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The Role of Perceived Value and Risk in Shaping Purchase Intentions in Live-Streaming Commerce: Evidence from Indonesia

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Abstract

This study examines how dual appraisals of value and risk jointly shape purchase intention in live-streaming commerce, refining the Stimulus–Organism–Response (S-O-R) framework for an understudied market context. Drawing on data from Indonesian live-stream shoppers, we demonstrate that stimuli such as streamer credibility, interactivity, and media richness enhance value perceptions and reduce perceived risk, which in turn increases purchase intention. The findings indicated that perceived value is the dominant pathway to intention, while perceived risk shows a small but positive association in this context. The study contributes by advancing S-O-R with dual appraisals and offers design guidance for stream formats. Practically, the findings provide explicit direction for allocating resources towards media richness and structured interactivity, while simultaneously emphasising the importance of safeguards. These design decisions consistently increase consumers' purchase intentions and perceived value.

Keywords: live-stream shopping; user behaviour; Stimulus–Organism–Response (SOR); perceived value; perceived risk; consumers' purchase intention

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1. Introduction

Digital technology has revolutionised people's shopping habits, making e-commerce a dominant force in the global retail industry. Among the many innovations, live streaming has emerged as a powerful tool for businesses [1]. Through live streaming, businesses or brands can interact with potential consumers in real-time [2], creating more personal and engaging shopping experiences [3,4]. In Indonesia, as one of the biggest e-commerce markets, platforms such as YouTube, Facebook, TikTok, Instagram, and specialised e-commerce sites, like Shopee and Tokopedia, are increasingly incorporating live streaming features, making this medium essential for businesses aiming to stand out in the crowded online marketplace [1].

The global COVID-19 pandemic has accelerated the use of the Internet and further accelerated the shift toward online shopping [5], driven by lockdowns and social distancing measures that have pushed businesses to adopt digital-first strategies. Studies confirm that live-streaming commerce (LSC) experienced exponential growth during this period. Recent reports indicate that nearly 80% of all digital transactions in Indonesia were conducted via social commerce [6], with 56% of these transactions involving purchases made via

live-streaming shopping [7]. LSC offers a unique opportunity to bridge the gap between physical and digital shopping experiences by providing real-time demonstrations and direct communication with consumers [8]. Additionally, LSC facilitates direct interaction between streamers and customers, and the success of these efforts depends on how effectively businesses comprehend and manage the factors that influence consumer trust and engagement in this context [3].

Prior LSC studies deploy SOR theory to examine single stimuli in isolation and emphasise value-driven aspects from the positive side of organismic states. Recent studies have shown that technical aspects [9,10] or people cues [2,4] play a crucial role as stimuli in customer behaviour in LSC. For example, media richness [9] and interactivity during live-stream events [11] can substantially improve social presence, which often leads to purchase intention, typically through value-focused organismic states in technical aspects. At the people-cue level, the credibility and social image of streamers influence trust and intention [11], thereby strengthening the importance of human signals in conjunction with technical affordance. While LSC also comes with uncertainty, other studies assess the role of perceived risk as an intervening variable between stimuli and response [12,13]. Yet, most models operationalise these pathways asymmetrically, focusing on value or risk as independent organismal factors and often examining stimuli in isolation, rather than within an integrated framework of human cues and technological affordances.

Therefore, despite the growing popularity of live streaming on social media and e-commerce platforms [14], a significant gap remains in understanding how various elements of live-streaming content influence consumer behaviour. We address this gap by integrating three complementary stimuli, including Streamer Credibility [2], Interactivity [15], and Media Richness [9], into one model to explain their joint effects on two organismic appraisals, Perceived Value [16] and Perceived Risk [17], and downstream purchase intention (response) in Indonesian LSC. This integration clarifies how technology affordances (Media Richness, Interactivity) and people factor (Credibility) work together rather than in parallel.

We also nuance SOR by treating risk as an active co-determinant (alongside value), showing how value and manageable risk can co-exist in shaping intention in real-time selling contexts [18]. In summary, this article examines the dual-appraisal explanation of intention, focusing on how live-stream stimuli enhance perceived value and mitigate perceived risk, and how these appraisals impact purchase intention. These advances refine SOR's application to technology-mediated commerce, offering more precise mechanisms for intervention.

Given these considerations, this study addresses critical gaps in the current literature by addressing the following research question:

RQ1. How do credibility, interactivity, and media richness shape consumers' perceived value and perceived risk in live-streaming commerce?

RQ2. How do perceived value and perceived risk influence users' purchase intentions?

By addressing these research questions, the study aims to provide a more comprehensive understanding of how businesses can optimise their live-streaming strategies to maximise consumer engagement and drive sales. This study contributes to the growing body of knowledge by examining the interplay between Interactivity, Media Richness, and Streamer Credibility and how these elements influence consumer perceptions and purchasing decisions. The findings are expected to offer practical implications for businesses that enhance their live-streaming strategies and better engage with their target audiences across different demographic segments. The remainder of this paper is structured as follows. Section 2 provides a literature review and hypothesis development. Section 3 outlines the research methodology. Section 4 presents the results and discusses the findings as well as a

theoretical contribution and practical implications. Finally, Section 5 concludes this study, explaining its limitations and outlining future work.

2. Literature Review

2.1. Live-Streaming Commerce (LSC)

As Internet technology has evolved, live streaming refers to the real-time transmission of video content online, originating from traditional broadcasting [1] but expanding rapidly with technological advancements, primarily via social media or e-commerce platforms. This technology has revolutionised how users purchase and interact [11] by enabling content creators, brands, and streamers to communicate instantly with viewers. This real-time engagement provides a dynamic and immersive experience, contributing to the growing significance of live streaming as a core feature of social media [1,19]. The introduction of live streaming on these platforms was a game-changer, allowing streamers and ordinary users to broadcast live events, product launches, and tutorials while interacting with viewers in real-time [4]. Social media live streaming has rapidly become an essential tool for engagement, as it allows for two-way communication between broadcasters and their audience [1]. This capability distinguishes it from traditional broadcasting and pre-recorded video content. Brands and streamers utilise platforms like Instagram Live and TikTok to promote products, address consumer inquiries, and provide live demonstrations [20]. Research has shown that consumers are more likely to engage with brands and make purchases after participating in live streams, as the interactive nature of these sessions helps build trust and foster stronger relationships [10].

Streamers actively interact with potential consumers during live streaming, review products in real-time, and share their experiences with them. The streamer's credibility fostered a positive emotional connection with the audience. Streamers with high credibility and good interaction can significantly enhance purchase intention [2,21]. Credibility is often based on several key factors: expertise, honesty, and similarity to the audience [22]. When viewers believe that the streamer possesses knowledge about the product, shares honest opinions, and is relatable, they are more likely to trust the quality and utility of the product [21]. This trust fosters a positive feedback loop, where viewers feel confident in their purchasing decisions.

2.2. Stimulus–Organism–Response (SOR) Theory

The SOR framework was first introduced by Mehrabian [23], who explained how environmental stimuli (S) influence emotional state (O), which in turn leads to specific behavioural responses (R). This model is foundational in understanding the relationship between environmental cues and human responses across various disciplines. In the SOR framework, stimuli can refer to external factors such as marketing messages, physical surroundings, or technological features; the organism encompasses the internal processes, emotions, and cognitive evaluations that arise in response to these stimuli; and response represents the behavioural outcomes, such as approach or avoidance actions [23].

