Do Virtual Livestreamer Attributes Drive Consumer Purchase Intention? An Empirical Analysis from the Perspective of Perceived Trust

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Abstract

AI-driven virtual livestreamers have moved from technical demonstration to large-scale commercial deployment in China's live-commerce market, yet their selling performance still trails that of human hosts and consumer acceptance remains limited. Drawing on the theory of planned behaviour and empathy theory, this secondary analysis of published survey results examines how four attributes of virtual livestreamers anthropomorphism, interactivity, intelligence and information quality shape consumer purchase intention, and tests whether perceived trust transmits those effects. The analysis draws on aggregate results from a survey of Chinese live-commerce viewers conducted between 9 and 15 June 2024 and published in Times of Economy & Trade (665 questionnaires, 508 valid responses, 76.391% validity rate). The source study reported analyses using SPSS 25.0, AMOS 24.0 and the PROCESS macro with 5,000 bootstrap resamples; no new survey was conducted for this paper. All four attributes significantly and positively predict both perceived trust and purchase intention, with information quality exerting the strongest effect ($\beta = 0.751$ on trust; $\beta = 0.770$ on purchase intention) and interactivity the weakest ($\beta = 0.523$; $\beta = 0.590$). Perceived trust itself is the single strongest predictor of purchase intention ($\beta = 0.770$, $R^2 = 0.560$) and partially mediates every attribute–intention path, carrying between 47.8% and 62.7% of the total effect. The findings reposition virtual livestreamer design away from visual realism alone and towards verifiable information delivery, and they align commercially with the disclosure obligations imposed by China's Measures for Labelling AI-Generated Synthetic Content, effective 1 September 2025. The paper also reports a reproduction audit confirming that all published inferential statistics are internally consistent.

Keywords: Virtual livestreamer; perceived trust; purchase intention; mediation analysis; live-commerce; artificial intelligence

Do Virtual Livestreamer Attributes Drive Consumer Purchase Intention? A Secondary Analysis of Published Survey Results

1. Introduction

Live-commerce has become a structural component of Chinese online retail rather than a marketing novelty. The China Internet Network Information Centre reports that, as of December 2025, the country had 1.125 billion internet users, an 80.1% penetration rate, and 937 million online shoppers, equivalent to 83.2% of all netizens. The China Netcasting Services Association reports 833 million livestreaming users as of December 2024, or 75.2% of netizens, served by roughly 38.8 million professional hosts — a figure that grew 1.5-fold year on year. Within this market, 54.2% of surveyed viewers reported watching e-commerce livestreams frequently.

Against that backdrop, virtual livestreamers — AI-driven digital humans that present and sell products without a human presenter on camera — have shifted from demonstration to deployment. iiMedia Research values China's core digital-human market at RMB 48.06 billion in 2025, projecting RMB 93.56 billion by 2030, with an associated driven-market value of RMB 478.53 billion in 2024. Enterprise procurement data show virtual hosts and presenters accounting for 30.30% of planned digital-human purchases, second only to virtual customer service at 34.63%. The commercial inflection point is usually dated to 15 June 2025, when a digital replica of entrepreneur Luo Yonghao, paired with a digital co-host, streamed for roughly six and a half hours on Baidu's e-commerce platform, drew more than 13 million viewer-sessions and generated over RMB 55 million in gross merchandise value — exceeding the per-category unit sales of Luo's own human debut three weeks earlier. Baidu subsequently disclosed that more than 100,000 merchants were operating digital-human streams, that such rooms averaged over six million daily users, and that merchants using them recorded a 31% lift in conversion alongside an 80% reduction in streaming cost.

These headline figures conceal a persistent asymmetry. Cost advantage is not the same as persuasive advantage, and the sector remains in an early stage in which consumer acceptance lags technical capability. Several platforms have classified certain digital-human streams as low-quality content and restricted them. Regulators have also tightened disclosure: the Measures for Labelling AI-Generated Synthetic Content, issued jointly by four ministries in March 2025 and effective 1 September 2025, together with mandatory national standard GB 45438-2025, require both explicit and implicit labelling of synthetic content. A virtual host must therefore now persuade an audience that knows it is watching a machine. That makes the mechanism by which virtual livestreamer attributes translate into purchase intention a question of direct commercial consequence rather than a theoretical curiosity.

Existing empirical work is narrow on two fronts. First, it has concentrated on interactivity, typically routed through immersive experience or social presence, leaving anthropomorphism, machine intelligence and information quality untested within a single model. Second, it has borrowed the stimulus–organism–response framework developed for human hosts, which assumes an interpersonal relationship that human–machine exchange does not straightforwardly reproduce. When a human host is replaced by a digital one, interpersonal trust becomes trust in a machine, and the substitution is not cosmetic.

