

Article

An Intelligent Survey-Data Analysis of TikTok Fashion-Brand Content, Consumer Brand Responses, and Purchase-Related Intentions

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Abstract

TikTok supports fashion discovery and creator-mediated brand communication. This study examines associations among TikTok fashion-brand content involvement, brand awareness, brand engagement, and purchase-related intentions among Bulgarian users and illustrates a human-governed analytical architecture for structured and open survey data. An online survey yielded 295 responses; 268 eligible TikTok users comprised the sample. The architecture organizes primary measurement and structural analysis, secondary prediction and moderation, exploratory response-structure and text analysis, and descriptive multi-criteria synthesis within processing stages. Content involvement was positively associated with awareness ($\beta = 0.683$), engagement ($\beta = 0.512$), and purchase-related intentions ($\beta = 0.283$). Awareness was associated with engagement ($\beta = 0.300$) but had no incremental direct association with purchase-related intentions; engagement showed the strongest direct association ($\beta = 0.496$). The model explained 52.5% of purchase-related-intention variance, and PLS-PM prediction produced lower errors than the training-mean benchmark for all four outcome indicators. No demographic interaction received Holm-adjusted support. Illustrative multi-criteria synthesis ranked engagement first, involvement second, and awareness third under sample-derived criteria. Dictionary-assisted open-response categories concerning presentation, creators, reviews, demonstrations, music, and humor were manually checked against the responses. All reported relationships are cross-sectional associations and do not establish causal effects, intervention effectiveness, or marketing priorities. Concentrated sampling, broad working constructs, and internal validation require cautious interpretation and independent external replication.

Keywords: TikTok; fashion-brand content; brand awareness; brand engagement; purchase-related intentions; intelligent survey-data analysis; PLS path modeling; business intelligence; machine learning; multi-criteria decision making



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1. Introduction

Social media influencers have become important intermediaries between brands and consumers. They combine personal communication, content creation, product demonstration, and audience interaction, thereby shaping how sponsored and organic brand messages are encountered during the consumer decision process [1,2]. TikTok intensifies this role through short, rapidly changing videos in which entertainment, product information, creator identity, comments, sharing, and shopping cues appear in the same interface.

Fashion is particularly suitable for this environment because apparel and accessories are visually inspectable, identity-related, and responsive to trends. TikTok research shows that humor and hedonic experience can support influencer marketing outcomes [3], while brand-influencer communication is associated with engagement and purchase likelihood [4]. Fashion-specific studies further connect content quality, parasocial interaction, influencer credibility, attractive selling content, and attitudes toward TikTok videos with purchase-related outcomes [5–8].

Influencers should nevertheless not be treated as a uniformly effective marketing input. Their persuasive role depends on identification, similarity, trust, expertise, content value, and the relationship between creator and product [9–11]. Moreover, awareness, engagement, and purchase-related intentions represent different parts of the consumer response. A short video may make a brand recognizable without generating sufficient involvement to affect continued purchase, loyalty, or recommendation. This distinction is especially relevant when users encounter fashion content incidentally in an algorithmically curated feed.

Existing studies provide substantial evidence on influencer credibility and purchase intention, but fewer examine brand awareness (BA), brand engagement (BE), and broader purchase-related intentions in one TikTok fashion model. The literature is also concentrated in Asian markets and frequently focuses on livestream shopping, named influencers, or specific brands. Evidence from Central and Eastern Europe remains comparatively limited, and open consumer comments are rarely used to interpret pathways estimated from structured survey items.

The present study addresses this gap using Bulgarian survey data [12]. It evaluates a theory-guided association model in which TikTok fashion-brand content involvement (TCI) is specified as an antecedent of brand awareness (BA), brand engagement (BE), and purchase-related intentions (PRIs), while BA and BE are specified as distinct correlates of PRIs. This ordering follows the conceptual logic developed in Section 3; the cross-sectional design cannot establish temporal direction, and reverse or reciprocal relationships remain plausible. The dataset also contains open questions on content elements that attract attention and examples associated with brand opinions or purchasing decisions.

In this article, intelligent survey-data analysis denotes a human-governed combination of statistical modeling, machine learning, computer-assisted text processing, and rule-based quality control rather than autonomous artificial intelligence. The proposed architecture is illustrated through this case study; its transferability and comparative efficiency are not empirically validated here.

The study addresses four substantive research questions:

RQ1: How is involvement with TikTok fashion-brand content associated with brand awareness, brand engagement, and purchase-related intentions?

RQ2: Do brand awareness and brand engagement show distinct direct and statistical indirect associations between TikTok fashion-brand content involvement and purchase-related intentions under the specified model?

RQ3: Which content and creator categories are identified by dictionary-assisted coding and confirmed through manual review as attracting attention or being associated with fashion-brand responses?

RQ4: What response-intensity patterns emerge when purchase-related intentions are excluded from cluster formation, and how accurately can the antecedent indicators predict that outcome under repeated cross-validation?

A prespecified robustness check examines whether the construct-reliability conclusions remain stable after straight-line response profiles are excluded. This check is limited to reliability and does not re-estimate the structural model.

Illustrative analytical question (IAQ): How do TCI, BA, and BE rank when total structural association, incremental direct contribution, and internal predictive contribution are combined in a limited-scope MCDM synthesis?

Exploratory RQ5: Do gender, recorded age category, residence size, household income, or education show multiplicity-adjusted evidence of modifying any of the six specified associations?

The study makes two substantive contributions. It integrates TCI, BA, BE, and broad PRIs in a compact association model and distinguishes the strong TCI–BA association from the more proximal BE–PRIs association. It also examines whether demographic characteristics modify the six specified relationships, while treating their directions as theory-guided rather than causal.

Methodologically, the study proposes and illustrates a candidate human-governed analytical architecture. The measurement and PLS-PM association model is primary; prediction and demographic analysis are secondary; clustering and manually reviewed open-response coding are exploratory; and MCDM addresses a separate illustrative analytical question. This hierarchy prevents the methods from being treated as interchangeable evidence and keeps the questionnaire’s evidential boundary explicit: creator mentions are observed in open responses, but influencer credibility is not measured as a separate latent construct.

The remainder of the article reviews intelligent dataset-analysis frameworks (Section 2), presents the theoretical background and hypotheses (Section 3), introduces the proposed framework (Section 4), describes the study methods (Section 5), reports the results (Section 6), discusses their implications (Section 7), and concludes the article (Section 8).

2. Related Work on Intelligent Dataset-Analysis Frameworks

2.1. General Analytical Process Models

Intelligent dataset analysis is commonly organized as an iterative process rather than as a single algorithm. The knowledge-discovery-in-databases framework connects data selection, preprocessing, transformation, data mining, and interpretation [13]. CRISP-DM similarly links business understanding, data understanding, preparation, modeling, evaluation, and deployment [14]. CRISP-ML(Q) extends this logic for machine-learning systems by making quality assurance and monitoring explicit [15], while empirical software-engineering research shows that production machine learning also requires data discovery, feature engineering, testing, deployment, and monitoring activities that extend beyond model training [16]. These frameworks establish the need for iterative quality checks and traceable outputs, but they are not tailored to theory-based survey measurement.

2.2. Intelligent Analysis of Structured and Open Survey Data

Survey datasets combine response scales, construct definitions, demographic variables, and sometimes open text. Their analysis therefore requires more than generic preprocessing and prediction: measurement quality, common-source limitations, multiple testing, respondent heterogeneity, and the distinction between explanatory and predictive results must

also be addressed. Clustering and machine learning can identify response patterns and internal predictive relationships, while natural-language processing can assist the coding of open answers. Research on automatic survey coding shows that model-assisted classification can reduce manual effort, but its validity depends on labeled data, coding design, and human verification [17]. Recent large-language-model annotation studies likewise indicate substantial potential for text coding while reinforcing the need for task-specific validation rather than assumed accuracy [18].

2.3. Research Gap

The reviewed approaches contribute important process, quality-assurance, engineering, and text-analytic elements, but none provides a survey-specific sequence connecting construct measurement, theory-guided structural analysis, exploratory segmentation, repeated prediction, open-text interpretation, and descriptive synthesis. Table 1 summarizes this gap. The candidate architecture assigns these roles to three nested processing levels and uses explicit pass/revise conditions under human review.

Table 1. Selected dataset-analysis frameworks and their relevance to intelligent survey-data analysis.

Framework or Approach	Main Contribution	Relevance and Limitation for Survey Analysis
KDD [13]	Iterative selection, preparation, mining, and interpretation	Provides a knowledge-discovery sequence but does not specify construct measurement or survey-bias diagnostics.
CRISP-DM [14]	Business- and data-centered analytical lifecycle	Supports iterative project organization but treats survey measurement and inferential boundaries only indirectly.
CRISP-ML(Q) [15]	Machine-learning lifecycle with explicit quality assurance	Strengthens validation and monitoring but is oriented toward ML products rather than mixed explanatory survey studies.
ML engineering workflow [16]	Operational tasks surrounding model development and deployment	Emphasizes testing and monitoring but does not integrate latent constructs, group tests, and open-response interpretation.
Automated survey-text coding [17,18]	Model-assisted classification and annotation of open responses	Supports scalable text analysis but requires labeled examples, error analysis, and human validation.
Proposed candidate architecture	Human-governed coordination of measurement, explanation, exploration, prediction, text analysis, and MCDM	Illustrated for one survey dataset; transferability, comparative efficiency, and external validity remain untested.

The comparison in Table 1 shows that the proposed architecture does not replace established process models; it combines their iterative and quality-assurance principles with requirements specific to theory-based survey research. Its role is to coordinate measurement assessment, explanatory modeling, exploratory segmentation, internal prediction, manually reviewed text analysis, and limited-scope multi-criteria synthesis while preserving the evidential limits of each method. This synthesis provides the methodological basis for the construct model in Section 3 and the governed analytical stages presented in Section 4.

3. Theoretical Background and Hypotheses

3.1. TikTok Fashion-Brand Content and Creator-Mediated Communication

Influencer communication combines source characteristics with message characteristics. Consumers may respond to a creator because the creator appears relatable or trustworthy, because the content is informative or entertaining, or because both mechanisms operate together [9–11]. In fashion, creators can reduce the distance between a product image and an imagined consumption experience by showing fit, styling, use situations, combinations, and personal evaluations. These demonstrations can also invite comments, imitation, and sharing.

The present questionnaire does not isolate creator credibility, attractiveness, expertise, or creator type. Its exogenous block measures interest in TikTok information about fashion brands, perceived information sufficiency, information sharing, and attention to fashion advertising. We refer to this block as TikTok fashion-brand content involvement (TCI). The reflective specification treats the four responses as manifestations of a shared underlying orientation to attend to, appraise, and use TikTok fashion-brand information. It was prioritized because the study asks whether this general orientation covaries with BA, BE, and PRIs, rather than whether four independently weighted content components jointly form an index. The specification is therefore parsimonious and consistent with the covariance-based interpretation of the item block, but it does not imply that the facets are interchangeable or that a formative or multidimensional conceptualization is invalid.

The theoretical distinction is therefore between manifestations of a latent orientation and components that create a composite: the present reflective model addresses the former question, whereas a formative specification would answer a different question about how distinct content-related activities combine and contribute.

