

Article

How Live Streaming Commerce Platforms Drive Consumer Purchase Intention: Dual Mediation of Trust and Perceived Value in a UK Sample

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Abstract

Live streaming commerce delivers conversion rates up to ten times higher than conventional online stores, yet research on the psychological mechanisms behind that lift has tested platform features in isolation, through single-mediator pathways. This study examines how three live streaming characteristics (streamer credibility, perceived interactivity, and product demonstration quality) shape consumer purchase intention through consumer trust and perceived value, operating both independently and sequentially. The stimulus–organism–response (S-O-R) framework provides the organising structure, with source credibility and value-based theories anchoring specific paths. A structural equation model was tested on survey data from 478 UK live streaming consumers. All three characteristics predicted consumer trust; only perceived interactivity and product demonstration quality predicted perceived value directly. Streamer credibility reached perceived value entirely through consumer trust. Credibility’s parallel path through value alone was not supported, but its serial path through trust and then value was. Eleven of twelve hypotheses were supported, and bootstrap analysis with 5000 resamples confirmed serial mediation through trust then value for all three antecedents. The asymmetric pattern positions trust as the gateway through which competence-based credibility reaches purchase decisions, with implications for platform-design choices that sequence trust signals before value-oriented promotional cues.

Keywords: live streaming commerce; live streaming platforms; consumer trust; perceived value; streamer credibility; perceived interactivity; product demonstration quality; serial mediation; S-O-R framework



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1. Introduction

The global live streaming commerce market was estimated at over \$500 billion in 2023, driven primarily by China and projected to grow rapidly across Western markets [1]. Platforms such as TikTok Shop, Amazon Live, Whatnot, and Instagram Live Shopping have turned passive product browsing into an interactive, real-time shopping experience. Unlike traditional e-commerce, live streaming commerce combines entertainment, social interaction, and immediate purchasing within a single interface [2,3]. McKinsey reports conversion rates as high as ten times those of conventional online stores [4,5]. Behind that headline figure, however, sits considerable cross-market variation. China’s live-commerce ecosystem is mature and tightly integrated within social super-apps; the United Kingdom and other Western markets are catching up through a more fragmented platform mix that includes auction-led entrants such as Whatnot alongside TikTok Shop and brand-owned

shows, with Facebook and Instagram having retired their dedicated live-shopping features in late 2022 and early 2023 [5]. Consumer-facing live-commerce strategies extrapolated from a single Chinese super-app do not transfer cleanly to this more pluralistic environment.

Several studies have examined isolated antecedents of purchase intention in this context. Credibility components, particularly trustworthiness and attractiveness, have been linked to consumer trust in influencer-mediated commerce [6]. Interactivity features have been associated with customer engagement and social presence in live and co-viewing contexts [7,8]. Product demonstration, a defining feature of live streaming that distinguishes it from static e-commerce listings, has received comparatively less attention, although recent work suggests it reduces product uncertainty and supports trust formation [9]. These three characteristics are not free-standing consumer cues. Each is something a platform builds and controls. How credible a streamer appears depends in part on how a platform verifies, ranks, and badges its sellers; perceived interactivity is an affordance the platform engineers through its chat and real-time reply features; and demonstration quality rests on the camera, streaming, and display tools the platform provides. What the literature still lacks is an integrated model showing which of these platform-engineered features move consumers towards purchase, and through which internal mechanisms they work. That is a question about how a platform functions, not only about how consumers behave [10]. Most studies isolate one feature and trace it through a single mediator [11], which leaves the relative weight of the platform's levers, and the order in which they operate, unresolved.

Trust and perceived value are the two constructs that theory and prior evidence suggest should serve as the key mediators. The stimulus–organism–response (S-O-R) framework [12] provides the organising architecture, positioning environmental stimuli as triggers of internal organism states that in turn produce behavioural responses. Within that structure, source credibility theory [13] anchors the path from streamer-related stimuli to trust, holding that credible communicators generate trust; value-based theory [14,15] anchors the path from organism states to behavioural response, holding that purchase decisions depend on whether consumers perceive sufficient value in the exchange. Despite this theoretical convergence, few studies have tested consumer trust and perceived value as dual mediators within a single live streaming model, and fewer still have tested whether the two operate sequentially, that is, whether trust feeds into value perceptions, which then drive purchase intention. Doong's [16] Taiwan study found a serial trust-then-value model fitted significantly better than a parallel one, but the question has not been tested at scale or in a Western sample. Luo et al.'s [11] systematic review of 201 live streaming commerce articles documents that 76% of publications and 85% of empirical samples are drawn from China, with only one of the 201 papers sampled in the UK, and explicitly calls for non-Chinese-context replications and integrated multi-mediator models. The present study addresses both calls.

The UK live-commerce environment makes such a test particularly pointed. UK consumers approach live selling differently from shoppers in the mature Asian markets where live commerce took shape, China above all. Years of disclosure rules for paid promotion have left British audiences more ready to read commercial intent into an endorsement [17], and persuasion-knowledge research suggests that this kind of learned scepticism weakens a sales message once its persuasive purpose is recognised [18,19]. Platform habits differ too. In China, live shopping sits inside super-apps that people already use for messaging, payments, and everyday purchases, so it forms part of an established routine; UK consumers meet it as a recent feature added to apps they think of mainly as social, entertainment, or marketplace tools, and the habit is still forming [5]. Data protection adds a further difference. Under the UK GDPR, consent prompts and data-use notices are a routine part of being online [20,21], which keeps the question of whether a platform can be trusted with

personal and payment details close to the surface [22]. These differences mean trust has to be earned in the UK rather than assumed, which is exactly why the trust pathways tested in this study merit examination in a Western market rather than the mature Asian markets that pioneered the format.

Early Western live streaming research focused largely on TikTok and Instagram and on samples that did not extend far beyond them, yet the UK platform mix is more diverse. Auction-style platforms such as Whatnot, the closest Western analogue to Taobao Live, now command a visible UK market share alongside TikTok Shop, Amazon Live, and brand-owned shows [5]. Merritt and Zhao [23] argued from qualitative evidence that the Chinese live-stream retailing model requires adaptation to UK consumer expectations rather than direct transfer. Hajli [24] showed in an earlier UK consumer sample that trust mediates the path from social-commerce constructs to purchase intention; Adaba et al.'s [25] more recent study of 232 Greater London consumers reported a counterintuitive twist in which a strong influencer-to-trust path failed to translate into purchase outcomes, suggesting that UK trust mechanisms in platform-mediated commerce may not generalise from Chinese-sample findings. Trust has long been foundational to consumer acceptance of online commerce [26] and central to social-commerce purchase decisions [27]; on digital platforms it now operates as part of the architecture that shapes how consumers process information and decide [10]. Live streaming commerce is a particularly demanding case for that architecture because consumers form trust beliefs about the streamer, the platform, and the product simultaneously, often within minutes of joining a stream.

This study tests a structural model in which streamer credibility, perceived interactivity, and product demonstration quality each influence consumer purchase intention through consumer trust and perceived value, operating both independently and in sequence. The model was tested with data from 478 UK consumers who had purchased through live streaming in the past six months.

The study makes three contributions. First, it integrates three categories of live streaming characteristics, each shaped by platform design, that have typically been studied in isolation. Second, it tests trust and perceived value as parallel and serial mediators, offering a more complete view of the pathway from stimulus to behaviour than single-mediator designs allow. Third, it provides empirical evidence from a Western live-commerce environment whose platform mix already includes formats (notably Whatnot) whose conventions sit closer to Taobao Live than to early Western social-commerce templates, with direct relevance for platform-design and trust-architecture questions central to recent platform research [10].

The remainder of the paper is organised as follows. Section 2 develops the theoretical background and hypotheses. Section 3 sets out the research design and methodology. Section 4 presents the results. Section 5 discusses the findings, sets out their theoretical and practical implications, considers limitations and directions for future research, and concludes.

2. Literature Review and Hypothesis Development

2.1. Theoretical Background

Three theoretical anchors underpin the study. The stimulus–organism–response (S-O-R) framework, introduced by Mehrabian and Russell [12] and adapted to online retailing by Eroglu et al. [28], provides the organising architecture. It posits that environmental stimuli (S) trigger internal psychological states in consumers (O), which in turn produce behavioural responses (R). The framework has been applied widely in online retail [28,29] and in live streaming research [7,30], where it is the single most-used theoretical lens in the field [11]. Live streaming environments are particularly suited to S-O-R analysis because

they layer sensory, social, and informational cues that traditional e-commerce does not provide. In the present model, the three live streaming characteristics serve as stimuli, consumer trust and perceived value as organism states, and purchase intention as the response. Source credibility theory and value-based theory of consumer behaviour anchor specific paths within this S-O-R structure.