This secondary analysis addresses both gaps by interpreting the published results for four virtual livestreamer attributes and perceived trust as the mediating mechanism, grounding the argument in the theory of planned behaviour and in empathy theory rather than in stimulus–response logic. It contributes in three ways: it broadens the attribute space beyond interactivity; it substitutes a trust-based mechanism suited to human–machine exchange for a stimulus-based one; and it establishes a rank ordering among attributes that carries direct design implications for a market now operating under mandatory AI disclosure.

2. Theoretical Background and Hypothesis Development

2.1 Empathy theory and artificial empathy

Empathy is the capacity to apprehend another party's internal state — to adopt their standpoint and register their thoughts, needs, motives and perspective, and to respond accordingly [19]. The construct has been extended to artificial agents. Asada [2] argues that artificial empathy can be approached developmentally, following the pathway of natural empathy, while Leite et al. [8] show that robots which mimic human characteristics and respond to human needs elicit empathic responses in interaction. Lv et al. [11] further find that highly empathic AI strengthens continued-use intention, with trust operating as the transmission mechanism.

Applied to live-commerce, the attributes of a virtual livestreamer are precisely the observable surface of its empathic capacity. Anthropomorphic form, responsive interaction, situational intelligence and accurate information all signal that the agent is attending to the viewer. That signal narrows the perceived distance between agent and consumer and provides the affective foundation on which purchase intention can form.

2.2 The theory of planned behaviour

The theory of planned behaviour holds that behavioural intention is a function of attitude, subjective norm and perceived behavioural control [1]. Trust enters this structure through attitude: consumer trust is positively associated with consumption attitude [17], and attitude in turn predicts purchase intention. Hong and Cha [7] demonstrate directly that trust in an online merchant mediates the relationship between perceived risk and purchase intention, completely mediating performance risk and partially mediating psychological risk. The inference relevant here is that virtual livestreamer attributes raise perceived trust, trust lowers perceived risk, and lowered risk raises purchase intention.

2.3 Virtual livestreamer attributes and purchase intention

Communication research associated with Mehrabian holds that the effectiveness of expression depends substantially on body language and vocal tone rather than on verbal content alone. The specific weightings often quoted — 55% body language, 38% tone, 7% words — derive from Mehrabian and Ferris [13] and Mehrabian and Wiener [14] and were established under narrow experimental conditions concerning the communication of feelings and attitudes; they should be treated as an indicative rationale for the salience of non-verbal cues, not as a general law of communication. On that qualified basis, the anthropomorphic fidelity of a virtual livestreamer plausibly conditions the emotional exchange between agent and viewer and the viewing experience itself [4], which in turn affects how effectively product information is conveyed.

H1a. Virtual livestreamer anthropomorphism positively affects consumer purchase intention.

Interactivity refers to a host's capacity to engage viewers by answering comment-stream questions, running giveaways and sustaining atmosphere. Host–viewer interaction in live-commerce functions as social behaviour, alleviating viewer loneliness and encouraging purchase [9]. Human–machine interaction differs in kind: a virtual host interacts through configured back-end flows and keyword triggers rather than spontaneous response. As a channel for affective connection, however, the perceived quality of that interaction still shapes emotional experience and therefore purchase intention.

H1b. Virtual livestreamer interactivity positively affects consumer purchase intention.

Intelligence denotes the technical capacity of a virtual host to operate autonomously in recommending merchandise. Current practice relies on fully AI-driven pipelines modelled on human hosts, imitating voice, affect and movement, with scripts imported into a back-end editing system. Because the field remains at an early stage, the level of intelligence achieved directly conditions whether consumers receive product information effectively [10].

H1c. Virtual livestreamer intelligence positively affects consumer purchase intention.

Information quality concerns the completeness and accuracy of the product information a host conveys. Liu and Zhang [10] show experimentally that excessive praise and false claims lead consumers to judge a host dishonest, unreliable, indifferent to their interests and professionally incompetent, depressing purchase intention. Script-driven description might appear more controllable than human improvisation, yet public unease persists about whether AI errs, behaves unexpectedly during a broadcast, or develops as intended [3]. Completeness and accuracy therefore condition trust in host, platform and product alike.

H1d. Virtual livestreamer information quality positively affects consumer purchase intention.

2.4 Virtual livestreamer attributes and perceived trust

Human hosts build affective connection and trust with viewers through the platform, but a virtual livestream is human–machine interaction and does not reproduce that relationship directly. Ramadan et al. [18] show that the anthropomorphic style of intelligent voice assistants supports affective bonding, generating trust and dependence particularly among lonelier consumers. Anthropomorphic design should therefore compress the perceived distance between virtual host and viewer.

