

Networked Influence and Advertising Effectiveness: A Social Network Analytics-Informed Structural Equation Modeling Framework for Consumer Engagement in Digital Markets

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Abstract

Purpose

This study develops a structural equation modeling (SEM) framework that integrates networked influence, contextual fit, influencer credibility, consumer engagement and advertising effectiveness in digital markets. It retains the original SAGraph social-network benchmark as a computational foundation and extends the paper toward a confirmatory latent-variable design.

Design/methodology/approach

The study follows a two-stage design. Stage 1 reuses the 2025 SAGraph benchmark comprising 345,039 unique users, 44,182 posts, 1,302,109 comments and 554,629 reposts across six advertising domains. Stage 2 specifies a respondent-level covariance-based SEM with five reflective constructs measured by fifteen multi-item indicators. The proposed empirical sequence is scale pre-testing, exploratory factor analysis where required, confirmatory factor analysis, reliability and validity assessment, and structural-path estimation using bootstrapped indirect effects.

Findings

The computational benchmark continues to show a strong positive association between influencer density and engagement intensity (Spearman $\rho = 0.943$, $p = 0.0048$), while context-rich influencer selection achieves higher mean G@10 than the classical structural benchmark. These results motivate, but do not substitute for, the proposed SEM. The revised model hypothesizes that networked influence, contextual fit and influencer credibility increase consumer engagement, while engagement, contextual fit and credibility increase advertising effectiveness.

Research limitations/implications

The available SAGraph evidence contains campaign-level digital traces rather than respondent-level multi-item measurements. Accordingly, no CFA fit statistics or SEM path coefficients are invented in this revision. The paper instead provides a complete SEM measurement instrument and estimation protocol that can be executed once primary survey responses are available.

Practical implications

Advertisers should combine structural visibility with campaign fit and credibility. The SEM framework enables managers to test whether engagement is the mechanism through which network position and influencer characteristics translate into advertising outcomes.

Originality/value

The revised paper links large-scale social-network analytics with a theory-driven SEM framework and clearly separates computational benchmark evidence from latent-variable inference, avoiding

unsupported measurement claims.

JEL classification – M31, M37, D85

1. Introduction

Influencer selection in digital advertising has moved beyond follower-count heuristics toward the identification of actors whose network position, audience fit and credibility make them capable of activating relevant consumers. Contemporary influencer marketing research shows that visibility, authenticity, source credibility, product congruence and audience identification jointly shape engagement and purchase-related responses (Hudders et al., 2021; Vrontis et al., 2021; Ye et al., 2021; Belanche et al., 2021). At the same time, platform traces such as comments, reposts and repeated interactions make relational influence observable at scale.

The original version of this study addressed this problem through the SAGraph benchmark and showed that influencer density was strongly associated with campaign engagement, while context-rich selection models recovered real promoters more effectively than classical centrality methods. Those findings establish an important computational regularity: structural prominence and contextual relevance appear to be distinct but complementary sources of advertising value. They do not, however, identify the latent psychological mechanism through which users interpret an influencer, engage with content and form advertising responses.

1.1 Research problem and scope

An important methodological gap therefore remains. Social-network analytics captures relational structure and behavioral traces, whereas structural equation modeling is designed to estimate relationships among theoretically defined latent constructs measured by multiple indicators. Treating a six-campaign aggregate benchmark as if it were a respondent-level latent-variable dataset would be statistically indefensible. A valid SEM extension requires a new measurement layer in which constructs such as contextual fit, influencer credibility, consumer engagement and advertising effectiveness are measured through multiple items at the individual level.

The revised paper addresses this gap by retaining the SAGraph analysis as Stage 1 and specifying a confirmatory SEM as Stage 2. This mirrors the logic of empirical SEM studies in which construct development, measurement-model validation and structural-path testing are treated as separate analytical steps. Covariance-based SEM is selected because the model is factor-based and confirmatory rather than composite-based or primarily predictive (Dash and Paul, 2021).

The study therefore has four objectives: (1) to preserve the real network benchmark that motivates the model; (2) to develop valid multi-item measures for networked influence, contextual fit, influencer credibility, consumer engagement and advertising effectiveness; (3) to specify a CFA and structural

model that can be estimated from respondent-level data; and (4) to explain how latent-variable evidence should be integrated with computational network evidence without conflating the two.