Source credibility theory, set out by Hovland, Janis and Kelley [13], provides the theoretical anchor for the streamer-credibility-to-trust path within the S-O-R structure. It holds that the persuasiveness of a message depends on the perceived credibility of its source. Hovland et al. identified two underlying factors, expertise and trustworthiness. Ohanian [31] later operationalised source credibility as a three-component construct by adding physical attractiveness, drawing on McGuire's source-attractiveness model. Recent live streaming research has begun to separate competence-based credibility (expertise and trustworthiness) from attractiveness on the grounds that the two operate through distinct psychological mechanisms, namely cognitive evaluation of source quality on the one hand, and affective response to physical or relational appeal on the other [32]. Zhou and Lou's dual-route framework is particularly explicit on this point. They show empirically that expertise and trustworthiness drive purchase intention through product trust, whereas attractiveness drives purchase intention through perceived pleasure. The present study follows that separation. Streamer credibility is conceptualised in competence-based terms, and the affective and parasocial influences associated with attractiveness are routed instead through perceived interactivity, where they belong analytically.

The third anchor is value-based theory of consumer behaviour, which explains why organism-state value perceptions predict the response. Zeithaml [15] defined perceived value as the consumer's overall assessment of the utility of a product based on perceptions of what is received and what is given. Subsequent work has proposed multidimensional value structures, most prominently Sweeney and Soutar's [14] PERVAL scale, which decomposes value into functional, social, emotional, and price-related components. A substantial line of e-commerce and live streaming research, however, treats perceived value as a unidimensional global construct that captures the give-get trade-off directly [30,33–35]. The present study adopts that unidimensional treatment. In live streaming contexts, what is given includes monetary cost, time, and cognitive effort; what is received includes the product itself, the entertainment value of the show, the real-time information from the streamer, and the sense of participation in the event.

This integrated S-O-R framing responds to recent calls in the live streaming literature for multi-mediator models tested outside the Chinese context that has dominated the field. Luo et al.'s [11] systematic review of the live streaming commerce (LSC) literature documents that Chinese samples account for 85% of empirical LSC studies, with most existing work testing single-mediator designs in isolation, and explicitly identifies integrated multi-mediator tests in non-Chinese contexts as a research priority. Even recent multi-mediator models leave this gap open. Yang et al. [36] traced streamer, product, and platform stimuli to purchase intention through consumer trust and impulsiveness in a large Chinese sample. Trust mediated those effects, but the two mediators were modelled in parallel, and the study did not include perceived value or test a sequence running from trust into value.

2.2. Streamer Credibility

Streamer credibility refers to the extent to which consumers perceive a live streamer as a competent and reliable source of product information, defined by the streamer's perceived expertise and trustworthiness [31]. The construct here is restricted to these two competence-based dimensions. Attractiveness, although a well-established third dimension of the broader source credibility construct [31], operates through different psychological

pathways and is excluded from credibility in the present model. This is consistent with recent live streaming work that argues the affective and relational influences associated with attractiveness should be modelled separately from the cognitive evaluation of source competence [32]. In the present model, those affective influences are captured through perceived interactivity. Attractiveness contributes through an affective response, the pleasure a viewer feels while watching, which Zhou and Lou [32] found to drive purchase on the experiential route while the trust-based rational route is driven by competence cues. In a recorded endorsement that response rests on the streamer's personal appeal; in a live stream it comes instead from responsive interaction, the two-way replies, the viewer's control over what is shown, and the synchronous exchange that Liu [37] treats as interactivity, which live streaming work ties to social presence and a more enjoyable experience [8,38]. Perceived interactivity therefore carries the affective pathway that attractiveness would otherwise supply; it does not measure attractiveness, but stands as the live mechanism that generates the same response, so excluding attractiveness removes a static personal cue rather than the affective route itself.

Two arguments link streamer credibility to consumer trust. The first is the standard source credibility logic. When consumers perceive a streamer as expert and trustworthy, they are more willing to accept the streamer's claims, which directly supports the formation of trust [13,39]. The second is information asymmetry. Online shopping is a high-uncertainty context in which consumers cannot directly inspect either the seller or the product, and credible streamers reduce this asymmetry by signalling that the product information being relayed is competent and honest [40,41]. Empirical support comes from Zhou and Lou [32], who found that streamer expertise and trustworthiness significantly predicted consumers' product trust in live streaming e-commerce, and from Jiang, Lee and Li [42], who reported a positive effect of streamer expertise on viewer trust in a Chinese live streaming sample. Lou and Yuan [6], working with social media influencers rather than live streamers, found that influencer trustworthiness predicted follower trust in branded content, although notably expertise alone did not in their data, suggesting that the relative weight of the two competence dimensions can vary by context.

The link from credibility to perceived value rests on a different mechanism. A credible streamer can function as a quality cue. When the streamer is perceived as expert and trustworthy, consumers are likely to infer that the products being demonstrated are worth purchasing. Park and Lin [43] found that source trustworthiness in live streaming product endorsement predicted purchase intentions through both hedonic and utilitarian attitudes. The strength of the credibility-to-value path is theoretically less clear than the credibility-to-trust path, however, because value perceptions are also shaped directly by what consumers actually see during the demonstration and how they engage with it during the stream, both of which are captured by the other two antecedents in the present model. The path is retained in the model to test whether credibility has an independent effect on value once trust, interactivity, and product demonstration quality are accounted for.

H1. *Streamer credibility positively influences consumer trust.*

H2. *Streamer credibility positively influences perceived value.*

2.3. Perceived Interactivity

Perceived interactivity refers to the extent to which a consumer perceives the live stream as facilitating responsive, two-way, real-time communication. Liu's [37] foundational scale identifies three theoretical facets, active control, two-way communication, and synchronicity. These are conceptually distinct, but they tend to co-occur in live-commerce settings, where viewers can ask questions, request demonstrations, and receive immediate

responses from the streamer in a single integrated interaction. Following this empirical pattern, recent live streaming work treats perceived interactivity as a single reflective construct rather than as three separate factors [7,38,44]. The present study adopts that approach.

Interactivity should support trust because responsive communication signals that the streamer is attentive and willing to address concerns transparently. Liu et al. [44], in a tourism live streaming sample, found that perceived interactivity significantly increased consumer trust. Sun et al. [3] reached a related conclusion through the IT affordance lens, showing that metavoicing affordance, which is the platform feature enabling real-time exchange, increased viewers' sense of social presence and immersion.

Interactivity should also support perceived value. Real-time interaction allows consumers to tailor what they see during the live stream to their own concerns, which raises the gains they obtain from the shopping process relative to the time and effort they invest. Wang et al. [38], drawing on a Chinese consumer sample, found that interactivity significantly predicted perceived utilitarian and hedonic value in live streaming shopping, and that these value perceptions in turn drove purchase intention.

H3. *Perceived interactivity positively influences consumer trust.*

H4. *Perceived interactivity positively influences perceived value.*

2.4. Product Demonstration Quality

Product demonstration quality captures the consumer's perception of how thoroughly, clearly, and vividly the product is presented during the live stream. The construct draws on Jiang and Benbasat's [45] work on the vividness of online product presentations and on Xu et al.'s [46] information quality construct in live commerce. Together, these define the qualities that distinguish a good product demonstration from a poor one, namely completeness of the information conveyed, accuracy and clarity of the presentation, and the ability of the consumer to see the product from multiple angles and in use. The defining advantage of live streaming over static e-commerce is its capacity to do all this in real time and on request.

A high-quality product demonstration should support trust because it directly reduces product uncertainty. Lu and Chen [9], drawing on signalling theory, argued that broadcasters' demonstrations of physical product characteristics function as quality signals that lower consumer perceived uncertainty and thereby cultivate trust. The same theoretical logic underpins Jiang and Benbasat's [45] earlier finding that vividness in product presentation enhances perceived diagnosticity and shopping enjoyment, with downstream effects on attitudes toward the seller. When demonstrations are detailed, consumers form more accurate expectations of what will arrive after purchase, which supports trust both in the product itself and in the streamer presenting it.