H2a. Virtual livestreamer anthropomorphism positively affects perceived trust.

Interaction with voice assistants — playing music, supplying news, operating smart-home applications — produces pleasure, convenience, sustained support and a sense of social presence. Repeated successful use makes the assistant appear safe and reliable and fosters a relatively intimate relationship [15]. Interaction between a virtual host and a viewer likewise delivers emotional value and usable information, and repetition consolidates trust.

H2b. Virtual livestreamer interactivity positively affects perceived trust.

A human host's product knowledge and expertise reduce perceived purchase risk and raise purchase intention [16]. A virtual host that uses algorithms to recommend merchandise precisely, push coupons responsively, explain products competently and demonstrate them in real time performs the same risk-reduction function.

H2c. Virtual livestreamer intelligence positively affects perceived trust.

Replacing a human host with a virtual one converts interpersonal trust into human–machine trust, so consumer trust in a virtual livestreamer depends partly on trust in the underlying AI. Because the technology remains immature and its use carries residual risk, that risk depresses perceived trust; conversely, if consumers expect the information conveyed and the instructions executed to be consistently correct and complete, perceived risk falls and trust forms more readily.

H2d. Virtual livestreamer information quality positively affects perceived trust.

2.5 Perceived trust and purchase intention

Mayer et al. [12] define trust as a means by which an individual reduces the uncontrollability and unpredictability of another party's behaviour and motives — a confidence, grounded in prior experience, that the other will act as expected. Where trust is absent, people avoid the behaviour altogether [6]. When consumers believe a virtual livestreamer will meet their requirements and attend to their interests, purchase intention follows.

H3. Consumer perceived trust positively affects purchase intention.

2.6 The mediating role of perceived trust

Anthropomorphism and interactivity displace the perception of machines as cold and mechanical. Interaction generates social enjoyment; to sustain that enjoyment consumers extend trust and participate more actively;

as product understanding deepens, insecurity about use dissipates and purchase intention strengthens. Fluent explanation and accurate, complete professional information work through the same channel by lowering expected performance risk.

H4a–H4d. Perceived trust mediates the relationship between each of anthropomorphism, interactivity, intelligence and information quality and consumer purchase intention.

Figure 1 (not reproduced here) summarises the resulting model: four exogenous attributes, one mediator, one outcome, with both direct and trust-mediated paths specified for each attribute.

3. Method

3.1 Measurement instrument

In the source study, all constructs were measured with multi-item scales adapted from established instruments, modified in wording to suit the virtual-livestreamer context. Each construct was measured with three items on a Likert scale. Table 1 reports the items and their sources.

Table 1. Measurement Items and Sources

Construct	Code	Item	Adapted from
Anthropomorphism (X1)	Y1	The virtual livestreamer's appearance is humanlike	Zhao et al. (2023)
	Y2	The virtual livestreamer's speech is humanlike	
	Y3	The virtual livestreamer's movements and posture are humanlike	
Interactivity (X2)	H1	The virtual livestreamer is capable of real-time interaction	Xiang (2024)
	H2	The virtual livestreamer's replies are relevant to my questions	
	H3	The virtual livestreamer interacts with me in varied ways	
Intelligence (X3)	Z1	The virtual livestreamer can recommend products in the stream	Gao et al. (2023)
	Z2	The virtual livestreamer can analyse differences against competing products	
	Z3	The virtual livestreamer can demonstrate product functions efficiently	
Information quality (X4)	L1	The virtual livestreamer describes products objectively	Cai et al. (2023)
	L2	The virtual livestreamer describes products accurately	
	L3	The product information the virtual livestreamer gives is complete	
Perceived trust (R1)	R1	I believe the products this virtual livestreamer recommends are genuine and reliable	Xiao et al. (2021)

Construct	Code	Item	Adapted from
	R2	I believe the products recommended match my consumption needs	
	R3	I believe the products recommended will meet my expectations	
Purchase intention (G1)	G1	The products this virtual livestreamer recommends are worth buying	Park et al. (2020)
	G2	I want to buy the products this virtual livestreamer recommends	
	G3	I would recommend this virtual livestreamer's stream to friends	

3.2 Source survey and sampling

The source study reported a questionnaire with three sections: respondent background; a screening section filtering out participants unfamiliar with virtual-livestreamer commerce; and the main body, which asked respondents to recall their most recent experience of watching a virtual livestreamer sell products before answering the scale items. To protect data quality, one attention-trap item and two instructed-response items were embedded at random positions.

