. This finding reveals that consumers may not form emotional bonds with offered products purely on practical utility. Furthermore, the rejection of the hypothesis connecting functional value to purchase intention suggests that functional benefits, while relevant, may not independently drive purchasing behavior [59]. One possible explanation for the absence of functional value is due to two factors: the characteristics of live streaming shopping and the buyer culture in Indonesia. Functional value does not significantly influence engagement or purchase intention in live streaming shopping because the context is emotionally driven, socially interactive, and entertainment-centered, where hedonic motivations dominate decision-making [60]. These characteristics are reinforced by Indonesian buyer culture, which prioritizes hedonic factors and ignores functional value [61]. These findings point reveal that we need a more holistic value offering, where practical utility must be supported by emotional or social appeal to effectively influence consumer decisions [62]. Overall, these results emphasize the complexity of consumer engagement, reinforcing the idea that no single value dimension can independently account for all facets of consumer.

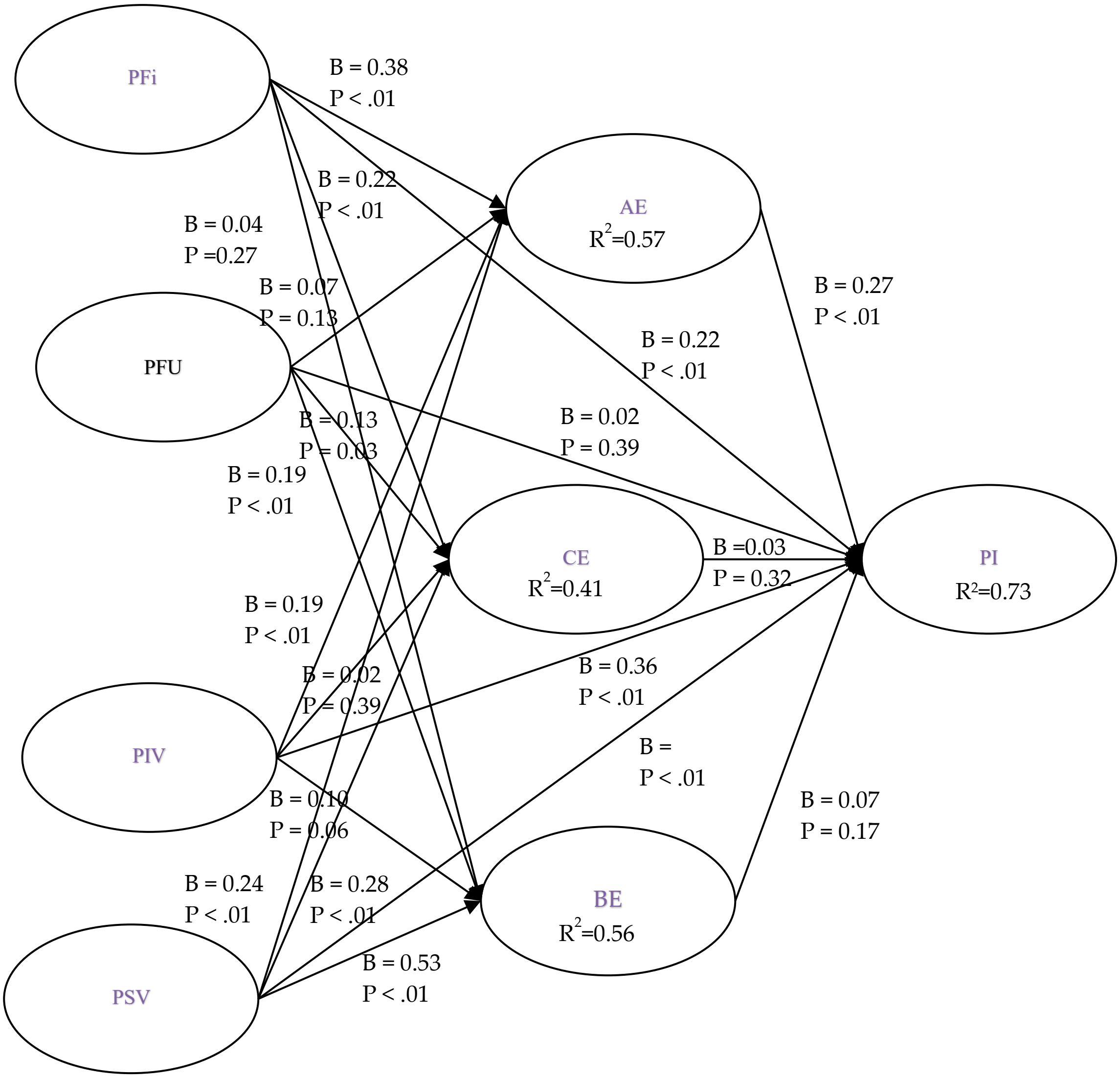


FIGURE 2. Final structure model result.

The presence of direct association between individual value and purchase intention suggests that consumers may personally identify the offered product, and this sense of identification leads to an actual purchase. This indicates that this factor along with other factors such as price sensitivity may play a decisive role in final purchase decisions. Furthermore, the results imply that translating engagement into tangible actions, such as purchasing, involves a more complex interplay of factors beyond personal alignment or active involvement.

The findings should be interpreted with the recognition that TikTok Indonesia reflects a unique market characterized by price sensitivity, strong social interaction, collectivist cultural tendencies, and rapid adoption of digital commerce. These characteristics make the context theoretically important for studying live stream shopping but may not fully represent consumer behavior in other countries or on other platforms such as Shopee Live. Nonetheless, the patterns observed provide insights that can inform broader theorization of perceived value and engagement in live commerce settings.

The relationship between different types of perceived value and varying levels of engagement underscores the importance of adopting a holistic approach to marketing and customer relationship management. Companies should aim to develop products and services that go beyond offering financial and functional benefits by also addressing consumers' individual identities and social needs. Perceived value, as understood from the customer's perspective, plays a pivotal role in motivating transactional behavior [39]. This can be achieved through targeted