ORIGINAL ARTICLE

Comparative Effects of Virtual and Human Influencer Endorsements on Purchase Intent among Digital Consumer Audiences in Lifestyle Marketing

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ABSTRACT
Influencer marketing has become a common way for brands to present products through familiar social media formats. At the same time, AI-generated virtual models have moved into the same promotional space that was previously occupied mainly by real-life creators. This shift raises a practical research question about how consumers respond when the visible source of endorsement is not a human person but a designed digital persona. The present paper examines purchase intent in response to endorsements from AI-generated virtual influencers and human influencers in lifestyle product contexts. The study uses a survey dataset with 480 participant observations distributed across two influencer conditions and three product categories. Purchase intent is treated as the main outcome, while perceived authenticity, trust, novelty, parasocial response, ad skepticism, product involvement, and background characteristics are included to describe the structure of consumer response. The analysis applies independent-samples tests, a two-way analysis of variance, scale reliability checks, and ordinary least squares regression models. The results suggest that the two source types produce distinct perception patterns. Human influencers are rated more highly in terms of perceived authenticity, trust, and parasocial response, while AI-generated virtual influencers score higher on novelty. Although purchase intention is slightly greater for human influencers in the raw comparison, the difference is relatively small.

Keywords: influencer marketing; virtual influencers; AI-generated influencers; purchase intention; perceived authenticity; consumer behavior

1 | Introduction

Influencer marketing now sits within an ordinary part of the digital advertising environment. Consumers encounter product endorsements while scrolling through short videos, image feeds, story formats, livestreams, product pages, and reposted campaign material. In these settings, the persuasive source is often presented as a person with a recognizable style, a history of content, and an implied relationship with followers. Prior work on social media influencers shows that influencer endorsements operate through perceived credibility, similarity, identification, trust, and product–endorser fit rather than through product information alone [1, 2, 3, 4]. Brands rely on this format because the message can appear less detached than a conventional advertisement and because the influencer can function as a cue for taste, social belonging, credibility, and everyday use. Even when consumers know that a post is commercial, persuasion-knowledge research suggests that audiences still evaluate the source, the sponsorship context, and the apparent motive behind the message [5, 6]. Purchase intent is therefore not shaped only by product claims. It is also shaped by judgments about who is speaking, how the product is shown, and whether the endorsement fits the expectations of the audience [7, 8, 9].

The entrance of AI-generated virtual influencers adds a different source form to the same communication setting. A virtual influencer may have a name, visual identity, posting style, audience interaction pattern, and brand partnership history, but the visible endorser is not a real-life human. Recent research describes virtual influencers as designed or computer-generated social media figures that can imitate influencer functions while raising different questions about agency, authenticity, transparency, and humanness [10, 11, 12]. This changes several features of the endorsement situation. On one hand, a designed digital persona may be visually consistent, easy to adapt to brand requirements, and capable of being placed in settings that would be costly or difficult to arrange with a human creator [13, 12]. It may also attract attention because the format still has a sense of novelty for many viewers. On the other hand, the same designed quality may reduce perceived authenticity or interpersonal credibility if the audience treats the source as less personally grounded [14, 15]. The marketing question is not simply whether people like or dislike the visual form. The question is how source type changes purchase intent when the endorsement is otherwise placed in a recognizable influencer-marketing format.

The comparison matters because human influencers and AI-generated virtual influencers can occupy similar positions on a campaign plan while carrying different assumptions about trust, realism, novelty, and social connection. A brand that uses a human creator may expect audiences to respond to lived experience, personal reputation, and a sense that the endorser has actually used or evaluated the product. These expectations are consistent with source-credibility theory, which emphasizes trustworthiness and expertise as central features of persuasive sources [16, 8]. A brand that uses a virtual persona may expect audiences to respond to visual control, distinctive identity, and the attention produced by a newer type of promotional character [13, 11]. These expectations are often discussed in broad terms, but the actual response can be more specific. A viewer may find a virtual endorser interesting while still trusting a human endorser more. A viewer may also enjoy the novelty of a digital model but hesitate to treat the endorsement as a reason to buy. These possibilities make it useful to examine purchase intent together with perceptions that plausibly sit between the endorsement source and the consumer response.

This paper studies the effectiveness of AI-generated virtual influencers relative to human influencers by focusing on purchase intent in lifestyle product contexts. The term effectiveness is used here in a restricted empirical sense. It refers to measured differences in consumer responses after exposure to endorsement conditions, not to every possible marketing outcome. The paper does not treat sales, long-term brand equity, community formation, creator labor, or campaign cost as outcomes. It stays close to the immediate response setting because purchase intent is a common early indicator in endorsement research and campaign testing [7, 4, 9]. The comparison is organized around a two-condition source contrast, with product category included so that the analysis is not tied to a single item. Product–endorser fit is relevant here because endorsement effects can depend on whether the source appears appropriate for the product being promoted [2, 15]. The central question is whether the AI-generated virtual influencer condition produces different purchase intent from the human influencer condition and whether perceptions such as authenticity, trust, novelty, parasocial response, and skepticism help describe the pattern of response.

The study is also useful as a measurement exercise because source type in influencer marketing is not a single psychological cue. A human influencer may carry cues of lived experience, personal accountability, and social presence. A virtual influencer may carry cues of design control, entertainment, and technical novelty. These cues can move in different directions. Authenticity research suggests that influencer endorsements are evaluated partly through perceived consistency, transparency, and fit between the source and the commercial message [17, 14]. Parasocial research also suggests that audiences may form one-sided feelings of familiarity or social connection with media figures and influencers, which can shape credibility and purchase-related outcomes [18, 19, 9]. If a virtual influencer is more novel but less trusted, an aggregate purchase-intent comparison may hide the route by which audiences respond. For this reason, the analysis includes both direct condition comparisons and models that add perception measures. The goal is to avoid treating the source label as the only meaningful information in the design. The broader issue is how a new type of promotional persona is received when it enters a format where audiences already have expectations about personality, recommendation, sponsorship, and credibility.

2 | Literature Framing

Influencer endorsements depend on source effects. In a conventional endorsement setting, the consumer evaluates the message partly through the apparent qualities of the person presenting it. The same product claim can be received differently when the source appears knowledgeable, likable, similar to the audience, or personally connected to the product. Social media intensifies this process because the source is usually embedded in a stream of repeated content rather than encountered only in a single advertisement. Followers may know the creator's aesthetic, posting habits, tone, and preferred products. Even when this knowledge is shallow, it can provide enough context for the endorsement to feel more personal than a brand-only message. The human influencer is therefore not only a visible model but a social signal. Purchase intent can be shaped by the sense that the endorsement fits a known person and a recognizable lifestyle.

Prior influencer-marketing research shows that endorsement effects depend strongly on perceived source credibility, authenticity, and the relationship that audiences form with the influencer. Source credibility is especially important because consumers do not evaluate influencer posts only as product information; they also evaluate whether the source appears trustworthy, knowledgeable, and appropriate for the product context [3, 4]. Authenticity is also central because influencer endorsements can lose persuasive force when the commercial partnership appears inconsistent with the influencer's usual identity, values, or content style [17]. Parasocial relationships add another layer to this process. Audiences may develop a sense of familiarity or social closeness with influencers, and this perceived relationship can strengthen influencer credibility, brand trust, and purchase intention [19, 20]. These findings suggest that purchase intent should not be interpreted only as a direct response to the product, but also as an outcome shaped by the perceived qualities of the endorsement source.

Virtual influencers complicate this source-evaluation process because they combine influencer-like presentation with an artificial or designed identity. Recent reviews show that virtual influencers share several functions with human influencers, including product presentation, brand partnership, and audience engagement, but they differ in perceived humanness, agency, transparency, and authenticity [11]. Studies comparing human and virtual influencers suggest that virtual influencers may attract attention through novelty and visual distinctiveness, while human influencers often retain advantages in perceived authenticity and credibility [15]. Work on virtual-influencer authenticity further shows that authenticity does not disappear in artificial-persona settings, but it must be constructed differently through narrative coherence, transparency, consistency, and fit with the surrounding brand world [14]. Therefore, the comparison between human and AI-generated virtual influencers should be understood as a comparison between different source profiles: one grounded more in perceived human experience and social presence, and the other grounded more in designed identity, novelty, and controlled presentation.