The source study reported distribution from 9 to 15 June 2024 via the Wenjuanxing platform, circulated through Weibo, WeChat, QQ and Xiaohongshu. Of 665 questionnaires, 508 were valid, a validity rate of 76.391%. These published aggregate results form the basis of the present secondary analysis; no new participants were recruited and no individual-level response file was available to us.

3.3 Sample profile

Table 2 summarises the characteristics of the 508 respondents in the source survey.

Table 2. Sample Characteristics

Variable	Category	Frequency	Percentage (%)
Gender	Male	266	52.362
	Female	242	47.638
Age	Under 18	2	0.394
	18–29	406	79.921
	30–45	94	18.504
	Over 45	6	1.181
Education	Junior secondary or below	9	1.772
	Senior secondary / vocational	44	8.661
	Bachelor's or associate degree	410	80.709
	Master's or above	45	8.858
Monthly income	RMB 1,000 or below	10	1.970
	RMB 1,001–4,000	272	53.543
	Above RMB 4,000	226	44.488

The gender split is close to parity. Respondents aged 18–29 account for 79.921% and those aged 30–45 for 18.504%, so the sample is overwhelmingly young — consistent with the observed audience for virtual-livestreamer commerce. Educational attainment is high, with 80.709% holding a bachelor's or associate degree and a further 8.858% a postgraduate qualification. Over half report monthly income between RMB 1,001 and 4,000, a profile consistent with value-oriented purchasing in virtual-host streams. The sample therefore corresponds reasonably to the population familiar with this format, though its skew is a limitation addressed in Section 6.

3.4 Analytical strategy

The source study reported reliability and exploratory factor analysis in SPSS 25.0; confirmatory factor analysis, composite reliability, average variance extracted and model fit in AMOS 24.0; regression estimates of direct effects; and mediation tests using the PROCESS macro with 5,000 bootstrap resamples and percentile confidence intervals. We reproduce the published estimates, audit their arithmetic consistency, and derive Cohen's f^2 and the variance accounted for (VAF) from the reported statistics. These calculations do not constitute re-estimation from individual-level data. An indirect effect is treated as significant where its reported bootstrap confidence interval excludes zero.

4. Results

4.1 Reproduction audit of reported statistics

Before interpreting the substantive findings, every published inferential statistic was recomputed from the reported degrees of freedom and effect sizes to verify internal consistency. Three checks were run. First, F statistics were regenerated from the reported R^2 and $N = 508$ using $F = [R^2 / (1 - R^2)] \times (N - 2)$; all nine regressions reproduce to within 0.4% of the published values, the small residual being attributable to rounding of R^2 to three decimals. Second, t statistics were checked against $\sqrt{F}$ for each single-predictor equation and match to three decimal places in every case. Third, 95% confidence intervals were rebuilt from β and t as $\beta \pm 1.9647 \times (\beta / t)$ with $df = 506$; all eighteen bounds reproduce to within 0.001. The square roots of the reported AVE values likewise match the Fornell–Larcker diagonal exactly, and the reported direct and indirect effects sum precisely to the reported total effects. Frequency counts sum to 508 within every demographic variable, and 508/665 returns 76.391%.

These checks establish that the published statistics are mutually consistent and arithmetically reproducible. They do not, and cannot, verify that the underlying responses were collected as described; that would require the raw response file. The distinction matters and is discussed in Appendix A.

4.2 Reliability

Cronbach's alpha for the composite virtual livestreamer attribute scale is 0.915. All four sub-dimensions exceed 0.700 and both the perceived trust and purchase intention scales exceed 0.800. Corrected item–total correlations all exceed 0.500, and deleting any item lowers the corresponding alpha, indicating that every item contributes to its scale (Table 3).

Table 3. Scale Reliability

Construct	Item	Corrected item–total correlation	Cronbach's α if item deleted
Anthropomorphism (α = 0.807)	Y1	0.661	0.703
	Y2	0.653	0.736
	Y3	0.650	0.741
Interactivity (α = 0.833)	H1	0.705	0.758
	H2	0.697	0.766
	H3	0.679	0.784
Intelligence (α = 0.754)	Z1	0.562	0.693
	Z2	0.583	0.669
	Z3	0.602	0.647
Information quality (α = 0.756)	L1	0.575	0.684
	L2	0.593	0.663
	L3	0.587	0.671
Perceived trust (α = 0.802)	R1	0.632	0.747
	R2	0.673	0.702
	R3	0.638	0.739

Construct	Item	Corrected item–total correlation	Cronbach's α if item deleted
Purchase intention (α = 0.813)	G1	0.659	0.745
	G2	0.673	0.731
	G3	0.656	0.750

4.3 Validity

Because all scales were adapted from established instruments, content validity is supported by construction. Kaiser–Meyer–Olkin values are 0.944 for the attribute battery, 0.709 for perceived trust and 0.716 for purchase intention, all above the 0.700 threshold, and Bartlett's test of sphericity is significant at $p < 0.001$ in each case. After rotation, every item loads above 0.500 on its intended factor (Table 4).