This theory has been widely applied in various areas, including e-commerce [11], communication [24], travel and tourism marketing [25], and Information Systems [26]. For example, the application of the SOR model to examine the role of website aesthetics revealed that interactivity plays a significant role in shaping consumer emotions and purchase behaviours [11]. Specifically, positive stimuli within the online environment can enhance consumers' perceived value, leading to increased purchase intentions. Another study examined how online travel experiences, including virtual tours and destination imagery, elicit emotional responses that influence travel intentions [25]. Their findings support the model's applicability in explaining how digital and sensory stimuli influence

tourist behaviour. Huang [24] combined several variables from other acceptance theories, such as the Theory of Planned Behaviour (subjective norm) and Technology Acceptance Theory (Perceived Usefulness and Perceived Ease of Use), as well as other theories, to develop a smartphone acceptance model. The authors concluded that the SOR provides valuable theoretical frameworks for predicting the factors that influence users' intentions to use specific technologies. As online games proliferate, Hew, et al. [26] recommend that game developers consider aspects of immediacy, social interaction, and competition to enhance gamers' experiences and promote a flow state.

In LSC, platform stimuli (e.g., interactivity and media richness) and people cues (streamer credibility) have a role in influencing viewers' perception before they decide to buy. We next describe how these stimuli translate into two co-evolving appraisals (perceived value and perceived risk) and develop testable hypotheses.

2.3. Concept Framework and Hypotheses Development

The study is grounded in a conceptual model based on SOR theory [23], as shown in Figure 1. We refine S–O–R by positioning perceived value and perceived risk as dual, co-evolving appraisals that translate platform and human stimuli into purchase responses. Interactivity and media richness can raise value (clarity, immersion, social presence) while simultaneously shaping risk. Streamer credibility serves as a people-centric cue that conditions both appraisals. This dual-channel view diverges from prior approaches that model risk as a simple inhibitor, clarifying when uncertainty may act as a signal rather than a deterrent. The framework serves as the basis for the analysis, which will test the ideas using data collected from individuals who engage in live streaming. The goal is to explain how live-stream stimuli shape value and risk appraisals that drive purchase intention. The remainder of this subsection will discuss and justify the hypothesis of this study.

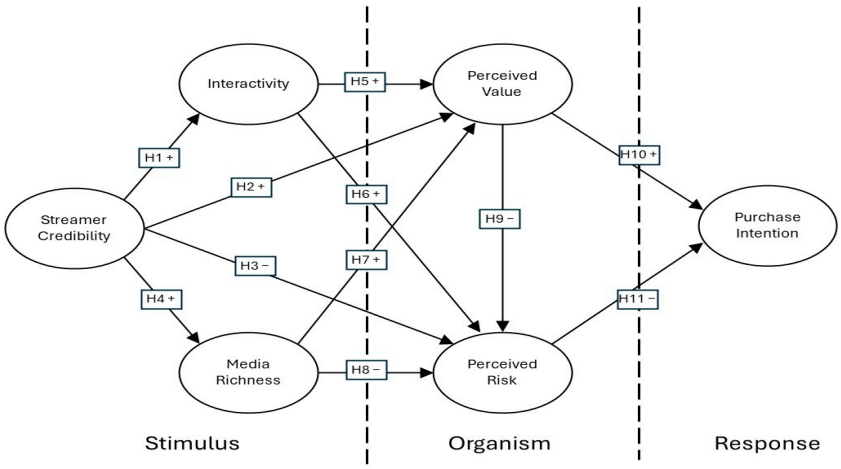

Figure 1. Conceptual Framework.

2.3.1. Streamer Credibility (SC) as Stimuli

Streamer credibility plays a crucial role in shaping the success of live-streaming content [11]. It affects how viewers perceive the streamer and influences their overall engagement and interaction with the content [4]. Consumers who perceive a streamer as credible, trustworthy, knowledgeable, and attractive are more inclined to actively engage with the content [22]. This trust fosters higher levels of participation, as viewers feel confident in the information being shared and are more likely to interact, ask questions, and contribute to discussions [10].

A credible streamer also elevates the perceived value of the products or services they promote [27]. Streamer credibility bundles expertise (diagnostic information), trustwor-

thiness (reduced ambiguity), and attractiveness (affective lift). The expertise of a streamer could enhance the product description. At the same time, trustworthiness could reduce suspicion of opportunistic persuasion. Meanwhile, parasocial cues heighten hedonic appreciation. Jointly, these mechanisms raise perceived benefits relative to costs, increasing perceived value of the products, which can drive consumer interest and intention to purchase [4].

Beyond influencing perceived value, streamer credibility is crucial in reducing the perceived risk of online purchases [28]. In the digital marketplace, where consumers cannot physically interact with products, perceived risk can be a significant barrier to purchase. Credible streamers help alleviate these concerns by providing clear, accurate, and detailed information, thereby reassuring viewers and minimising the uncertainty often associated with online shopping decisions [4]. This reduction in perceived risk can make viewers more comfortable with the idea of purchasing products promoted through the live stream.

Furthermore, credible streamers tend to use the media to enhance the effectiveness of live streaming as a marketing tool [9]. Rich media, which includes high-quality visuals, audio, and interactive elements, enhances the overall quality of the content presented [29]. By leveraging their trustworthiness and expertise, credible streamers are better positioned to deliver compelling interactivity and high-quality content that captures their audience's attention. The use of rich media by credible streamers not only makes the content more engaging but also helps to communicate product details more effectively, leading to a more immersive and informative experience for viewers [30]. The following hypotheses explore the impact of Streamer Credibility on Interactivity, Perceived Value, Perceived Risk, and Media Richness:

H1: *Streamer credibility positively influences interactivity.*

H2: *Streamer credibility negatively influences Perceived Risk.*

H3: *Streamer credibility positively influences Perceived Value.*

H4: *Streamer credibility positively influences Media Richness.*

2.3.2. Interactivity (IT) as Stimuli

Interactivity in live streaming refers to the ability of viewers to actively engage with the content, including direct communication with the streamer and participation in real-time discussions or polls [10]. This interactive environment provides consumers with a more personalised experience, which can significantly enhance their connection to the products or services being showcased [2]. When consumers interact directly with the content and the streamer, it fosters a sense of involvement and engagement, making the shopping experience more dynamic and tailored to individual preferences [31]. This heightened level of engagement often increases the perceived value of the products or services offered [32]. Consumers are more likely to perceive value in a shopping experience that feels responsive and personalised, where they can actively influence the content and have their questions or concerns addressed in real-time.

However, the spontaneous and sometimes unpredictable nature of interactivity can also introduce an element of uncertainty [12]. In a highly interactive setting, content is often delivered in real-time, lacking the polish and predictability of pre-recorded videos or traditional marketing materials [14]. This immediacy, while engaging, may also lead to increased perceived risk as consumers might feel less confident about the accuracy of the information or the outcome of their interactions [12]. The direct and unfiltered nature of live interactions can sometimes leave consumers uncertain about their purchase decisions,

as they may not have all the necessary information or may question the reliability of what is being presented. The following hypotheses investigate the dual impact of interactivity on perceived value and perceived risk:

H5: *Interactivity positively influences Perceived Risk.*

H6: *Interactivity positively influences Perceived Value.*

2.3.3. Media Richness (MR) as Stimuli

Media Richness refers to the capacity of a communication medium to deliver information effectively, encompassing various sensory channels such as visuals, audio, and Interactivity [33]. In live streaming, media richness plays a critical role in shaping consumer perceptions by enhancing the quality and depth of the content. This factor contributes to a more immersive and engaging viewer experience by offering high-quality visuals, detailed audio, and interactive features [9]. These elements work together to give consumers a comprehensive understanding of the product or service. As a result, rich media elevate the perceived value of the content, making it more appealing and persuasive. When viewers are presented with detailed and vivid information, they are more likely to perceive the content as valuable and worthwhile [29]. This enhanced perception of value is crucial in driving consumer interest and fostering a deeper connection with the product or service.