Authenticity is central to this process, although it is not a simple property of the endorser. In digital marketing, authenticity often refers to whether the message appears consistent with the source, whether the recommendation seems grounded in experience, and whether the commercial motive appears to overwhelm the personal voice. A human influencer can be perceived as authentic when the endorsement seems to fit prior content and when the product appears to be part of a believable routine. The same human source can be perceived as inauthentic when the product fit is weak, the post looks scripted, or the sponsorship feels mechanically inserted. For a virtual influencer, authenticity works differently. The persona can have continuity and style, but the audience may know that the visible source is designed. This may make authenticity depend less on lived experience and more

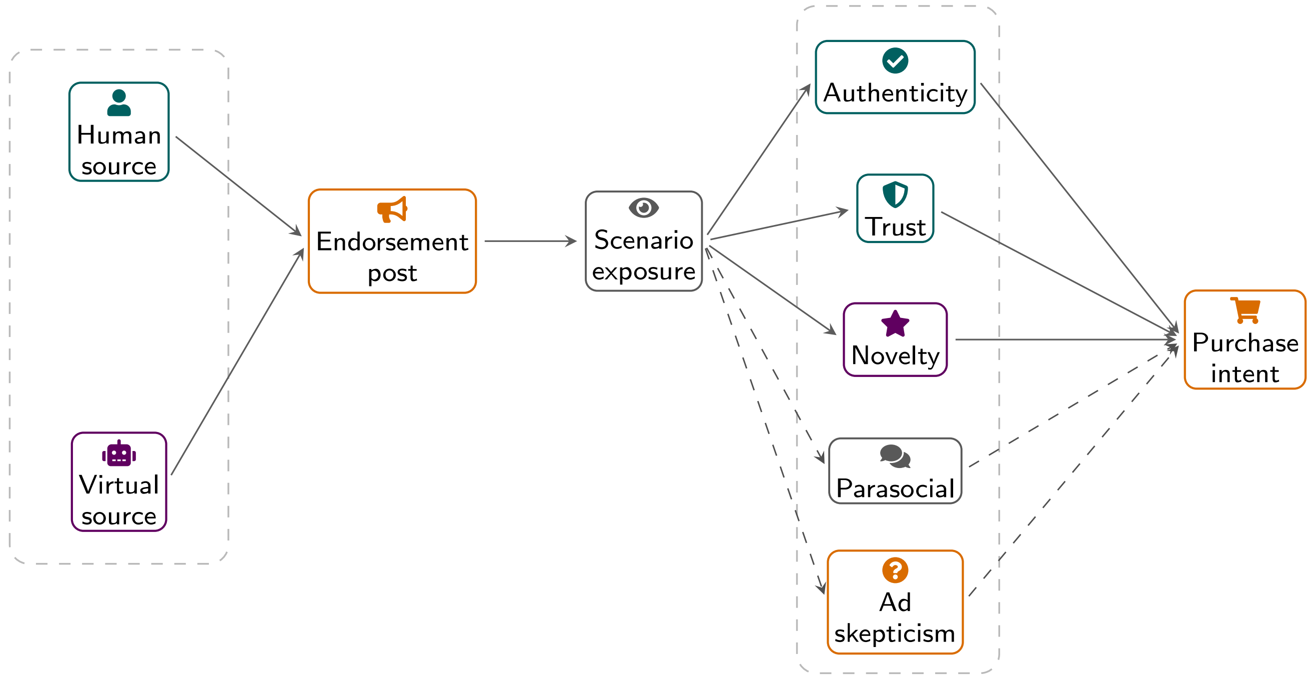

Figure 1: Endorsement-source architecture linking human and AI-generated virtual influencer conditions to exposure, perception formation, and purchase intent in a lifestyle-product setting.

on narrative coherence, transparency, and brand fit. Trust is related to authenticity but is not identical to it. A viewer may believe that an endorsement is stylistically authentic while still doubting whether it provides reliable product information. Trust in influencer marketing includes confidence in the source's judgment, confidence in the honesty of the recommendation, and confidence that the post does not hide important facts. Human influencers may benefit from an assumption that they can physically try a product, report personal experience, and face reputational costs if followers feel misled. Virtual influencers may have a different trust basis. They may be trusted when the audience treats the persona as a creative brand vehicle, but they may be distrusted when the viewer expects an endorser to have personal experience. The trust question is therefore especially relevant for purchase intent because buying requires more than noticing the post. It requires enough confidence to move from exposure to possible action.

Novelty offers a contrasting pathway. AI-generated virtual influencers can attract attention because they are visually distinct, technically interesting, or culturally current. Novelty can make a post more memorable and can increase willingness to share or discuss the campaign. It may also signal that a brand is modern or experimental. However, novelty does not necessarily convert into purchase intent. A consumer can be interested in the format without becoming interested in buying the product. In some cases, the novelty of the endorser may draw attention away from the product. In other cases, it may help the product feel more current. The same cue can therefore support different responses depending on how the audience integrates the endorser with the product category and the selling message.

Parasocial response is another part of the endorsement environment. Human influencers often build one-sided relationships with audiences through repeated exposure, personal storytelling, and interactive cues. Followers may feel that they know the influencer even when the relationship is mediated and asymmetrical. This sense of social closeness can increase receptivity to product recommendations because the endorsement appears to come from a familiar figure rather than from an unknown advertiser. Virtual influencers can also be designed to invite parasocial response, but the character of that response may differ. Some viewers may relate to the persona as an entertainment figure, while others may hold back because the source is not a human person. In either case, the measure helps separate social response from trust and novelty.

Ad skepticism also matters because influencer marketing frequently mixes entertainment, identity, and commerce. Viewers may enjoy a post while recognizing that it is sponsored. Skepticism can arise

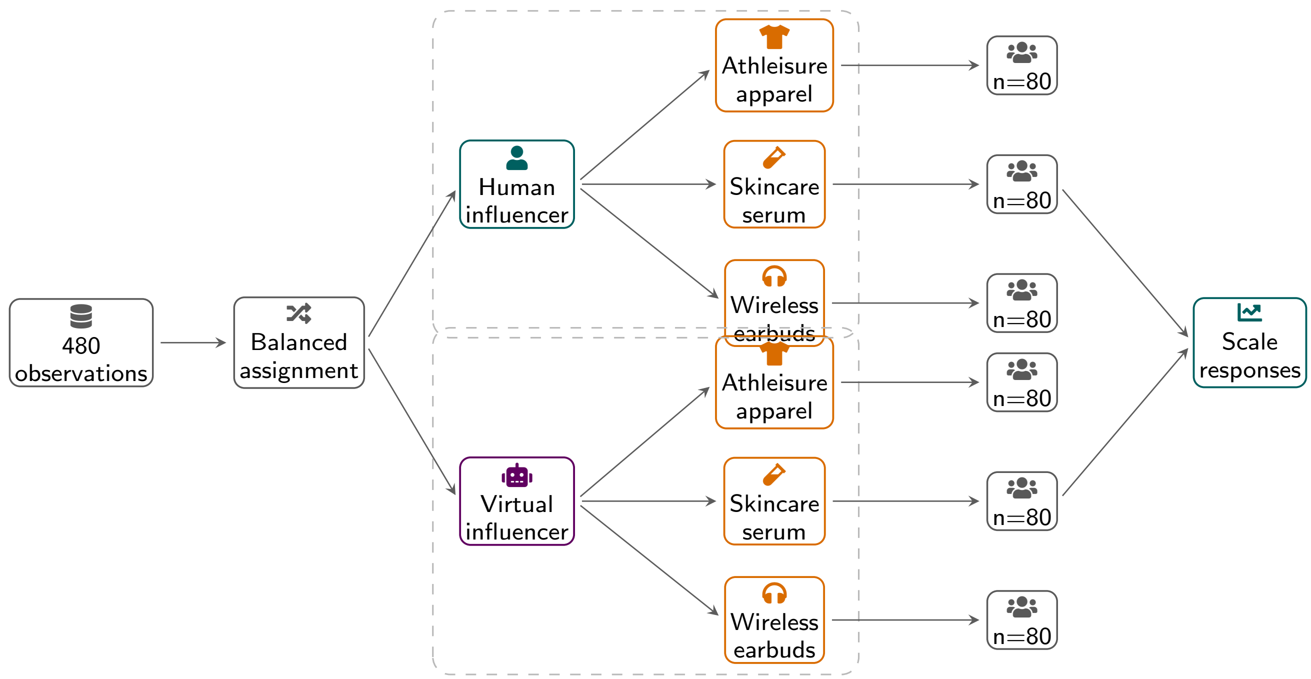

Figure 2: Balanced two-by-three experimental layout showing source condition, product-category cells, equal cell allocation, and the downstream response measurement stage.

when the commercial motive is salient, when the product fit seems weak, or when the endorsement appears heavily controlled by the brand. AI-generated virtual influencers may increase skepticism if the viewer sees the persona as a brand instrument. Human influencers may also increase skepticism when sponsorships appear frequent or formulaic. A comparison between source types should therefore include skepticism as a potential counterweight to attraction, authenticity, and trust. Purchase intent is likely to be lower when the audience reads the endorsement mainly as a selling device with little independent credibility.

Product category provides a further context for source evaluation. Lifestyle products vary in the type of evidence consumers expect. Apparel is often evaluated through appearance, fit, style, and identity. Skincare can involve performance claims, personal routines, and trust in experience. Consumer electronics can involve functional features and technical reliability. A human endorser may be especially relevant when bodily experience or everyday use is important, while a virtual endorser may work better when visual presentation and aesthetic identity are central. The present study includes three categories to avoid building the comparison around one product setting. The analysis does not assume that every product context will produce the same response, but it keeps the design compact enough for a clear empirical comparison.

3 | Research Design

The study uses a between-participant endorsement design. Each participant observation is assigned to one influencer source condition and one product category. The two source conditions are a human influencer and an AI-generated virtual influencer. The three product categories are athleisure apparel, skincare serum, and wireless earbuds. This creates a two by three design with equal allocation across the six cells. The total dataset contains 480 participant observations, with 80 observations in each source-by-category cell and 240 observations in each influencer source condition. The balanced structure supports direct comparisons between source types while also allowing product category to be examined as a contextual factor. The design keeps the focal contrast simple: the consumer response is measured after exposure to an endorsement scenario where the source form differs but the response scales and product-category structure remain consistent.