Table 4. Exploratory Factor Analysis

Construct	Item	Rotated loading	KMO
Anthropomorphism	Y1	0.766	Attribute battery: 0.944
	Y2	0.760	
	Y3	0.617	
Interactivity	H1	0.775	
	H2	0.781	
	H3	0.699	
Intelligence	Z1	0.835	
	Z2	0.584	
	Z3	0.518	
Information quality	L1	0.662	
	L2	0.711	
	L3	0.794	
Perceived trust	R1	0.836	Perceived trust: 0.709
	R2	0.863	
	R3	0.841	
Purchase intention	G1	0.851	Purchase intention: 0.716
	G2	0.859	
	G3	0.848	

Convergent validity is satisfactory across all six constructs: composite reliability ranges from 0.754 to 0.834 and average variance extracted from 0.506 to 0.626, exceeding the conventional thresholds of 0.700 and 0.500 respectively [5]. The AVE values for intelligence (0.506) and information quality (0.508) clear the threshold only narrowly (Table 5).

Table 5. Convergent Validity

Construct	CR	AVE	√AVE
Anthropomorphism (X1)	0.808	0.583	0.764
Interactivity (X2)	0.834	0.626	0.791
Intelligence (X3)	0.754	0.506	0.711
Information quality (X4)	0.756	0.508	0.713
Perceived trust (R1)	0.803	0.577	0.760
Purchase intention (G1)	0.817	0.592	0.770

Table 6 reports the confirmatory factor analysis model fit from the source study.

Table 6. Confirmatory Factor Analysis Fit

	CFI	IFI	GFI	TLI	RMR	RMSEA	CMIN/DF
Model	0.953	0.953	0.922	0.953	0.029	0.059	2.773
Threshold	> 0.800	> 0.800	> 0.800	> 0.800	< 0.050	< 0.080	< 3.000

Discriminant validity was assessed with the Fornell–Larcker criterion. The square root of each construct's AVE, shown on the diagonal of Table 7, exceeds its correlations with every other construct, so the criterion is formally satisfied. The margins are thin in several cells, however. The gap between √AVE for intelligence

(0.711) and its correlation with purchase intention (0.698) is only 0.013; between perceived trust (0.760) and its correlation with purchase intention (0.749) only 0.011; and between intelligence and information quality only 0.019. Constructs separated by margins this narrow should be regarded as empirically adjacent rather than cleanly distinct, and a heterotrait–monotrait ratio test would provide a more demanding assessment.

Table 7. Discriminant Validity

	X1	X2	X3	X4	R1	G1
X1	0.764					
X2	0.716	0.791				
X3	0.639	0.645	0.711			
X4	0.621	0.580	0.692	0.713		
R1	0.593	0.559	0.645	0.686	0.760	
G1	0.587	0.613	0.698	0.685	0.749	0.770

Diagonal entries in bold are √AVE; off-diagonal entries are inter-construct correlations.

4.4 Direct effects

Table 8 reports the regression results, with Cohen's f^2 added by the present author as $f^2 = R^2 / (1 - R^2)$. All nine coefficients are positive and significant at $p < 0.001$, and every confidence interval excludes zero. All four attributes therefore positively affect purchase intention, supporting H1a to H1d; all four positively affect perceived trust, supporting H2a to H2d; and perceived trust positively affects purchase intention, supporting H3.

Table 8. Regression Results

DV	IV	R^2	F	β (t)	95% CI	f^2
R1	X1	0.351	273.896***	0.636 (16.550)	[0.561, 0.712]	0.541
R1	X2	0.313	230.102***	0.523 (15.169)	[0.456, 0.591]	0.456
R1	X3	0.416	359.930***	0.672 (18.972)	[0.603, 0.742]	0.712
R1	X4	0.471	450.368***	0.751 (21.222)	[0.682, 0.821]	0.890
G1	X1	0.344	265.824***	0.648 (16.304)	[0.570, 0.726]	0.524
G1	X2	0.376	304.267***	0.590 (17.443)	[0.523, 0.656]	0.603
G1	X3	0.488	481.461***	0.749 (21.942)	[0.682, 0.816]	0.953
G1	X4	0.469	446.324***	0.770 (21.126)	[0.699, 0.842]	0.883
G1	R1	0.560	645.764***	0.770 (25.412)	[0.710, 0.829]	1.273

*** $p < 0.001$. All f^2 values exceed 0.35, conventionally a large effect. Each row is a separate single-predictor equation; see the caveat below.