3.2. Brand Awareness

Brand awareness concerns the accessibility of brand knowledge in memory, including recognition and recall [19]. Repeated exposure to distinctive visual, verbal, and sonic cues can make fashion brands easier to identify. On TikTok, creator demonstrations, recurring formats, hashtags, and participatory trends can reinforce these cues. Informative and credible influencer content has previously been connected with brand awareness [11]. Accordingly:

H1: *Involvement with TikTok fashion-brand content is positively associated with brand awareness.*

3.3. Brand Engagement

Consumer brand engagement represents cognitive, affective, and behavioral investment in brand interactions [20]. In a short-video environment, engagement can include focused attention, positive affect, perceived connection with other users, and participation in brand-related activities. Entertaining, useful, and relatable creator content may be associated with these responses. Under the specified model, BA was hypothesized to be positively associated with BE.

H2: *Involvement with TikTok fashion-brand content is positively associated with brand engagement.*

H4: *Brand awareness is positively associated with brand engagement.*

3.4. Purchase-Related Intentions

Purchase intention is a stated willingness or likelihood to buy and is a proximal, imperfect indicator of subsequent behavior [21,22]. The present four-item block additionally

includes continued purchase, loyalty, and recommendation. These items share a favorable future-oriented response to fashion brands encountered on TikTok, which motivates their use as a broad reflective working block named purchase-related intentions (PRIs). However, they refer to different behavioral stages and may presuppose different levels of prior brand experience. PRIs should therefore not be interpreted as a pure purchase-probability measure, a homogeneous single behavior, or observed sales.

The reflective working specification assumes that planned purchase, continued purchase, loyalty, and recommendation covary as manifestations of a more general favorable future orientation toward the focal brands. This higher-order interpretation is appropriate for the present construct-level association model, but it does not imply that the four intentions occur at the same behavioral stage or have interchangeable managerial meaning. Research concerned with transitions among these outcomes should model them separately or compare multidimensional and formative alternatives.

H3: *Involvement with TikTok fashion-brand content is positively associated with purchase-related intentions.*

H5: *Brand awareness is positively associated with purchase-related intentions.*

H6: *Brand engagement is positively associated with purchase-related intentions.*

The association model is informed by stimulus–organism–response (SOR) reasoning [23]. TCI is positioned first as a content-related appraisal, BA as cognitive accessibility, BE as relational investment, and PRIs as the broad stated outcome. This ordering provides the theoretical rationale for the arrows, but the variables were measured at one time point. The arrows therefore denote theory-guided associations rather than observed temporal or causal effects; reverse, reciprocal, and contemporaneous alternatives remain plausible. Recent short-video studies similarly connect content appraisals with internal evaluations and purchase-related intentions [24,25]. Figure 1 summarizes the specified relationships.

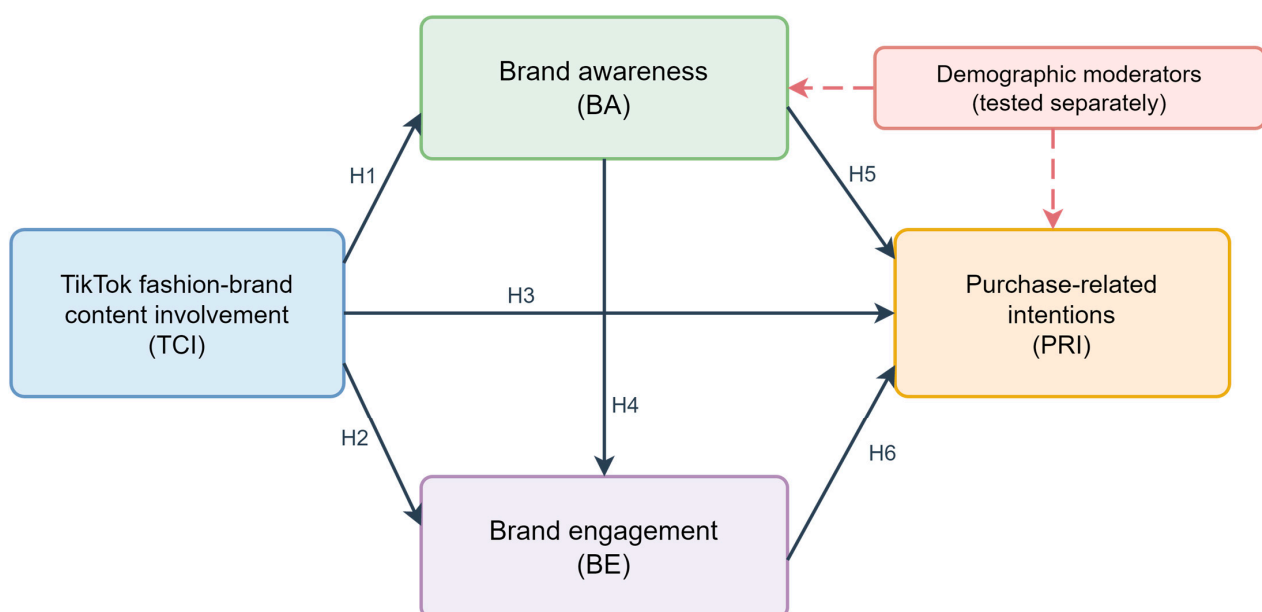


Figure 1. Main-effects conceptual association model and hypotheses H1–H6. RQ5 examines demographic moderation of the six displayed paths. Note: The red dashed arrows indicate that demographic effects were examined separately for all four constructs and were not included in the primary structural model.

3.5. Demographic Moderation as an Exploratory Research Question

Consumer responses to fashion-brand content may differ with digital familiarity, purchasing resources, education, and residential context. However, existing evidence does not establish consistent directional predictions for five demographic characteristics across all six model relationships. Demographic moderation is therefore examined as an exploratory research question rather than a single omnibus hypothesis.

RQ5: Do gender, recorded age category, residence size, household income, or education show multiplicity-adjusted evidence of modifying any of the six specified associations?

3.6. Comparison with Previous Empirical Models

Table 2 positions the model against selected empirical studies. Previous work commonly emphasizes credibility, trust, attitude, entertainment, or parasocial interaction. The present study complements these approaches by testing whether awareness and engagement have distinct roles in a TikTok fashion context, describing outcome-excluded response-intensity patterns, evaluating internal prediction, and using manually reviewed open responses to identify concrete content and creator categories.

Table 2. Selected empirical studies on influencer, TikTok, and fashion-related consumer responses.

Study	Context and Method	Main Result Relevant to This Study
Lou and Yuan [11]	Social media influencer followers; PLS path modeling	Informative value and source credibility supported trust in branded posts, which was related to awareness and purchase intention.
Barta et al. [3]	TikTok influencer marketing	Humor and followers' hedonic experience were important to influencer-marketing effectiveness.
Hazari et al. [4]	TikTok brand influencers; SEM	Brand-influencer impact was associated with prior engagement and purchase likelihood.
Gomes et al. [5]	Fashion consumers; mixed methods	Content quality, parasocial interaction, and attitudes toward sponsored posts were related to purchase intention.
Alcantara-Pilar et al. [6]	TikTok influencer credibility	Credibility and relational mechanisms were linked to purchase intentions and loyalty.
Thuy and Quang [7]	TikTok fashion livestreaming; SEM	Content affected purchase intention directly and indirectly; streamer influence operated indirectly through attitude and trust.
Lin et al. [8]	TikTok sustainable-apparel videos	Attitudes toward TikTok videos and sustainable apparel were associated with purchase intention.

Table 2 indicates that previous studies support links between content appraisals, awareness, engagement-related mechanisms, and purchase intentions, but generally examine only subsets of the relationships combined here. The present model specifies TCI as an antecedent construct, BA and BE as distinct consumer responses, and PRIs as a broad outcome, while demographic moderation is examined separately. These directions define the explanatory component of the analytical architecture introduced in Section 4; they do not establish temporal ordering and do not exclude reverse or reciprocal models.

4. Proposed Human-Governed Framework for Intelligent Survey-Data Analysis

4.1. Framework Logic

The proposed candidate architecture adapts the iterative logic of KDD, CRISP-DM, and CRISP-ML(Q) to theory-based survey research [13–15]. Intelligent analysis denotes a governed combination of statistical modeling, data mining, machine learning, computer-assisted text processing, and rule-based quality control rather than autonomous artificial intelligence. The architecture is demonstrated here as a case-specific workflow, not as an empirically validated universal model.

Figure 2 organizes the architecture into three nested levels. Level 1 defines the analysis cycle; Level 2 specifies governed processing, quality gates, corrective feedback, and human interpretation; and Level 3 integrates measurement assessment, complementary analytical branches, diagnostic review, and illustrative synthesis. Human decisions remain necessary when defining constructs, checking eligibility, validating text categories, selecting synthesis criteria and weights, and interpreting results.

An additional advantage is software independence. The analytical stages can be implemented using paid commercial platforms or free and open-source environments, allowing researchers and organizations to select tools according to expertise, data-governance requirements, interoperability, infrastructure, and budget. In this study, the principal workflow was executed in R 4.4.1 using RStudio 2024.04.2, illustrating a reproducible implementation without mandatory software-license costs. Because the architecture defines analytical roles, quality gates, feedback loops, and outputs rather than vendor-specific commands, the same governed sequence can be implemented in other software ecosystems.

The methodological novelty claimed here lies in the survey-specific orchestration of established procedures, not in any individual statistical, machine-learning, text-coding, or MCDM technique. The contribution is the explicit allocation of evidential roles, quality gates, human review points, corrective feedback, and traceable outputs within one workflow for structured and open questionnaire data.

4.2. Analytical Stages

At Level 1, the analysis begins with the research objective and explicitly delimited decision question. Level 2 governs the ingestion of structured items, open responses, and metadata. Its first gate checks the input schema, codebook agreement, eligibility rule, missingness, valid 1–5 integer responses, duplicate and near-duplicate flags, response quality, translation, and categorical coding. A failed check leads to correction, exclusion under a stated rule, or documented limitation before analysis proceeds.

Level 3 begins with measurement assessment. It estimates construct scores and evaluates loadings, alpha, omega, composite reliability, AVE, and HTMT. These diagnostics are admissibility checks rather than proof of conceptual unidimensionality; uninterpretable measures require revision before downstream analysis, and AVE is not used as a marketing-relevance criterion.

To control analytical scope, the architecture assigns distinct evidential roles. Measurement assessment and the PLS-PM structural association model are primary; repeated internal prediction and demographic analyses are secondary; response-quality auditing, clustering, heatmaps, and manually verified open-response coding are exploratory; and MCDM is an illustrative descriptive synthesis. These roles answer different questions and do not validate one another independently.

The second gate evaluates measurement and reliability sensitivity, bootstrap-supported structural conclusions, demographic robustness, internal prediction benchmarks, cluster-validation indices, multiplicity-controlled tests, and completion of the manual text-

verification procedure. Failed checks return the workflow to data processing, specification, or analysis revision. Outputs that pass may enter the limited-scope synthesis of total association with PRIs, direct f^2 on PRIs, and grouped predictive importance.