Participants were recruited through an online survey panel in 2025. Eligibility was limited to adult respondents who reported using social media at least several times per week and who were able to complete

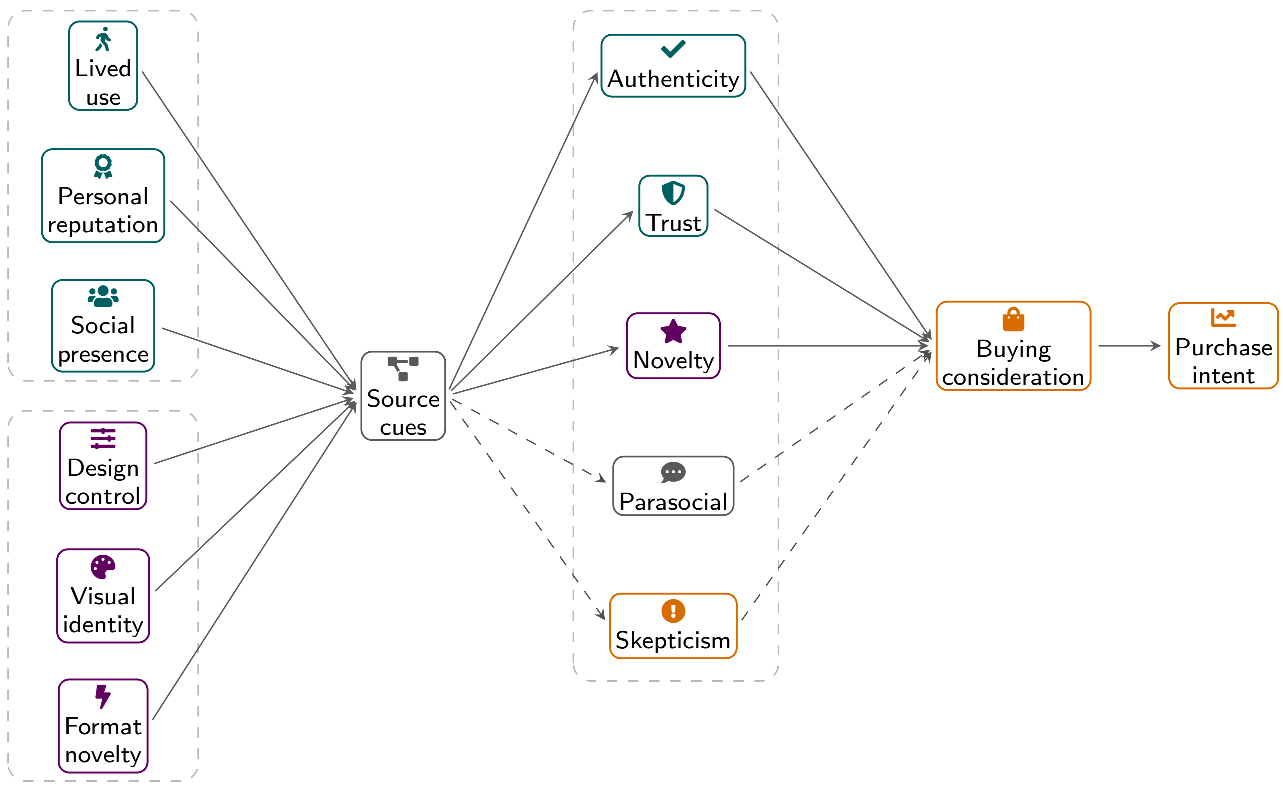

Figure 3: Perceptual mechanism map separating human-source cues from virtual-source cues before the measured constructs converge on buying consideration and purchase intent.

the survey in English. Before beginning the survey, participants viewed an informed-consent statement describing the purpose of the study, the voluntary nature of participation, the approximate completion time, the use of anonymous responses, and the absence of personally identifying information in the analytic dataset. The study involved a short exposure to mock influencer-endorsement material followed by rating-scale questions about the endorsement source, product, and purchase intent. Participants received a small fixed payment through the survey platform after completing the questionnaire. No formal IRB review was obtained; this is acknowledged as a limitation. The study was treated as anonymous, minimal-risk survey research. No identifying personal information was retained in the analytic dataset. Data quality was assessed before analysis. The survey included a source-recognition manipulation check, one instructed-response attention check, duplicate-response screening, and a minimum completion-time rule. Responses were excluded when participants failed the attention check, did not complete the survey, gave duplicate submissions, or completed the questionnaire in an implausibly short time. Of 523 submitted responses, 43 were removed for these reasons, leaving the final analytic sample of 480 participant observations.

The unit of analysis is the individual participant observation. The outcome is purchase intent after viewing the assigned endorsement condition. The source condition is not treated as a broad identity judgment about people or technology. It is treated as an experimental attribute of the endorsement source in a lifestyle marketing context. This distinction matters because consumers may respond to the product, the visual execution, the source, and the sponsorship cue at the same time. The design therefore includes additional variables that describe perceived authenticity, trust, novelty, parasocial response, and ad skepticism. These measures help examine whether the source contrast appears as a direct difference in purchase intent or whether the contrast is better understood through the perceptions surrounding the endorsement.

The product categories were selected to represent common lifestyle-marketing contexts without requiring specialized knowledge from participants. Athleisure apparel is visually oriented and closely tied to personal style. Skincare serum involves bodily use, trust, routine, and claims about experience. Wireless

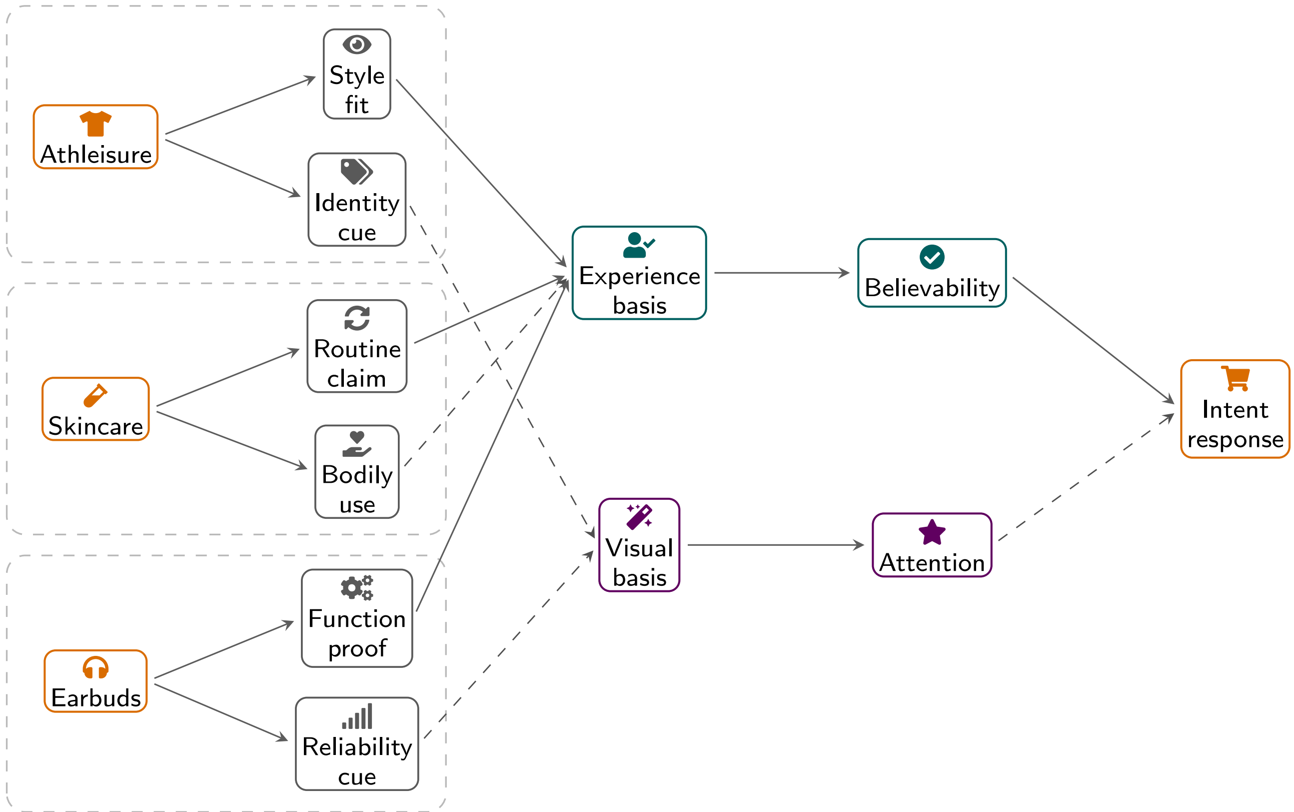

Figure 4: Product-category pathway diagram showing how apparel, skincare, and earbuds can activate different evidence expectations before source basis and intent response are evaluated.

earbuds involve lifestyle imagery but also contain a functional technology component. These categories provide a modest range of product contexts while staying within the general space of consumer goods often promoted through social media. The design does not attempt to represent the full universe of influencer marketing. It focuses on a manageable set of product contexts in which both human and AI-generated virtual influencers could plausibly appear.

The exposure scenario assumes that participants view a social-media-style endorsement. After exposure, they respond to scale items that assess the main outcome and related perceptions. The response format uses seven-point scales, with higher values representing more of the named construct. Purchase intent reflects how likely the participant would be to consider buying the endorsed product. Perceived authenticity reflects whether the endorsement source and message seem genuine within the scenario. Trust reflects confidence in the endorser and the recommendation. Novelty reflects whether the presentation feels new or distinctive. Parasocial response reflects a sense of social closeness or personal connection to the source. Ad skepticism reflects suspicion toward the endorsement as a persuasive commercial message. Background variables include age, gender, social media use, prior familiarity with AI-related content, frequency of following influencers, and product involvement.

The study structure is intentionally compact. It is large enough to permit stable descriptive comparisons and regression models with several predictors, but it is not so large that small numerical differences should dominate the reading of the design. Equal cell sizes reduce avoidable imbalance across source and product-category conditions. The inclusion of perception measures reflects the view that purchase intent is rarely a direct consequence of source type alone. A consumer may evaluate whether the endorser is believable, whether the post feels interesting, whether the product fits the endorser, and whether the message appears overly commercial. By measuring these perceptions in the same dataset, the analysis can compare the raw source difference with models that account for the way participants describe the endorsement experience.