Moreover, one of the key challenges in online shopping is the uncertainty of being unable to inspect products physically [33]. Media richness helps mitigate this issue by providing comprehensive and detailed information, which reduces ambiguity and uncertainty. When consumers are exposed to rich media that thoroughly showcases a product's features and benefits, their perceived risk associated with purchasing the product decreases [34]. The detailed information provided through rich media makes consumers feel more informed and confident in their decision-making, lowering perceived risk and increasing their likelihood of purchasing [29]. Media richness is vital in reassuring consumers and enhancing their trust in the content by minimising doubts and uncertainties. The following hypotheses explore the impact of Media richness on perceived value and perceived risk:

H7: *Media Richness positively influences Perceived Value.*

H8: *Media Richness has a negative influence on Perceived Risk.*

2.3.4. Organismic Appraisals: Perceived Value (PV) and Perceived Risk (PR)

Perceived value and perceived risk are fundamental determinants in consumer decision-making, playing essential roles in shaping purchase intentions [35]. Perceived value refers to the consumer's evaluation of the benefits they expect from a product or service relative to the costs involved [36]. When consumers perceive high value, they tend to feel more confident that the benefits of the purchase outweigh any potential downsides. This confidence can reduce perceived risk, as the value assurance provides a buffer against uncertainties and concerns about the purchase [17]. When consumers perceive a product or service as offering substantial value, they are more likely to move forward with their purchase. This behavior is driven by their expectation of receiving benefits that justify the cost and effort involved. Conversely, perceived risk represents potential adverse outcomes, such as product failure, financial loss, or dissatisfaction. High levels of perceived risk can significantly deter consumers from making a purchase, as the fear of potential negative consequences can overshadow the perceived benefits [37]. However, risk does not always become an inhibitor of intention, as meta-analytic and experimental evidence show that

scarcity tactics and time pressure can potentially offset risk aversion [38], especially in live-stream commerce [39].

The interplay between perceived value and perceived risk is crucial: as perceived value increases, perceived risk often decreases, leading to stronger purchase intentions [17]. Conversely, higher perceived risk can undermine the likelihood of purchase, even when the product or service appears valuable. The following hypotheses explore these relationships:

H9: *Perceived Value negatively influences Perceived Risk.*

H10: *Perceived Value positively influences Purchase Intention.*

H11: *Perceived Risk negatively influences Purchase Intention.*

3. Methodology

This study employed a quantitative research design, aligning with the positivist viewpoint [40]. This paradigm is based on the principles of measurement and reason, asserting that knowledge is derived from an impartial and quantitative observation of activities.

3.1. Respondent & Data Collection

Researchers employed a non-probabilistic sampling technique, specifically purposive sampling, to ensure that respondents had relevant experience and knowledge, as well as watched or purchased via live streaming in the past 6 months. Data was collected between May and July 2024 through online surveys administered via Google Forms. The invitation was distributed through messaging applications (such as Line and WhatsApp). In addition, prior studies [41,42] have emphasised the importance of ensuring a sufficient sample size to draw valid research conclusions. It is recommended that the sample size should be about 15 to 20 observations for each independent variable [43]. The research model identified five independent variables that required 75–100 samples. We also examine sample size through power analysis [41,44], using G*Power 3.1.9.7 (effect size = 0.15, α = 0.05, power = 0.95). The minimum sample size required is 166. This study successfully collected 223 valid responses, exceeding the recommended number as presented in Table 1.

Table 1. Respondent demography.

Measures	Description	Frequency (n)	Percentage (%)
Gender	Female	178	80.5
	Male	43	19.5
Age	<18 years	17	7.7
	18–22 years	103	46.6
	23–29 years	78	35.3
	>30 years	23	10.4
Education	Senior High School	122	55.2
	Diploma 3	11	11.7
	Bachelor	79	35.7
	S2/S3	1	0.5
	Other	8	2.7
Income	<3,000,000	160	72.4
	3,000,001–6,000,000	43	19
	6,000,001–10,000,000	14	6.3
	>15,000,000	5	2.3

Notes: Income in Rupiah (IDR).

Table 1 indicates that the dataset is heavily skewed toward younger consumers (46.6% aged 18–22, 35.3% aged 23–29) and females (80.5%), reflecting the mainstream live-streaming context in Indonesia. A recent study indicates that the majority of Indonesian live-streaming users are women and younger in age [45]. This media appeals to them for both entertainment and purchasing.

3.2. Instrument Development

The questionnaire used in this study consisted of two parts: the first part was designed to obtain respondents' demographic data, and the second part was intended to capture respondents' perceptions of the constructs under study. To measure perception, the study adapted all measurement items from previous related studies, as presented in Table 2. Each construct was measured using 5-item indicators [43]. As the point scale requires more time and potentially leads to respondent fatigue [46], this study employed a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). Items were translated into Bahasa Indonesia using forward-back translation and pretesting to ensure clarity and content equivalence. Only minor wording adjustments were made before data collection began.

Table 2. Measurement items and distribution assumption.

Constructs/Indicators		Sources	Kurtosis	Skewness
Purchase Intention (PI)				
PI1	I am willing to buy a product or service from a live-stream seller	[17,47]	0.654	−0.927
PI2	I will buy products/services from live streaming		−0.023	−0.576
PI3	I plan to shop online using live streaming.		0.029	−0.545
PI4	I would recommend online purchasing through live streaming		0.664	−0.849
PI5	I predict that I will shop online using live streaming in the next 3 months.		−0.139	−0.740
Perceived Value (PV)				
PV1	Product purchase live-streaming shopping is reliable in quality	[48,49]	−0.115	−0.651
PV2	I feel much better after using streaming services.		−0.029	−0.516
PV3	Products purchased through live-stream shopping are value for money.		0.731	−0.988
PV4	This discount makes the product more affordable		2.507	−1.618
PV5	I enjoy live-streaming shopping via social media.		1.250	−1.101
Perceived Risk (PR)				
PR1	I might get overcharged if I shop online through a live stream	[12,17]	−0.974	0.512
PR2	I might not get what I ordered through a live stream		−0.905	0.425
PR3	Delivery may be sent to the wrong place.		−0.736	0.452
PR4	Finding the right product online can take some time		−1.301	−0.071
PR5	I am afraid that the after-sales service is not good.		−0.714	0.039
Streamer Credibility (SC)				
SC1	The streamer is trustworthy	[12,50]	−0.156	−0.330
SC2	The streamer gives viewers information about the product/service.		0.247	−0.557
SC3	I think the streamer has an appealing appearance		0.542	−0.747
SC4	Streamers have extensive experience and are experts in reviewing products and services.		−0.319	−0.544
SC5	Watching a live stream is entertaining.		0.040	−0.668

Table 2. *Cont.*

Constructs/Indicators		Sources	Kurtosis	Skewness
Media Richness (MR)				
MR1	During live-streaming shopping, I can see detailed pictures of the product	[1,9]	1.792	−1.308
MR2	I can use a variety of media (text, pictures, video) to share the information I get from live-streaming shopping.		1.229	−0.940
MR3	The streamer responded quickly to my questions.		0.019	−0.667
MR4	Streamer provides clear guidelines for shopping		0.768	−0.989
MR5	I can provide opinions in a variety of languages		0.798	−0.909
Interactivity (IT)				
IT1	The streamer is willing to communicate with me	[12,51]	−0.416	−0.385
IT2	The streamer can respond to my specific questions quickly and efficiently.		0.746	−0.858
IT3	The information that streamers offer in real-time may affect the quality of the stream.		−0.170	−0.722
IT4	When watching a live stream, I feel closer to the streamer.		−0.274	−0.553
IT5	I can get a lot of good advice from the streamer.		0.203	−0.636

Considering ethical practice, this study obtained ethical clearance approval from the University's REC. Participants were provided with an information sheet and an electronic informed consent form. Additionally, participants were clearly informed about the study's purpose, the voluntary nature of their participation, and the guarantee of confidentiality. Further, no personal information was collected, and responses were anonymous, with the right to withdraw at any time.