2. Review of literature

Social Network Theory treats influence as relational. Actors occupying advantageous positions can access and diffuse information more effectively than peripheral actors, and measures such as degree centrality, eigenvector centrality and network expansion can indicate structural opportunities for visibility. However, structural prominence is not equivalent to persuasive effectiveness. Empirical work shows that influencer size, community structure and content strategy interact with engagement outcomes (Gross and von Wangenheim, 2022; Cascio Rizzo et al., 2024; Tafesse and Wood, 2023).

A second stream emphasizes contextual fit and credibility. Followers respond not only to reach but also to perceived sincerity, expertise, authenticity, identification and product-endorser congruence (Ki et al., 2020; Lee and Eastin, 2020; Schouten et al., 2020; Belanche et al., 2021; Ren et al., 2023). Source expertise, originality and homophily influence trust and purchase intention (Li and Peng, 2021), while cross-platform cue consistency can strengthen identification and behavioral intentions (Hsieh, 2023).

A third stream focuses on consumer engagement as the intermediate response connecting exposure and advertising outcomes. Engagement encompasses attention, interaction, commenting, sharing and active information seeking. Followers are heterogeneous in their motivations and response patterns, which means that a structurally central influencer may perform poorly when audience-product fit is weak (Farrell et al., 2022; Pradhan et al., 2023). Context-rich selection is therefore theoretically attractive because it combines opportunity for diffusion with relevance to the campaign.

2.1 Theoretical integration and SEM logic

The revised model integrates relational influence and persuasion mechanisms. Networked influence represents perceived structural prominence and diffusion potential. Contextual fit captures the perceived compatibility among influencer, audience, message and product category. Influencer credibility captures trustworthiness, expertise and authenticity. Consumer engagement is modeled as a proximal behavioral and cognitive response, while advertising effectiveness represents the downstream attitudinal and behavioral consequences of the campaign.

This separation is important because a network can create exposure without necessarily producing persuasion. A consumer may recognize that an influencer is highly visible yet still judge the sponsored content to be irrelevant or inauthentic. Conversely, a moderately central influencer with strong product fit and credibility may generate deeper engagement. The SEM framework allows these mechanisms to be estimated simultaneously and permits engagement to be evaluated as a mediating process rather than treating every network metric as a direct proxy for advertising effectiveness.

2.2 Hypothesis development

Networked influence should increase engagement because visible and well-connected influencers create repeated opportunities for exposure, social proof and diffusion. The preliminary SAGraph result that influencer density is strongly related to interaction intensity provides computational support for this direction, while the SEM tests whether consumers perceive this relationship at the individual level.

H1. Networked influence has a positive effect on consumer engagement.

Contextual fit should increase engagement because congruent influencer-product relationships reduce perceived mismatch and make sponsored communication easier to process and accept (Schouten et al., 2020; Ren et al., 2023).

H2. Contextual fit has a positive effect on consumer engagement.

Influencer credibility should increase engagement because trustworthy, expert and authentic sources are more likely to attract attention and motivate interaction (Belanche et al., 2021; Saima and Khan, 2021).

H3. Influencer credibility has a positive effect on consumer engagement.

Engagement should translate exposure into advertising response because active interaction and information seeking increase the likelihood that consumers form favorable brand attitudes, consideration and behavioral intentions (Pradhan et al., 2023; Herrando and Martin-De Hoyos, 2022).

H4. Consumer engagement has a positive effect on advertising effectiveness.

Contextual fit can also affect advertising effectiveness directly because consumers may evaluate an advertisement more favorably when the endorsement is perceived as compatible with the influencer and product category.

H5. Contextual fit has a positive direct effect on advertising effectiveness.

Credibility may likewise exert a direct persuasive effect beyond engagement, particularly when expertise and authenticity reduce skepticism about sponsored communication.

H6. Influencer credibility has a positive direct effect on advertising effectiveness.