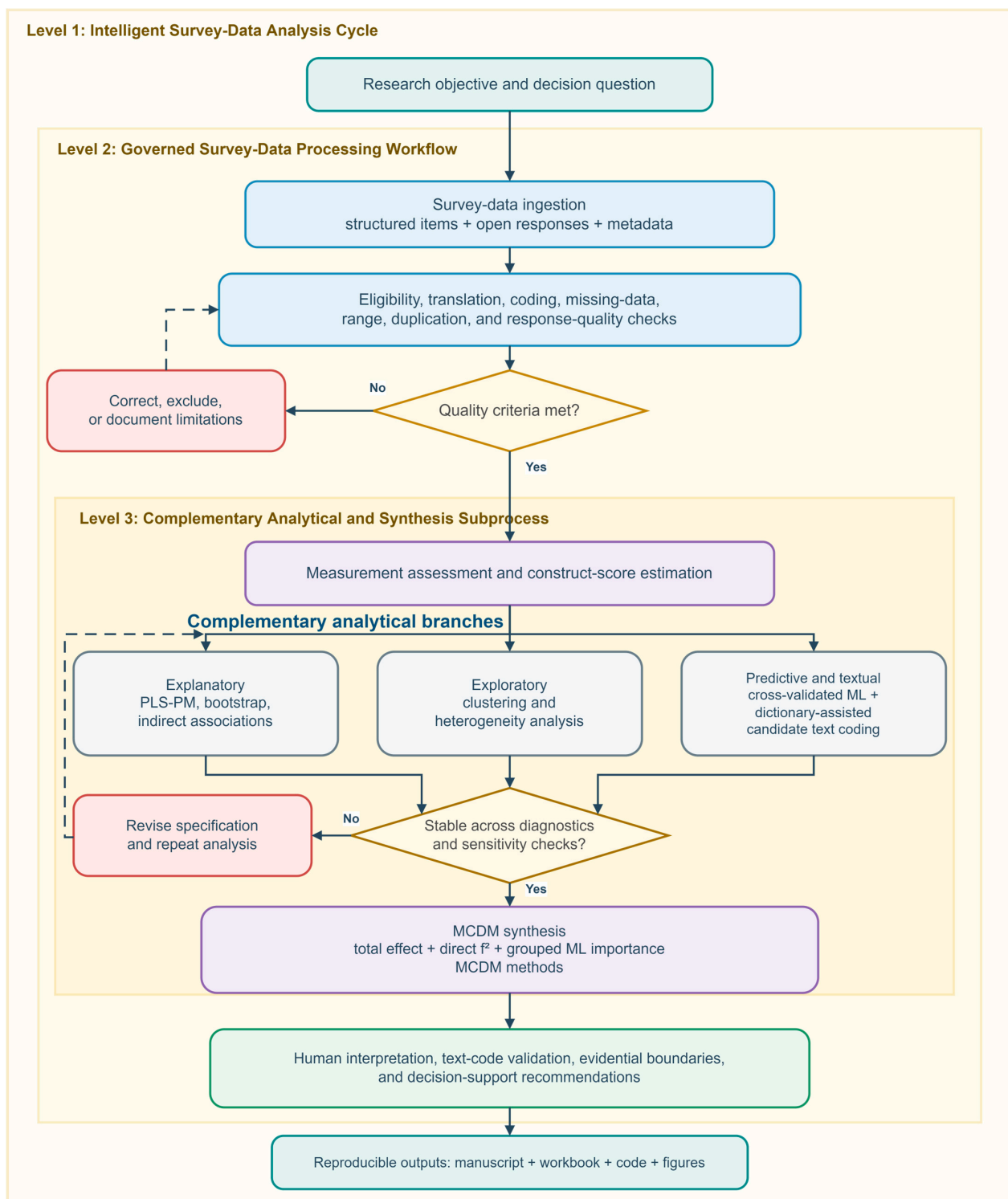


Figure 2. Proposed human-governed intelligent framework for survey-data analysis. Note: Blue dashed arrows indicate iterative feedback loops for data-quality correction and analytical-specification revision; solid arrows show the main workflow.

Level 1 defines the overall analysis cycle. Level 2 specifies ingestion, operational quality checks, corrective feedback, and human interpretation. Level 3 integrates measure-

ment assessment, complementary analytical branches, diagnostic review, and illustrative synthesis. Dictionary-assisted open-response assignments were manually verified before descriptive reporting.

5. Materials and Methods

5.1. Data Collection and Analytical Sample

The source file contained 295 anonymous online questionnaire responses recorded in Bulgaria between 30 November 2025 and 7 May 2026. Participation was restricted to respondents aged 18 years or older. The questionnaire was administered in Bulgarian. Structured variables and response categories were translated into English, while the original values were retained in the analysis workbook. For the open questions, one member of the research team manually checked all English translations and category assignments against the original Bulgarian responses; ambiguous cases were discussed within the research team. Because the available file contains neither a complete sampling frame nor an invitation log, the data are treated as a nonprobability, self-selected sample, and a conventional response rate cannot be reconstructed.

The principal analysis includes respondents who reported using TikTok and having encountered fashion-brand content. This deterministic eligibility rule retained 268 cases and excluded 27 records before model estimation. The excluded responses were not reintroduced as a robustness sample because they fall outside the population defined for the analysis. All sixteen Likert indicators were complete in the principal sample. The de-identified source dataset is publicly available in Mendeley Data [12].

5.2. Measurement Instrument

The model contains four reflectively specified working constructs measured on a five-point Likert scale (1 = strongly disagree; 5 = strongly agree). BA items follow recognition and recall logic [19], and BE items represent attention, affect, connection, and participation [20]. PRIs combines planned purchase, continued purchase, loyalty, and recommendation as a broad favorable behavioral-intention block [21]; these outcomes are related but not conceptually identical. TCI represents a proposed general orientation to attend to, appraise, and use TikTok fashion-brand information, manifested through interest, perceived information sufficiency, sharing, and advertising attention. A reflective Mode A specification was used because the analysis focuses on shared variance among these responses and relates the resulting common orientation to BA, BE, and PRIs. Treating TCI and PRIs as reflective and approximately continuous remains an empirical working specification, not proof of unidimensional conceptual identity. Full item wording is reported in Table 3.

Table 3. Constructs and measurement items.

Construct	Code	Abbreviated Item Content	Specification
TikTok fashion-brand content involvement	TCI1–TCI4	Interest; information sufficiency; sharing with friends; advertising attention	Reflective (Mode A)
Brand awareness	BA1–BA4	Awareness; multimedia information; brand recall; brand recognition	Reflective (Mode A)
Brand engagement	BE1–BE4	Attention; pleasure; user connection; stronger engagement	Reflective (Mode A)
Purchase-related intentions	PRIs1–PRIs4	Planned purchase; continued purchase; loyalty; recommendation	Reflective (Mode A)

The item pool was assembled at the construct level rather than copied as a complete previously validated scale. Its development was informed by an earlier openly available dataset structured around TikTok content marketing, brand awareness, brand engagement, and purchase intention in the context of local fashion brands [26]. For the present study, the items were selected, adapted, and conceptually refined to correspond to the defined TCI, BA, BE, and PRIs working constructs. BA wording was further informed by the recognition-and-recall conceptualization in [19], and BE wording was adapted to the TikTok fashion-brand context from the cognitive, affective, and behavioral engagement dimensions in [20]. The planned-purchase item was additionally informed by the behavioral-intention formulation in [21], while the remaining items broadened PRIs for the purposes of this study.

5.3. Quantitative Analysis

The quantitative results were produced in R 4.4.1 using RStudio 2024.04.2 under Windows 10. The principal packages were plspm 0.6.0, psych 2.6.5, pwr 1.3-0, cluster 2.1.6, mclust 6.1.1, ranger 0.18.0, e1071 1.7-16, and gbm 2.2.3.

PLS-PM was selected for the primary prediction-oriented association model; it was not selected to establish causality. Among the complementary analyses, standardized PLS-PM construct scores were used in the two-stage demographic moderation models. The remaining complementary analyses used purpose-specific inputs: clustering used standardized equal-weight TCI, BA, and BE means; machine learning used the 12 TCI, BA, and BE indicators to predict the equal-weight PRIs mean; and MCDM combined total structural association with PRIs, direct f^2 on PRIs, and grouped predictive Δ RMSE. Reflective measurement assessment used loadings, Cronbach's alpha, McDonald's omega total (ω_{total}), composite reliability, AVE, and HTMT [27–29]. Structural assessment used standardized path coefficients, bootstrap intervals, R^2 , structural VIF, f^2 , and statistical indirect associations [30]. The model used path weighting, reflective Mode A blocks, and scaled data. No post hoc formative TCI model was estimated because such a model would define a different composite through theoretically specified indicator contributions rather than test the same latent construct under an interchangeable estimator. The reported structural coefficients are therefore conditional on the reflective working specification. Parallel-predictor, formative-composite, multidimensional, and alternative BA–BE specifications remain priorities for independent sensitivity analysis.

Main-path and indirect-effect uncertainty was estimated from 10,000 case-resampling bootstrap samples using `sample.int()`; `stats::sd()` and `stats::quantile()` supplied bootstrap standard errors and percentile intervals. HTMT was evaluated against the prespecified 0.85 descriptive threshold; no bootstrapped HTMT inference was performed. With $n = 268$ and a maximum of three predictors in an endogenous equation, `pwr::pwr.f2.test()` indicated a minimum detectable f^2 of 0.041 at $\alpha = 0.05$ and power = 0.80 for the main-effect regression setting. This sensitivity calculation does not establish adequate power for small demographic interactions or sparse subgroup contrasts.

Out-of-sample prediction was examined through repeated 10-fold cross-validation with 10 repetitions. The script's `run_pls_predict()` routine re-estimated the PLS model, scaling, structural regressions, and indicator prediction equations within every training fold. Fold-specific regressions and predictions used `stats::lm()` and `stats::predict()`. Q^2 predict was calculated against the training-mean benchmark, and RMSE and MAE were also compared with a linear-regression benchmark [31]. The full-collinearity diagnostic was derived from auxiliary `stats::lm()` regressions; values below 3.3 do not eliminate same-source bias in a cross-sectional survey [32,33]. The 27 ineligible records were retained in the raw-data sheet but were not used in the sensitivity model.

To assess whether use intensity or fashion-content exposure distinguished the observed outcomes, Kruskal–Wallis tests compared equal-weight BA, BE, and PRI means across the original categories. The tests were obtained with `stats::kruskal.test()`, and `stats::p.adjust(method = "holm")` controlled family-wise error across the six tests [34]. These comparisons are descriptive and do not identify causal exposure effects.

Demographic moderation was evaluated exploratorily using two-stage interaction models based on standardized PLS-PM construct scores [27,28]. Five binary moderators were used to avoid sparse categories: women versus men; the youngest recorded age category ('Under 20') versus the two older recorded categories (21–30 and 31 or older); residence in settlements with 50,000 residents or fewer versus larger settlements; household income below versus above BGN 1547 (approximately EUR 791) per household member; and secondary versus higher education. All participants were at least 18 years old. However, the supplied age categories do not separately identify respondents aged 18, 19, or 20; consequently, the moderation contrast is interpreted as a recorded age-category comparison rather than a precise age threshold. Each structural equation included its original predictors, the moderator main effect, and all corresponding interactions. Holm correction controlled the 30 path-specific tests. RQ5 was addressed by asking whether any interaction received adjusted support; omnibus block tests were treated as secondary diagnostics.

As a complementary robustness analysis, the five demographic variables were also entered simultaneously as direct covariates in the BA, BE, and PRI equations. The companion `fit_demographic_effect_equation()` routine used `stats::lm.fit()` for the original and adjusted equations and `stats::pf()` for the nested demographic-block comparisons. Case-resampling bootstrap intervals were calculated for each adjusted demographic direct effect and for changes in the six original structural coefficients. Holm correction through `stats::p.adjust()` was applied separately to the three demographic-block tests, the 15 direct-effect tests, the six adjusted structural paths, and the six coefficient-change tests. This analysis assesses robustness to demographic adjustment and is distinct from the interaction-based moderation analysis.