The same demonstrations should also raise perceived value. Visual evidence of a product in use, demonstrated under variable conditions and in response to questions, conveys information that text descriptions and still photographs cannot. Wang et al. [38] found that visualisation, defined as the visual presentation of products in live streaming, significantly predicted both perceived utilitarian and hedonic value. Zhang [47] reported a similar pattern across three separate studies, showing that the vividness, richness, and interactivity of live product presentations directly raised perceived product value, and that perceived product value fully mediated the effect of product presentation on purchase intention.

H5. *Product demonstration quality positively influences consumer trust.*

H6. *Product demonstration quality positively influences perceived value.*

2.5. Consumer Trust and Perceived Value

Consumer trust in this study refers to the consumer's belief that the live streamer is honest in the presentation of products and acts with the viewer's interests in mind when making recommendations. This corresponds to two of McKnight et al.'s [48] three classical trusting beliefs, namely integrity (the streamer's honesty and consistency in keeping promises) and benevolence (the streamer's care for, and motivation to act in, the viewer's interests). The third trusting belief, competence, is treated separately under streamer credibility, because competence is conceptually identical to the expertise dimension of source credibility [31,48]. Routing competence upstream into the streamer credibility construct avoids construct overlap and aligns the trust construct with the relational beliefs (honesty and benevolent intent) that are theoretically distinct from the source-evaluation beliefs captured by credibility. Recent live streaming research provides direct empirical warrant for the three-facet decomposition. Wang et al. [49] confirmed in a two-study design that streamer trust is composed of perceived integrity, ability, and benevolence in human-streamer settings, and reported that integrity plays the decisive role for human streamers. Their finding aligns with the present study's focus on the integrity-benevolence relational beliefs as the operative trust construct, with the ability dimension captured upstream by streamer credibility.

Trust is a well-established predictor of purchase intention in e-commerce settings [24, 40,41,50,51] and has been confirmed as significant in live streaming contexts [3,52]. Beyond its direct effect on purchase intention, trust should also feed into perceived value. Kim et al. [33] argued that perceived trust reduces the non-monetary transaction costs (time, effort, and risk) that consumers face when shopping online, which raises the net give-get assessment and therefore perceived value. The argument applies particularly well to live streaming, where consumers cannot inspect products in person and where the cost and friction of returns can be substantial [52]. When consumers believe the streamer is honest and benevolent, they are more confident that the products will deliver what is promised, which raises the perceived value of the transaction.

H7. *Consumer trust positively influences perceived value.*

H8. *Consumer trust positively influences purchase intention.*

Perceived value reflects the consumer's overall assessment of what is received against what is sacrificed [15]. Recent social-commerce and live-commerce research consistently identifies perceived value as a predictor of purchase intention [53–55]. The mechanism is straightforward. Consumers who perceive a transaction as offering favourable value, whether through better prices, richer information, or a more enjoyable experience, are more inclined to buy. The present study treats perceived value as a unidimensional global construct integrating monetary, time, and effort components of the give-get trade-off, consistent with recent live streaming work that operationalises value as an overall assessment of transaction utility [33–35]. In the S-O-R structure this single valuation is precisely what the organism stage represents, the consumer's net judgement of the exchange that the stimuli feed and that in turn drives the response. The separate sources of that value, the enjoyment of the show, the social experience, and the perceived quality of the product, enter the model earlier as the stimuli themselves, through perceived interactivity and through product demonstration quality and streamer credibility. Splitting value into the emotional, social, and functional components that a multidimensional scale separates would fold those stimuli back into the mediator, whereas a single give-get judgement lets value sit downstream as the state through which the stimuli reach purchase intention.

H9. *Perceived value positively influences purchase intention.*

2.6. Mediation Hypotheses

The model predicts that the three live streaming characteristics shape purchase intention not only through direct paths but also indirectly, via consumer trust and perceived value as mediators. Two complementary patterns of mediation are expected, parallel mediation through each mediator independently, and serial mediation in which trust precedes value formation.

Looking at the parallel mediation first: If streamer credibility, perceived interactivity, and product demonstration quality each shape consumer trust (H1, H3, H5) and perceived value (H2, H4, H6), and if trust and value each shape purchase intention (H8, H9), then the antecedents' effects on purchase intention should pass through both mediators independently. This expectation is consistent with the S-O-R logic followed throughout the model. Stimuli (the live streaming characteristics) trigger organism states (trust and value), which produce the response (purchase intention) [12,28]. It is also consistent with prior live streaming research showing that trust and value each significantly mediate the influence of live streaming features on purchase outcomes [16,43].

H10. *Consumer trust mediates the positive effect of (a) streamer credibility, (b) perceived interactivity, and (c) product demonstration quality on purchase intention.*

H11. *Perceived value mediates the positive effect of (a) streamer credibility, (b) perceived interactivity, and (c) product demonstration quality on purchase intention.*

A second, more demanding pattern is also predicted. Trust serially precedes value formation, so that the antecedents' effects pass first through trust and then through perceived value before reaching purchase intention. The theoretical case rests on three points.

First, value assessment is conditional on trust. Consumers cannot meaningfully evaluate whether a transaction offers favourable value if they do not trust that the information on which the value assessment depends is accurate. Kim et al. [33] formalised this argument in an Internet-shopping context, showing that perceived trust is theoretically prior to perceived value because trust reduces the non-monetary transaction costs (effort, risk, uncertainty) that enter the give–get calculation. Without trust, the perceived costs side of the give–get calculation inflates, depressing perceived value; with trust, the costs side contracts, raising perceived value.

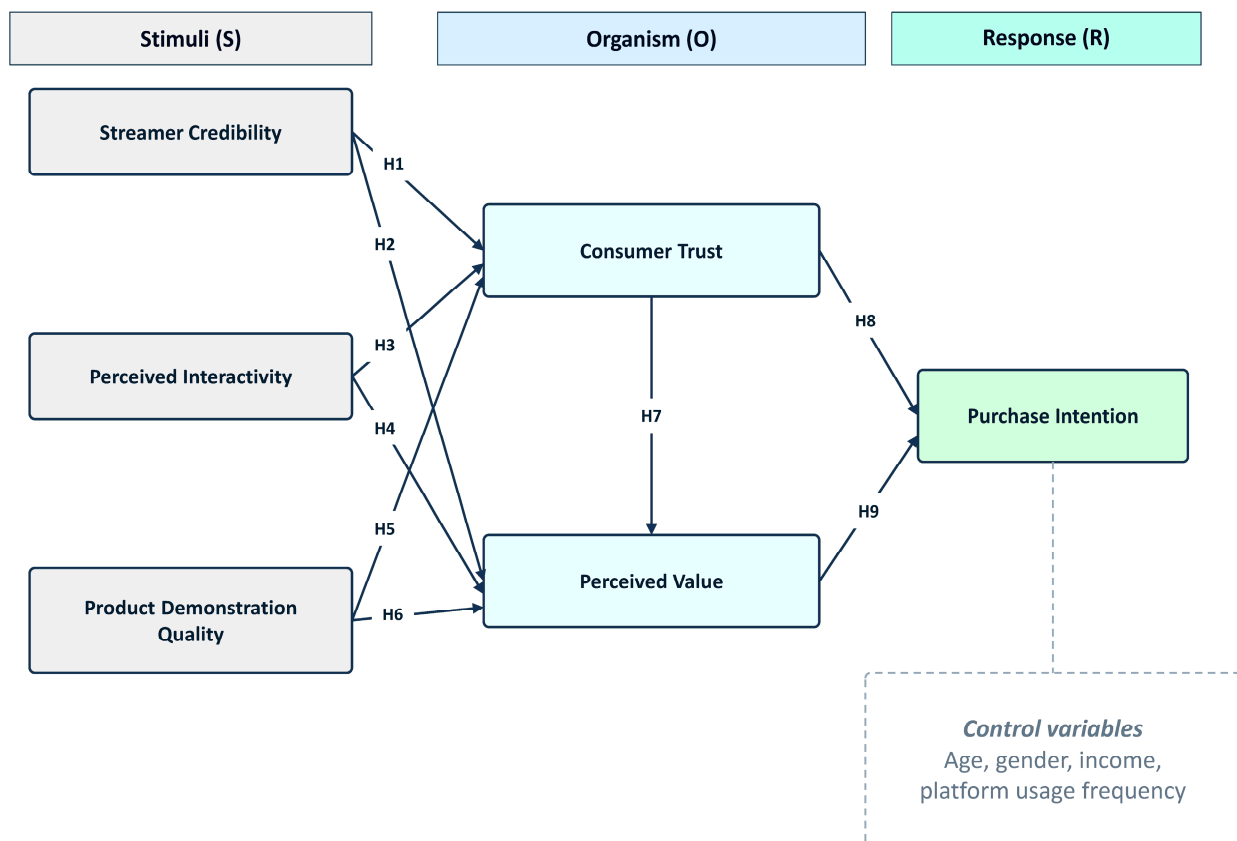
Second, in live streaming contexts the temporal sequence is particularly clear. Consumers encounter the streamer and the product demonstration before they form a value assessment [3,52], and their value assessment is conditional on whether they believe the streamer is being honest [43]. A consumer who suspects the streamer is exaggerating product quality cannot assess the value of the offered transaction at face value, since detected persuasive intent activates scepticism [18] and inflates the perceived cost component of the give–get calculation [33]. Trust formation must come first.