Table 1
Structural hypotheses in the revised SEM framework

Hypothesis	Structural path	Expected direction
H1	Networked Influence -> Consumer Engagement	Positive
H2	Contextual Fit -> Consumer Engagement	Positive
H3	Influencer Credibility -> Consumer Engagement	Positive
H4	Consumer Engagement -> Advertising Effectiveness	Positive
H5	Contextual Fit -> Advertising Effectiveness	Positive
H6	Influencer Credibility -> Advertising Effectiveness	Positive

3. Methodology

3.1 Research design and analytical logic

The revised study adopts a sequential two-stage design. Stage 1 is a secondary social-network benchmark based on SAGraph. Stage 2 is a confirmatory latent-variable design intended for respondent-level survey data. The stages answer different questions. The network benchmark assesses whether campaign-level structural signals and context-rich selection procedures correspond with observed digital engagement and real-promoter recovery. The SEM assesses whether individual perceptions of networked influence, fit and credibility explain consumer engagement and advertising effectiveness.

The separation prevents ecological inference from campaign aggregates to individual psychological constructs. The existing digital traces are therefore used to motivate and triangulate the SEM rather than being converted into artificial multi-item indicators.

3.2 Stage 1: SAGraph network benchmark

SAGraph (Zhang et al., 2025) is a 2025 social-advertising benchmark released under CC BY 4.0. It contains 345,039 unique user profiles, 44,182 posts, 1,302,109 comments and 554,629 reposts across six advertising domains: hygiene, education, technology, skincare, linguistics and home products. Graphs were built from comments and reposts over six collection rounds. Because approximately 18% of users appear in more than one domain, domain counts are not additive as unique users.

Table 2
SAGraph campaign statistics retained as the Stage 1 computational benchmark

Domain	Product	Users	Interactions	R6 influencers
Hygiene	Electric Toothbrush	43,611	163,016	48
Education	Spark Thinking	58,510	490,431	201
Technology	Intelligent Floor Scrubber	63,619	370,176	190
Skincare	Ruby Face Cream	66,248	126,859	55
Linguistics	ABCReading	70,258	458,513	206
Home	SUPOR Boosted Showerhead	138,427	247,741	81

Stage 1 operationalizes engagement intensity as reported interactions divided by domain users, influencer density as final-round influencers per 10,000 domain users, six-round expansion as $R6/R1$ and interaction heterogeneity as the published interaction variance. Influencer-selection effectiveness is measured by $G@10$ against real product promoters. These measures remain observed variables; they are not treated as reflective indicators of latent constructs.

3.3 Stage 2: SEM construct development and measurement

The SEM component is designed around five reflective latent constructs measured through a seven-point agreement scale ranging from strongly disagree to strongly agree. The items are adapted conceptually from recent influencer-marketing research on structural influence, credibility, congruence, engagement and purchase-related responses (Belanche et al., 2021; Li and Peng, 2021; Gross and von Wangenheim, 2022; Farrell et al., 2022; Ren et al., 2023). Each construct contains three indicators so that the measurement model is identified while remaining parsimonious.

Table 3
Proposed latent constructs and reflective measurement indicators

Construct	Code	Proposed item
Networked Influence	NI1	The influencer has visible reach across relevant online communities.
Networked Influence	NI2	The influencer's content frequently spreads beyond the immediate follower group.
Networked Influence	NI3	The influencer appears structurally prominent in online conversations about the category.
Contextual Fit	CF1	The influencer's usual content fits the advertised product category.
Contextual Fit	CF2	The interests of the influencer's audience match the advertised product.
Contextual Fit	CF3	The sponsored message is consistent with the influencer's normal content and identity.
Influencer Credibility	IC1	The influencer appears trustworthy when recommending products.
Influencer Credibility	IC2	The influencer demonstrates relevant expertise or knowledge.
Influencer Credibility	IC3	The influencer appears authentic and sincere in sponsored communication.
Consumer Engagement	CE1	The advertisement captures my attention.
Consumer Engagement	CE2	I would be willing to like, comment on, share or otherwise interact with the advertisement.
Consumer Engagement	CE3	The advertisement makes me want to seek more information about the product or brand.
Advertising Effectiveness	AE1	The advertisement improves my attitude toward the advertised brand or product.
Advertising Effectiveness	AE2	The advertisement increases my likelihood of considering the brand or product.
Advertising Effectiveness	AE3	The advertisement increases my purchase or recommendation intention.