5.4. Exploratory Data Quality, Response Structure, and Machine-Learning Analysis

An additional data-quality audit examined duplicate response identifiers and timestamps, exact and near-duplicate structured profiles, missingness, response-range and integer consistency, eligibility-flag agreement, straight-line responding, and low within-person variation. Exact structured profiles were flagged with `duplicated()`, while near-duplicate item profiles within the same response context were screened using `stats::dist(method = "manhattan")`. Row-wise `stats::sd()` and run-length encoding through `rle()` supported the straight-line and long-string checks. Flagged profiles were documented rather than automatically deleted because anonymous response similarity does not establish respondent identity. Reliability diagnostics included standardized alpha, approximate omega total, corrected item-total correlations, alpha if an item was deleted, and item-level floor and ceiling percentages. As a prespecified robustness check, the 25 straight-line profiles were excluded, and construct reliability was re-estimated [35,36]. The structural, clustering, predictive, and MCDM analyses were not re-estimated after this exclusion; therefore, the check supports only the stability of the reported reliability conclusions.

The exploratory response structure was first visualized from the 16 standardized indicators using pairwise Euclidean respondent dissimilarities and Ward.D2 hierarchical heatmaps. Standardization used `scale()`; Euclidean distances, Ward trees, and heatmaps used `stats::dist()`, `stats::hclust(method = "ward.D2")`, and `stats::heatmap()`, respectively. One heatmap clustered respondents and a second clustered indicators; respondent labels were suppressed because records were anonymous and the dendrograms were used

descriptively. Exploratory clustering then used standardized equal-weight means for TCI, BA, and BE; PRIs was excluded from cluster formation. K-means solutions for $k = 2-6$ were estimated with `stats::kmeans(nstart = 100, iter.max = 1000)` and assessed using `cluster::silhouette()`, a directly calculated Calinski–Harabasz index, and the custom `davies_bouldin_index()` function [37–39]. The solutions for $k = 2-5$ were projected onto the first two principal components using `stats::prcomp()`, while cluster selection remained based on the full standardized equal-weight TCI, BA, and BE mean-score space. Ward hierarchical clustering and `mclust::adjustedRandIndex()` provided an algorithmic stability comparison [40]. Cluster means were interpreted only as lower- and higher-response-intensity partitions of this sample, not as consumer profiles, population segments, or causal types.

A separate internal prediction analysis estimated the equal-weight PRIs mean from the 12 TCI, BA, and BE indicators using 10-fold cross-validation repeated five times. The target was an equal-weight PRIs score, not the PLS-PM construct score, so the predictive and structural outcomes are closely related but not identical. Linear regression, ridge regression, radial-basis support-vector regression, random forest [41], extra trees, and gradient boosting were compared with the training-mean benchmark. Hyperparameters were fixed before performance evaluation as transparent, nonoptimized specifications; no outcome-based search was conducted. Performance was summarized across 50 held-out folds. Grouped permutation importance was descriptive, and no formal uncertainty test compared the ensemble models. Outcome indicators were never included among their own predictors.

5.5. Open-Response Analysis

The two open questions asked which TikTok content elements attract attention to a fashion brand (column Z) and requested an example associated with a brand opinion or purchase decision (column AA). The English translations were analyzed after applying the principal-sample eligibility rule. An R 4.4.1 script normalized the text and produced multi-label dictionary assignments, candidate counts, and token frequencies. The coding dictionary and category set were fixed before manual verification, and no new categories were introduced during that stage. One member of the research team manually reviewed all row-level English translations and dictionary-assisted assignments against the original Bulgarian responses. Ambiguous cases were discussed within the research team, after which the final assignments and reported counts were confirmed. Punctuation-only entries were retained in the non-empty denominators and coded as no relevant answer. Percentages use the number of non-empty responses to each question and may exceed 100% because labels are nonexclusive. This procedure is limited to descriptive, deductive category classification and is not a rigorous independent thematic analysis [42]. Because the records were not independently double-coded, no intercoder-agreement statistic was calculated; consequently, the classifications should be treated as researcher-verified descriptive counts rather than independently reproducible qualitative findings. The text categories were not used in structural estimation, prediction, clustering, or MCDM and were not interpreted as evidence of marketing effectiveness.

For reproducibility, the category dictionary, indicative lexical cues, and row-level assignment and verification rules are provided in Supplementary File S1. The cues generated candidate assignments only; the final multi-label classifications depended on manual comparison with the complete response and the original Bulgarian wording.

5.6. Illustrative Multi-Criteria Synthesis

MCDM addressed the illustrative analytical question after the measurement, structural, and predictive analyses. The limited-scope comparison considered TCI, BA, and BE under three sample-derived benefit criteria: total structural association with PRIs, direct f^2 on PRIs, and grouped predictive Δ RMSE. Measurement quality was an admissibility condition and was not weighted; the alternatives were measured constructs rather than campaigns or interventions.

TOPSIS, VIKOR, EDAS, and WASPAS were applied to the same fixed decision matrix under equal criterion weights, with CRITIC weights used as a sensitivity check [43–47]. Agreement across these combinations evaluates only aggregation and weighting sensitivity for this matrix.

Within the architecture, the purpose of this component is methodological rather than prescriptive: it demonstrates how heterogeneous construct-level outputs can be translated into a transparent, auditable summary under explicit criteria and weights. Its added value lies in making the synthesis step traceable and sensitivity-checkable, not in producing a market recommendation; with only three constructs and sample-derived criteria, the resulting order remains internal to this dataset.

6. Results

6.1. Respondent Profile and Construct Descriptives

The principal sample consisted predominantly of women (76.9%) and respondents in the youngest recorded age category ('Under 20'; 66.4%); a further 30.6% were recorded as aged 21–30 (Table 4). Daily TikTok use was reported by 87.7%, and 70.9% reported often encountering fashion-brand content. The profile therefore represents a young, highly active TikTok audience rather than the Bulgarian population as a whole.

Table 4. Profile of the principal analysis sample ($n = 268$).

Characteristic	Category	<i>n</i>	%
Gender	Female	206	76.9
	Male	62	23.1
Age	Under 20	178	66.4
	21–30	82	30.6
	31 or older	8	3.0
Residence	>50,000 residents	139	51.9
	1000–50,000	115	42.9
	<1000	14	5.2
TikTok use	Daily	235	87.7
	Weekly	13	4.9
	Rarely	20	7.5
Fashion content	Often	190	70.9
	Sometimes	64	23.9
	Very rarely	14	5.2

The data-quality audit found no duplicate response identifiers or timestamps, no missing Likert responses, no out-of-range or non-integer Likert values, and no disagreement between the stored eligibility flag and the questionnaire rule. Three pairs of identical profiles across the predefined structured comparison variables were identified. Two pairs—records 4 and 50 and records 13 and 57—were among the 268 eligible respondents, whereas one pair—records 264 and 281—was among the 27 excluded respondents. These are not completely duplicated records because timestamps, municipalities, and/or open responses

differ. Twenty-five principal-sample records showed straight-line responding across all 16 audited indicators; they were retained in the primary analysis and examined through sensitivity checks rather than treated as automatically invalid.

In terms of geographic distribution, municipality names were normalized to correct spelling, capitalization, and administrative-prefix variants before calculating the distributions. Among the 268 eligible respondents, the largest share was from Plovdiv Municipality (125 respondents; 46.6%), followed by Asenovgrad (11 respondents; 4.1%). Burgas and Pazardzhik were each represented by nine respondents (3.4%). Overall, the eligible sample was strongly concentrated in the South Central Region (217 respondents; 81.0%), followed by the South East Region (40 respondents; 14.9%) and the South West Region (6 respondents; 2.2%). The remaining five respondents (1.9%) were distributed across the North West, North Central, and North East regions.

Brand awareness had the highest mean ($M = 3.422$), followed by TCI ($M = 3.042$) and brand engagement ($M = 2.937$) (Table 5). Purchase-related intentions were lower ($M = 2.565$), indicating that recognition and content involvement did not automatically translate into strong purchase-related responses. All construct correlations were positive, with the strongest associations between TCI and BE ($r = 0.710$) and between BE and PRIs ($r = 0.696$).

Table 5. Construct descriptives and correlations.

Construct	Mean	SD	TCI	BA	BE	PRIs
TCI	3.042	0.974	1.000			
BA	3.422	0.982	0.683	1.000		
BE	2.937	0.989	0.710	0.647	1.000	
PRIs	2.565	0.992	0.633	0.509	0.696	1.000

Respondent-level distances based on all 16 standardized indicators showed a broad, continuous response-intensity gradient (Figure 3). Blocks of relatively similar profiles were visible, but no sharp discontinuity justified treating the sample as naturally dichotomous. The matrix is a descriptive diagnostic and did not enter the PLS-PM estimation.

6.2. Reflective Measurement Assessment

All indicator loadings exceeded 0.70 (Table 6). Alpha and CR values exceeded 0.80, approximate omega ranged from 0.834 to 0.932, and AVE ranged from 0.665 to 0.831. The lowest corrected item-total correlation was 0.561 (TCI2), and item-deletion diagnostics did not provide a reliability-based reason to remove an indicator. The largest HTMT value was 0.822 (TCI–BE), below the prespecified 0.85 descriptive threshold; bootstrapped HTMT inference was not conducted. After excluding the 25 straight-line profiles, alpha remained acceptable for every construct (0.797–0.914). These diagnostics support the internal consistency of the four working reflective blocks in this sample, but they do not establish content validity or rule out formative or multidimensional TCI specifications and narrower PRIs specifications.

Table 6. Reflective measurement-model assessment.

Construct	Items	Loading Range	Alpha	Omega	CR	AVE
TCI	4	0.730–0.871	0.832	0.834	0.888	0.665
BA	4	0.805–0.882	0.882	0.884	0.919	0.740
BE	4	0.851–0.890	0.890	0.890	0.924	0.751
PRIs	4	0.897–0.927	0.932	0.932	0.952	0.831

Note: Omega denotes approximate omega total.

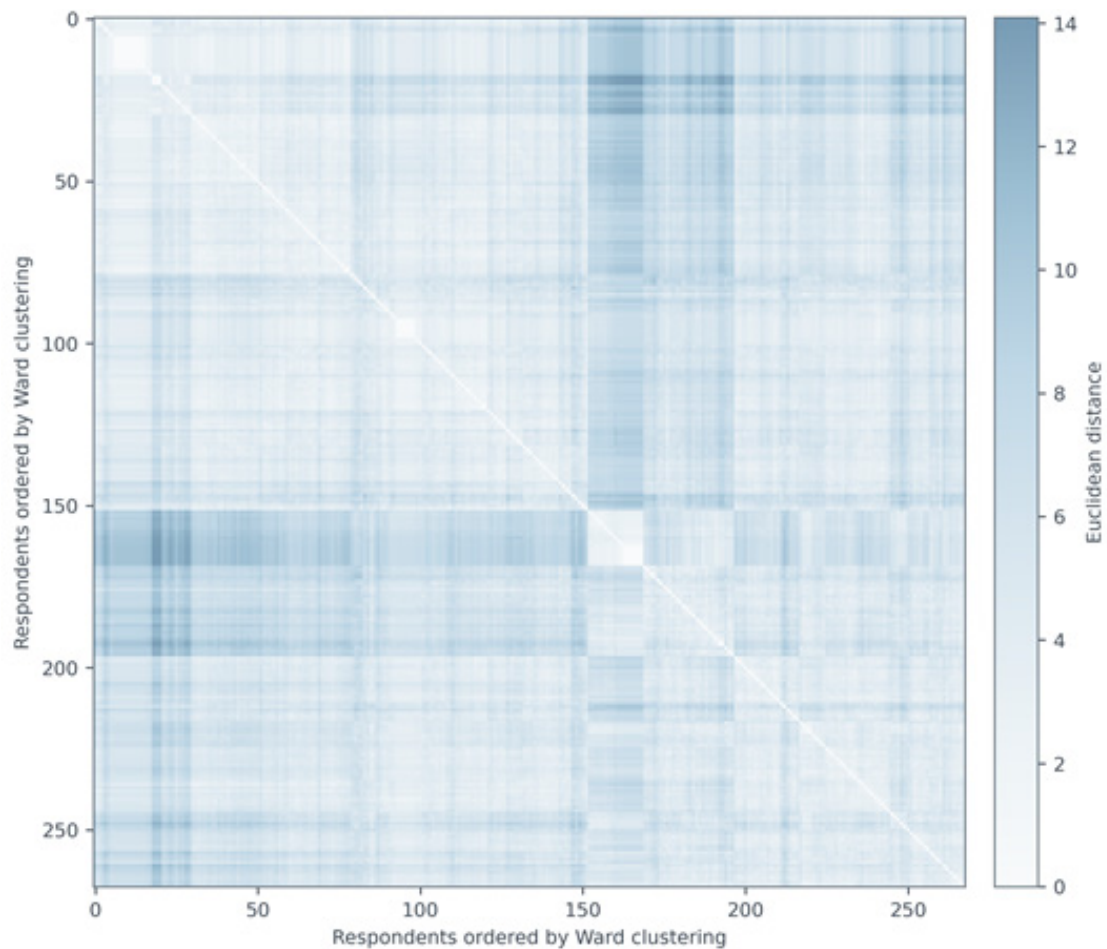


Figure 3. Respondent-level Euclidean dissimilarity matrix based on the 16 standardized indicators in the principal sample ($n = 268$). Darker cells indicate greater dissimilarity.