3.3. Data Quality Screening and Cleaning

Next, we examine whether the dataset was free from any significant issues that could compromise the validity of the results [52]. Two responses were removed since they never use e-commerce or live-streaming shopping. We screened for unengaged responses, where respondents provide the same answer to all questions or show no variation in their answers, and found 11 responses. Therefore, these responses were removed, and the remaining 210 responses were subjected to statistical processes.

For the data analysis method, the study applied a structural equation model partial least square (SEM-PLS). SEM-PLS has gained high popularity in the fields of marketing [14], management [53], and information systems [42]. Although SEM-PLS is non-parametric and does not require normally distributed data, some researchers recommend examining the distribution, as extremely non-normal data could influence the results [54,55]. For this purpose, we checked the kurtosis and skewness as presented in Table 2. The result indicated that most of the scores ranged between −2 and +2. Only one indicator score exceeded an absolute value of two (kurtosis PV4 = 2.507); therefore, we employed bootstrapping with corrected and accelerated (BCa) bootstrapping for the confidence interval method [42].

We followed a two-step procedure [52]. Before doing it, we test the existence of common method bias (CMB). In the first stage, the reliability and validity of the instruments were assessed using indicators of reliability, internal consistency, convergent validity, and discriminant validity. After ensuring the reliability and validity of the measurement, the second process is carried out to test the hypothesis.

4. Results

After a satisfactory preliminary assessment, the process continued to the data analysis using SEM-PLS. This process consists of four stages: (1) common method bias [56], (2) measurement model assessment, (3) structural model evaluation, and (4) robustness check [57].

4.1. Common Method Bias (CMB)

In research that relies on self-reported data, CMB can be problematic as responses for multiple variables may be influenced by similar method-related factors [56]. This issue can lead to artificially inflated correlations among variables, which could falsify the validity of the findings [58]. This study deployed full collinearity testing [59] by examining the variance inflation factors (VIFs) calculated for each construct in the research model. The values above 3.3 indicated the potential presence of CMB [59], while another recommended a value above 5.0 [60]. The researchers used a dummy variable and regressed all other variables on it. In this study, all constructs yielded VIFs below the 3.3 threshold (ranging from 1.070 to 2.461), indicating that collinearity among constructs is not excessive and that CMB is unlikely to impact the results significantly. We also deployed Harman's single-factor test (HSF) to triangulate the risk of bias. Based on this method, CMB exists if the factor extracted explains more than 50% of the variance [56]. The results indicate that a single factor accounts for only 39.3% of the variance, suggesting that common method bias is not pervasive in our data.

4.2. Measurement Model Assessment

Reliability and validity instruments are essential for the quantitative study [61]. The assessment rigorously evaluates the research instrument through a series of tests to examine indicator reliability, internal consistency, convergent validity, and discriminant validity. The evaluation began by examining the reliability of individual indicators, specifically their factor loadings, which should be above the recommended threshold of 0.708 [52]. Despite carefully selecting previously validated indicators, it was necessary to confirm their reliability [57]. This analysis identified that indicators MR5 and PR4 did not meet the recommended threshold and were therefore excluded from the next analysis process. Following this, the study evaluated the internal consistency for sets of indicators related to the same construct by calculating Cronbach's alpha (CA) and Composite Reliability (CR). The results consistently exceeded the threshold of 0.70 [54], confirming that the indicators reliably measured a unified construct. Convergent validity was next assessed using the Average Variance Extracted (AVE) to determine how well the indicators converge in representing their constructs [62]. All constructs demonstrated AVE values above the accepted threshold of 0.50, confirming the instruments' convergent validity. The results of this comprehensive evaluation are summarised in Table 3.

Table 3. Summary of measurement model (outer model) assessment.

Constructs	Items	Loadings	CA	CR	AVE
Interactivity (IT)	IT1	0.822	0.852	0.895	0.630
	IT2	0.717			
	IT3	0.783			
	IT4	0.796			
	IT5	0.845			
Media Richness (MR)	MR1	0.789	0.790	0.865	0.616
	MR2	0.706			
	MR3	0.751			
	MR4	0.884			

Table 3. *Cont.*

Constructs	Items	Loadings	CA	CR	AVE
Purchase Intention (PI)	PI1	0.835	0.868	0.904	0.654
	PI2	0.835			
	PI3	0.846			
	PI4	0.753			
	PI5	0.771			
Perceived Risk (PR)	PR1	0.827	0.822	0.871	0.629
	PR2	0.765			
	PR3	0.864			
	PR5	0.685			
Perceived Value (PV)	PV1	0.785	0.822	0.871	0.629
	PV2	0.786			
	PV3	0.845			
	PV4	0.776			
	PV5	0.853			
Streamer Credibility (SC)	SC1	0.813	0.840	0.887	0.611
	SC2	0.838			
	SC3	0.777			
	SC4	0.754			
	SC5	0.720			

Finally, although perceived value (PV) and perceived risk (PR) are conceptually multidimensional, our theory focuses on their overall, co-evolving appraisals within the S-O-R chain during live streams. Consistent with common practice in LSC [11,63], where the theoretical target is a global appraisal, we therefore model PV and PR as single-layer reflective constructs for parsimony and identification. The study evaluated discriminant validity by assessing whether the constructs differed distinctly from one another [52] using the Heterotrait–Monotrait Ratio (HTMT) criterion. Initial results revealed an HTMT value higher than 0.90 between Interactivity and Media Richness, indicating insufficient discriminant validity. Following the prior study recommendations [64], the highly correlated items (IT2 and MR3) were removed. This action reduced the HTMT value to 0.883, which now meets the acceptable threshold of 0.90 [57].

For triangulation purposes, we also include the Fornell–Larcker Criterion analysis and cross-loading assessment for transparency. In every case, the square root of AVE on the diagonal exceeds all inter-construct correlations in the corresponding rows or columns, supporting discriminant validity alongside HTMT as indicated in Table 4.

Table 4. Discriminant validity assessment result.