The rank ordering is identical for both outcomes: information quality > intelligence > anthropomorphism > interactivity. Information quality is the strongest predictor of trust (β = 0.751) and of purchase intention (β = 0.770); interactivity is the weakest on both (β = 0.523 and 0.590). Perceived trust is the single strongest predictor in the model, explaining 56.0% of the variance in purchase intention on its own.

An important qualification applies. Each row of Table 8 is a separate bivariate regression, not a simultaneous multiple regression. Because the four attributes intercorrelate substantially — between 0.580 and 0.716 — these coefficients absorb shared variance and cannot be read as unique contributions. The stated ordering therefore describes relative bivariate association rather than incremental explanatory power, and it may not

survive joint estimation. Re-estimating all four attributes simultaneously, with variance inflation factors reported, is the single most valuable robustness check a replication could perform.

4.5 Mediation

The source study tested mediation using PROCESS with 5,000 bootstrap resamples. For all four attributes, both the direct and the indirect effects have bootstrap confidence intervals excluding zero, so perceived trust partially mediates each attribute–intention relationship, supporting H4a to H4d. The variance accounted for (VAF), computed here as the indirect effect divided by the total effect, is reported in the final column (Table 9).

Table 9. Trust Mediation Effects

Predictor	Effect	Estimate	BootSE	95% bootstrap CI	VAF
Anthropomorphism (X1)	Total	0.644	0.040	[0.565, 0.723]	—
	Direct	0.240	0.039	[0.163, 0.317]	—
	Indirect	0.404	0.039	[0.326, 0.482]	62.7%
Interactivity (X2)	Total	0.585	0.034	[0.518, 0.652]	—
	Direct	0.271	0.032	[0.209, 0.334]	—
	Indirect	0.314	0.031	[0.255, 0.376]	53.7%
Intelligence (X3)	Total	0.749	0.035	[0.681, 0.817]	—
	Direct	0.391	0.038	[0.317, 0.466]	—
	Indirect	0.358	0.038	[0.286, 0.433]	47.8%
Information quality (X4)	Total	0.772	0.037	[0.699, 0.845]	—
	Direct	0.365	0.043	[0.281, 0.450]	—
	Indirect	0.407	0.044	[0.322, 0.495]	52.7%

VAF = indirect effect / total effect, computed by the present author from the reported estimates.

The mediation pattern is substantively informative. Trust carries the largest share of the effect for anthropomorphism (62.7%) and the smallest for intelligence (47.8%). Anthropomorphic design, in other words, works on purchase intention almost entirely through the trust it engenders and has comparatively little independent pull; a lifelike avatar that fails to generate trust contributes little. Perceived intelligence, by contrast, retains the largest direct effect (0.391), suggesting it also operates through channels this model does not capture — plausibly perceived usefulness or reduced search cost. Table 10 summarises the hypothesis test results.

Table 10. Hypothesis Test Results

Hypothesis	Path	β	Result
H1a	Anthropomorphism → purchase intention	0.648***	Supported
H1b	Interactivity → purchase intention	0.590***	Supported
H1c	Intelligence → purchase intention	0.749***	Supported
H1d	Information quality → purchase intention	0.770***	Supported
H2a	Anthropomorphism → perceived trust	0.636***	Supported
H2b	Interactivity → perceived trust	0.523***	Supported
H2c	Intelligence → perceived trust	0.672***	Supported
H2d	Information quality → perceived trust	0.751***	Supported

Hypothesis	Path	β	Result
H3	Perceived trust → purchase intention	0.770***	Supported
H4a	Trust mediates anthropomorphism → purchase intention	0.404	Supported (partial)
H4b	Trust mediates interactivity → purchase intention	0.314	Supported (partial)
H4c	Trust mediates intelligence → purchase intention	0.358	Supported (partial)
H4d	Trust mediates information quality → purchase intention	0.407	Supported (partial)

*** $p < 0.001$. Hypothesis labelling note: the source study's results section reports the attribute→trust findings under labels H1a–H1d and the attribute→purchase-intention findings under H2a–H2d, reversing its own hypothesis development. Table 10 restores the original labelling.

5. Discussion

5.1 Principal findings

Three findings stand out. First, information quality dominates. It is the strongest predictor of both trust and purchase intention, outperforming the anthropomorphic realism that dominates industry investment and press coverage. Second, interactivity is the weakest attribute on every outcome — a direct challenge to the existing literature, which has concentrated on interactivity to the near exclusion of other attributes. The plausible explanation is that scripted, keyword-triggered interaction is transparent to viewers; interaction that is visibly automated does not deliver the social reassurance that spontaneous human interaction provides. Third, perceived trust is not merely a mediator but the strongest single predictor in the model, accounting for 56.0% of variance in purchase intention on its own.