6.3. Structural Model and Hypothesis Tests

Five of the six hypothesized associations received bootstrap support (Figure 4 and Table 7). TCI was positively associated with BA ($\beta = 0.683$), BE ($\beta = 0.512$), and PRIs ($\beta = 0.283$). BA was positively associated with BE ($\beta = 0.300$) but had no incremental direct association with PRIs after TCI and BE were included ($\beta = -0.002$, $p = 0.940$). BE showed the strongest direct association with PRIs ($\beta = 0.496$). The model explained 46.7% of BA variance, 56.2% of BE variance, and 52.5% of PRIs variance. Structural VIFs ranged from 1.000 to 2.474. Effect sizes were large for TCI $\rightarrow$ BA ($f^2 = 0.876$), moderate for TCI $\rightarrow$ BE (0.318) and BE $\rightarrow$ PRIs (0.227), small for BA $\rightarrow$ BE (0.109) and TCI $\rightarrow$ PRIs (0.068), and negligible for BA $\rightarrow$ PRIs. These coefficients apply to the aggregate working specifications of TCI and broad PRIs and should not be attributed to their individual facets.

Table 7. Structural paths and hypothesis results.

Hypothesis	Relationship	β	SE	95% CI	p	Decision	VIF	f^2
H1	TCI $\rightarrow$ BA	0.683	0.043	[0.591, 0.760]	<0.001	Supported	1.000	0.876
H2	TCI $\rightarrow$ BE	0.512	0.075	[0.364, 0.655]	<0.001	Supported	1.876	0.318
H3	TCI $\rightarrow$ PRIs	0.283	0.077	[0.135, 0.438]	<0.001	Supported	2.474	0.068
H4	BA $\rightarrow$ BE	0.300	0.081	[0.142, 0.462]	<0.001	Supported	1.876	0.109
H5	BA $\rightarrow$ PRIs	−0.002	0.085	[−0.168, 0.163]	0.940	Not supported	2.082	0.000
H6	BE $\rightarrow$ PRIs	0.496	0.081	[0.332, 0.651]	<0.001	Supported	2.282	0.227

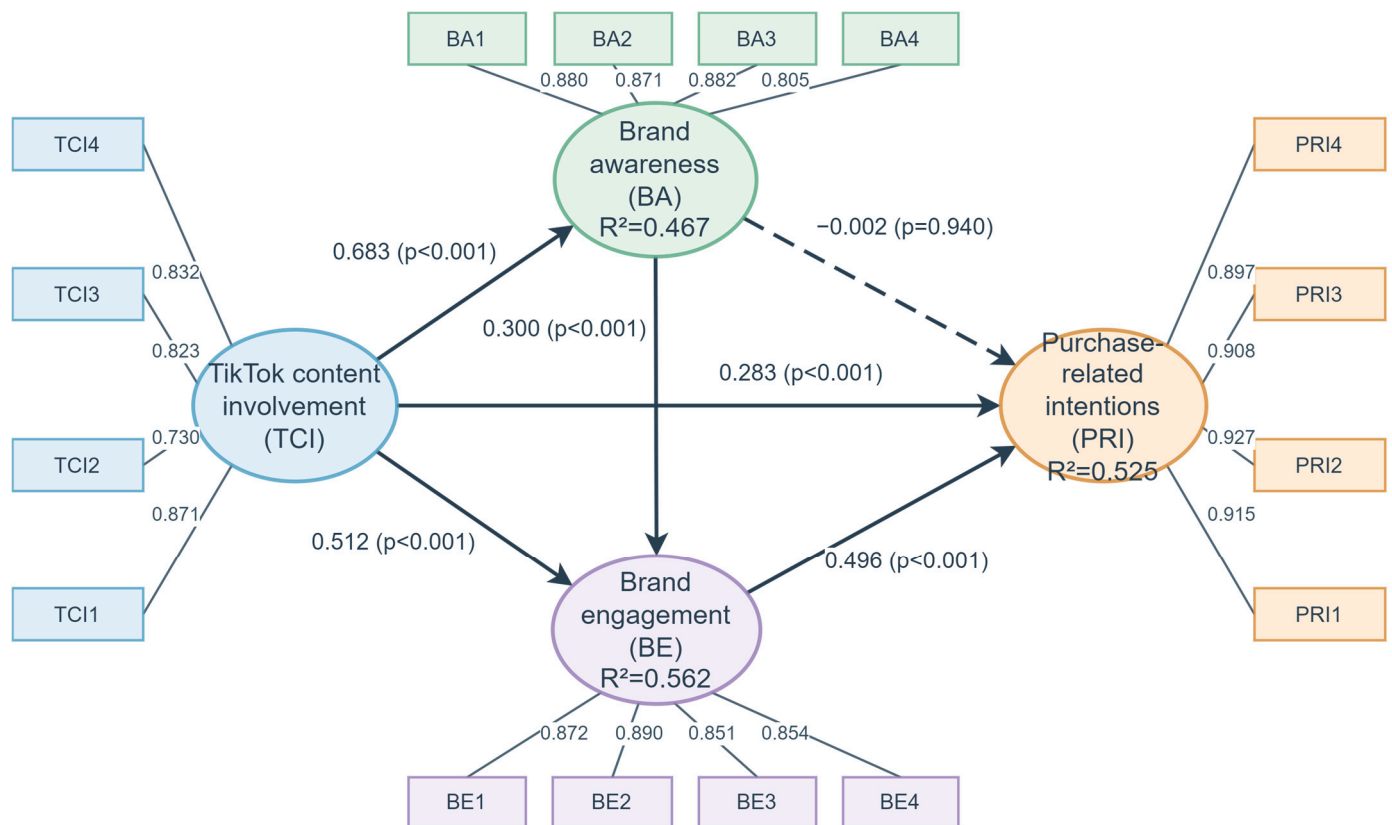


Figure 4. R 4.4.1-derived PLS-PM measurement and structural model. Values beside indicators are reflective loadings; values on paths are standardized coefficients with bootstrap p -values; values inside endogenous constructs are R^2 . The dashed BA $\rightarrow$ PRIs path was nonsignificant.

6.4. Indirect Effects

The specified model yielded a nonsignificant TCI–BA–PRIs statistical indirect association and positive TCI–BE–PRIs and TCI–BA–BE–PRIs indirect associations (Table 8). Under this model, BA was statistically associated with PRIs through BE ($\beta = 0.149$), while its incremental direct association with PRIs was negligible. The total statistical indirect association from TCI to PRIs was 0.354. These coefficient products describe model-dependent associations in cross-sectional data and do not establish temporal or causal mediation.

Table 8. Bootstrapped indirect effects.

Indirect Relationship	β	SE	95% CI	p
TCI $\rightarrow$ BA $\rightarrow$ PRIs	−0.001	0.058	[−0.118, 0.109]	0.940
TCI $\rightarrow$ BE $\rightarrow$ PRIs	0.254	0.051	[0.160, 0.356]	<0.001
TCI $\rightarrow$ BA $\rightarrow$ BE $\rightarrow$ PRIs	0.102	0.037	[0.041, 0.185]	<0.001
BA $\rightarrow$ BE $\rightarrow$ PRIs	0.149	0.052	[0.062, 0.265]	<0.001
TCI total indirect	0.354	0.058	[0.236, 0.465]	<0.001

6.5. Prediction and Group Comparisons

Repeated 10-fold cross-validation produced positive Q^2 predict values for all four PRIs indicators (Table 9). PLS RMSE and MAE values were lower than those of the training-mean benchmark in every case and were close to the linear-regression benchmark. The comparison therefore supports useful internal prediction without implying that PLS is uniformly superior to a simple linear model. The result has not been externally validated and should not be interpreted as a forecast of observed fashion purchases.

Table 9. Repeated cross-validated prediction of purchase-related-intention indicators.

Indicator	Q ² Predict	PLS RMSE	Linear RMSE	Mean RMSE	PLS MAE	Linear MAE	Mean MAE
PRIs1	0.453	0.823	0.842	1.113	0.644	0.654	0.948
PRIs2	0.464	0.793	0.806	1.083	0.604	0.614	0.926
PRIs3	0.374	0.832	0.836	1.051	0.617	0.625	0.899
PRIs4	0.390	0.874	0.882	1.119	0.678	0.683	0.965

Full-collinearity VIFs ranged from 2.082 to 2.799, below 3.3. This auxiliary result reduces concern about severe common-method inflation but does not eliminate same-source or self-report bias. The 27 records failing the TikTok-use/content-exposure eligibility rule were not included in structural sensitivity analysis.

TikTok-use frequency did not distinguish BA, BE, or PRIs after Holm correction. In contrast, self-reported fashion-content exposure distinguished all three outcomes (Table 10): BA, $H(2) = 20.807$, $p_{\text{Holm}} < 0.001$; BE, $H(2) = 9.976$, $p_{\text{Holm}} = 0.027$; and PRIs, $H(2) = 23.948$, $p_{\text{Holm}} < 0.001$. Effect sizes were small to moderate ($\epsilon^2 = 0.030$ – 0.083). Respondents reporting frequent exposure had higher mean BA, BE, and PRIs than those reporting very rare exposure. These unadjusted group differences may reflect self-selection or pre-existing interest and do not identify exposure effects.

Table 10. Kruskal–Wallis comparisons across TikTok-use and fashion-content-exposure categories.

Grouping Variable	Outcome	H	df	p	pHolm	ϵ^2
TikTok use frequency	BA	4.092	2	0.129	0.259	0.008
TikTok use frequency	BE	1.168	2	0.558	0.558	0.000
TikTok use frequency	PRIs	5.495	2	0.064	0.192	0.013
Fashion-content exposure	BA	20.807	2	<0.001	<0.001	0.071
Fashion-content exposure	BE	9.976	2	0.007	0.027	0.030
Fashion-content exposure	PRIs	23.948	2	<0.001	<0.001	0.083

6.6. Demographic Moderation

No path-specific demographic interaction received Holm-adjusted support; the smallest corrected value was $p_{\text{Holm}} = 0.948$. The only nominal result was a gender interaction for BA → PRIs ($\Delta\beta = -0.309$, bootstrap $p = 0.032$, 95% CI $[-0.615, -0.033]$), but it did not survive correction. Its omnibus PRIs interaction block added $\Delta R^2 = 0.016$ ($F(3, 260) = 3.081$, raw $p = 0.028$, $p_{\text{Holm}} = 0.420$, Table 11). RQ5 therefore received no multiplicity-adjusted support in this sample; small moderation effects may remain undetected. The nominal result is reported for transparency and is not treated as a reproducible subgroup difference.