messaging, personalized experiences, and the cultivation of communities that foster a sense of belonging and shared identity [63] Moreover, it is important to recognize that engagement is not a uniform construct—its affective, cognitive, and behavioral dimensions may be influenced by distinct drivers. To build meaningful and lasting relationships with consumers, businesses must tailor their strategies to respond to the unique motivations behind each type of engagement [12]. This research reinforces the role of financial, functional and social values over individual values in shaping consumer engagement, highlighting the need for more value-aligned and emotionally resonant marketing practices.

Businesses can foster deeper customer engagement by adopting sustainable and participatory practices that resonate with modern consumer values [64]. Implementing community engagement strategies that encourage active participation can further strengthen this relationship [65]. In the context of live stream shopping, companies have a unique opportunity to enhance customer relationships by leveraging real-time interaction, which helps build trust and emotional resonance [66]. This can be achieved through personalized communication, loyalty programs, and exclusive experiences that make customers feel recognized and appreciated [67]. To remain competitive, companies must move beyond traditional marketing methods and embrace strategies that promote authentic connection and collaboration with consumers. A holistic engagement approach not only strengthens customer relationships but also contributes to brand loyalty and long-term business sustainability [68]. Research shows that customer engagement plays a vital role in sustaining long-term interactions, improving customer retention, and enhancing overall firm performance [69, 70]. In live streaming contexts, engagement can be enriched by incorporating cognitive, emotional, behavioral, and social components [71]. Additionally, consumer actions such as transactions and brand-related content sharing on social media serve as powerful forms of organic promotion and advocacy [72].

At this stage, we infer certain design and managerial recommendations from the outcomes of our data. First, live-stream shopping interfaces should present economic and functional cues side by side. Prominent yet unobtrusive elements such as real-time discount tags, limited-time vouchers, and stock counters reinforce financial value, which the study shows to be a direct driver of viewers' emotions and buying intent. Equally important especially to trigger engagement are clear functional aids: high-resolution product rotations, concise specification panels, and structured Q&A modules that allow audiences to verify quality and fit without leaving the stream. A layout that lets users toggle easily between "Deals" and "Details" addresses both the emotional appeal of savings and the practical need for information, thereby supporting affective, cognitive, and behavioral engagement.