5.2 Theoretical implications

The study makes two theoretical contributions. It widens the attribute space: prior empirical work on e-commerce virtual livestreamers has focused on interactivity, whereas anthropomorphism, intelligence and information quality all prove consequential, and two of them prove more consequential than interactivity. It also substitutes an explanatory mechanism. Where earlier host–consumer research has generally relied on the stimulus–organism–response framework, this study grounds the mechanism in the theory of planned behaviour and empathy theory and specifies perceived trust as the mediator, allowing the distinction between interpersonal trust and human–machine trust to do analytical work.

5.3 Managerial implications

The results argue for reallocating investment. Where budgets are finite, accuracy and completeness of product information should take priority over incremental gains in visual realism. Practically, this means constraining generated scripts against verified product specifications, restricting unsupported superlatives, and building comparative claims on auditable data rather than generated copy — particularly given that exaggeration and false claims are known to damage host credibility.

Anthropomorphic design should not be abandoned, but it should be understood as a trust instrument rather than a persuasion instrument in its own right: 62.7% of its effect runs through trust. This favours consistency and predictability — stable voice, coherent persona, movement that neither stalls nor overreaches — over maximal realism, which risks uncanny-valley effects without corresponding gain.

Interactivity requires rethinking rather than expansion. Adding more scripted triggers is unlikely to help if viewers recognise the scripting. Improvement depends on genuine responsiveness: faster reaction, better handling of unanticipated queries, and stronger text-analysis capability, so that responses register as contingent on what the viewer actually said. Operationally, this means systems that trigger automatically on comment-stream keywords, dialogue frequency and volume — running giveaways and adapting patter in real time — rather than executing a fixed sequence.

5.4 Policy implications

These findings bear directly on the regulatory position. Since 1 September 2025 the Measures for Labelling AI-Generated Synthetic Content, supported by mandatory standard GB 45438-2025, have required explicit and implicit labelling of AI-generated content, so viewers of a compliant virtual livestream now know they are watching a synthetic host. Any commercial strategy premised on concealing that fact is both non-compliant and, on this evidence, misdirected: the attribute that matters most is not undetectability but information quality, which disclosure does not impair. Trust in a virtual livestreamer is partly trust in the underlying technology, which makes platform review, clear operating rules for virtual hosts, and enforcement against false advertising complements to — not constraints on — commercial effectiveness.

6. Limitations and Future Research

Six limitations qualify these conclusions. First, and most consequentially, the direct effects come from separate bivariate regressions rather than a simultaneous model. Given inter-attribute correlations between 0.580 and 0.716, the reported coefficients confound shared variance, and the attribute ordering may not persist under joint estimation with variance inflation factors reported.

Second, no common-method bias test is reported. All measures were self-reported by the same respondents at one point in time, which is the classic condition for inflated associations. A Harman single-factor test or, preferably, a marker-variable or unmeasured latent-method-factor approach should accompany any replication.

Third, discriminant validity is satisfied only narrowly for several construct pairs, with margins as small as 0.011 between perceived trust and purchase intention. Whether respondents genuinely distinguish these constructs is an open question that an HTMT analysis should address.

Fourth, the sample is heavily skewed: 79.921% aged 18–29 and 89.567% holding tertiary qualifications. This reflects the current audience but limits generalisation to older or less-educated consumers, whose trust formation towards AI agents may differ substantially.

Fifth, the design is cross-sectional and recall-based. Respondents reported on a remembered viewing episode, so causal ordering is assumed rather than demonstrated, and recall bias is possible. Scenario experiments manipulating information quality and anthropomorphism independently, or field data linking exposure to actual conversion, would test the causal claim properly.

Sixth, the data were collected in June 2024, before both the commercial scaling events of mid-2025 and the September 2025 labelling regime. Consumer familiarity with virtual hosts, and the disclosure conditions under which they are now viewed, have both changed materially. Replication under the current regime is warranted, and the labelling requirement itself offers a natural experiment for identifying how disclosure moderates the attribute–trust relationship.

7. Conclusion

Anthropomorphism, interactivity, intelligence and information quality all positively affect consumer purchase intention in virtual-livestreamer commerce, and perceived trust partially mediates every one of those relationships, carrying between 47.8% and 62.7% of the total effect. Information quality is the strongest

attribute and interactivity the weakest, an ordering that inverts the emphasis of both the prior literature and much industry practice.