	IT	MR	PI	PR	PV	SC
Heterotrait-Monotrait Ratio (HTMT)						
IT						
MR	0.883					
PI	0.740	0.721				
PR	0.092	0.183	0.099			
PV	0.806	0.896	0.866	0.152		
SC	0.852	0.817	0.680	0.106	00.774	
Fornell-Larcker Criterion						
IT	0.825					
MR	0.714	0.822				
PI	0.633	0.591	0.809			
PR	−0.055	−0.190	−0.058	0.758		
PV	0.692	0.736	0.759	−0.174	0.810	
SC	0.718	0.658	0.586	−0.069	0.663	0.781

This study also reports cross-loading to strengthen the evaluation of discriminant validity. The cross-loading, in particular, refers to an indicator's outer loading on the relevant constructs, which must exceed any of its cross-loadings on alternative constructs [65]. Table 5 shows that the retained items load highest on their intended constructs, ensuring that each item uniquely measures the construct.

Table 5. Cross-loading for Discriminant Validity Test.

	IT	MR	PI	PR	PV	SC
IT1	**0.812**	0.64	0.554	−0.065	0.6	0.566
IT3	**0.805**	0.611	0.513	−0.084	0.583	0.557
IT4	**0.818**	0.474	0.493	0.043	0.512	0.603
IT5	**0.865**	0.626	0.529	−0.08	0.588	0.642
MR1	0.570	**0.835**	0.470	−0.157	0.654	0.500
MR2	0.518	**0.752**	0.454	−0.043	0.489	0.485
MR4	0.662	**0.874**	0.532	−0.252	0.657	0.626
PI1	0.462	0.507	**0.835**	−0.145	0.624	0.467
PI2	0.522	0.527	**0.835**	0.003	0.645	0.487
PI3	0.554	0.531	**0.846**	−0.046	0.69	0.534
PI4	0.469	0.366	**0.754**	−0.109	0.535	0.433
PI5	0.553	0.441	**0.771**	0.049	0.559	0.438
PR1	−0.0076	−0.186	−0.056	**0.831**	−0.178	−0.073
PR2	0.020	−0.095	0.015	**0.780**	−0.052	−0.026
PR3	−0.066	−0.19	−0.09	**0.851**	−0.197	−0.079
PR5	0.007	−0.056	0.028	**0.701**	0.010	0.031
PV1	0.541	0.526	0.519	−0.121	**0.784**	0.563
PV2	0.565	0.542	0.656	−0.065	**0.786**	0.538
PV3	0.569	0.624	0.646	−0.140	**0.845**	0.536
PV4	0.488	0.642	0.544	−0.275	**0.777**	0.471
PV5	0.631	0.642	0.691	−0.130	**0.853**	0.579
SC1	0.594	0.537	0.506	−0.034	0.563	**0.814**
SC2	0.578	0.536	0.514	−0.041	0.579	**0.838**
SC3	0.532	0.491	0.367	−0.037	0.429	**0.778**
SC4	0.511	0.53	0.404	−0.205	0.484	**0.752**
SC5	0.584	0.471	0.484	0.034	0.523	**0.720**

Next, we examine the CA, CR, and AVE values before and after removing the highly correlated items. The post-deletion reliability demonstrated that CA, CR, and AVE were maintained after pruning, as presented in Table 6. The measurement refinements indicate that the constructs are empirically distinct and reliably measured.

Table 6. Post-deletion reliability (before vs after item pruning).

Construct	CA		CR		AVE		Items Kept
	Before	After	Before	After	Before	After	
IT	0.852	0.844	0.895	0.895	0.630	0.681	IT1, IT3, IT4, IT5
MR	0.790	0.760	0.865	0.862	0.616	0.676	MR1, MR2, MR4

4.3. Structural Model Evaluation

This study followed [52] as guidelines for structural relationship analysis to assess the strength and significance of the relationships between constructs in the research model. First, we examined the existence of multicollinearity by examining the inner VIF (variance inflation factor). Our assessment indicated that the value of VIF was below the threshold of 5.0 [60] and even less than 3.3 [59], which is considered an ideal number of VIF [52], confirming that no collinearity exists among the latent and observed variables of the structural model.

The bootstrapping technique examined the structural path using 10,000 subsamples, one-tailed, and a significance level of 0.05. Table 7 presents the summary of the structural model assessment. We assessed the significance and relevance of the structural model

relationship and tested the hypotheses. Each hypothesis was evaluated based on the path coefficient, t-value, *p*-value, and confidence intervals (CI LL and CI UL) for the path, as well as the effect size (f^2).

Table 7. Summary of structural model (inner model) evaluation.

Hypothesis Relationship	β	t	p	95% CI		Sig.	Supported?	f^2	VIF
				LL	UL				
H1. SC → IT	0.718	19.046	0.000	0.648	0.774	***	Yes	1.063	1.000
H2. SC → PV	0.215	1.979	0.024	0.038	0.400	*	No	0.054	2.264
H3. SC → PR	0.074	0.664	0.253	−0.119	0.245	NS	Yes	0.002	2.385
H4. SC → MR	0.658	14.890	0.000	0.575	0.722	***	Yes	0.762	1.000
H5. IT → PV	0.230	2.507	0.006	0.080	0.385	**	Yes	0.053	2.620
H6. IT → PR	0.187	1.692	0.045	−0.019	0.348	*	Yes	0.014	2.759
H7. MR → PV	0.431	4.827	0.000	0.277	0.573	***	Yes	0.218	2.237
H8. MR → PR	−0.249	2.504	0.006	−0.381	−0.044	**	Yes	0.024	2.725
H9. PV → PR	−0.174	1.455	0.073	−0.355	0.022	NS	No	0.012	2.626
H1. PV → PI	0.773	22.873	0.000	0.711	0.823	***	Yes	1.385	1.033
H11. PR → PI	0.079	2.118	0.017	0.019	0.140	**	No	0.014	1.033

Note: β = Standardized coefficient; CI = Confidence Interval; VIF = inner VIF; f^2: 0.02/0.15/0.35 = small/medium/large *p*-value = * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, NS: not significant.

The results indicate that nine hypotheses were supported, while two others were not. The relationship between perceived value and purchase intention (H10) had the strongest relationship among the other hypotheses ($\beta = 0.773$; $p < 0.001$). We also examined the 95% confidence interval [66], which does not straddle zero (1.385 to 1.445), further supporting the strength and stability of the effect of perceived value on purchase intention. As the effect sizes of 0.02, 0.15, and 0.35 correspond to small, medium, and sizable effects, respectively [67], therefore, perceived value had a significant effect size on purchase intention ($f^2 = 1.385$). This strong relationship suggests that enhancing the perceived value of products or services can be a crucial strategy for streamers and content creators seeking to increase purchase intentions among their target audience.

Furthermore, the relationship between media richness and perceived risk presents a fascinating contrast supporting the hypothesis of H8. Media richness reduces the perceived risk ($\beta = -0.249$; $p = 0.006$), indicating that detailed visuals or audio and clearer demonstrations lower ambiguity and uncertainty. The confidence intervals for this relationship range from −0.381 (BCI LL) to −0.044 (BCI UL) and indicate consistent adverse effects across different scenarios.

However, two paths are not significant (H3 and H9), which indicate that streamer credibility does not directly reduce perceived risk ($\beta = 0.074$, $p = 0.253$) and higher perceived value did not reliably translate into lower risk in this context ($\beta = -0.174$, $p = 0.073$). By contrast, the relationship between perceived risk and purchase intention (H11) is positive and significant ($\beta = 0.079$; $p = 0.017$). However, because our hypothesis predicted a negative effect, we classify H11 as not supported (sign-inconsistent). These exceptions help delimit the model's risk pathway, while the remaining estimates align with expectations and are interpreted through the mediation results reported next.