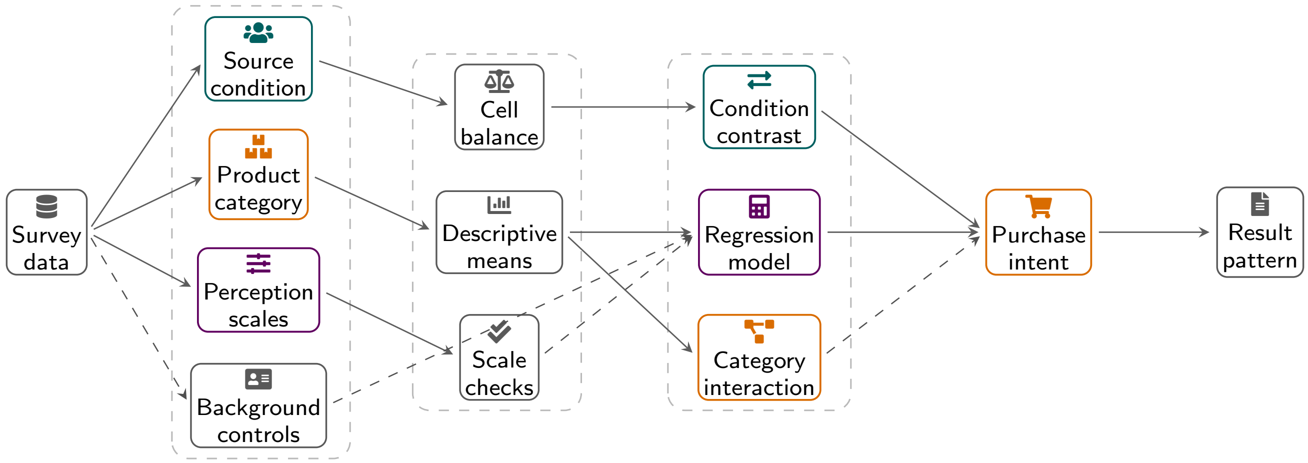

Figure 5: Analysis workflow connecting the balanced survey dataset to condition comparisons, perception-adjusted models, product-category interaction checks, and the final purchase-intent pattern.

4 | Measures and Analytic Strategy

Purchase intent is the primary dependent variable. It is measured on a one-to-seven scale and treated as approximately continuous for the main analyses. This treatment is common for multi-point rating scales when the goal is to compare condition means and model linear associations. A higher score represents stronger intent to consider buying the endorsed product. A binary high-intent indicator is also used as a supporting outcome, coded one when purchase intent is at least five on the seven-point scale. This secondary indicator describes whether the endorsement moves respondents into a relatively favorable range, but the main analysis remains focused on the continuous scale because it preserves more information.

The central independent variable is influencer source type. The regression models code the AI-generated virtual influencer condition as one and the human influencer condition as zero. With this coding, a negative coefficient means that the AI-generated virtual influencer condition is lower than the human influencer condition on the outcome, while a positive coefficient means that it is higher. Product category is represented with athleisure apparel as the reference category and indicators for skincare serum and wireless earbuds. Demographic and background controls include age, gender indicators, social media hours, prior AI familiarity, frequency of following influencers, and product involvement. These variables are included because they can plausibly shape the way a participant responds to endorsement material.

The perception measures are treated as explanatory variables in the fullest regression model. Perceived authenticity, trust, novelty, parasocial response, and ad skepticism are not framed as final causal mechanisms in the statistical design. They are used to describe how the source comparison changes once measured reactions to the endorsement are included. This distinction is important because the measures are collected in the same response session. The analysis can show whether the source coefficient is reduced or changes direction after these perceptions enter the model, but it does not require a strong temporal claim about one perception preceding another. The perception model is best understood as a structured description of the response pattern.

The first analytic step is scale reliability. Three item sets are used for perceived authenticity, trust, purchase intent, and parasocial response. Cronbach's alpha is calculated for each set to assess internal consistency. The second analytic step is descriptive comparison by condition. The analysis reports sample size, age, social media use, prior AI familiarity, product involvement, the percentage identifying as women, and the percentage in the high purchase-intent range. These descriptive statistics help situate the condition groups before the main outcome tests. The third step uses independent-samples Welch tests to compare the human influencer condition with the AI-generated virtual influencer condition on identity recognition, perceived authenticity, trust, novelty, parasocial response, purchase intent, share intent, and ad skepticism.

The fourth analytic step is a two-way analysis of variance for purchase intent. This test includes influencer source, product category, and their interaction. The purpose is to examine whether the purchase-intent comparison is only a source contrast or

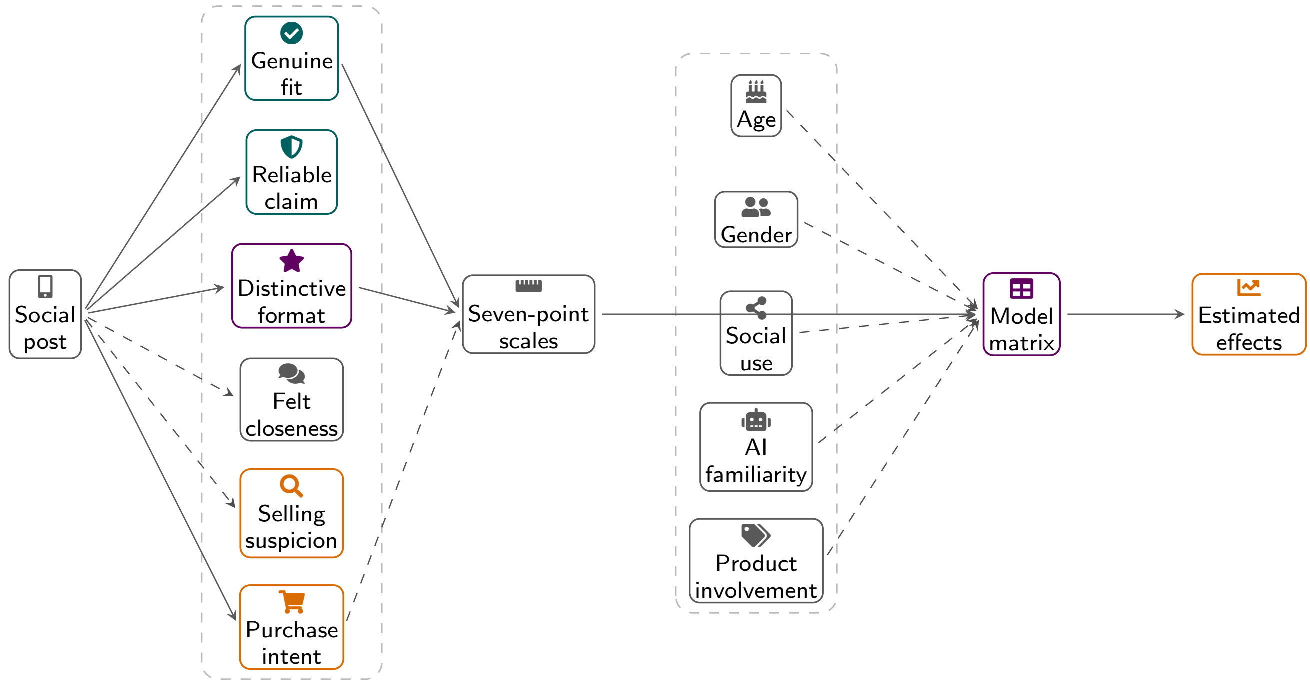

Figure 6: Measurement map aligning post-exposure construct scales with background controls so that purchase-intent estimates can be interpreted alongside authenticity, trust, novelty, parasocial response, and skepticism.

whether it varies across the three product contexts. The fifth analytic step uses ordinary least squares regression. Model 1 includes only source condition. Model 2 adds demographics, background variables, product involvement, and product-category indicators. Model 3 adds perceived authenticity, trust, novelty, parasocial response, and ad skepticism. The progression from Model 1 to Model 3 is designed to show how the condition coefficient behaves when the analysis moves from a raw comparison to a more detailed response model.

All tests are reported with conventional statistics such as means, standard deviations, mean differences, confidence intervals, test statistics, and p-values. Regression estimates are reported as unstandardized coefficients with standard errors. The figures are used to make the main numerical patterns easier to inspect. One figure shows the design flow, one shows purchase-intent means by source and product category, and one shows selected coefficients from the full regression model. The analysis is descriptive and comparative. It answers how the two source conditions differ in this dataset and how the purchase-intent outcome is associated with measured perceptions of the endorsement.

A parallel mediation analysis was also conducted to test whether the relationship between influencer source type and purchase intent was statistically carried by the measured perception variables. Influencer source type was coded as 1 for the AI-generated virtual influencer condition and 0 for the human influencer condition. Purchase intent was entered as the outcome. Perceived authenticity, trust, novelty, parasocial response, and ad skepticism were entered as parallel mediators. Product category, age, gender, social media use, prior AI familiarity, influencer-following frequency, and product involvement were included as covariates. Indirect effects were estimated with nonparametric bootstrapping using 5,000 resamples and 95% confidence intervals. An indirect effect was treated as statistically supported when its bootstrapped confidence interval did not include zero [21, 22].