Third, recent live streaming research provides direct empirical precedent for the serial structure. Doong [16] tested both parallel and serial mediation models in a live-commerce sample and reported that the serial model (antecedents → trust → perceived value → purchase intention) fitted the data better than the parallel alternative. The pattern of indirect effects in Doong's study is also informative. For source-related cues such as reputation, the indirect path through trust dominated; for interaction-related cues, the indirect path through perceived value dominated. This asymmetry suggests that different antecedents may load differently on the two stages of the serial chain. In the present model, the same logic predicts that streamer credibility, which is a source-related cue [13,31],

should route disproportionately through trust, whereas perceived interactivity and product demonstration quality, which carry informational and experiential content, may load more heavily on the value stage.

H12. Consumer trust and perceived value sequentially mediate the positive effect of (a) streamer credibility, (b) perceived interactivity, and (c) product demonstration quality on purchase intention.

Figure 1 presents the proposed research model.



Notes: Mediation hypotheses (H10, H11, H12) are tested in the structural model and not shown.

Figure 1. The research model.

3. Methodology

3.1. Research Design and Context

This study employed a cross-sectional survey design to test the proposed structural model among UK consumers with recent live streaming shopping experience. The United Kingdom is a substantive empirical setting for this investigation. The UK is the leading European market for live streaming commerce. UK consumers have purchased through live streams at roughly twice the EU average, the country accounts for 19.2% of the European live streaming market by share [56], and the UK social-commerce market is projected to more than double to £16 billion by 2028 [57]. TikTok Shop, the most widely used live-commerce platform in the present sample, selected the UK as its first Western launch in late 2021 [58]. By 2024 the platform hosted more than 6000 live-shopping events daily across the UK and was named the fastest-growing online retailer in the country, with a 131% year-on-year increase in shoppers and a 180% rise in revenue [58]. The UK is therefore a contemporary, high-growth setting in which the psychological mechanisms tested in this study are likely to be observable and consequential.

3.2. Sample and Data Collection

The survey was built in Qualtrics and administered online through Prolific. Ethical approval was obtained from the relevant institutional ethics review board prior to data collection. Prolific was selected because it provides access to a demographically diverse panel and has been shown to produce higher-quality responses than alternative crowd-sourcing platforms [59,60]. Eligibility was confirmed through three screening questions at the start of the survey, requiring respondents to be UK-based adults aged 18 or above who had watched at least one live streaming shopping session and made at least one purchase during or after a live streaming session in the past six months. The purchase requirement was included because several construct items, particularly those measuring perceived value, presuppose actual purchase behaviour. Respondents who failed any screener were excluded. Before the main questions, respondents were asked to recall their most recent live streaming shopping experience and to answer all subsequent statements with that single session in mind. Anchoring responses to one concrete, recent stream, rather than to a platform in general, was intended to stabilise the ratings across the different platform formats in the sample. An attention check item was embedded within the questionnaire, and responses that failed the check were excluded before analysis.

Data were collected in January 2026. A total of 512 eligible responses were obtained. After removing 34 that failed the attention check, 478 valid responses were retained for analysis. The sample of 478 exceeds the conventional minimum of 200 for SEM and the observations-to-parameters ratio recommended for covariance-based SEM [61,62].

Female respondents made up the majority of the sample (61.9%); the remainder were male (35.8%), non-binary (1.9%), or chose not to disclose (0.4%). The largest age band was 25–34 (35.1%), followed by 35–44 (21.8%) and 18–24 (21.1%); only 8.2% were aged 55 or above. Just under half held a bachelor’s degree (47.5%), with secondary school (22.4%) and master’s degree (21.3%) the next two most common categories. Annual household income was spread across bands, with about half (52.1%) reporting £20,001 to £60,000. The most frequently reported viewing pattern was 2–3 times a month (26.2%), and 7.3% reported daily viewing. TikTok Shop was the dominant platform (33.3%), followed by Whatnot (19.9%) and Instagram Live (15.3%); Amazon Live, YouTube Shopping, and Facebook Live each accounted for less than 14% of the sample. Table 1 presents the full respondent profile.

Table 1. Respondents’ profile ($n = 478$).

Characteristic	<i>n</i>	%	Characteristic	<i>n</i>	%
Gender			Age group		
Male	171	35.8	18–24	101	21.1
Female	296	61.9	25–34	168	35.1
Non-binary	9	1.9	35–44	104	21.8
Prefer not to say	2	0.4	45–54	66	13.8
			55 or above	39	8.2
Education			Annual household income		
Secondary school	107	22.4	Under £20,000	110	23
Bachelor’s degree	227	47.5	£20,001–£40,000	128	26.8
Master’s degree	102	21.3	£40,001–£60,000	121	25.3
Doctoral degree	15	3.1	£60,001–£80,000	67	14
Other	27	5.6	Over £80,000	52	10.9

Table 1. *Cont.*

Characteristic	<i>n</i>	%	Characteristic	<i>n</i>	%
Usage frequency			Preferred platform		
Daily	35	7.3	TikTok Shop	159	33.3
3–4 times a week	61	12.8	Instagram Live	73	15.3
About once a week	101	21.1	Amazon Live	65	13.6
2–3 times a month	125	26.2	Facebook Live	36	7.5
About once a month	103	21.5	YouTube Shopping	39	8.2
Less often (a few times a year)	53	11.1	Whatnot	95	19.9
			Other	11	2.3

Note(s): Author’s own work.

3.3. Measurement Scales

All constructs were measured with multi-item reflective scales adapted from the established literature (see Appendix A) and rated on a seven-point Likert scale (1 = strongly disagree to 7 = strongly agree); each was modelled as a single reflective dimension. Minor wording adjustments were made to fit the live streaming context.

Streamer credibility was measured with four items adapted from Ohanian [31] and Lou and Yuan [6], capturing the competence-based dimensions of source credibility, namely expertise and trustworthiness. Consistent with recent live-commerce research focusing on cognitive credibility judgements [32,42], attractiveness and similarity were not included. Perceived interactivity was measured with four items adapted from Liu [37], with contextual wording informed by Jiang et al. [63], capturing the three core facets of interactivity in a live streaming context, namely synchronicity, two-way communication, and active viewer participation. This unidimensional treatment, rather than modelling the three facets separately, is consistent with prior live-commerce research [38,44]. Product demonstration quality was measured with four items developed based on the conceptualisations of Jiang and Benbasat [45] and Xu et al. [46], capturing the consumer’s perception of how thoroughly, clearly, and vividly the product was presented during the live stream.

Consumer trust was measured with four items adapted from McKnight et al. [48], capturing the integrity and benevolence dimensions of trusting beliefs in the live streamer. Perceived value was measured with four items adapted from Kim et al. [33], following Zeithaml’s [15] give–get conceptualisation, with items capturing the consumer’s overall assessment of value based on monetary, time, and effort components of the trade-off; this unidimensional global treatment is consistent with prior live streaming research [30,34,35]. Purchase intention was measured with four items adapted from Dodds et al. [64] and Pavlou [26]. Three items captured likelihood, consideration, and willingness to purchase (adapted from Dodds et al.), and one item captured behavioural intention (adapted from Pavlou). All items were anchored to products demonstrated during live streaming sessions.

3.4. Control Variables

Four control variables were included: age, gender, income, and platform usage frequency. Age, gender, and income have been examined as predictors of online shopping behaviour in prior research, with mixed findings of significant and non-significant effects [65–67]. Platform usage frequency has been linked to online purchase behaviour in general e-commerce contexts [65] and to purchase decisions in live streaming commerce specifically [68], supporting its inclusion alongside the demographic controls.