In the complementary demographic-adjustment models, adding gender, age, residence size, household income, and education increased R^2 from 0.467 to 0.481 for BA, from 0.562 to 0.576 for BE, and from 0.525 to 0.540 for PRIs ($\Delta R^2 = 0.014$, 0.015, and 0.015, respectively). None of the three demographic blocks was significant after Holm correction (all $p_{\text{Holm}} = 0.345$). None of the 15 adjusted demographic direct effects survived correction; the smallest corrected value was $p_{\text{Holm}} = 0.216$ for the gender coefficient in the BE equation. All five supported structural paths remained significant after adjustment, BA → PRIs remained nonsignificant, and none of the six coefficient changes survived Holm correction. The original structural conclusions were therefore stable to simultaneous demographic adjustment.

Table 11. Omnibus demographic interaction-block tests across the endogenous constructs.

Moderator	Outcome	ΔR^2	F (df1, df2)	p	pHolm	Significant
Gender	BA	0.002	0.758 (1, 264)	0.385	1.000	No
Gender	BE	0.000	0.053 (2, 262)	0.948	1.000	No
Gender	PRIs	0.016	3.081 (3, 260)	0.028	0.420	No
Age	BA	0.009	4.370 (1, 264)	0.038	0.525	No
Age	BE	0.002	0.591 (2, 262)	0.555	1.000	No
Age	PRIs	0.009	1.689 (3, 260)	0.170	1.000	No
Residence size	BA	0.008	4.004 (1, 264)	0.046	0.603	No
Residence size	BE	0.006	1.894 (2, 262)	0.153	1.000	No
Residence size	PRIs	0.003	0.526 (3, 260)	0.665	1.000	No
Household income	BA	0.005	2.568 (1, 264)	0.110	1.000	No
Household income	BE	0.001	0.151 (2, 262)	0.860	1.000	No
Household income	PRIs	0.005	0.849 (3, 260)	0.468	1.000	No
Education	BA	0.001	0.389 (1, 264)	0.533	1.000	No
Education	BE	0.003	0.772 (2, 262)	0.463	1.000	No
Education	PRIs	0.000	0.071 (3, 260)	0.975	1.000	No

Note: Omnibus *p*-values were Holm-adjusted across 15 interaction-block tests. RQ5 was evaluated primarily through 30 bootstrapped path-specific interactions; none received adjusted support.

6.7. Exploratory Response Structure and Machine-Learning Prediction

Across $k = 2$ – 6 , $k = 2$ had the strongest internal validation indices: the highest silhouette coefficient (0.449) and Calinski–Harabasz index (278.755), and the lowest Davies–Bouldin index (0.865; Table 12). Ward and *k*-means agreement was substantial but not near-perfect (adjusted Rand index = 0.769). The solution separated 87 lower-rating and 181 higher-rating response-intensity partitions. Because TCI, BA, and BE were strongly positively correlated, this division primarily reflects a gradient in general response intensity rather than distinct consumer groups. PRIs was excluded from cluster formation; its post-cluster difference is descriptive and is expected to some extent from its correlations with the clustering variables. Temporal stability and external cluster validity were not assessed.

Table 12. Internal validation of outcome-excluded *k*-means solutions.

k	Total Within-Cluster SS	Silhouette	Calinski–Harabasz	Davies–Bouldin	Selected
2	391.123	0.449	278.755	0.865	Yes
3	275.159	0.356	253.213	0.956	No
4	224.581	0.311	225.864	1.069	No
5	196.209	0.289	202.666	1.136	No
6	171.927	0.284	191.730	1.135	No

Note: Clusters were estimated from standardized equal-weight TCI, BA, and BE scores; PRIs was excluded. Higher silhouette and Calinski–Harabasz values and lower Davies–Bouldin values indicate stronger separation. The within-cluster sum of squares decreases mechanically as *k* increases and was not used alone for selection.

The hierarchical views give a complementary item-level description. The respondent heatmap (Figure 5) shows broad lower- and higher-response bands while preserving substantial within-band variation. The indicator heatmap (Figure 6) recovers coherent within-construct groupings and also visualizes the comparatively close TCI–BE and BE–PRIs relationships found in the correlation and structural analyses. These dendrograms summarize similarity; they do not establish a fixed number of latent classes.

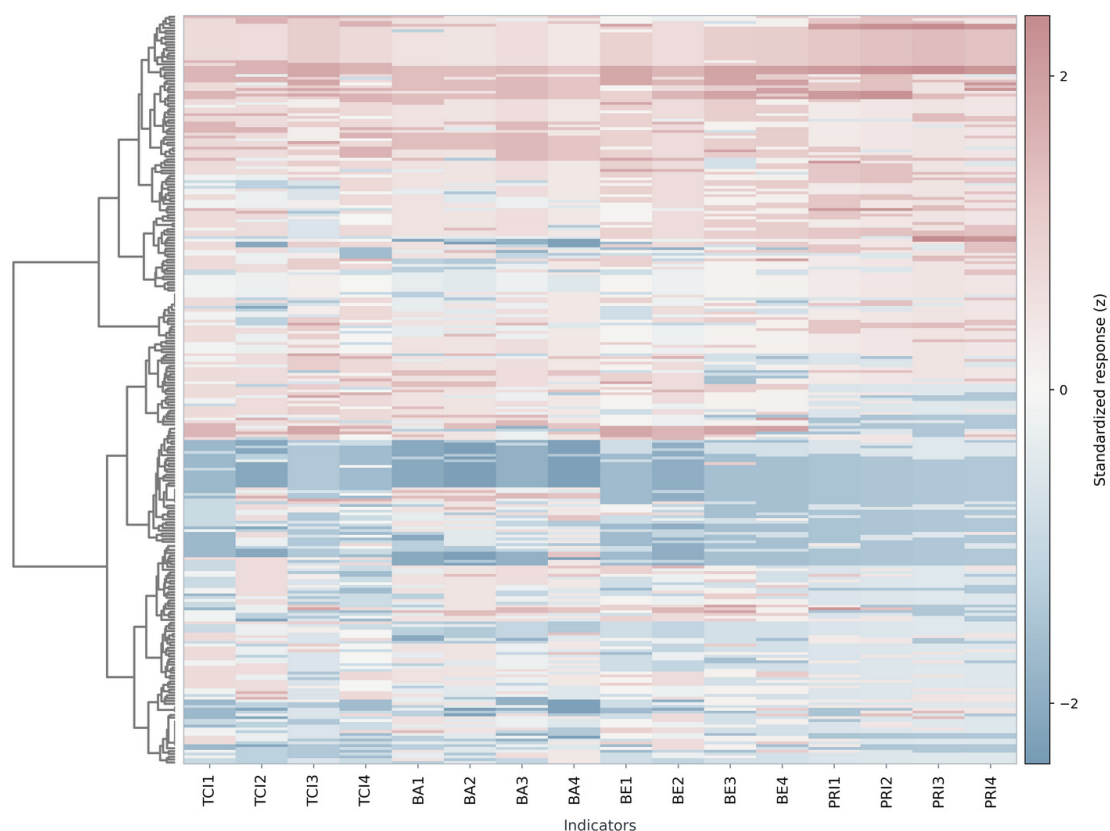


Figure 5. Ward hierarchical-clustering heatmap of respondents based on the 16 standardized indicators. Dendrogram labels are suppressed because rows represent anonymous response records.

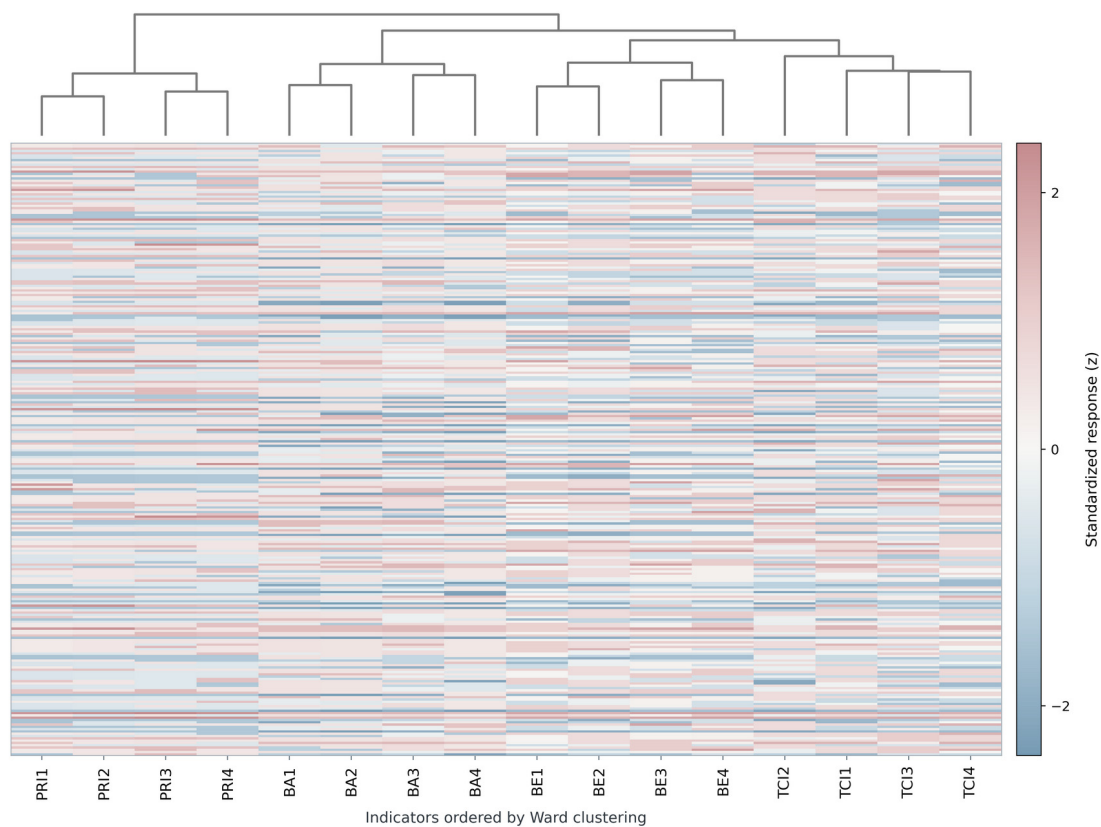


Figure 6. Ward hierarchical heatmap of the 16 standardized indicators across respondents. The color scale represents within-indicator standardized values.

The principal-component projections in Figure 7 make the selection trade-off visible. The $k = 2$ panel provides the clearest broad separation; solutions with three to five clusters subdivide the same response continuum and show increasing overlap in the two-dimensional projection. Because the panels display only the first two components, the formal selection is based on the full-space indices in Table 12 rather than on visual separation alone.