5 | Results

The dataset contains 480 participant observations, with 240 observations assigned to the human influencer condition and 240 assigned to the AI-generated virtual influencer condition. Each of the three product categories contains 160 observations, divided equally between the two source conditions. The descriptive statistics in Table 1 show that the two source conditions are similar in age and social media use. The mean age is 29.73 years in the human influencer condition and 29.28 years in the AI-generated virtual

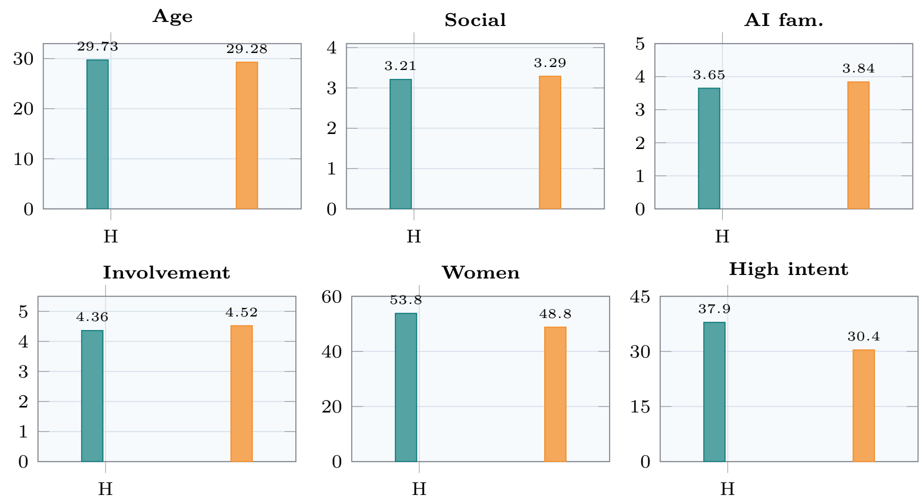

Figure 7: Participant profiles are closely matched across source conditions, with the largest descriptive separation appearing in high purchase-intent share.

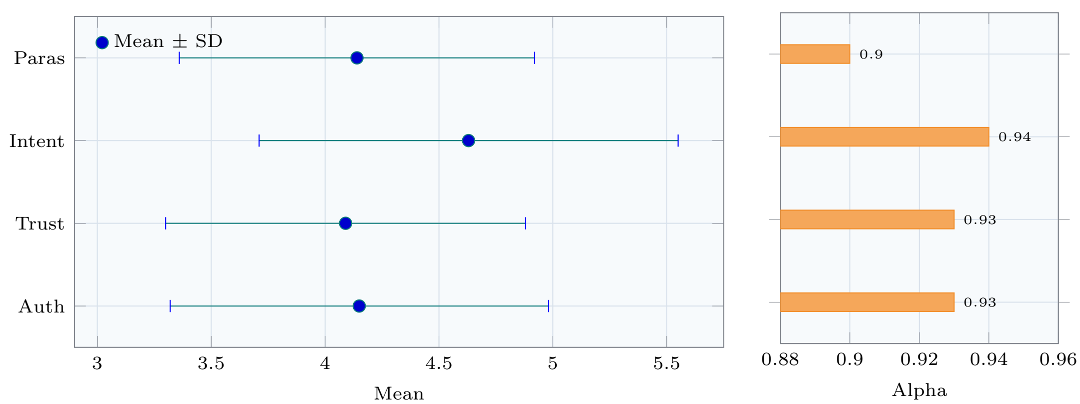

Figure 8: Reliability is high for all multi-item scales while central tendency remains in the moderately favorable range.

influencer condition. Mean daily social media use is 3.21 hours in the human influencer condition and 3.29 hours in the AI-generated virtual influencer condition. Prior AI familiarity is 3.65 in the human influencer condition and 3.84 in the AI-generated virtual influencer condition. Product involvement is 4.36 in the human influencer condition and 4.52 in the AI-generated virtual influencer condition. Women account for 53.8% of the human influencer condition and 48.8% of the AI-generated virtual influencer condition. The high purchase-intent share is 37.9% in the human influencer condition and 30.4% in the AI-generated virtual influencer condition.

The multi-item scales show high internal consistency. Table 2 reports Cronbach's alpha values for perceived authenticity, trust, purchase intent, and parasocial response. Perceived authenticity has an alpha of 0.93, trust has an alpha of 0.93, purchase intent has an alpha of 0.94, and parasocial response has an alpha of 0.90. The scale means range from 4.09 for trust to 4.63 for purchase intent. These reliability estimates support the use of averaged scale scores in the comparisons and regression models. The scale means also indicate that responses are concentrated around the middle to moderately favorable part of the seven-point scale rather than at the extremes.

The manipulation check strongly separates the two source conditions. Participants in the human influencer condition score the identity real-person check at a mean of 5.72, while participants in the AI-generated virtual influencer condition score it at a mean of 2.41. The mean difference is 3.31 scale points,

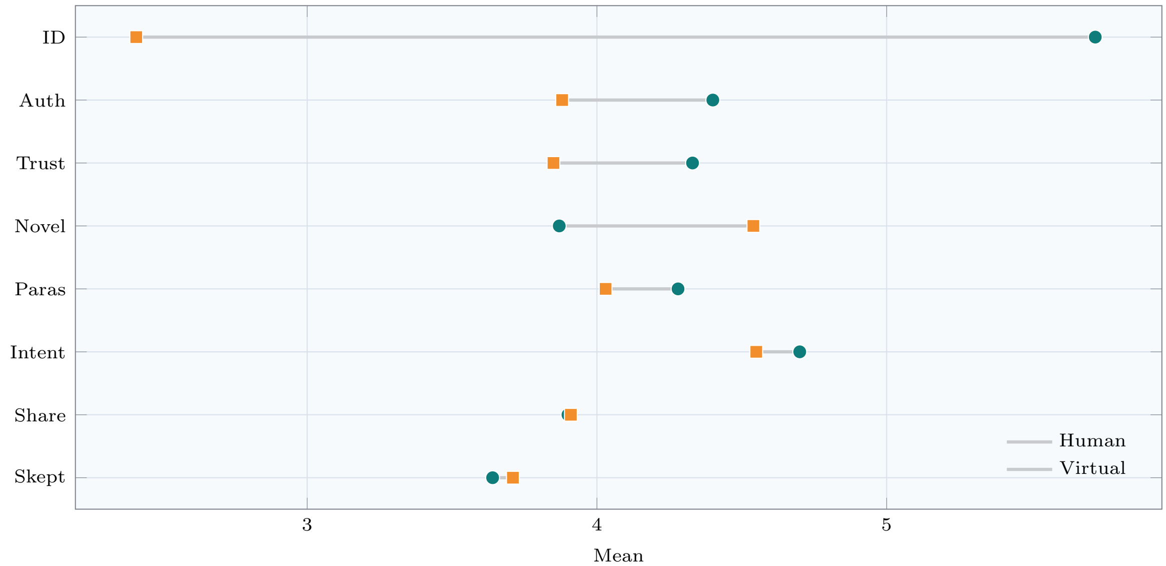

Figure 9: Mean response profiles show large identity separation, higher human-source credibility, and higher virtual-source novelty.

Table 1: Condition descriptives

Condition	N	Age M	Age SD	Social hrs M	AI fam. M	Prod. inv. M	High intent %
Human influencer	240	29.73	6.88	3.21	3.65	4.36	37.9
AI virtual influencer	240	29.28	7.42	3.29	3.84	4.52	30.4

Table 2: Scale reliability and descriptive statistics

Scale	Items	Alpha	Mean	SD
Perceived authenticity	3	0.93	4.15	0.83
Trust	3	0.93	4.09	0.79
Purchase intent	3	0.94	4.63	0.92
Parasocial response	3	0.90	4.14	0.78

with a 95% confidence interval from 3.18 to 3.45. The Welch test is $t = 48.35$, with $p < 0.001$ and Cohen's $d = 4.41$. This result shows that the condition label and presentation are reflected in participant perception of the source identity. The check is not used as a substantive outcome, but it confirms that the two source conditions are psychologically distinct in the expected direction.

The main outcome comparison is reported in Table 3. Purchase intent is 4.70 in the human influencer condition and 4.55 in the AI-generated virtual influencer condition. The mean difference is 0.15 scale points in favor of the human influencer condition. The 95% confidence interval ranges from -0.01 to 0.31, the Welch statistic is $t = 1.86$, the p-value is 0.063, and Cohen's d is 0.17. The binary high-intent comparison shows 37.9% high purchase intent in the human influencer condition and 30.4% in the AI-generated virtual influencer condition, a difference of 7.5 percentage points with $z = 1.74$ and $p = 0.082$. The continuous and binary tests both point in the same direction, although the observed source difference in purchase intent is small in magnitude.

The perception measures show clearer differences than purchase intent. Perceived authenticity is higher in the human influencer condition, with a mean of 4.40 compared with 3.88 in the AI-generated virtual influencer condition. The mean difference is 0.52 scale points and the test is statistically clear, $t = 7.41$ and $p < 0.001$. Trust follows a similar pattern, with a human condition mean of 4.33 and an AI-generated virtual condition mean of 3.85. The difference is 0.48 scale points, with $t = 7.08$ and $p < 0.001$. Parasocial response is also higher for the human influencer condition, with a mean of 4.28 compared with 4.03, a difference of 0.25 points, $t = 3.76$ and $p < 0.001$. These results indicate that the human source condition is evaluated more favorably on interpersonal and credibility-related dimensions.