We also examine the mediation effects to clarify how person and platform-level stimuli translate into purchase intention. We estimated specific indirect effects with bias-corrected bootstrapping (10,000 resamples; two-tailed 95% CIs). Indirect effects are deemed significant when the CI excludes zero [65]. The results indicate that perceived value is the primary medium for the stimuli to purchase intention, whereas perceived risk carries small and

mixed indirect effects. The IT → PV → PI pathway is significant (β = 0.178, $p = 0.007$), as is MR → PV → PI (β = 0.333, $p < 0.001$), and multi-step chains from streamer credibility via MR/IT → PV → PI are also significant (β = 0.219 and β = 0.128, respectively). Risk-based routes are small and non-significant (e.g., MR → PR → PI β = −.020, $p = 0.071$; IT → PR → PI β = 0.015, $p = 0.115$). The direct PR → PI path remains positive and significant (β = 0.079, $p = 0.017$), indicating no suppression. We classify mediation and report the specific indirect effects [68] in Table 8.

Table 8. Specific Indirect Effect on Purchase Intention.

From	Via	Indirect β	5.0%	95.0%	Sig.	Mediation Type
SC	PV → PR	−0.003	−0.014	−0.000	No	No mediation
SC	PR	0.006	−0.005	0.027	No	No mediation
SC	MR → PV → PR	−0.004	−0.014	−0.000	No	No mediation
SC	MR → PV	0.219	0.137	0.303	Yes	Indirect-only
SC	MR → PV	0.283	0.178	0.389	Yes	Complementary
SC	MR → PR	−0.013	−0.031	−0.002	No	No mediation
SC	IT → PV → PR	−0.002	−0.009	−0.000	No	No mediation
SC	IT → PV	0.128	0.044	0.216	Yes	Indirect-only
SC	IT → PV	0.165	0.057	0.277	Yes	Complementary
SC	IT → PR	0.011	0.000	0.031	No	No mediation
IT	PV → PR	−0.003	−0.013	−0.000	No	No mediation
IT	PV	0.178	0.061	0.300	Yes	Indirect-only
IT	PR	0.015	0.001	0.042	No	No mediation
MR	PV → PR	−0.006	−0.020	−0.000	No	No mediation
MR	PV	0.333	0.212	0.446	Yes	Indirect-only
MR	PR	−0.020	−0.046	−0.002	No	No mediation
MR	PV → PR	−0.006	−0.020	−0.000	No	No mediation
MR	PV	0.333	0.212	0.446	Yes	Indirect-only
MR	PR	−0.020	−0.046	−0.002	No	No mediation
PV	PR	−0.014	−0.042	−0.001	No	No mediation

Table 9 summarises the extent to which each predictor's total effect on purchase intention operates through mediators (VAF). The pattern indicates indirect-only mediation via perceived value for Interactivity (VAF = 0.94) and Media Richness (VAF = 1.00), and partial (complementary) mediation for Streamer Credibility (VAF = 0.68). For Perceived Value and Perceived Risk, VAF is 0.00, indicating no meaningful mediation of their effects on purchase intention.

Table 9. Mediation summary.

From (Predictor)	Indirect Sum (β)	Total Effect to PI (β)	VAF (=Indirect/Total)	Mediation Type
IT → PI	0.178	0.190	0.94	Indirect-only via PV
MR → PI	0.307	0.308	1.00	Indirect-only via PV
SC → PI	0.346	0.507	0.68	Partial (complementary)
PV → PI	−0.014	0.760	0.00	No mediation
PR → PI	0.00	0.079	0.00	No mediation

Notes: VAF = share of the total effect carried out by mediators.

Based on Tables 8 and 9, we report the specific indirect and total effects alongside direct paths, following the recommended practice in PLS-SEM and mediation reports [57,68]. Interactivity and media richness influence purchase intention almost entirely through perceived value, consistent with S–O–R accounts, in which affordances elevate clarity, immersion, and social presence, which then convert to intention (indirect-only mediation; VAF = 0.94–1.00). Streamer credibility operates through both MR and IT to PV channels, retaining a meaningful total effect (partial/complementary mediation; VAF = 0.68), suggesting that credibility amplifies value creation via affordances. By contrast, risk-based

pathways are small and generally insignificant, indicating that in this context, cues move intention mainly through value, rather than risk reduction. Notably, the positive PR → PI direct effect persists after accounting for all indirect, ruling out suppression and supporting a context-bound interpretation (e.g., authenticity/scarcity signals under time pressure with visible transaction safeguards).

Having established the significance and strengths of the relationships within our structural model, we now consider evaluating the model's overall explanatory power [57]. This assessment is crucial, as it confirms the robustness of the relationships and underscores the model's practical utility in forecasting outcomes based on the studied constructs [69]. The R-squared values provide substantial insights, especially for PV and PR. With an R-squared value of 0.619, PV has the most significant explanatory power, indicating that the model accounts for 61.9% of the variation. Conversely, PR has the lowest value of 0.064, suggesting that the model explains only a small fraction of its variability. It also suggests that the model used in this study does not account for the influence of external factors, which are not taken into consideration. Both perceived value and risk contributed moderately [52], explaining 58.2% of the variance in PI. Figure 2 shows the structural model analysis findings.

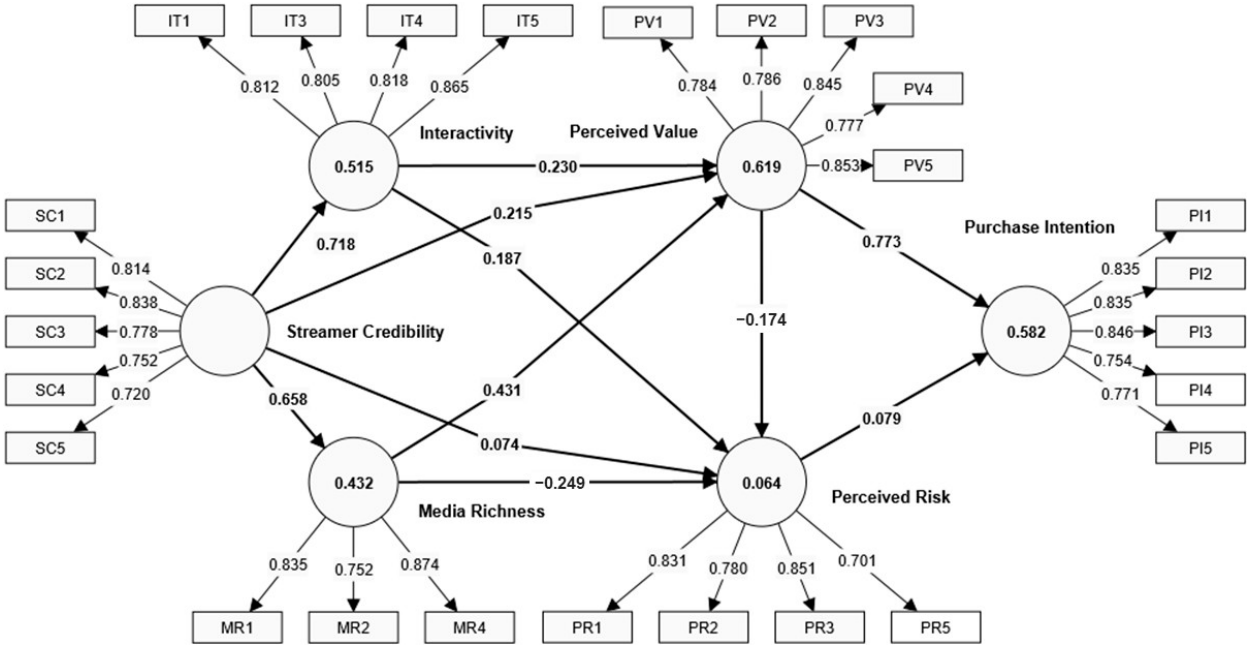

Figure 2. Structural model analysis results.