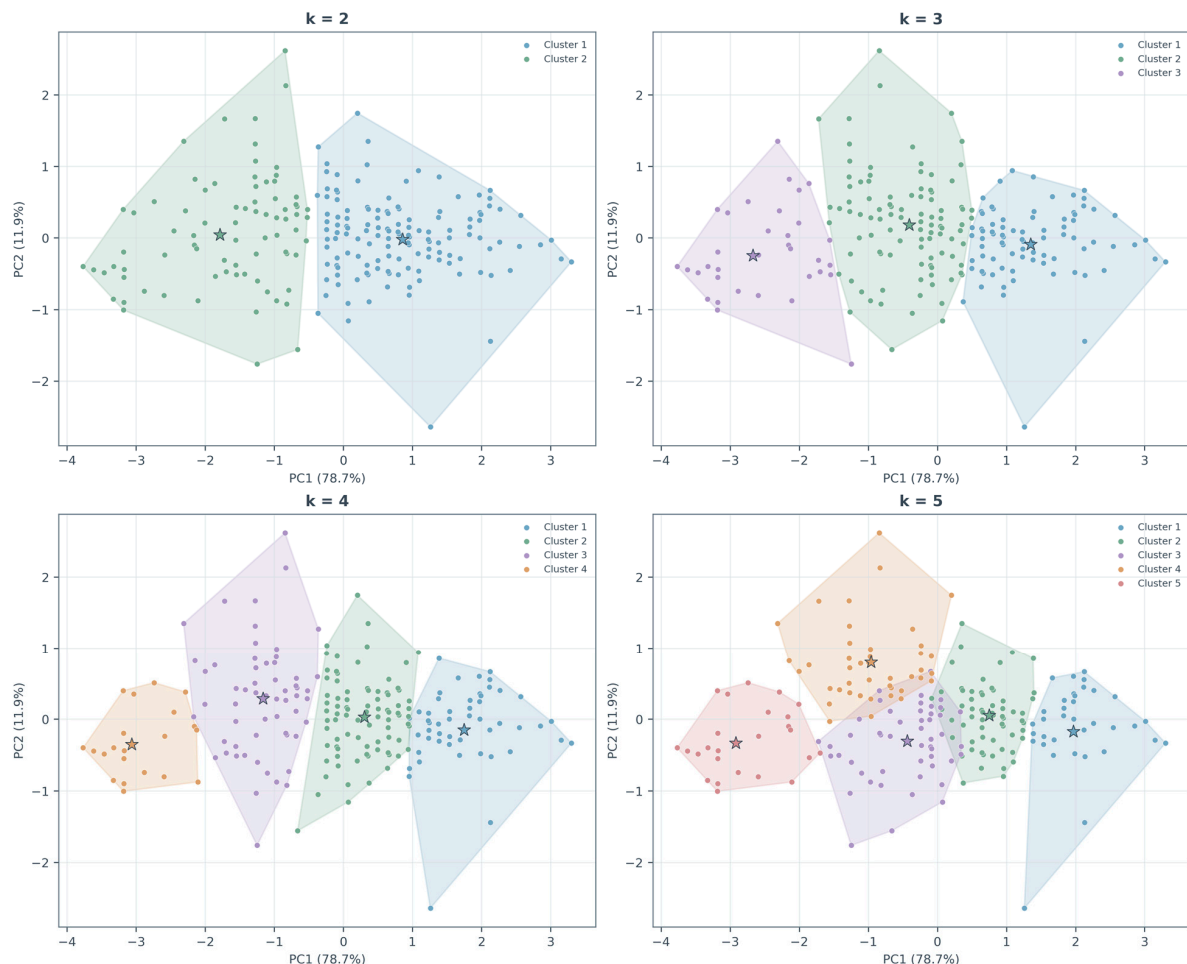


Figure 7. Principal-component visualization of k -means solutions for $k = 2$ –5. The panels are descriptive projections; cluster selection was based on the full standardized equal-weight TCI, BA, and BE mean-score space. Note: Stars indicate the cluster centroids in the two-dimensional PC1–PC2 projection; they do not denote statistical significance.

The selected $k = 2$ solution yielded a higher-response-intensity partition ($n = 181$) and a lower-response-intensity partition ($n = 87$), with consistently higher mean TCI, BA, and BE scores in the former; the PRIs mean, assessed only after partition assignment, showed the same descriptive pattern (Table 13).

Table 13. Outcome-excluded exploratory response-intensity partitions.

Response-Intensity Partition	n	TCI Mean	BA Mean	BE Mean	PRIs Mean
1: Higher response intensity	181	3.528	3.887	3.443	2.975
2: Lower response intensity	87	2.032	2.454	1.882	1.713

Note: PRIs was not used to define the response-intensity partitions and was compared only after partition assignment. These partitions describe an overall response-intensity gradient and should not be interpreted as distinct consumer segments.

Random forest achieved the lowest mean fold-level error (RMSE = 0.651, SD = 0.103; MAE = 0.481, SD = 0.078) and the highest mean held-out R^2 (0.521, SD = 0.170), improving RMSE by 34.1% relative to the training-mean benchmark (Table 14). Gradient boosting and extra trees produced closely similar results, and no formal uncertainty test compared the ensemble methods. Grouped permutation analysis identified BE as the largest predictor group, followed by TCI and BA. The target was the equal-weight PRIs mean rather than the PLS-PM construct score. These results describe internal predictive performance and require external validation.

Table 14. Repeated 10-fold cross-validated prediction of the purchase-related-intentions mean.

Model	RMSE (SD)	MAE (SD)	R^2 (SD)	RMSE Improvement (%)
Training-mean benchmark	0.987 (0.120)	0.841 (0.113)	−0.053 (0.087)	0.0
Linear regression	0.696 (0.110)	0.533 (0.078)	0.451 (0.196)	29.6
Ridge regression	0.692 (0.110)	0.531 (0.078)	0.457 (0.192)	29.9
SVR-RBF	0.774 (0.133)	0.586 (0.098)	0.305 (0.305)	21.6
Random forest	0.651 (0.103)	0.481 (0.078)	0.521 (0.170)	34.1
Extra trees	0.673 (0.112)	0.493 (0.084)	0.486 (0.193)	31.9
Gradient boosting	0.671 (0.104)	0.512 (0.078)	0.493 (0.169)	32.1

Note: Values are means and standard deviations across 50 held-out folds (five repetitions of 10-fold cross-validation). R^2 was computed separately within each held-out fold and then summarized across folds.

6.8. Open-Response Findings

The attention question contained 230 non-empty eligible responses, including three punctuation-only entries. After manual verification of the dictionary-assisted assignments against the original Bulgarian responses, presentation and visual style was assigned to 84 responses (36.5%), reviews or product demonstrations to 62 (27.0%), influencers or creators to 61 (26.5%), and music, humor, or entertainment to 48 (20.9%). No relevant experience was assigned to 12 responses (5.2%), authenticity or credibility to 9 (3.9%), and trends or participation to 7 (3.0%); price, promotion, or availability was not assigned for this question (Figure 8). The categories are descriptive and nonexclusive and do not measure the relative effectiveness of the identified content elements.

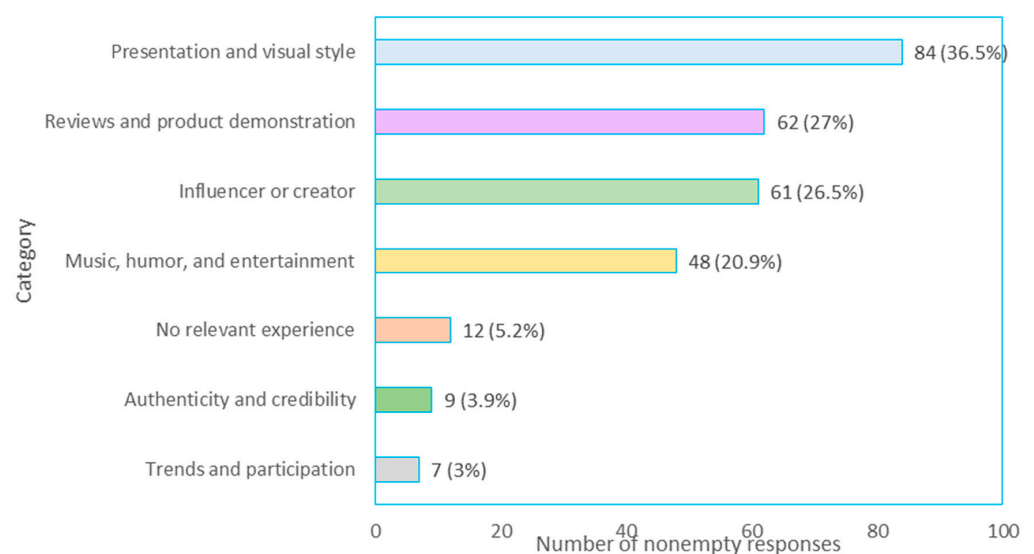


Figure 8. Manually verified multi-label categories in responses concerning attention to TikTok fashion-brand content ($n = 230$ non-empty eligible responses). Dictionary-assisted assignments were checked against the original Bulgarian responses; the categories are descriptive and nonexclusive.

The influence-case question contained 201 non-empty eligible responses, including six punctuation-only entries. Manual verification assigned no relevant experience or recall to 38 responses (18.9%), presentation and visual style to 35 (17.4%), reviews or product demonstrations to 32 (15.9%), influencers or creators to 22 (10.9%), authenticity or credibility to 6 (3.0%), price, promotion, or availability to 6 (3.0%), and music, humor, or entertainment to 2 (1.0%). In the separate consequence coding, no relevant case or influence was assigned to 38 responses (18.9%), positive opinion or increased interest to 22 (10.9%), completed purchase to 9 (4.5%), brand discovery or awareness to 8 (4.0%), purchase consideration or intention to 8 (4.0%), and negative opinion, avoidance, or return to 3 (1.5%). The categories are descriptive, nonexclusive, and do not claim exhaustive thematic coverage or causal effects.

6.9. Results of the Illustrative Multi-Criteria Synthesis

Table 15 presents the fixed three-construct decision matrix. TCI had the largest total association with PRIs, whereas BE had the largest direct f^2 and grouped predictive contribution; BA had a negligible direct f^2 .

Table 15. Inputs to the illustrative, sample-internal MCDM synthesis of construct-level analytical relevance.

Construct	Total Association with PRIs	Direct f^2 on PRIs	Grouped ML Δ RMSE	Quality Check
TCI	0.637	0.068	0.139	Passed
BA	0.147	0.000	0.071	Passed
BE	0.496	0.227	0.242	Passed

Note: The first three columns are benefit criteria. Total association includes direct and estimated indirect structural pathways. Δ RMSE is the deterioration in cross-validated prediction after grouped permutation; a larger value denotes greater predictive contribution. All constructs passed the separate measurement-quality assessment reported in Table 6; this status was not weighted in the MCDM. All criteria and values are derived from the present sample and model. The resulting order is an internal descriptive summary and does not represent a stakeholder-informed priority ordering for marketing practice.

All four methods produced the same order under equal and CRITIC weights: BE first, TCI second, and BA third. This result indicates insensitivity only to the examined aggregation formulas and weighting schemes for the fixed sample-derived matrix. It is not a stakeholder-informed priority ordering and should not be transferred to marketing practice.

7. Discussion

7.1. Interpretation of the Main Findings

The results distinguish awareness from broader purchase-related responses. TCI had its strongest association with BA, consistent with TikTok's capacity to expose users repeatedly to distinctive fashion-brand cues. The manually verified open-response categories provide descriptive context: presentation and visual style was most frequent, while creators, demonstrations, music, and humor were also identified. These categories do not explain the structural association and should not be interpreted as comparative effectiveness evidence.

BE showed the strongest direct association with PRIs, and the specified model yielded positive TCI–BE–PRIs and BA–BE–PRIs statistical indirect associations. Under this model, BA was associated with PRIs indirectly through BE rather than through a separate direct association. This pattern is consistent with recognition being insufficient once attention, affect, connection, and participation are considered. Because PRIs also includes continued purchase, loyalty, and recommendation, the interpretation concerns a broad purchase-related block rather than purchase intention alone.