Second, sellers and platform managers should nurture individual identification with the brand and a sense of community among viewers. Stream hosts ought to act as facilitators rather than purely as sales promoters. Greeting returning viewers, highlighting user testimonials, and inviting polls or style suggestions help viewers see how the product aligns with their individual value while also signaling social acceptance (social value). Simple recognition tools loyalty badges, shout-outs for helpful comments, or collaborative challenges can transform passive spectators into active contributors, strengthening the affective links that ultimately lead to purchase intention.

Finally, organizations should monitor engagement quality as carefully as they track conversion. Indicators such as average viewing time during demonstrations, sentiment trends in chat messages, and repeat attendance rates can reveal whether the combined financial, functional, individual, and social value propositions are resonating. Budgets should reflect this layered strategy: episodic promotions can create bursts of excitement, whereas sustained investment in host training, content curation, and community management maintains long-term interest. By coordinating these efforts, firms can turn live-stream shopping from a short-term sales tactic into a durable relationship channel that consistently generates both engagement and revenue.

Live streamers could adopt concrete strategies to combine multiple value dimensions based on this study findings. For instance, they can highlight financial value by offering flash discounts, enhance functional value through live demonstrations, foster social value by recognizing buyers and showcasing community participation, and strengthen individual value by giving personalized shout-outs or tailored product suggestions. These integrated approaches will stimulate immediate purchase intention through financial and individual values directly, and at the same time also nurture sustained engagement and long-term loyalty using social value and functional value respectively.

V. CONCLUSION

The findings confirm the substantial impact of perceived value on customer behavioral intention. Specifically, financial value and individual value emerge as a strong driver of engagement and purchase intention. Additionally, social value is identified as key contributors to all three dimensions of engagement, underscoring their relevance in fostering meaningful consumer interaction within the live stream shopping environment. On the other hand, functional value unexpectedly has no significant effect on purchase intention either directly or indirectly.

This research contributes to the existing literature to unshed that perceived value is a critical determinant of consumer behavioral intention in live stream shopping. First, the finding highlights that not all value types are equal. This result advances theory by clarifying the distinct pathways of value. Second, contrary to prior literature that often assumes functional utility matters most in online purchases, this study reveals that functional value has no significant direct or indirect effect on purchase intention. This challenges conventional models and suggests context (such as, experiential/entertainment nature of live shopping) moderates the role of functionality. There are actionable insights for both scholars and practitioners based on the result. Platform designers should focus more on experiential, emotional, and social aspects to stimulate engagement and conversion by developing loyalty programs, influencer credibility, or gamified interactions rather than over-investing in functional assurances.

1. LIMITATIONS AND FUTURE RESEARCH

While the study provides valuable insights, several limitations should be acknowledged. First, the findings are derived solely from TikTok live stream shopping. Consumer perceptions, engagement mechanisms, and purchase behaviors may differ on other platforms (such as, Instagram, Shopee Live). This might limit the generalizability of results across the broader live commerce ecosystem. Second, the study relies on self-reported data, which may be subject to common method bias, recall bias, and social desirability effects. Although statistical remedies were applied, perception-based measures cannot fully capture actual behavioral outcomes.

The unexpected insignificance of functional value opens avenues for future work by investigating cultural, demographic, or platform-specific moderators. Expanding the study to multiple platforms would help validate whether the identified value–engagement–intention dynamics are consistent across different technological and cultural environments. Other approaches can be done in the future research e.g. by combining perceptual measures with behavioral data (e.g., clickstream analysis, purchase records) that could reduce bias and provide a more holistic picture of consumer behavior in live stream shopping.

Funding Statement

The APC was funded by Telkom University.

Author Contributions

Conceptualization, Adhi Prasetio; methodology, Nurvita Trianasari and Chin Lay Gan; software, Puspita Kencana Sari; formal analysis, Adhi Prasetio; writing—original draft preparation, Adhi Prasetio; writing—

review and editing, Tze Wei Liew.; supervision, Ratri Wahyuningtyas. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data is available from the authors upon request.

Acknowledgments

The authors would like to acknowledge the assistance of the Editor and Reviewers in the preparation of the article for publication.

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