The practical conclusion is that virtual livestreamers should be developed as reliable information channels first and as convincing personae second. Under a disclosure regime in which viewers know they are watching a machine, the competitive question is no longer whether a digital host can pass as human, but whether what it says can be trusted. The evidence assembled here indicates that trust is built primarily on the accuracy and completeness of what is said, and only secondarily on who appears to be saying it.

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Author Contributions

Conceptualization, X.L.C.; Methodology, X.L.C.; Formal Analysis, X.L.C.; Investigation, X.L.C. and B.L.C. and T.C.L.; Data Curation, X.L.C. and B.L.C. and T.C.L.; Software, X.L.C. and B.L.C. and T.C.L.; Validation, X.L.C. and B.L.C. and T.C.L.; Resources, B.L.C. and T.C.L.; Visualization, X.L.C. and B.L.C. and T.C.L.; Writing – Original Draft, X.L.C.; Writing – Review & Editing, X.L.C. and B.L.C. and T.C.L.; Supervision, X.L.C.; Project Administration, X.L.C. We have read and approved the final manuscript and take responsibility for the work.

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Conflicts of Interest

We declare no conflicts of interest.

Ethical Approval and Consent

This paper uses published aggregate survey results and involved no new participant recruitment, intervention or access to individual-level personal records. The original survey's ethics approval and consent procedures were not documented in the source material available to us.

Data Availability Statement

The published aggregate statistics used in this secondary analysis are reproduced in Tables 2–10, and the derived calculations are described in Section 4. We did not have access to the original individual-level survey responses and cannot provide those records.

Declaration of Generative AI Use

Generative AI was used to assist with language editing, manuscript organisation and formatting. We take responsibility for the content and interpretation of this manuscript.

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Appendix A. Data Provenance and Verifiability

Because verifiability was a design requirement for this paper, the status of every class of figure it contains is stated explicitly below. The distinction drawn is between figures a reader can check independently against a public source and figures that can only be checked against the study that produced them.

The survey statistics originate in a study conducted between 9 and 15 June 2024 and published in Times of Economy & Trade. They are reported here in full and without alteration, and no new survey results have been generated. What Section 4.1 establishes is that these statistics are mutually consistent — F values regenerate from R^2 and N, t values equal $\sqrt{F}$, confidence intervals rebuild from β and t, $\sqrt{AVE}$ matches the Fornell–Larcker diagonal, direct and indirect effects sum to totals, and all frequency counts sum to 508. Internal consistency of this kind is a necessary condition for data integrity but not a sufficient one; it demonstrates that the reported figures were computed from a coherent dataset, not that the dataset was collected as described.

This paper is a secondary analysis of published aggregate survey results, rather than a new primary-data investigation. Future replication should collect independent survey data and incorporate the design improvements identified in Section 6: simultaneous rather than bivariate estimation, a common-method-bias test, HTMT discriminant validity, a broader age and education distribution, and collection under the post-September-2025 labelling regime. The measurement instrument, source sampling protocol and reported analytical strategy are described in Sections 3.1–3.4 to support comparison with future studies.

Category	Examples	Verification status
Market and industry statistics	Netizen and online-shopper counts; livestreaming users; digital-human market size; Baidu and JD campaign metrics; enterprise procurement shares	Independently verifiable. Each traces to a named public report or news source listed under Industry and regulatory sources, with URLs.
Regulatory facts	Measures for Labelling AI-Generated Synthetic Content; GB 45438-2025; issuing bodies and effective dates	Independently verifiable against the Cyberspace Administration of China notice.
Academic citations	Ajzen (1991); Mayer et al. (1995); Gefen (2000); Pavlou and Gefen (2004); Hong and Cha (2013); Asada (2015); Leite et al. (2013); Wieseke et al. (2012); Ramadan et al. (2021)	Verified against journal records. Volume, issue and page numbers confirmed; the base study's Hong et al. (2011) attribution corrected to Hong and Cha (2013).
Chinese-language citations	Zhao et al. (2023); Xiang (2024); Gao et al. (2023); Cai et al. (2023); Xiao et al. (2021); Liu et al. (2024); Zuo et al. (2023)	Carried over from the base study without independent verification; full bibliographic details were not available in the source. Marked in the reference list and to be

Category	Examples	Verification status
		completed before submission.
Survey statistics	N = 508; demographics; Cronbach's α; KMO; CR and AVE; CFA fit; regression coefficients; bootstrap mediation estimates	Primary data from the base study. Arithmetically reproduced and internally consistent (Section 4.1), but not independently verifiable without the raw response file.
Author-derived statistics	Cohen's f^2 (Table 8); VAF (Table 9); reproduction audit (Section 4.1); discriminant-validity margins (Section 4.3)	Computed by the present author from the published estimates; the formulas are given in situ so each figure can be recalculated.