In the final step of this assessment, we evaluate the PLSpredict analysis to assess the out-of-sample predictive power of an SEM-PLS model by generating case-level predictions using the default settings (10-fold cross-validation and 10 repetitions) [69]. This evaluation reports on Q^2 predictions and compares whether PLS has more predictive power than the linear model (LM) by comparing the RMSE and MAE [57]. For this analysis, we follow the guidelines for using PLSpredict [70]. All PI items show the Q^2 predict value greater than zero (between 0.178 and 0.264), indicating that the PLS model predicts the indicators better than the naïve LM benchmark. Furthermore, we compare the RMSE and MAE values between the PLS and LM models.

As displayed in Table 10, one indicator (PI3) shows that among the five indicators used, its LM has a lower value than PLS. Based on the guideline, it can be concluded that the PLS model has medium out-of-sample predictive power. In other words, PLS outperforms the LM benchmark on 4/5 indicators, with only a negligible LM advantage on PI3. The

result supports using the model to forecast PI beyond the estimation sample, as presented in Table 10.

Table 10. Out-of-Sample Prediction Power Analysis.

Indicator Items	Q^2 Predict	PLS		LM		$RMSE_{PLS} - RMSE_{LM}$	$MAE_{PLS} - MAE_{LM}$
		RMSE	MAE	RMSE	MAE		
PI1	0.208	0.755	0.581	0.769	0.588	−0.014	−0.007
PI2	0.224	0.745	0.584	0.761	0.592	−0.016	−0.008
PI3	0.264	0.721	0.576	0.719	0.564	0.002	0.012
PI4	0.178	0.791	0.608	0.797	0.614	−0.006	−0.006
PI5	0.184	0.954	0.756	0.963	0.759	−0.009	−0.003

4.4. Robustness Check

According to the latest recommendations of PLS analysis [52,71], we ran robustness checks to verify that the model's results are consistent and not overly sensitive to specific assumptions or variations in data. First, we conducted a quadratic effect analysis to assess the robustness of the linear effects using bootstrapping with 10,000 samples and a 2-tailed significance level of 5% [65]. The results indicate that all relationships between variables were linear, as the relationships between the latent variables were insignificant, as presented in Table 11.

Table 11. Nonlinear effect assessment.

Nonlinear Effect	β	t-Values	p Values	PCI	Sig?
QE (SC) → IT	0.074	1.180	0.238	[−0.061–0.173]	No
QE (SC) → MR	0.011	0.185	0.854	[−0.111–0.104]	No
QE (SC) → PR	−0.101	1.566	0.117	[−0.221–0.036]	No
QE (SC) → PV	0.047	0.656	0.512	[−0.113–0.156]	No
QE (MR) → PR	−0.073	1.199	0.230	[−0.184–0.132]	No
QE (MR) → PV	0.027	0.508	0.612	[−0.082–0.184]	No
QE (IT) → PR	0.042	0.551	0.581	[−0.116–0.184]	No
QE (IT) → PV	−0.036	0.558	0.577	[−0.175–0.084]	No
QE (PV) → PI	0.038	1.152	0.249	[−0.022–0.107]	No
QE (PV) → PR	0.033	0.498	0.618	[−0.084–0.182]	No
QE (PR) → PI	0.048	1.345	0.179	[−0.022–0.119]	No

Note: PCI = percentile confidence interval.

Next, we assessed endogeneity, which occurs when a predictor construct is correlated with the error term of the dependent construct [57]. Endogeneity refers to a situation in regression analysis or structural equation modelling where an independent variable is correlated with the error term [52]. To address potential endogeneity, we employed Gaussian copula approaches [65]. Our analysis indicated that none of the paths reached statistical significance, indicating no endogeneity issues.

Finally, we conducted the unobserved heterogeneity to ensure that our model's results are not biased by variations within subgroups of the data that were not captured by the observed variables. For this purpose, we employed the Finite Mixture Partial Least Squares (FIMIX-PLS) approach to detect and control for potential segments within the data that could exhibit distinct behavioural patterns [71]. Table 12 shows that (a) AIC3 and CAIC were pointing to different segments, (b) AIC4 and BIC were pointing to the fourth segment, and (c) MDL5 was pointing to the first segment. Therefore, since the analysis calculation indicated no specific segmentation, we assumed that heterogeneity was not a significant issue and supported the results of the one-dataset analysis [71].

Table 12. Heterogeneity evaluation (one to four segment solutions).

Criteria	Segment			
	1	2	3	4
AIC (Akaike's information criterion)	2.34.884	2.223.753	2.211.754	2.101.249
AIC3 (modified AIC with Factor 3)	2.356.884	2.256.753	2.261.754	2.168.249
AIC4 (modified AIC with Factor 4)	2.372.884	2.289.753	2.311.754	2.235.249
BIC (Bayesian information criterion)	2.394.437	2.334.208	2.379.109	2.325.505
CAIC (consistent AIC)	2.41.437	2.367.208	2.429.109	2.392.505
MDL5 (minimum description length with factor 5)	2.736.652	3.04.026	3.448.531	3.758.530
EN (normed entropy statistic)	0.000	0.573	0.578	0.779

Our robustness checks, guided by the latest recommendations in PLS analysis, have verified that the model's results are consistent and robust against various statistical assumptions and data variations. The discussion of the findings serves as the basis for our conclusion that the model is adequately strong and the relationships within it are reliably estimated, leading to confidence in the broader applicability of our findings.

5. Discussion

Our structural model suggests that streamer credibility and media richness primarily influence perceived value, with media richness also mitigating perceived risk. In turn, perceived value emerges as the dominant pathway to purchase intention. This section discusses the results and compares them with previous research to highlight similarities, differences, and possible explanations. Additionally, we discuss the theoretical contributions of this study, as well as its practical implications.

5.1. Effect of Streamer Credibility in Interactivity and Media Richness

On the live-streaming platform, the streamer is a crucial aspect of the success of live-streaming marketing. The findings confirm the statement that streamer credibility has a positive influence on interactivity ($\beta = 0.718$) and media richness ($\beta = 0.658$). These findings align with previous research, which emphasises the importance of streamers in promoting active audience engagement and high-quality content [4,22]. Streamers perceived as trustworthy and knowledgeable create an environment where audiences are more willing to interact [12,72]. However, while prior studies often focus on the trust aspect of credibility [50], this study highlights the balanced role of expertise and attractiveness in enhancing interactivity and media richness, providing a nuanced understanding of the dimensions of credibility.

Our findings also show that respondents believe the streamer has a significant impact on perceived value ($\beta = 0.215$, $p = 0.024$), suggesting that streamers play a crucial role in shaping how audiences perceive the benefits and value of the products being shown [4]. This result underscores the importance of streamers effectively communicating product information, demonstrating its usage, and engaging audiences in ways that enhance their perception of value.