Novelty moves in the opposite direction. The AI-generated virtual influencer condition has a novelty

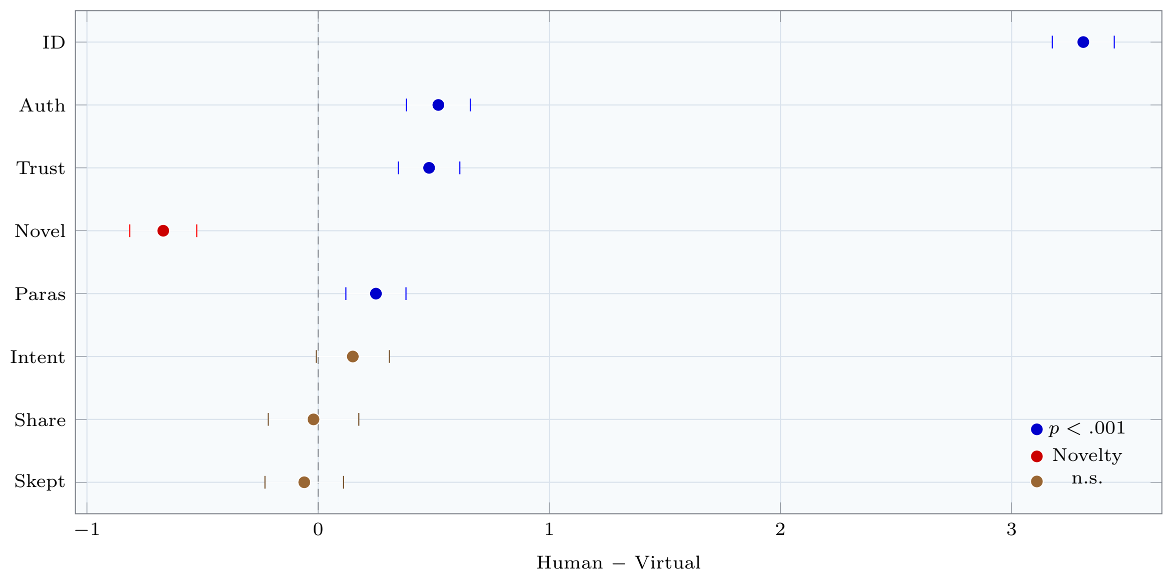

Figure 10: Estimated source contrasts indicate strong perception effects and comparatively small purchase, sharing, and skepticism differences.

Table 3: Between-condition tests for response measures

Measure	Human M	Human SD	Virtual M	Virtual SD	Difference	t	p
Identity check	5.72	0.68	2.41	0.82	3.31	48.35	< 0.001
Perceived authenticity	4.40	0.76	3.88	0.77	0.52	7.41	< 0.001
Trust	4.33	0.75	3.85	0.73	0.48	7.08	< 0.001
Novelty	3.87	0.81	4.54	0.81	-0.67	-9.06	< 0.001
Parasocial response	4.28	0.76	4.03	0.67	0.25	3.76	< 0.001
Purchase intent	4.70	0.88	4.55	0.92	0.15	1.86	0.063
Share intent	3.90	0.90	3.91	0.83	-0.02	-0.20	0.843
Ad skepticism	3.64	1.04	3.71	0.97	-0.06	-0.69	0.488

mean of 4.54, while the human influencer condition has a novelty mean of 3.87. The human-minus-virtual difference is -0.67 scale points, with $t = -9.06$ and $p < 0.001$. This is the largest substantive perception difference after the identity check. Share intent is nearly identical across conditions, with a mean of 3.90 for the human influencer condition and 3.91 for the AI-generated virtual influencer condition. Ad skepticism is also similar, with a mean of 3.64 in the human influencer condition and 3.71 in the AI-generated virtual influencer condition. These two measures do not show a meaningful condition difference in the independent-samples tests.

The product-category pattern for purchase intent is shown in Table 4 and Figure 2. In athleisure apparel, purchase intent is 4.75 for the human influencer condition and 4.55 for the AI-generated virtual influencer condition. In skincare serum, purchase intent is 4.83 for the human influencer condition and 4.62 for the AI-generated virtual influencer condition. In wireless earbuds, purchase intent is 4.53 for the human influencer condition and 4.48 for the AI-generated virtual influencer condition. The human influencer condition is higher in all three product categories, but the observed gap is smaller for wireless earbuds than for the other two categories. The category means also show that skincare serum has the highest purchase-intent level in both source conditions, while wireless earbuds has the lowest human-condition mean and a similar virtual-condition mean.

The two-way analysis of variance is reported in Table 5. The influencer source main effect has $F = 2.09$ with $p = 0.149$ in the model that also includes product category and the interaction. The product-category effect has $F = 2.33$ with $p = 0.098$. The source-by-category interaction has $F = 0.39$ with $p = 0.675$. These results show that the source comparison in purchase intent is not strongly

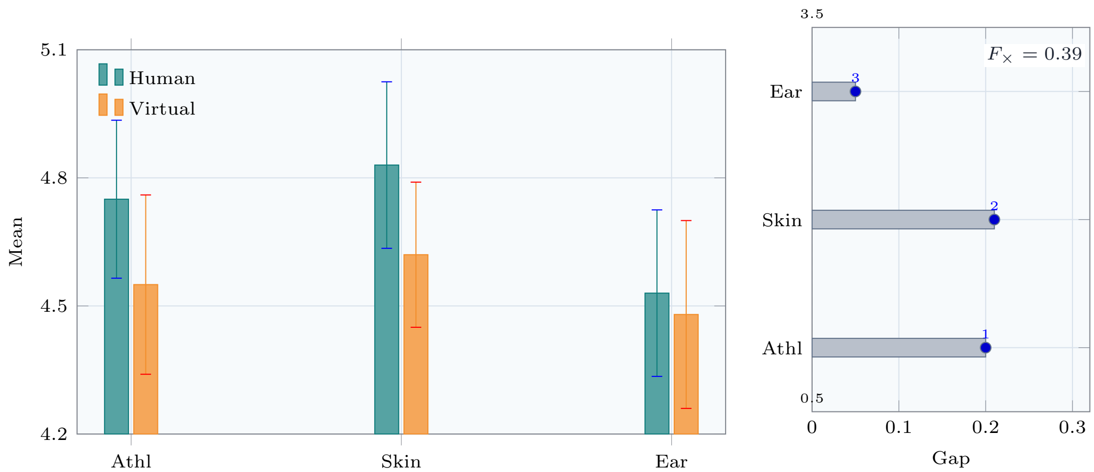

Figure 11: Purchase-intent means remain slightly higher for human influencers across categories, with the weakest gap for wireless earbuds.

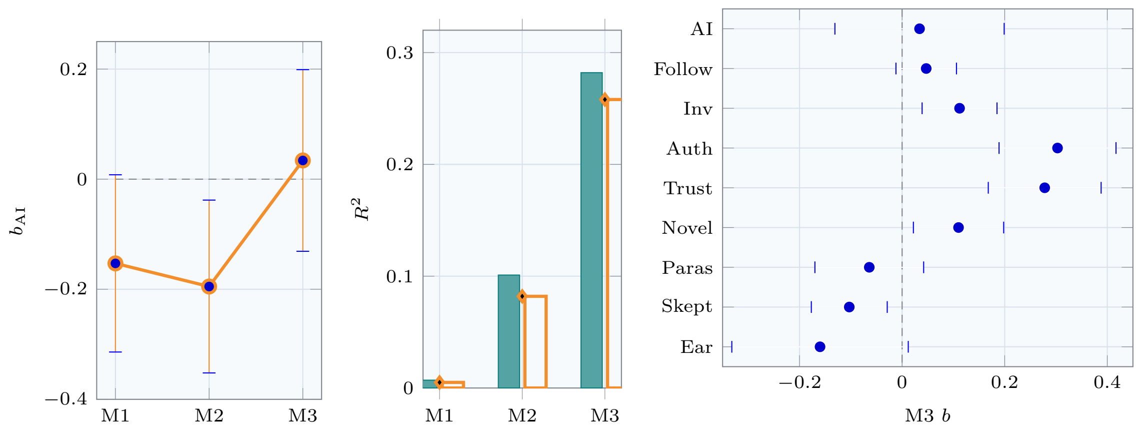

Figure 12: Model adjustment moves the AI-source coefficient toward zero while explanatory fit rises after perception variables enter the model.

moderated by the three product categories in this design. The product-category pattern varies descriptively, especially for wireless earbuds, but the interaction term does not indicate a clear departure from a common source effect across categories.
The regression models add more detail to the purchase-intent analysis. Table 6 reports unstandardized coefficients for three ordinary least squares models. Model 1 includes only the AI-generated virtual influencer indicator, with the human influencer condition as the reference. The coefficient is -0.153 with a standard error of 0.082 and $p = 0.063$. This matches the raw mean comparison because the model includes no additional predictors. Model 1 explains a very small share of variance, with $R^2 = 0.007$ and adjusted $R^2 = 0.005$. In this first model, source condition by itself is only a weak predictor of purchase intent.
Model 2 adds age, gender indicators, social media hours, prior AI familiarity, influencer-following frequency, product involvement, and product category. In this model, the AI-generated virtual influencer coefficient is -0.195 with a standard error of 0.080 and $p = 0.015$. Product involvement is positively associated with purchase intent, with a coefficient of 0.217 and $p < 0.001$. Influencer-following frequency is also positive, with a coefficient of 0.076 and $p = 0.020$. The wireless earbuds category is lower than athleisure apparel by 0.147 scale points, although this coefficient has $p = 0.132$. The model fit rises to $R^2 = 0.101$ and adjusted $R^2 = 0.082$. The control model therefore shows that background involvement and

Table 4: Purchase intent by source condition and product category

Product category	Condition	N	Mean	SD	95% CI
Athleisure apparel	Human influencer	80	4.75	0.85	4.57 to 4.94
Athleisure apparel	AI-generated virtual influencer	80	4.55	0.96	4.34 to 4.76
Skincare serum	Human influencer	80	4.83	0.89	4.63 to 5.02
Skincare serum	AI-generated virtual influencer	80	4.62	0.79	4.45 to 4.79
Wireless earbuds	Human influencer	80	4.53	0.89	4.34 to 4.73
Wireless earbuds	AI-generated virtual influencer	80	4.48	1.01	4.26 to 4.70

Table 5: Two-way analysis of variance for purchase intent

Term	df1	df2	F	p
Influencer type	1	474	2.09	0.149
Product category	2	474	2.33	0.098
Influencer type by product category	2	474	0.39	0.675

influencer-following behavior explain part of the purchase-intent variation.