3.5. Data Analysis Procedure

To test the proposed model, covariance-based structural equation modelling (CB-SEM) was conducted in IBM SPSS AMOS version 29.0 (IBM Corp., Armonk, NY, USA). CB-SEM

was preferred over variance-based methods such as PLS-SEM because this study takes a confirmatory approach grounded in established theory. While PLS-SEM is primarily suited for prediction or exploratory model building [61], CB-SEM allows a direct evaluation of how well the theoretical model reproduces the observed covariance structure against global fit criteria. Following Anderson and Gerbing's [69] two-step approach, the measurement model (confirmatory factor analysis) was assessed first, followed by the structural model. All analyses were conducted using IBM SPSS Statistics and IBM SPSS AMOS version 29.0 (IBM Corp., Armonk, NY, USA).

Common method bias was assessed using Harman's single-factor test and the common latent factor (CLF) approach, in both constrained and unconstrained forms [70]. Reliability was evaluated through Cronbach's alpha and composite reliability (CR). Convergent validity was assessed through factor loadings and average variance extracted (AVE). Discriminant validity was evaluated using the Fornell–Larcker criterion [71] and the maximum shared variance (MSV) criterion [61]. Mediation effects were tested using bootstrap analysis with 5000 resamples and bias-corrected 95% confidence intervals, following the recommendations of Preacher and Hayes [72] and Zhao et al. [73].

4. Results

4.1. Common Method Bias

To address potential common method bias (CMB) from self-reported data, procedural and statistical remedies were applied [70]. Procedurally, the survey was administered anonymously through Prolific, an attention check item was included to identify and exclude inattentive respondents, and items adapted from well-established scales were used.

Statistically, three tests were conducted. Harman's single-factor test [70] showed that the first factor accounted for 34.97% of the variance, below the 50% threshold. A constrained common latent factor (CLF) test was then performed [74]; differences in standardised regression weights between the models with and without the CLF were below 0.04 for all 24 indicators, well within the 0.2 threshold. An unconstrained CLF was also estimated as an additional check, with the average squared standardised loading on the common factor at 0.23, below the 0.5 threshold. Together, these results indicate that CMB does not substantially affect the findings.

4.2. Measurement Model

A confirmatory factor analysis (CFA) using AMOS 29 was conducted to assess the six-factor measurement model, following Anderson and Gerbing's [69] two-step approach in which the measurement model is evaluated before the structural model. The CFA fitted the data well: $\chi^2(237) = 526.394$, $p < 0.001$, $\chi^2/df = 2.221$, $CFI = 0.956$, $TLI = 0.949$, $RMSEA = 0.051$, 90% CI [0.045, 0.056], $PCLOSE = 0.424$, $SRMR = 0.0447$. All indices met or exceeded the recommended thresholds [61,75]. Table 2 reports the measurement items, model fit statistics, factor loadings, and reliability and validity indices for each construct.

Convergent validity was supported. Standardised factor loadings ranged from 0.674 to 0.902, all above the 0.50 threshold [61]. Cronbach's alpha ranged from 0.838 to 0.884, and composite reliability ranged from 0.837 to 0.885 [76]. Average variance extracted ranged from 0.565 to 0.661, all above the 0.50 threshold [71]. Four standardised loadings fell marginally below the 0.70 level (SC2 = 0.674, SC4 = 0.699, PDQ2 = 0.696, and PV3 = 0.680). These four items were retained rather than dropped. Hair et al. [61] advise keeping reflective indicators with loadings between 0.40 and 0.70 unless their removal raises composite reliability or AVE above the required levels. As both measures already exceeded their thresholds for every construct, removing the items would not have improved

the measurement model, which fitted the data well with convergent and discriminant validity supported.

Table 2. Measurement items, CFA, and reliability and validity results.

Model fit: $\chi^2 = 526.394$ ($p < 0.001$), $df = 237$, $\chi^2/df = 2.221$ $CFI = 0.956$, $TLI = 0.949$, $RMSEA = 0.051$, 90% CI [0.045, 0.056], $PCLOSE = 0.424$; $SRMR = 0.0447$					
Constructs	Items	SL	CR	AVE	MSV
Streamer Credibility ($\alpha = 0.838$)	1. The live streamer I watched was knowledgeable about the products they presented	0.743	0.837	0.565	0.437
	2. The live streamer appeared to be trustworthy	0.674			
	3. The live streamer was experienced in the product category	0.875			
	4. The live streamer was a reliable source of product information	0.699			
Perceived Interactivity ($\alpha = 0.868$)	1. The live stream allowed me to communicate with the streamer in real time	0.719	0.869	0.626	0.309
	2. I felt that the live stream was responsive to my questions and comments	0.867			
	3. The live stream offered effective two-way communication	0.708			
	4. I could actively participate in the live streaming session	0.856			
Product Demonstration Quality ($\alpha = 0.840$)	1. The product demonstration in the live stream provided detailed information about the product's features	0.853	0.839	0.568	0.350
	2. The product was presented thoroughly during the live stream, showing its key attributes clearly	0.696			
	3. The product demonstration was visually rich and realistic	0.733			
	4. The live stream covered all the important aspects of the product, including how it works and how it appears	0.722			
Consumer Trust ($\alpha = 0.858$)	1. The live streamer is honest about the products presented during the live stream	0.828	0.858	0.603	0.437
	2. The live streamer keeps the commitments they make about the products	0.716			
	3. The live streamer acts in viewers' best interests when recommending products	0.833			
	4. The live streamer would do their best to help viewers with questions about the products	0.722			
Perceived Value ($\alpha = 0.879$)	1. Considering the money I spend, shopping through live streaming offers good value	0.755	0.880	0.649	0.484
	2. Considering the time I spend watching, shopping through live streaming is worthwhile	0.873			
	3. Considering the effort involved, shopping through live streaming is rewarding	0.680			
	4. Overall, live streaming shopping delivers good value to me	0.895			
Purchase Intention ($\alpha = 0.884$)	1. I am likely to purchase products demonstrated during live streaming sessions	0.884	0.885	0.661	0.484
	2. I intend to purchase products demonstrated during live streaming sessions	0.734			
	3. I would consider purchasing products demonstrated during live streaming sessions	0.902			
	4. I am willing to purchase products demonstrated during live streaming sessions	0.714			

Note(s): SL = standardised factor loading; α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted; MSV = maximum shared variance. All factor loadings significant at $p < 0.001$.

Discriminant validity was assessed through three criteria. The square root of AVE for each construct exceeded its correlations with the other constructs, satisfying the Fornell–Larcker criterion (Table 3). Maximum shared variance was below average variance extracted for all six constructs (Table 2). As a further check, the heterotrait–monotrait (HTMT) ratio was computed for every construct pair (Table 3); all values ranged from 0.301 to 0.646, below the conservative 0.85 threshold [77]. Table 3 also reports the construct means and standard deviations.

Table 3. Descriptive statistics, correlations, and discriminant validity.

Construct	M	SD	SC	INTER	PDQ	CT	PV	PI
SC	4.57	1.16	0.752	0.428	0.301	0.628	0.430	0.478
INTER	4.50	1.20	0.457	0.791	0.380	0.485	0.534	0.397
PDQ	4.54	1.18	0.289	0.399	0.753	0.475	0.548	0.442
CT	4.56	1.17	0.661	0.506	0.471	0.777	0.544	0.616
PV	4.53	1.23	0.420	0.556	0.592	0.563	0.806	0.646
PI	4.66	1.22	0.489	0.428	0.462	0.649	0.696	0.813

Note(s): M = mean; SD = standard deviation, both based on composite scores. Diagonal values (bold) are the square root of AVE. Values below the diagonal are inter-construct correlations (Fornell–Larcker criterion). Values above the diagonal are heterotrait–monotrait (HTMT) ratios; all are below the 0.85 threshold [77]. SC = streamer credibility; INTER = perceived interactivity; PDQ = product demonstration quality; CT = consumer trust; PV = perceived value; PI = purchase intention.