The positive direct TCI–PRIs association indicates that TCI retains an association with purchase-related intentions after the measured awareness and engagement blocks are considered. Reviews, product demonstrations, links, promotions, and creator recommendations were not separately modeled as mechanisms; therefore, the present data cannot determine whether any of them changes search effort or purchasing responses. The coefficient is cross-sectional and should not be interpreted as the effect of changing TikTok content.

The exploratory analyses describe a broad response-intensity gradient rather than sharply isolated natural classes. The outcome-excluded two-cluster solution separated lower- and higher-rating partitions, but the correlated TCI, BA, and BE inputs mean that the solution largely reflects general response positivity. The post-cluster PRIs difference is therefore descriptive and partly expected from PRIs's correlations with those inputs. The adjusted Rand index of 0.769 shows substantial, not near-perfect, agreement between k-means and Ward clustering. The partitions are not validated consumer groups, and their temporal stability is unknown.

The machine-learning results align descriptively with the structural model at the construct level: BE produced the largest grouped permutation contribution and was also the strongest direct structural correlate of PRIs. Random forest had the lowest mean held-out error, but gradient boosting and extra trees were close, and no formal uncertainty test established a difference between them. Moreover, machine learning predicted the equal-weight PRIs mean, whereas PLS-PM used a model-derived construct score. The analyses are complementary rather than independent validation.

The illustrative synthesis ordered BE first, TCI second, and BA third across the examined formulas and weights. Because all criteria came from the same fixed sample-derived matrix and no external business criteria or stakeholder judgments were included, the order is an internal descriptive summary rather than a marketing-practice priority ordering or evidence about interventions.

The moderation analysis provided no Holm-adjusted evidence that the specified associations differed by gender, recorded age category, residence size, household income, or education. The nominal gender interaction did not survive correction and is not treated as evidence of a gender difference. The results show only that no corrected evidence of moderation was detected in this sample; they do not establish demographic invariance, and small-to-moderate interactions may remain undetected.

7.2. Comparison with Previous Studies

The strong TCI–awareness association is consistent with Lou and Yuan [11], who connected trust in influencer-branded content with brand awareness and purchase intentions. The present model adds an important qualification: BA had no incremental direct association with PRIs after BE and TCI were modeled simultaneously. This difference may arise because Lou and Yuan explicitly modeled trust in influencer posts, whereas the present TCI block measures content involvement and information behavior rather than creator credibility.

The central role of engagement is consistent with Hazari et al. [4] and complements studies emphasizing content quality, parasocial interaction, credibility, and relational mechanisms [5,6]. The manually verified categories concerning creators, presentation, reviews, and demonstrations provide descriptive context for this comparison.

The statistical indirect pattern also resembles the Vietnamese TikTok fashion-livestream study by Thuy and Quang [7], which linked streamer influence to purchase intention through attitude and trust. In the present model, the TCI–BA–BE–PRIs coefficient product describes a corresponding indirect association involving BA and BE.

Music, humor, and entertainment were also identified in the manually reviewed categories, a descriptive pattern compatible with Barta et al. [3]. The structured results similarly align with Lin et al. [8], who connected attitudes toward TikTok videos with sustainable-apparel purchase intention. These cross-study comparisons are interpretive only: the cross-sectional paths and descriptive text categories do not test temporal mechanisms or content effectiveness.

7.3. Theoretical and Methodological Implications

The study contributes to short-video and creator-mediated brand research by separating a cognitive brand outcome from a relational outcome. The association sequence is compatible with SOR reasoning, but TCI is a respondent appraisal rather than an experimentally controlled stimulus. Accordingly, the model shows that awareness and engagement do not have equivalent relationships with PRIs without claiming a tested temporal stimulus–response mechanism.

The interpretation is also sensitive to the TCI measurement specification. Under the present reflective model, the four indicators are treated as manifestations of a common involvement orientation, and the structural paths relate that shared score to BA, BE, and PRIs. Under a formative specification, the indicators would instead contribute potentially unequal and noninterchangeable components to a composite; indicator weights, construct scores, collinearity assessment, and the resulting structural coefficients could therefore differ. A multidimensional model could further separate attention, information appraisal, and sharing. Consequently, the direction and magnitude of the reported TCI paths should be understood as conditional on the reflective working specification rather than as measurement-model-invariant findings. A numerical comparison was not presented because no formative weighting scheme was prespecified; future preregistered analyses should compare these alternatives directly.

The findings also clarify the level at which influencer claims can be made. The data support a role for TikTok fashion-brand content and creator cues, but not a comparison of influencer types or a causal effect of influencer credibility. Future models should add explicit measures of trustworthiness, expertise, similarity, parasocial interaction, sponsorship disclosure, and creator–brand fit to distinguish source effects from message effects.

Methodologically, the study illustrates a candidate human-governed architecture that separates primary PLS-PM analysis, secondary prediction and moderation, exploratory clustering and manually verified text coding, and descriptive synthesis. The roles are software-independent and can be implemented in commercial or free and open-source tools; R 4.4.1 and RStudio provide the present reproducible route. Transferability requires comparison with alternative workflows and testing in new samples and domains.

7.4. Managerial Implications

For exploratory managerial assessment, fashion brands could examine TikTok activity beyond reach and recall indicators while treating the present findings as associative rather than prescriptive. Visual consistency and memorable presentation may be monitored alongside awareness, whereas sustained viewing, meaningful comments, saves, shares, creator–audience interaction, and product-related questions may serve as candidate engagement indicators for subsequent campaign-level testing. The present survey does not show that changing any of these features will increase purchasing.

The manually verified presentation, creator, review, demonstration, and entertainment categories can be treated as research-informed content hypotheses rather than proven tactics. Managerial use would require testing them against campaign exposure, clickstream, conversion, and sales data.

The lower- and higher-rating partitions may be used only as provisional descriptions of response intensity and should not be treated as consumer segments or converted into targeting rules. Before any operational use, brands would need to determine in new data whether the separation reflects stable substantive differences rather than general response positivity or prior interest in fashion content.

7.5. Limitations and Future Research

Several limitations apply. First, the nonprobability Bulgarian sample is concentrated among women, younger respondents, and the South Central Region. Recruitment-channel coverage and a conventional response rate cannot be reconstructed. Participation was restricted to adults. Nevertheless, the recorded category 'Under 20' does not distinguish respondents aged 18 from those aged 19 and does not explicitly represent age 20; the age composition and moderation results should therefore be interpreted as recorded category contrasts rather than precise age thresholds. Second, all key constructs were measured in one cross-sectional survey, so temporal order and causality cannot be established, and common-method bias remains possible.

Third, TCI combines interest, information sufficiency, sharing, and advertising attention as a reflective working construct; formative or multidimensional alternatives would define and estimate the construct differently and could change construct scores and structural coefficients. Fourth, PRIs combines planned purchase, continued purchase, loyalty, and recommendation across different behavioral stages and does not measure actual sales. Fifth, the sample may have limited statistical power for small-to-moderate demographic interactions, sparse subgroup contrasts, or nonlinear moderation. The absence of Holm-adjusted findings therefore cannot establish that demographic moderation is absent. No competing structural specification was estimated; parallel-predictor, formative-composite, multidimensional TCI, reverse BA–BE, and other contemporaneous orderings should be evaluated in independent longitudinal or experimental data.

Sixth, the illustrative MCDM analysis ranks only three constructs using overlapping criteria derived from the same sample and does not incorporate external business criteria, stakeholder input, or uncertainty in sampling and criterion selection. Its order is therefore an internal descriptive summary, not a priority ordering for marketing practice, and requires replication with independent data and stakeholder-defined alternatives, criteria, and weights.

Seventh, one researcher manually verified all dictionary-assisted assignments against the original Bulgarian responses using a category set fixed in advance; ambiguous cases were discussed within the team. Because no independent second coder was used, inter-coder reliability could not be assessed. The procedure supports only descriptive deductive category counts; it is neither independently validated coding nor rigorous inductive thematic analysis, and the categories should not be used to infer marketing effectiveness or exhaustive meaning coverage.

Future work should use probability-based or stratified samples, record age precisely, and collect longitudinal or experimental data linked to observed exposure and transactions. Measurement research should compare reflective, formative, and multidimensional TCI specifications and separate purchase intention from loyalty and recommendation. Competing structural directions, cluster stability, pooled out-of-fold predictive metrics, and uncertainty in MCDM ranks should be examined in independent samples. Preregistered external validation would permit stronger conclusions.

8. Conclusions

This study examined TikTok fashion-brand content using 268 eligible Bulgarian respondents. Under the specified PLS-PM model, TCI was positively associated with BA, BE, and broad PRIs. BA was associated with BE but had no incremental direct association with PRIs, whereas BE was the strongest direct correlate of PRIs. All four PRIs indicators showed positive internal predictive performance relative to a training-mean benchmark.

No demographic interaction received Holm-adjusted support across the 30 path-specific tests. RQ5 therefore yielded no multiplicity-adjusted evidence of moderation in this sample. This finding does not establish the absence of demographic moderation because small-to-moderate effects may remain undetected.

The exploratory two-cluster solution described lower- and higher-rating response-intensity partitions without using PRIs to form them. Because the inputs were strongly correlated and external or temporal cluster stability was not tested, the partitions are not distinct consumer types. Random forest provided the lowest mean prediction error for the equal-weight PRIs mean, but other ensemble methods were close.

The illustrative synthesis ranked BE first, TCI second, and BA third for the fixed sample-derived matrix; this order is descriptive, incorporates no external business criteria or stakeholder input, and does not establish causal or managerial priority.

The structured results indicate that TikTok fashion communication cannot be reduced to visibility: PRIs was more closely associated with BE than with BA's incremental direct contribution. Dictionary-assisted categories concerning presentation, creators, reviews, demonstrations, music, and humor were manually checked against the responses and may inform subsequent research. They remain descriptive categories rather than evidence that these content elements cause consumer outcomes.

The study therefore offers two limited-scope contributions. Substantively, it documents model-dependent associations among content involvement, awareness, engagement, and broad purchase-related intentions in a young, active Bulgarian TikTok sample. Methodologically, it proposes and illustrates a candidate human-governed architecture that assigns primary, secondary, exploratory, textual, and descriptive-synthesis roles to reproducible analytical stages. The architecture can be implemented using paid software or free and open-source tools; R 4.4.1 and RStudio provide the present reproducible route. Transferability and comparative effectiveness require testing in new samples, domains, and workflows.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/app16189364/s1>, Supplementary File S1. Contains the open-response coding dictionary, indicative lexical cues, and the decision rules used for dictionary-assisted candidate assignment and manual verification.

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Institutional Review Board Statement: Ethical review and approval were not required for this anonymous, non-interventional questionnaire study involving adults aged 18 years or older. Participation was voluntary, no experimental manipulation or clinical procedures were involved, and no sensitive or directly identifiable personal data were collected. Data collection and processing com-

plied with Regulation (EU) 2016/679 (General Data Protection Regulation) and applicable Bulgarian data-protection requirements. No formal ethics exemption or waiver is claimed.

Informed Consent Statement: Participants were informed about the purpose of the study, its voluntary and anonymous nature, and the intended use of the collected data. Participation was restricted to adults aged 18 years or older, and proceeding with the questionnaire was treated as informed consent.

Data Availability Statement: The de-identified dataset analyzed in this study is openly available in Mendeley Data, Version 2, at <https://data.mendeley.com/datasets/dv9zw7cs5x/2> (accessed on 30 August 2026) [12].

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