However, the findings indicate that there is no significant influence of streamer credibility on perceived risk ($\beta = 0.074$, $p = 0.253$), contrasting with prior studies [4,28]. We expect higher streamer credibility to lower perceived risk; however, the direct effect is absent because credibility's influence on risk is mediated by factors that pull in opposite directions. For example, looking at PR-mediated routes to purchase intention (Table 8), streamer credibility shows a small and opposing effect, risk-reducing route via media richness

($\beta = -0.021$, $p < 0.10$) and risk-increasing via interactivity ($\beta = 0.018$, $p < 0.10$). Meanwhile, the PR-mediated routes are a substantive and significant relationship (SC—MR—PV—PI: $\beta = 0.198$, $p < 0.001$; SC—IT—PV—PI: $\beta = 0.115$, $p < 0.0$; SC—PV—PI: $\beta = 0.150$, $p < 0.05$). These opposing, small PR routes and the dominant PV routes explain why the direct SC → PR effect is not significant.

5.2. Interactivity and Media Richness Effect

The findings show that interactivity has a positive and significant impact on both perceived value (H6; $\beta = 0.230$, $p < 0.01$) and risk (H5; $\beta = 0.187$, $p < 0.05$). The significant relationship between interactivity and perceived risk indicates that higher interactivity potentially increases the viewer's perception of risk [12]. The result highlights the importance of interactive features in making content more engaging and valuable to viewers, validating the findings of prior studies [31,32].

Similarly, media richness also significantly influences both perceived value (H7; $\beta = 0.431$, $p < 0.001$) and perceived risk, though in opposite directions (H8; $\beta = -0.249$, $p < 0.01$). These findings strengthen existing knowledge [9,29,34]. When product information is presented in a clear, engaging, and immersive manner, it helps reassure viewers and reduces the uncertainty associated with online purchases. Together, these findings highlight the dual benefit of media richness: it not only increases perceived value but also decreases perceived risk, making it a crucial element in the effectiveness of live-streaming content.

5.3. Perceived Value and Perceived Risk

Concerning the SOR model, we examined the influence of internal evaluation (Organism), represented by PV and PR as dual appraisal, on purchase intentions (Response). The results confirm that perceived value has a significant and positive effect on Purchase Intention ($\beta = 0.773$, $p < 0.001$). This relationship highlights the substantial impact of perceived value, a cognitive-affective evaluation that influences viewers' purchasing decisions [36]. When users perceive that the product or service promoted during a live stream provides high utility, quality, or emotional benefits, their intention to purchase increases significantly [73]. This finding supports the SOR theory, where the organism's positive evaluation (high perceived value) is a critical precursor to a favourable behavioural response (intended purchase). The enormous effect size further confirms that perceived value is a dominant factor driving decision-making in this context. The indirect and total effect also indicated that PV serves as the dominant conduit translating IT and MR into PI. The findings also reveal that risk-based pathways are small and generally non-significant.

However, although perceived risk is typically expected to reduce purchase intention, our model shows a different direction. The finding of H11 showed a significant effect on purchase intention; however, the result pointed in a different direction ($\beta = 0.130$), thereby rejecting H11. This finding contradicts a prior study [17,37], which suggested a negative relationship between perceived risk and intention. We found the positive PR → PI direct path persists after accounting for all indirect, ruling out a suppression artefact and pointing instead to complementary dynamics, indicating the value-driven persuasion co-exists with a context-bound risk signal. LSC is commonly used for limited-time offers or products with limited quantities. This scarcity tactic effectively increases purchase intention [38] as time pressure and scarcity cues raise impulsive or accelerated buying [39]. In live-stream shopping, consumers may acknowledge risk (e.g., uncertainty, return hassle) yet still intend to buy because urgency dominates in the moment. While unexpected, within the S-O-R framework, the findings suggest that not all negative organismic states, in this case, perceived risk, necessarily suppress behavioural responses.

In S–O–R, these results refine the negative organismic state view, where Perceived Risk does not necessarily suppress behavioural responses. In live broadcasts rich in urgency, Perceived Value remains the dominant driver of Purchase Intention. Meanwhile, perceived risk can show a positive relationship with perceived value and stimulus. Practically, platforms need to pair urgency cues with visible protection (badges or estimated delivery times).

5.4. Theoretical and Practical Implications

The findings indicate that the combination of person and platform as stimuli (Streamer Credibility, Interactivity, and Media Richness) operates together via organismic appraisals (Perceived Value and Perceived Risk) to influence Purchase Intention. This model supports the SOR view that technology affordance (richness and interactivity) and source cues (credibility) work collaboratively to create value-risk evaluation that then guides consumers' behaviour.

From a theoretical perspective, the findings provide empirical evidence that people and technology cues operate in a complementary manner rather than as substitutes. These findings help explain why single-factor models can overstate or understate downstream effects on intention. Also, the results support a co-production view, where perceived value consistently emerges as the main link between stimuli and response. Perceived risk, however, has a comparatively minor and more context-dependent effect. In addition, Streamer credibility serves as a persuasive cue, and it is also linked to the orchestration of streams, such as through richer demonstrations and structured Q&A, thereby connecting the speaker's identity with the method of content delivery. This effort broadens the Stimulus layer from isolated cues to stimuli that interact with one another. Furthermore, based on the findings of H11, this result refines S-O-R by showing that negative organismic states (risk) can exhibit context-bound, positive links to intention [38] when urgency [39] is salient and value is accounted for.

The findings also provide practical implications for managers, platforms, and streamer teams. First, the findings of the proposed model suggest the need to maximise perceived value, considering the most reliable path value (H10). These findings can be translated to demonstrate purchasing benefits, minimise costs, and enhance moments of enjoyment. When consumers can quickly see how a product solves their problems and feel satisfied with their decision, purchase intention increases [39]. Another implication is to prioritise media richness as the primary design factor. Comprehensive demonstrations (for example, multi-angle close-ups and quick recap banners) consistently increased perceived value and, at the same time, reduced perceived risk (H7 and H8). Finally, the finding indicates that perceived risk does not always have a negative impact on purchase intention. Practically, time or supply-based scarcity mechanisms (flash discounts, countdowns) [38] can enhance short-term purpose despite significant risk perceptions. Therefore, platforms should combine urgency with apparent protection (such as returns and buyer protection) to prevent long-term repercussions.

6. Conclusions, Limitations, and Recommendations

6.1. Conclusions

This study aimed to investigate the key factors influencing consumer purchase intention in a social media live-streaming context, grounded in the Stimulus–Organism–Response (SOR) framework. Specifically, it examined how external stimuli (streamer credibility, interactivity, and media richness) shape internal evaluations (Organism) in the form of perceived value and perceived risk, which in turn affect purchase intention (Response). The results confirmed that perceived value becomes the strongest predictor of purchase intention, while perceived risk has a minor but still relevant role. Media richness

and interactivity both substantially increase perceived value, and in the case of media richness, they also reduce perceived risk. Interestingly, streamer credibility indirectly increases purchase intention by influencing interactivity and perceived value; however, it does not have a direct impact on risk perception.

6.2. Limitations and Recommendations

Despite the valuable insights, this study is not without limitations. Initially, the majority of participants were younger and predominantly female, reflecting the mainstream live-streaming context, but raising concerns about representation. Therefore, findings should be generalised with caution to mainly male and older audiences. Furthermore, the cross-sectional self-report approach limits causal inference and may preserve residual variance from CMB despite procedural (anonymity, neutral wording, item randomisation) and statistical checks. Third, the study focused on live-stream commerce in general, without considering the distinctions in product category or platform, which could potentially influence consumer perceptions in different ways. Finally, cultural factors were not investigated, despite their potential to substantially impact risk perceptions, trust, and credibility.

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