3.4 Proposed sampling, pre-testing and data collection

The SEM stage requires a new primary dataset because the existing campaign aggregates cannot support CFA or latent structural paths. The target population should comprise adult social-media users who have encountered influencer advertising within a defined recent period. A pilot study should first assess item clarity, wording and response variability. The final survey should then obtain a sample of several hundred usable responses, sufficient for stable estimation of a five-construct, fifteen-indicator CB-SEM and for sensitivity checks across demographic or platform groups.

Screening questions should confirm exposure to influencer advertising and familiarity with at least one recent sponsored post. Respondents should evaluate a specific advertisement or influencer encounter rather than answering only in the abstract. This improves construct validity because networked influence, fit, credibility and engagement are judged with reference to the same advertising stimulus.

3.5 Measurement model assessment

The measurement model should be evaluated before any structural-path interpretation. Item distributions and missingness should be reviewed first. If scale development requires exploratory purification, EFA may be conducted on the pilot or a split sample. CFA should then estimate the five-factor measurement model. Standardized factor loadings should be statistically significant and preferably at least 0.70, although loadings above 0.50 may be retained when construct reliability and content validity remain satisfactory. Internal consistency should be evaluated using Cronbach's alpha and composite reliability, and convergent validity using average variance extracted. Discriminant validity should be assessed using HTMT and cross-construct correlations. This sequence is consistent with contemporary SEM practice and with the logic of factor-based CB-SEM (Dash and Paul, 2021; Sarstedt et al., 2022a, 2022b).

Table 4
Measurement and structural model evaluation protocol

Assessment	Recommended decision rule / reporting
Indicator reliability	Standardized loading preferably ≥ 0.70 ; investigate items below 0.50.
Internal consistency	Cronbach alpha and composite reliability ≥ 0.70 .
Convergent validity	Average variance extracted (AVE) ≥ 0.50 .
Discriminant validity	HTMT below 0.85–0.90 and no problematic cross-loading pattern.
Global model fit	Report CMIN/DF, CFI, TLI, RMSEA and SRMR; interpret jointly rather than by one index.
Structural paths	Report standardized beta, standard error, critical ratio or bootstrap interval, p value and R ² .
Indirect effects	Use bootstrap confidence intervals for mediation through Consumer Engagement.

3.6 Structural model estimation

After acceptable measurement quality is established, the structural model in Fig. 1 should be estimated using maximum likelihood or a robust alternative when distributional assumptions require it. H1-H6 are evaluated using standardized path coefficients and confidence intervals. The model should also report explained variance in Consumer Engagement and Advertising Effectiveness. Indirect effects from Networked Influence, Contextual Fit and Influencer Credibility to Advertising Effectiveness through

Consumer Engagement should be tested with bootstrap confidence intervals. Model modification should be theory-driven; modification indices should not be used to create post hoc paths without substantive justification.

4. Preliminary empirical evidence and SEM model specification

4.1 Network benchmark findings

The six SAGraph campaigns display substantial structural heterogeneity. Education records the highest engagement intensity at 8.38 interactions per user, followed by Linguistics at 6.53 and Technology at 5.82. Influencer density ranges from 5.85 to 34.35 per 10,000 users. The benchmark association between influencer density and engagement intensity is strong and positive (Spearman $\rho = 0.943$, $p = 0.0048$). Six-round expansion is positive but not conventionally significant ($\rho = 0.714$, $p = 0.1108$), while interaction heterogeneity is also positive but does not reach the 0.05 threshold ($\rho = 0.771$, $p = 0.0724$).

Table 5
Preliminary network associations retained from the original computational analysis

Observed relationship	Effect	p value	Interpretation
Influencer density -> engagement intensity	$\rho = 0.943$	0.0048	Strong positive association
Expansion ratio -> engagement intensity	$\rho = 0.714$	0.1108	Positive, not significant at 0.05
Interaction variance -> engagement intensity	$\rho = 0.771$	0.0724	Positive, not significant at 0.05
Standardized OLS: density -> engagement	$\beta = 0.967$	0.0016	$R^2 = 0.935$; descriptive robustness only

4.2 Influencer-selection effectiveness

The original promoter-ranking benchmark provides complementary evidence for the SEM variables Contextual Fit and Influencer Credibility. Mean $G@10$ is 0.413 for the eight-method classical benchmark, 0.552 for KB-TIM, 0.465 for GPT-4, 0.530 for GPT-4 with profiles and 0.653 for GPT-4 with profiles plus reasoning. The profile-and-reasoning approach exceeds the classical mean in all six domains and also exceeds profile-only selection. This pattern suggests that structural prominence alone is insufficient and that context-rich information improves campaign-specific selection.