Model 3 adds perceived authenticity, trust, novelty, parasocial response, and ad skepticism. In this full model, the AI-generated virtual influencer coefficient changes to 0.034 with a standard error of 0.084 and $p = 0.685$. Perceived authenticity is positively associated with purchase intent, with a coefficient of 0.303 and $p < 0.001$. Trust is also positive, with a coefficient of 0.278 and $p < 0.001$. Novelty has a smaller positive coefficient of 0.110 with $p = 0.015$. Product involvement remains positive, with a coefficient of 0.112 and $p = 0.003$. Ad skepticism is negative, with a coefficient of -0.103 and $p = 0.006$. Parasocial response is not positive in the full model after the other perception measures are included, with a coefficient of -0.064 and $p = 0.236$. The model fit rises to $R^2 = 0.282$ and adjusted $R^2 = 0.258$.

5.1 Mediation analysis

A parallel mediation analysis was conducted to formally test whether the source-condition effect on purchase intent was statistically carried by the perception variables. The AI-generated virtual influencer condition was coded as 1 and the human influencer condition as 0. The model included perceived authenticity, trust, novelty, parasocial response, and ad skepticism as parallel mediators, with product category, age, gender, social media use, prior AI familiarity, influencer-following frequency, and product involvement included as covariates. Indirect effects were estimated using 5,000 bootstrap resamples.

The results show a significant negative total indirect effect of the AI-generated virtual influencer condition on purchase intent through the perception variables, $b = -0.229$, 95% bootstrap CI $[-0.341, -0.118]$. The strongest negative indirect paths operated through perceived authenticity and trust. The AI-generated virtual influencer condition reduced perceived authenticity, and perceived authenticity positively predicted purchase intent, producing a negative indirect effect, $b = -0.169$, 95% bootstrap CI $[-0.252, -0.096]$. The same pattern appeared for trust, with a negative indirect effect of $b = -0.142$, 95% bootstrap CI $[-0.213, -0.081]$.

Novelty showed the opposite pattern. The AI-generated virtual influencer condition increased perceived novelty, and novelty positively predicted purchase intent, producing a positive indirect effect, $b = 0.072$, 95% bootstrap CI $[0.016, 0.134]$. The indirect paths through parasocial response and ad skepticism were not statistically supported because their confidence intervals included zero. After the mediators were included, the direct effect of influencer source type on purchase intent was small and not statistically supported, $b = 0.034$, 95% bootstrap CI $[-0.140, 0.209]$. The covariate-adjusted total effect was negative, $b = -0.195$, 95% bootstrap CI $[-0.354, -0.024]$.

These results clarify the mechanism implied by the regression models. The AI-generated virtual influencer condition did not simply reduce purchase intent directly. Instead, it produced competing indirect paths. Lower authenticity and trust reduced purchase intent, while higher novelty partly offset those negative paths. This explains why the raw purchase-intent difference between source conditions was modest: the virtual influencer condition combined credibility-related disadvantages with a novelty advantage.

The movement of the source coefficient across the three regression models is central to the analysis. In

Table 6: Ordinary least squares regression models predicting purchase intent

Predictor	M1 b	M1 SE	M2 b	M2 SE	M3 b	M3 SE
AI-generated virtual influencer	-0.153	0.082	-0.195	0.080	0.034	0.084
Age			0.004	0.006	0.004	0.005
Woman			-0.079	0.082	-0.069	0.074
Nonbinary or another identity			0.207	0.200	0.138	0.181
Social media hours			-0.030	0.028	-0.012	0.026
Prior AI familiarity			-0.017	0.030	-0.031	0.027
Influencer following frequency			0.076	0.033	0.047	0.030
Product involvement			0.217	0.038	0.112	0.037
Skincare serum			0.038	0.098	0.035	0.088
Wireless earbuds			-0.147	0.097	-0.160	0.088
Perceived authenticity					0.303	0.058
Trust					0.278	0.056
Novelty					0.110	0.045
Parasocial response					-0.064	0.054
Ad skepticism					-0.103	0.038
R^2	0.007		0.101		0.282	
Adjusted R^2	0.005		0.082		0.258	
N	480		480		480	

Table 7: Parallel mediation results predicting purchase intent

Mediator or effect	*a* path	*b* path	Indirect effect	Boot SE	95% Boot CI
Perceived authenticity	-0.556	0.303	-0.169	0.040	[-0.252, -0.096]
Trust	-0.512	0.278	-0.142	0.033	[-0.213, -0.081]
Novelty	0.656	0.110	0.072	0.030	[0.016, 0.134]
Parasocial response	-0.249	-0.064	0.016	0.013	[-0.007, 0.044]
Ad skepticism	0.058	-0.103	-0.006	0.011	[-0.030, 0.014]
Total indirect effect	–	–	-0.229	0.057	[-0.341, -0.118]
Direct effect	–	–	0.034	0.089	[-0.140, 0.209]
Total effect	–	–	-0.195	0.083	[-0.354, -0.024]

the raw model, the AI-generated virtual influencer condition is lower than the human influencer condition by 0.153 scale points. After adding controls, the coefficient becomes -0.195. After adding perceptions of the endorsement, the coefficient becomes close to zero. This pattern indicates that the source contrast in purchase intent is closely tied to the measured perceptions rather than operating as a large independent condition effect after those perceptions are included. In particular, the AI-generated virtual influencer condition is lower on authenticity and trust but higher on novelty. The full model shows that authenticity, trust, and novelty are all positively associated with purchase intent, while ad skepticism is negatively associated with purchase intent. The source condition itself does not retain a separate association once these perceptions are in the same model.

The combined results present a mixed response pattern. The human influencer condition is rated higher on authenticity, trust, and parasocial response. The AI-generated virtual influencer condition is rated higher on novelty. Purchase intent is numerically higher for the human influencer condition, but the difference is small in the raw comparison and is not retained after perception measures are added to the full regression. Share intent does not differ across conditions, and ad skepticism is similar across conditions. The product-category analysis does not show a clear source-by-category interaction. Overall, the results show that source type changes how participants evaluate the endorsement source, while purchase intent depends more on the perception profile of the endorsement than on the source label alone.

6 | Discussion

The results indicate that human and AI-generated virtual influencers are not evaluated in the same way, even when they are placed in the same general endorsement format. The clearest differences appear in perceived authenticity, trust, novelty, and parasocial response. The human influencer condition receives higher scores on authenticity and trust, which are closely connected to the idea that a recommendation comes from a source with personal experience or reputational accountability. The AI-generated virtual influencer condition receives higher novelty scores, which is consistent with the idea that a designed digital persona can stand out in an environment crowded with familiar creator formats. These perception differences are larger than the direct difference in purchase intent, which suggests that consumer response to the source is more differentiated than a simple buying-intent comparison alone would show.

This pattern is consistent with prior influencer-marketing research. Human influencers may benefit from authenticity and credibility cues because audiences can imagine them as people with personal experience, reputation, and accountability [17, 3, 4]. The virtual influencer condition, by contrast, appears to benefit mainly from novelty, which fits research describing virtual influencers as distinctive and attention-generating but potentially more difficult to evaluate as authentic endorsers [11, 15]. The positive association between novelty and purchase intent in the full model suggests that novelty can contribute to consumer response, but the stronger coefficients for authenticity and trust indicate that novelty alone is not enough. This supports the interpretation that virtual-influencer campaigns need credibility-building cues, such as transparent identity, coherent persona design, and strong product fit, rather than relying only on the technical or visual newness of the source [14, 23].

Purchase intent shows a small advantage for the human influencer condition in the raw comparison. The mean difference of 0.15 points on a seven-point scale is modest, and the confidence interval includes values close to zero. The high purchase-intent indicator also favors the human influencer condition by 7.5 percentage points. These results do not describe a large separation in immediate buying interest. Instead, they show a limited advantage for the human source condition before accounting for the full response profile. This is important because campaign decisions often depend on whether a new source type produces a clearly different consumer action tendency. In this dataset, the main source contrast is more visible in perceptions of the endorser than in purchase intent itself.

The regression results sharpen this point. When only source condition is included, the AI-generated virtual influencer indicator is negative. When demographic variables, product involvement, category, and background social media variables are added, the negative coefficient becomes somewhat larger. When perceptions of the endorsement are added, the source coefficient becomes small and positive, with no meaningful independent association. The formal mediation test supports this interpretation statistically, while still requiring caution because all perception measures and purchase intent were collected in the same survey session. The AI-generated virtual influencer condition had negative indirect paths through authenticity and trust, a positive indirect path through novelty, and no remaining direct association with purchase intent once the mediators were included. The results therefore support a competing-mediation interpretation rather than a simple claim that one source type directly produces higher or lower purchase intent. It would be incomplete to say that one source type simply produces stronger purchase intent across the board. The source type appears to change the ingredients of the response, and those ingredients are what carry most of the predictive information in the full model.

Authenticity and trust have the strongest positive associations with purchase intent in the full regression. These results are consistent with the idea that endorsement effectiveness depends heavily on whether the recommendation seems grounded and reliable. For human influencers, this may be easier because the audience can imagine the endorser using the product, making a personal judgment, and risking reputation with followers. For AI-generated virtual influencers, authenticity and trust may require different supports. A virtual source may need clear character consistency, transparent presentation, strong product fit, and careful integration with the brand context. The source does not need to imitate every feature of human endorsement, but it must still give the audience a reason to treat the endorsement as meaningful rather than merely decorative.