4.3. Structural Model and Hypothesis Testing

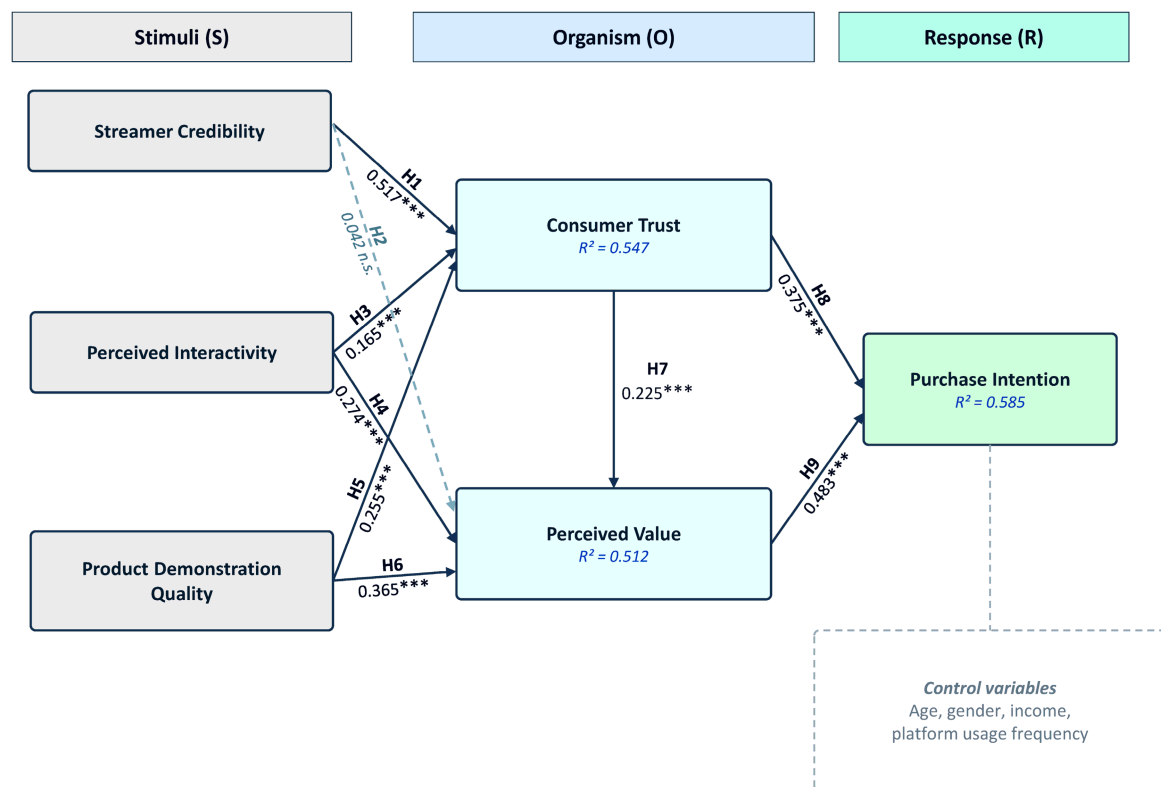
The structural model was estimated in AMOS 29 with nine hypothesised paths and four control paths to purchase intention. The model fitted the data well: $\chi^2(320) = 595.974$, $p < 0.001$, $\chi^2/df = 1.862$, $CFI = 0.959$, $TLI = 0.951$, $RMSEA = 0.043$, 90% CI [0.037, 0.048], $PCLOSE = 0.991$, $SRMR = 0.0412$. All indices comfortably exceed the conventional cut-offs [61,75]. Table 4 presents the model fit statistics, the standardised path coefficients, and the support status of each hypothesis. Similarly, Figure 2 presents the structural model results.

Eight of the nine direct effects were supported. Streamer credibility had the largest effect on consumer trust ($\beta = 0.517$, $p < 0.001$), followed by product demonstration quality ($\beta = 0.255$, $p < 0.001$) and perceived interactivity ($\beta = 0.165$, $p < 0.001$), supporting H1, H3, and H5. The pattern on perceived value diverged. Perceived interactivity ($\beta = 0.274$, $p < 0.001$) and product demonstration quality ($\beta = 0.365$, $p < 0.001$) both predicted perceived value, supporting H4 and H6. The direct path from streamer credibility to perceived value did not reach significance ($\beta = 0.042$, $p = 0.480$), so H2 was not supported. Consumer trust predicted perceived value ($\beta = 0.225$, $p < 0.001$), supporting H7. Consumer trust ($\beta = 0.375$, $p < 0.001$) and perceived value ($\beta = 0.483$, $p < 0.001$) both predicted purchase intention, supporting H8 and H9.

Table 4. Structural model results and hypothesis testing.

Model fit: $\chi^2 = 595.974$ ($p < 0.001$), $df = 320$, $\chi^2/df = 1.862$, $CFI = 0.959$, $TLI = 0.951$, $RMSEA = 0.043$, 90% CI [0.037, 0.048], $PCLOSE = 0.991$; $SRMR = 0.0412$					
Path	β	SE	C.R.	p	Result
Hypothesised paths					
H1: SC $\rightarrow$ CT	0.517	0.067	9.397	***	Supported
H2: SC $\rightarrow$ PV	0.042	0.068	0.706	n.s.	Not supported
H3: INTER $\rightarrow$ CT	0.165	0.050	3.350	***	Supported
H4: INTER $\rightarrow$ PV	0.274	0.047	5.442	***	Supported
H5: PDQ $\rightarrow$ CT	0.255	0.054	5.412	***	Supported
H6: PDQ $\rightarrow$ PV	0.365	0.056	6.940	***	Supported
H7: CT $\rightarrow$ PV	0.225	0.062	3.393	***	Supported
H8: CT $\rightarrow$ PI	0.375	0.051	7.715	***	Supported
H9: PV $\rightarrow$ PI	0.483	0.057	9.523	***	Supported
Control variable paths					
Age $\rightarrow$ PI	−0.019	0.038	−0.521	n.s.	−
Gender $\rightarrow$ PI	0.020	0.080	0.588	n.s.	−
Usage Frequency $\rightarrow$ PI	−0.025	0.031	−0.733	n.s.	−
Income $\rightarrow$ PI	−0.032	0.036	−0.890	n.s.	−

Note(s): *** $p < 0.001$, n.s. = not significant; β = standardised path coefficient; SE = standard error; C.R. = critical ratio. SC = streamer credibility; CT = consumer trust; INTER = perceived interactivity; PDQ = product demonstration quality; PV = perceived value; PI = purchase intention.



Notes: Standardised path coefficients (β) shown on each path. H2 (dashed grey) is the only non-supported direct effect; all other direct paths are significant at $p < 0.001$. Control variables (in dotted callout) were non-significant.

Figure 2. Structural model results. $*** p < 0.001$.

The model explained 54.7% of the variance in consumer trust ($R^2 = 0.547$), 51.2% in perceived value ($R^2 = 0.512$), and 58.5% in purchase intention ($R^2 = 0.585$).

None of the four control variables predicted purchase intention. The standardised effects of age ($\beta = -0.019$), gender ($\beta = 0.020$), platform usage frequency ($\beta = -0.025$), and income ($\beta = -0.032$) were all small and non-significant, with critical ratios below 1.0 in absolute terms. As a further check on the mixed platform composition of the sample, construct scores were compared across the platforms respondents used most often. One-way analyses of variance showed no significant differences on any of the six constructs (all $p > 0.25$), with platform explaining under 2% of the variance in each case. In a direct comparison of the auction-led platform (Whatnot) against the others, only streamer credibility differed at the uncorrected level ($p = 0.019$), and this difference did not survive Bonferroni correction for six tests. The constructs were therefore perceived consistently across the different platform types.

4.4. Mediation Analysis

Indirect effects were tested using bootstrap analysis with 5000 resamples and bias-corrected 95% confidence intervals. Mediation is supported when the confidence interval for an indirect effect excludes zero [72,73]. Table 5 reports the nine specific indirect effects.

Consumer trust mediated the effects of all three antecedents on purchase intention. The indirect effect was largest for streamer credibility ($\beta = 0.249$, 95% CI [0.167, 0.349], $p < 0.001$), followed by product demonstration quality ($\beta = 0.115$, 95% CI [0.070, 0.179], $p < 0.001$) and perceived interactivity ($\beta = 0.066$, 95% CI [0.029, 0.112], $p = 0.001$). H10a, H10b, and H10c were supported.

The pattern through perceived value was different. Perceived interactivity ($\beta = 0.140$, 95% CI [0.089, 0.201], $p < 0.001$) and product demonstration quality ($\beta = 0.212$, 95% CI

[0.146, 0.289], $p < 0.001$) had significant indirect effects on purchase intention through perceived value, supporting H11b and H11c. The corresponding indirect effect for streamer credibility was not significant ($\beta = 0.026$, 95% CI $[-0.054, 0.108]$, $p = 0.514$), and H11a was not supported. This is the only failed mediation in the set, and it tracks the structural finding that streamer credibility has no direct effect on perceived value.

Table 5. Mediation analysis (standardised indirect effects).