Table 6
Mean influencer-selection effectiveness across the
six campaigns

Model family	Mean G@10
Classical SNA/diffusion mean	0.413
KB-TIM context-aware diffusion	0.552
GPT-4	0.465
GPT-4 + profile	0.530
GPT-4 + profile + reasoning	0.653

4.3 CFA and SEM interpretation protocol

The Stage 1 findings are consistent with the directional logic of the proposed SEM but should not be reported as latent-variable evidence. Once survey data are collected, the first confirmatory question is whether the five constructs are empirically distinct. A satisfactory CFA would show strong loadings of NI1-NI3, CF1-CF3, IC1-IC3, CE1-CE3 and AE1-AE3 on their intended factors, with adequate reliability, convergent validity and discriminant validity. Only after the measurement model is established should the structural paths H1-H6 be interpreted.

If H1 is significant, the result would indicate that consumers who perceive an influencer as structurally prominent and diffusion-capable also report stronger engagement. Significant H2 and H3 paths would show that contextual fit and credibility independently contribute to engagement. H4 would test the core conversion mechanism from engagement to advertising effectiveness, while H5 and H6 would identify any direct persuasive effects of fit and credibility beyond engagement. Bootstrap indirect effects would then determine whether engagement partially or fully mediates the upstream relationships.

5. Major findings and implications

5.1 Conclusion

The revised paper establishes a methodologically defensible route from social-network analytics to structural equation modeling. The existing SAGraph benchmark demonstrates that influencer density is strongly associated with campaign engagement and that context-rich selection procedures recover real promoters more effectively than purely structural heuristics. These findings justify a latent-variable extension but do not themselves constitute SEM evidence.

The proposed SEM therefore shifts the unit of analysis from six campaign aggregates to individual consumers and separates five constructs: Networked Influence, Contextual Fit, Influencer Credibility, Consumer Engagement and Advertising Effectiveness. This design makes it possible to distinguish

exposure opportunity from relevance and persuasion, while explicitly testing engagement as the principal mechanism linking influencer characteristics to advertising outcomes.

5.2 Critical review

The most important conceptual implication is that structural influence and persuasive influence should not be treated as synonymous. Network position can increase the probability that content is seen and circulated, but contextual fit and credibility determine whether that exposure is accepted as useful and authentic. This interpretation is consistent with research showing that influencer-brand fit, authenticity, credibility and content strategy influence engagement and purchase-related responses (Belanche et al., 2021; Ren et al., 2023; Tafesse and Wood, 2023).

The SEM framework also improves causal discipline at the level of theory, even though cross-sectional SEM by itself does not prove causality. It requires the researcher to define constructs, validate measurement and estimate competing relationships simultaneously. This is a substantial improvement over relabeling network metrics as latent constructs without multi-item measurement.

5.3 Managerial suggestions

For advertising practice, influencer selection should use a sequential decision rule. First, network analytics can identify actors with sufficient reach, community access and diffusion potential. Second, marketers should assess product-audience fit and source credibility before final selection. Third, campaign evaluation should measure not only reach but also consumer engagement and downstream brand or behavioral response. The SEM framework provides a diagnostic structure for identifying whether weak performance arises from insufficient visibility, poor contextual fit, low credibility or failure to convert engagement into advertising effectiveness.

For model deployment, computational ranking outputs should be treated as decision-support signals rather than complete measures of advertising effectiveness. A profile-aware model may identify a candidate who resembles real promoters, but consumer-level validation is still needed to establish whether audiences actually perceive that candidate as credible and relevant.