Novelty is also positively associated with purchase intent in the full model, although its coefficient is smaller than the coefficients for authenticity and trust. This is a useful finding because it shows that novelty is not just an attention cue with no purchase relevance. Participants who rate the endorsement as more novel also report somewhat higher purchase intent, after the other variables are included. At the same time, novelty alone does not overcome lower authenticity and trust in the raw source comparison. The AI-generated virtual influencer condition is more novel, yet it does not produce higher purchase intent overall. This suggests that novelty can contribute to favorable response, but it is not a substitute for credibility-related perceptions. Ad skepticism has a negative association with purchase intent in the full model. This is expected in an endorsement context where the audience may question whether the post is mainly a selling device. The condition comparison does not show a meaningful difference in ad skepticism, so skepticism does not explain a large source gap by itself. Still, the negative coefficient matters because it shows that skepticism remains relevant even when authenticity, trust, novelty, and parasocial response are included. In practical terms, both source types can be weakened by an endorsement that appears overly commercial or insufficiently connected to the product. A human influencer can appear scripted, and a virtual influencer can appear like a direct extension of the brand. The issue is not restricted to one source type.

The product-category results are moderate. The human influencer condition is numerically higher in all three categories, but the source-by-category interaction is not statistically clear. The smallest gap appears in wireless earbuds, while larger gaps appear in athleisure apparel and skincare serum. One possible reading is that categories involving bodily presentation, routine, or personal style may leave more room for human-source advantages in authenticity and trust. Another reading is that the category differences are simply small within this design. The ANOVA results support the more restrained reading. Product category is relevant enough to include, but it does not produce a strong interaction pattern in this dataset.

The absence of a share-intent difference is also informative. AI-generated virtual influencers may attract novelty, but this does not translate into greater stated willingness to share the endorsement in the present analysis. Human influencers receive stronger authenticity and trust evaluations, but this does not produce higher share intent either. Sharing may depend on entertainment value, social identity signaling, humor, platform norms, or the perceived social cost of sharing commercial content. Purchase intent and share intent should therefore not be treated as interchangeable measures of endorsement effectiveness. A campaign designed for discussion or reach might evaluate different outcomes from a campaign designed to increase product consideration.

The result pattern also has implications for how endorsement briefs are written. A human influencer brief often benefits from allowing space for the creator's own voice, personal routine, and practical product use. If that space is removed, the source may still be human, but the post can lose the qualities that make the source valuable. A virtual influencer brief begins from a different problem. The source can be visually controlled, but the endorsement needs a reason to be credible within the persona's world. A virtual character that only displays a product may produce novelty, yet the product recommendation may remain thin. The results suggest that the brief should specify how the product belongs in the source's narrative, what evidence the audience is expected to accept, and how the campaign will avoid making the source look like a neutral display surface for brand claims.

The comparison also points to a difference between source novelty and campaign distinctiveness. Novelty is measured as a participant's response to the influencer presentation, but distinctiveness in a campaign setting would include the fit between the source, product, brand voice, platform format, and surrounding posts. A virtual influencer can be novel without being distinctive in a useful marketing sense if the execution looks generic or disconnected from the product. A human influencer can be familiar without being dull if the creator has a recognizable way of showing product use. The results do not make novelty unimportant. They show that novelty works best when it is joined to credibility-related perceptions. This is relevant because brands sometimes treat a new source format as if the format itself is the strategy. The evidence here supports a more specific view in which the format is one element of the endorsement design.

The general pattern suggests that AI-generated virtual influencers should not be evaluated only by asking whether they beat human influencers on immediate purchase intent. The more useful question is what perception profile they create and whether that profile fits the campaign goal. If a campaign requires credibility, product testimony, or embodied experience, the human influencer condition has advantages in this dataset. If a campaign requires distinctive presentation or a signal of novelty, the AI-generated virtual influencer condition has a measurable advantage on that dimension. For purchase intent, however, authenticity and trust remain strongly associated with favorable response. This means that virtual influencer campaigns may need to build credibility more deliberately rather than relying on visual novelty alone.

7 | Limitations

The study also uses self-reported purchase intent rather than behavioral purchasing. Purchase intent is useful as an early indicator because it captures stated consideration after exposure, but it is not the same as buying a product, clicking a link, saving a post, searching for reviews, or returning to the brand later. People may report interest without acting on it. They may also purchase for reasons not captured by a short exposure scenario. Future empirical work with real data could connect endorsement exposure to click behavior, cart addition, coupon redemption, or sales conversion. Such outcomes would allow the comparison to move beyond stated response.

The source conditions are broad. A human influencer can vary in fame, expertise, attractiveness, disclosure style, history with followers, and fit with the product. An AI-generated virtual influencer can vary in visual realism, stylization, backstory, interactivity, transparency, and brand ownership. The present design treats source type as a general contrast, so it cannot identify which specific design features make a virtual influencer more or less effective. It also cannot identify which kind of human influencer provides the most appropriate comparison. A more detailed study could cross source type with realism, disclosure, creator credibility, follower count, or product-fit strength.

The product categories are limited to athleisure apparel, skincare serum, and wireless earbuds. These categories offer a modest range of lifestyle contexts, but they do not represent all goods and services promoted through influencers. Food, travel, financial services, gaming, luxury goods, and health-related products may involve different levels of risk, expertise, sensory experience, and trust. The results should therefore not be extended across all product contexts without additional data. Product category may matter more strongly when the product requires expertise, personal trial, or safety confidence.

The models include several perception measures collected in the same response session. This makes it possible to describe how authenticity, trust, novelty, parasocial response, and skepticism are associated with purchase intent, but it limits causal ordering among the perceptions. A participant may form trust before purchase intent, but purchase interest may also influence how favorably the participant rates the source. A stronger design could use temporal separation, repeated exposure, experimental manipulation of trust cues, or mediation tests with validated ordering. The present analysis is best read as a structured comparison of associations.

8 | Conclusion

This paper compared AI-generated virtual influencers and human influencers in relation to consumer purchase intent across three lifestyle product categories. The analysis shows that the two source types create different perception profiles. Human influencers receive higher ratings on perceived authenticity, trust, and parasocial response, which is consistent with prior research linking influencer credibility, authenticity, and parasocial connection to consumer response [3, 4, 19, 9]. AI-generated virtual influencers receive higher ratings on novelty, which also fits research describing virtual influencers as distinctive designed personas that can attract attention while raising separate questions about authenticity and humanness [11, 12, 15]. Purchase intent is slightly higher in the human influencer condition in the raw comparison, but the size of the difference is modest. Once perception measures are included in the full regression model, the source-condition coefficient no longer carries an independent association with purchase intent.

The results support a measured account of influencer source effectiveness. Human influencers appear to retain advantages on credibility-related dimensions that are strongly associated with purchase intent. These advantages are not surprising because human endorsement can imply direct experience, personal judgment, and accountability to an audience, all of which are central to source credibility and endorsement effectiveness [16, 8, 2]. AI-generated virtual influencers appear to offer novelty, which also has a positive association with purchase intent but does not replace authenticity and trust. The central issue is not whether a virtual source can attract attention. It is whether the attention is paired with enough credibility and product fit to support consumer consideration [17, 14, 15].

For marketing practice, the analysis suggests that source selection should follow the intended function of the campaign. A campaign centered on testimony, routine, personal experience, or trust-sensitive product claims may benefit from a human influencer format because credibility and perceived authenticity are repeatedly shown to shape trust and purchase intention in influencer contexts [3, 4, 9]. A campaign centered on visual distinctiveness, brand experimentation, or controlled character identity may have reasons to use an AI-generated virtual influencer, especially when novelty and creative consistency are part of the intended communication effect [13, 12, 11]. The purchase-intent outcome in this study is most strongly connected to authenticity, trust, product involvement, novelty, and skepticism rather than to the source label alone. This means that execution quality and perceived fit remain central even when the source type is new [2, 15].

For research, the study shows the value of measuring intermediate perceptions alongside purchase intent. A direct comparison between source conditions can miss the way different perceptions offset one another. The AI-generated virtual influencer condition has a clear novelty advantage, while the human influencer condition has authenticity and trust advantages. These dimensions do not collapse into one general attitude. Future work can build on this structure by testing specific design features, using actual consumer samples, and examining behavioral outcomes. The question should move from whether virtual influencers are generally better or worse than human influencers toward when each source form produces the response profile needed for a particular product and campaign [11, 15, 14].

AI-generated virtual influencers and human influencers should be treated as distinct endorsement sources with different strengths. In the present analysis, human influencers show stronger credibility-related perceptions and a small raw advantage in purchase intent. AI-generated virtual influencers show stronger novelty but not stronger purchase intent. The full regression indicates that purchase intent is more closely tied to perceived authenticity, trust, novelty, product involvement, and skepticism than to source condition by itself. This makes the comparison less a simple contest between source types and more a question of how each source form shapes the consumer's evaluation of the endorsement [17, 19, 12].

The study also indicates that purchase intent should be connected to the surrounding communication task. A campaign that needs product explanation may depend on trust more than novelty. A campaign that needs attention in a crowded feed may benefit from novelty but still needs a reason for the viewer to connect the product to the source. A campaign that needs longer-term creator relationship may depend on parasocial response and perceived continuity over repeated posts [18, 19, 9]. The same source type can perform differently across these tasks. For this reason, the human versus AI-generated virtual comparison is most useful when it is tied to a defined campaign function rather than treated as a general ranking of source types.

The results point toward careful matching rather than replacement logic. Human influencers are not valuable only because they are human; they are valuable when their experience, voice, and audience relationship make the endorsement credible. AI-generated virtual influencers are not valuable only because they are technologically new; they are valuable when their designed identity creates a coherent and distinctive product context. The strongest purchase-intent associations in the analysis come from perceptions that can be affected by creative execution. Authenticity, trust, novelty, and skepticism are not fixed outcomes of source type. They are responses to how the endorsement is built, presented, and understood by the audience [5, 6, 17, 14].

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