	Indirect Path	Effect	LL 95% CI	UL 95% CI	Sig.	Result
H10a	SC $\rightarrow$ CT $\rightarrow$ PI	0.249	0.167	0.349	<0.001	Supported
H10b	INTER $\rightarrow$ CT $\rightarrow$ PI	0.066	0.029	0.112	0.001	Supported
H10c	PDQ $\rightarrow$ CT $\rightarrow$ PI	0.115	0.070	0.179	<0.001	Supported
H11a	SC $\rightarrow$ PV $\rightarrow$ PI	0.026	−0.054	0.108	0.514	Not supported
H11b	INTER $\rightarrow$ PV $\rightarrow$ PI	0.140	0.089	0.201	<0.001	Supported
H11c	PDQ $\rightarrow$ PV $\rightarrow$ PI	0.212	0.146	0.289	<0.001	Supported
H12a	SC $\rightarrow$ CT $\rightarrow$ PV $\rightarrow$ PI	0.072	0.030	0.129	<0.001	Supported
H12b	INTER $\rightarrow$ CT $\rightarrow$ PV $\rightarrow$ PI	0.019	0.006	0.041	0.001	Supported
H12c	PDQ $\rightarrow$ CT $\rightarrow$ PV $\rightarrow$ PI	0.033	0.014	0.065	<0.001	Supported

Note(s): LL = lower limit; UL = upper limit; CI = confidence interval. Indirect effects and 95% CIs were obtained via bias-corrected bootstrap with 5000 resamples. Mediation is significant when the 95% CI does not include zero.

The serial pathway from each antecedent through consumer trust and then perceived value to purchase intention was significant in all three cases. The serial indirect effect was largest for streamer credibility ($\beta = 0.072$, 95% CI $[0.030, 0.129]$, $p < 0.001$), followed by product demonstration quality ($\beta = 0.033$, 95% CI $[0.014, 0.065]$, $p < 0.001$) and perceived interactivity ($\beta = 0.019$, 95% CI $[0.006, 0.041]$, $p = 0.001$). H12a, H12b, and H12c were supported. For streamer credibility, the serial route through trust and then value remained significant even though the parallel route through value alone (H11a) did not. In this dataset, the contribution of credibility to perceived value runs through trust.

Eleven of the twelve hypotheses were supported. The single non-supported hypothesis was H11a, the parallel mediation of streamer credibility on purchase intention through perceived value.

5. Discussion

5.1. General Discussion

Eleven of the twelve hypotheses received empirical support. The single non-supported hypothesis is the most theoretically informative result in the model and must be interpreted in conjunction with two related findings. The direct path from streamer credibility to perceived value (H2) was not supported ($\beta = 0.042$, $p = 0.480$); the parallel mediation through perceived value (H11a) was likewise not supported; the serial mediation through consumer trust and subsequently perceived value (H12a) was supported ($\beta = 0.072$, $p < 0.001$). Viewed in isolation, the H2 null result might suggest a limited role for streamer credibility in shaping perceived value. Read alongside H11a and H12a, however, the three results constitute a coherent pattern. Within a competence-based specification of streamer credibility, the construct exerts no direct effect on perceived value; its influence operates exclusively through consumer trust. Streamer credibility predicts consumer trust strongly ($\beta = 0.517$), consumer trust predicts perceived value ($\beta = 0.225$), and the serial pathway is the only route through which streamer credibility reaches perceived value in the model. This asymmetric pattern represents a substantive theoretical finding rather than a limitation of the credibility construct or the empirical model.

This pattern lands precisely where Zhou and Lou's [32] dual-route framework predicts. They distinguish a rational trust route (driven by expertise and trustworthiness) from an experiential pleasure route (driven by attractiveness). Because the present model

defined credibility around competence and routed affective influences through perceived interactivity instead, the rational route should fire and the experiential route should not. That is what the data show. Na et al.'s [78] virtual-streamer study sharpens the same point from the opposite direction. Their attractiveness predicts affection but not trust, while intelligence predicts trust but not affection. Cognitive cues route through trust; affective cues route through affection. The credibility of the messenger and the value of the message are distinct constructs connected by trust.

The closest empirical precedent is Doong [16], whose Taiwanese live-commerce study found that a serial trust-then-value model fitted significantly better than a parallel one and that reputation reached value indirectly through trust rather than directly. The present results show the same structural pattern in a UK sample with a fully specified parallel-and-serial design. The theoretical anchor is Kim et al. [33], who argue that trust functions as a precondition for perceived value because it reduces the non-monetary transaction costs (perceived risk, evaluation effort, information search) that consumers fold into their give-get calculus. The serial finding is the empirical complement to that argument. An instructive contrast comes from Adaba et al.'s [25] UK study of social media influencers, where a strong influencer-to-trust path failed to translate into purchase outcomes the way a simple mediation logic would predict. In their data the chain broke at the conversion step, with influencers building trust yet trust relating negatively to purchase intention, an overtrust pattern they read through persuasion knowledge, where a polished commercial persona invites the scepticism it seeks to allay. Trust does the opposite work in the present model. It is the sole route by which competence-based credibility reaches perceived value, it supports purchase intention in its own right, and the chain completes rather than breaking. The difference is unlikely to be that UK consumers trust more in live commerce. It is more plausibly that the live, demonstration-led setting attaches trust to a concrete exchange the viewer can appraise on the spot and channels it into a give-get judgement about that exchange, rather than leaving it to act on a persona whose endorsements stand at one remove from any single purchase.

5.2. Theoretical Implications

The findings contribute to the live streaming commerce literature in four ways.

First, the model demonstrates that consumer trust and perceived value function as parallel and sequential mediators with different roles depending on the antecedent. Prior live streaming work has typically examined either trust or perceived value in single-mediator designs. By including both and testing the serial pathway, the study shows them to be complementary rather than competing. Trust feeds value, which independently affects purchase intention, and the only indirect route from credibility to value is the serial one. This dual-mediator structure responds to Luo et al.'s [11] systematic-review call for integrated multi-mediator tests in non-Chinese contexts.

Second, the findings offer a methodological clarification for a recurring puzzle in the literature. Studies that fold attractiveness into credibility routinely report direct credibility-to-outcome paths; studies built on competence alone tend to report partial or fully mediated effects. Yun and Meng [79] show that streamer attractiveness produces direct shifts in product preference and purchase intention through a halo mechanism. Li et al. [80] find anchor attractiveness to be the strongest predictor of consumer pleasure on the path to impulse buying, ahead of similarity, professionalism, and interactivity. The reasonable inference is not that one type of study is wrong, but that "credibility" measured with attractiveness folded in is a composite of two psychologically distinct routes; the composite path can disappear when the affective component is moved out of the construct, exactly

as occurs here. Future live streaming commerce work should report results by credibility component rather than by composite.

Third, the study extends the application of the S-O-R framework to live streaming platforms by specifying both stimuli and organisms with greater precision. Where earlier studies have used broad categories such as “environmental cues” or “platform features” as stimuli [7], the present model distinguishes streamer-related, interaction-related, and product-related features as platform-design dimensions that can be configured and measured separately. The largest direct effect on perceived value came from product demonstration quality, which is consistent with Lu and Chen’s [9] argument that what consumers see during a vicarious product trial provides an informational basis distinct from the social interaction with the streamer. Wang et al.’s [49] finding that integrity is the strongest predictor of trust in human streamers also supports the integrity-and-benevolence focus of the trust construct here.

Fourth, the results speak to a growing body of platform research that treats trust less as a private belief than as something platforms build into their design. Mattathil et al. [10] describe platform trust as a behavioural architecture, assembled from structural cues such as verification, ratings, and guarantees that steer how consumers process a transaction. The present model locates the three antecedents in that architecture, since each rests on platform affordances, credibility on how the platform verifies and ranks sellers, interactivity on its chat and real-time reply features, and demonstration quality on its camera and display tools. What the findings add to this view is a route. In live commerce the credibility a platform signals does not reach perceived value on its own; it reaches value only after passing through trust. Value, in turn, is not a fixed property of the product but is produced within the stream, by what the demonstration shows and how the interaction unfolds, so value creation here is itself platform-mediated. Trust is the conversion point at which a platform’s credibility signals become value, which gives the trust-architecture account a specific mechanism to test rather than a general claim that platforms manufacture trust.