5.4 Limitations and future empirical validation

The main limitation of the current revision is that the attached empirical dataset is a six-campaign secondary benchmark and does not include respondent-level multi-item survey responses. This prevents legitimate estimation of CFA loadings, reliability, AVE, discriminant validity, global SEM fit or structural path coefficients. Reporting such statistics without raw data would create unsupported evidence. The present paper therefore stops at a fully specified and testable SEM framework.

Future research should collect the fifteen-item instrument from a sufficiently large sample of consumers exposed to influencer advertising, pre-test the scale, estimate the five-factor CFA and then test H1-H6. Longitudinal or experimental designs could strengthen temporal and causal inference, while multi-group SEM could examine whether path strengths differ by platform, product category, influencer size or

consumer demographic profile. The strongest future design would combine respondent-level perceptions with matched digital-trace exposure and campaign outcomes.

Declarations

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Declaration of Conflicting Interests

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Author Contribution

Dr. Gurwinder Singh Badal, Dr. Balveer Singh Sidhu, Dr. Firdous Ahmad Malik, Dr. Subodh Saluja, and Dr. Rahul Hakhu contributed to the conceptualization, methodology, analysis, and development of the manuscript. Dr. Gurwinder Singh Badal prepared the main manuscript text and coordinated the overall study. Dr. Balveer Singh Sidhu, Dr. Firdous Ahmad Malik, Dr. Subodh Saluja, and Dr. Rahul Hakhu contributed to the analysis, interpretation, and revision of the manuscript. All authors reviewed and approved the final manuscript.