5.3. Practical Implications

For live streaming platform operators and the streamers who use them, the findings translate into a clearer prioritisation of platform-design and training investments than a single-mediator model would suggest. Streamer credibility is the strongest lever for building consumer trust; product demonstration quality is the strongest direct predictor of perceived value; perceived interactivity contributes to both. Platforms should invest in streamer vetting and training programmes and provide tools that enable thorough product demonstrations, including multiple camera angles, close-up capabilities, lighting controls, and real-time comparison features. Streamers should be trained to demonstrate products substantively rather than relying on verbal description or personal endorsement alone. Platforms that drift towards a broadcast-style experience risk sacrificing the trust-building potential that distinguishes live streaming from pre-recorded content [4].

The trust-and-value mechanism is not symmetric across antecedents, and the investment logic differs accordingly. For credibility, trust is the load-bearing mediator. Investments in streamer competence pay off through trust formation, not directly through value perception. For interactivity and product demonstration quality, both pathways are operative, so platforms can lean on whichever is more cost-effective for a given category. The serial finding has a specific sequencing implication for platform interface design. Trust is a gateway to value perceptions. In interface terms, the cues that build trust should be encountered before, or placed above, the cues that promote a deal. In Mattathil et al.’s [10] terms these trust cues function as structural heuristics, verification badges, third-party authentication, and visible seller history or review consistency, and a platform can position

them early in the viewing path so the trust state is in place before flash-promotional devices such as countdown timers and discount coupons appear. Leading with the promotion and leaving verification to a buried profile tab inverts the order the data imply. The non-significant effects of all four control variables on purchase intention indicate the mechanism operates similarly across demographic groups within the UK sample, which simplifies targeting decisions.

The UK platform mix matters. The descriptive data show TikTok Shop as the dominant platform, with Whatnot at 19.9% as the second-most-used, ahead of Instagram Live, Amazon Live, YouTube Shopping, and Facebook Live. Whatnot is the closest Western analogue to Taobao Live. It is auction-style, live streamer-led, and anchored in collectibles and resale communities [5]. Its visible share suggests the UK live-commerce environment is more diverse than early studies (focused on TikTok and Instagram) reflected, and strategies extrapolated from a single Chinese super-app will not transfer cleanly. Live-commerce maturity, user profile, and engagement conventions differ substantially across markets and require platform-tailored approaches [5]. Mattathil et al.'s [10] Trust Architecture Framework offers a vocabulary for designing trust signals more deliberately at the platform level. Multidimensional credibility indicators (verified expertise, disclosure history, demonstration-quality scores) tighten the credibility-to-trust link the model identifies as the gateway to both behavioural and value-based outcomes, whereas a generic five-star reputation cue does not. The two formats that dominate the UK sample ask different things of the sellers who use them, even though the underlying logic is the same. On Whatnot, where the fast auction format trades in high-value, often non-returnable goods [5], the binding constraint for a seller is trust in authenticity. The priorities are a visible track record, third-party authentication or grading, and demonstration good enough to show condition in close-up, all established before the bidding and its built-in urgency take hold. Because the auction format supplies value and scarcity cues of its own, a seller who has not earned trust first has little to fall back on. TikTok Shop runs the other way, leading with entertainment and discovery, often with unfamiliar sellers and lower-involvement goods bought on impulse [81]. The risk there is the one Adaba et al. [25] document, attention and even intention that do not convert once commercial intent becomes salient, so a seller's task is to carry credibility and substantive demonstration into fast, entertaining content rather than leaning on promotion alone. The model points the same way on both platforms, trust before value, but the cue in shortest supply differs, authentication on Whatnot and credible demonstration on TikTok Shop.

5.4. Limitations and Future Research

The cross-sectional design prevents causal inference; longitudinal or experimental designs would be needed to establish causality, particularly since trust and perceived value plausibly develop over repeated interactions. The sample is exclusively UK, and consumer expectations, parasocial norms, and platform ecosystems differ across markets [5,11,23]. The sample was further restricted to consumers who had purchased through live streaming in the past six months, which excludes the perspectives of viewers who watch without buying.

The credibility construct was restricted to its competence-based dimensions. The exclusion is theoretically motivated but is not the only defensible choice; a specification that re-introduces attractiveness as a separate antecedent alongside competence would test the dual-route prediction directly. Perceived value was modelled as a single global give-get construct. This specification suits the mediating role value plays in the model, but a single construct cannot separate the dimensions of value that a multidimensional scale distinguishes, so it leaves open which of them carries the effect. Given how hedonic

and social live streaming is, future work using dimension-specific value items, separating emotional, social, functional, and price value [14], could show whether the stimuli operate mainly through emotional value or through monetary value. Adaba et al.’s [25] overtrust finding raises a related boundary question. Under what conditions does the credibility-to-trust link tip from beneficial to counterproductive? Moderation analyses testing perceived commercialisation, persuasion-knowledge cues, or platform familiarity would address this. Self-reported purchase intention was used rather than actual behaviour [26]; behavioural data from platform analytics would strengthen the design. Brand-hosted and influencer-hosted streams may activate different routes; a specification separating the two would clarify whether the present pattern is a feature of one streaming format or of UK consumer behaviour more generally. A platform-stratified replication, particularly contrasting an auction-led platform like Whatnot with a brand-host platform like TikTok Shop, would address platform specificity.

6. Conclusions

Streamer credibility, perceived interactivity, and product demonstration quality all matter for purchase intention in UK live streaming commerce, but they do not all matter in the same way. Interactivity and product demonstration quality reach purchase intention through both trust and value, in parallel. Competence-based credibility does not. Its only route to value runs serially through trust. The contribution of this paper is to set out that pattern empirically, in a UK sample, with a fully specified parallel-and-serial design, and to show that the apparent weak link (credibility’s failure to predict value directly) is the signature of a particular psychological route rather than a weakness. For platform operators and researchers working across an increasingly diverse UK live-commerce environment, including platforms such as Whatnot whose conventions sit closer to Taobao Live than to early Western social-commerce models, the model provides a clearer basis for designing platform features and training streamers around the trust-mediated architecture through which competence-based credibility reaches value and behaviour.

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Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki and was approved by the Loughborough Business School Research Ethics Committee (Project ID: 24559) on 1 December 2025.

Informed Consent Statement: Informed consent was obtained from all participants involved in the study. Respondents reviewed a participant information sheet on Prolific and provided active consent by ticking a consent confirmation before starting the survey.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The author declares no conflicts of interest.

Appendix A. Measurement Items

Code	Measurement Item
Streamer Credibility (adapted from Ohanian [31] and Lou and Yuan [6])	
SC1	The live streamer I watched was knowledgeable about the products they presented.
SC2	The live streamer appeared to be trustworthy.
SC3	The live streamer was experienced in the product category.
SC4	The live streamer was a reliable source of product information.

Code	Measurement Item
Perceived Interactivity (adapted from Liu [37] and Jiang et al. [63])	
INTER1	The live stream allowed me to communicate with the streamer in real time.
INTER2	I felt that the live stream was responsive to my questions and comments.
INTER3	The live stream offered effective two-way communication.
INTER4	I could actively participate in the live streaming session.
Product Demonstration Quality (adapted from Jiang and Benbasat [45] and Xu et al. [46])	
PDQ1	The product demonstration in the live stream provided detailed information about the product's features.
PDQ2	The product was presented thoroughly during the live stream, showing its key attributes clearly.
PDQ3	The product demonstration was visually rich and realistic.
PDQ4	The live stream covered all the important aspects of the product, including how it works and how it appears.
Consumer Trust (adapted from McKnight et al. [48])	
CT1	The live streamer is honest about the products presented during the live stream.
CT2	The live streamer keeps the commitments they make about the products.
CT3	The live streamer acts in viewers' best interests when recommending products.
CT4	The live streamer would do their best to help viewers with questions about the products.
Perceived Value (adapted from Kim et al. [33], following Zeithaml [15])	
PV1	Considering the money I spend, shopping through live streaming offers good value.
PV2	Considering the time I spend watching, shopping through live streaming is worthwhile.
PV3	Considering the effort involved, shopping through live streaming is rewarding.
PV4	Overall, live streaming shopping delivers good value to me.
Purchase Intention (adapted from Dodds et al. [64] and Pavlou [26])	
PI1	I am likely to purchase products demonstrated during live streaming sessions.
PI2	I intend to purchase products demonstrated during live streaming sessions.
PI3	I would consider purchasing products demonstrated during live streaming sessions.
PI4	I am willing to purchase products demonstrated during live streaming sessions.

Note(s): All items were rated on a seven-point Likert scale (1 = strongly disagree to 7 = strongly agree).

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