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Figures

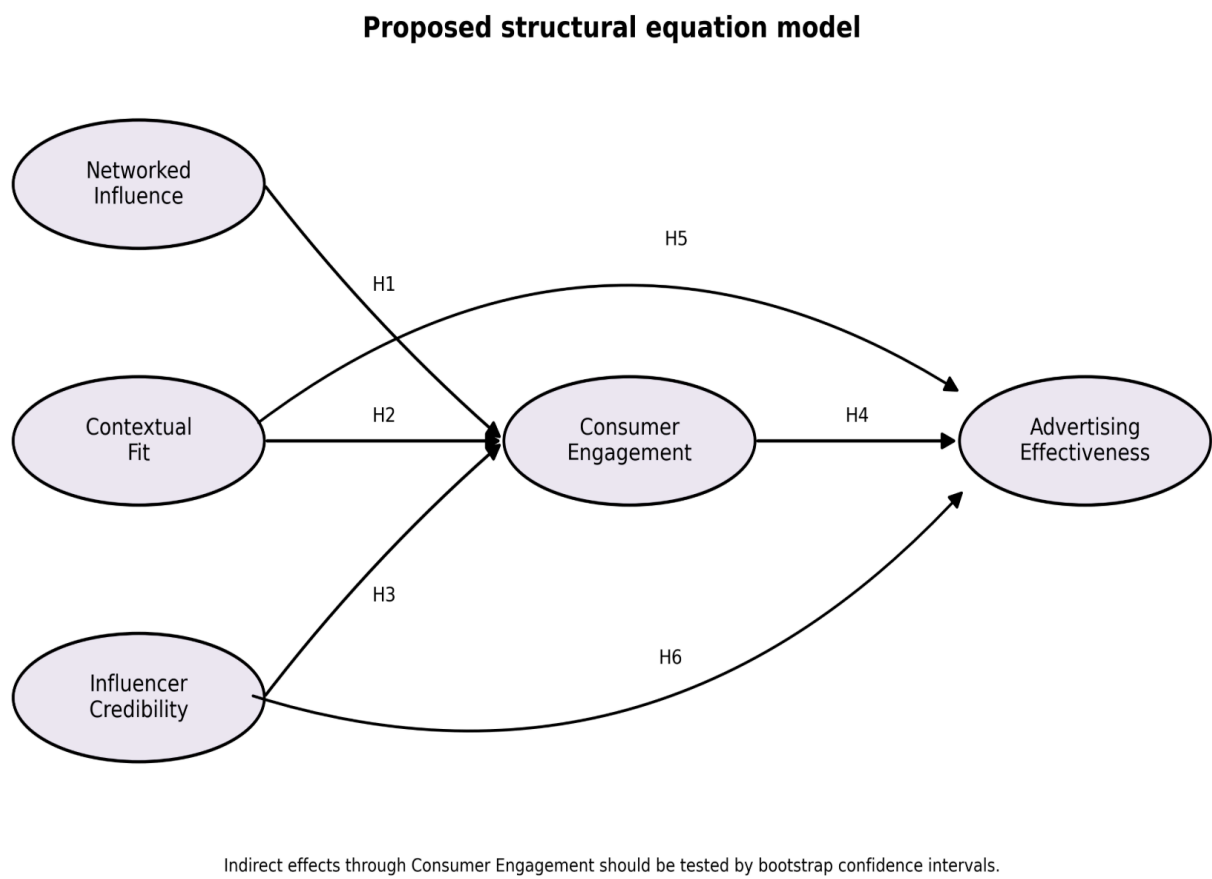
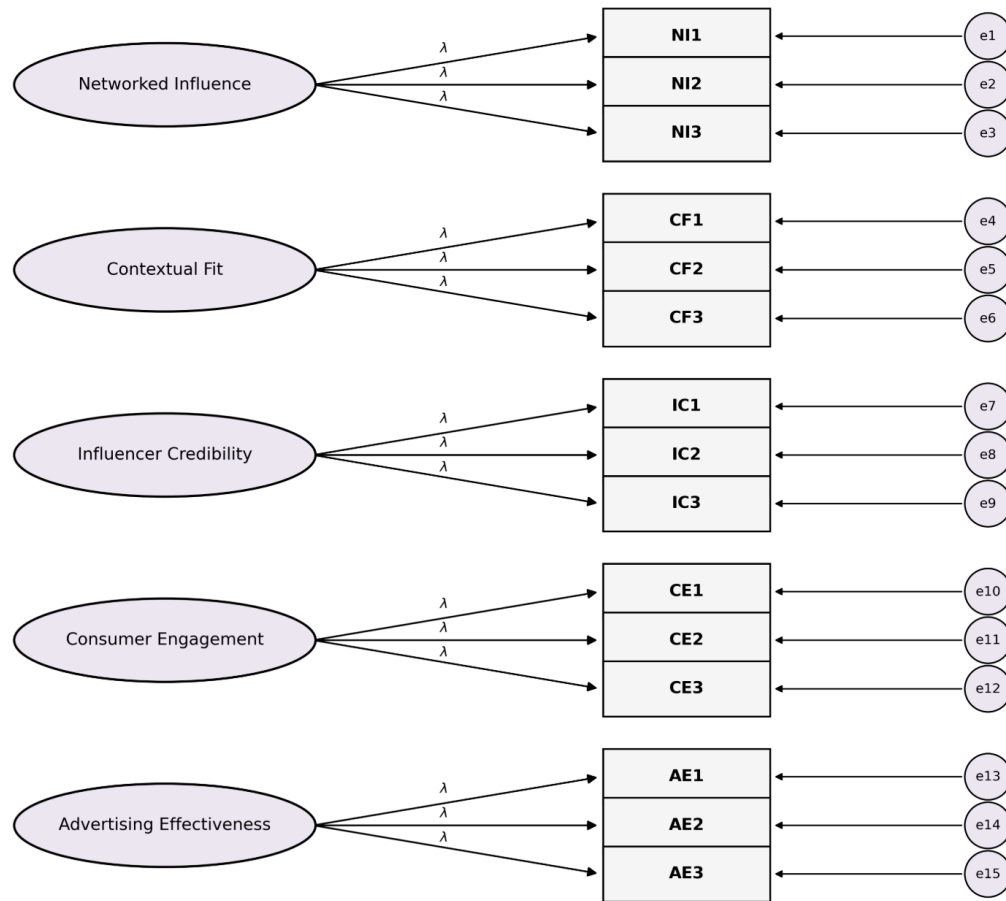


Figure 1

Proposed structural equation model linking networked influence, contextual fit, influencer credibility, consumer engagement and advertising effectiveness

Proposed confirmatory factor analysis measurement model



Each latent construct is measured by three reflective indicators; standardized loadings and residuals are to be estimated from respondent-level data.

Figure 2

Proposed CFA measurement model for the five latent constructs; loadings and residuals are to be estimated from respondent-level data

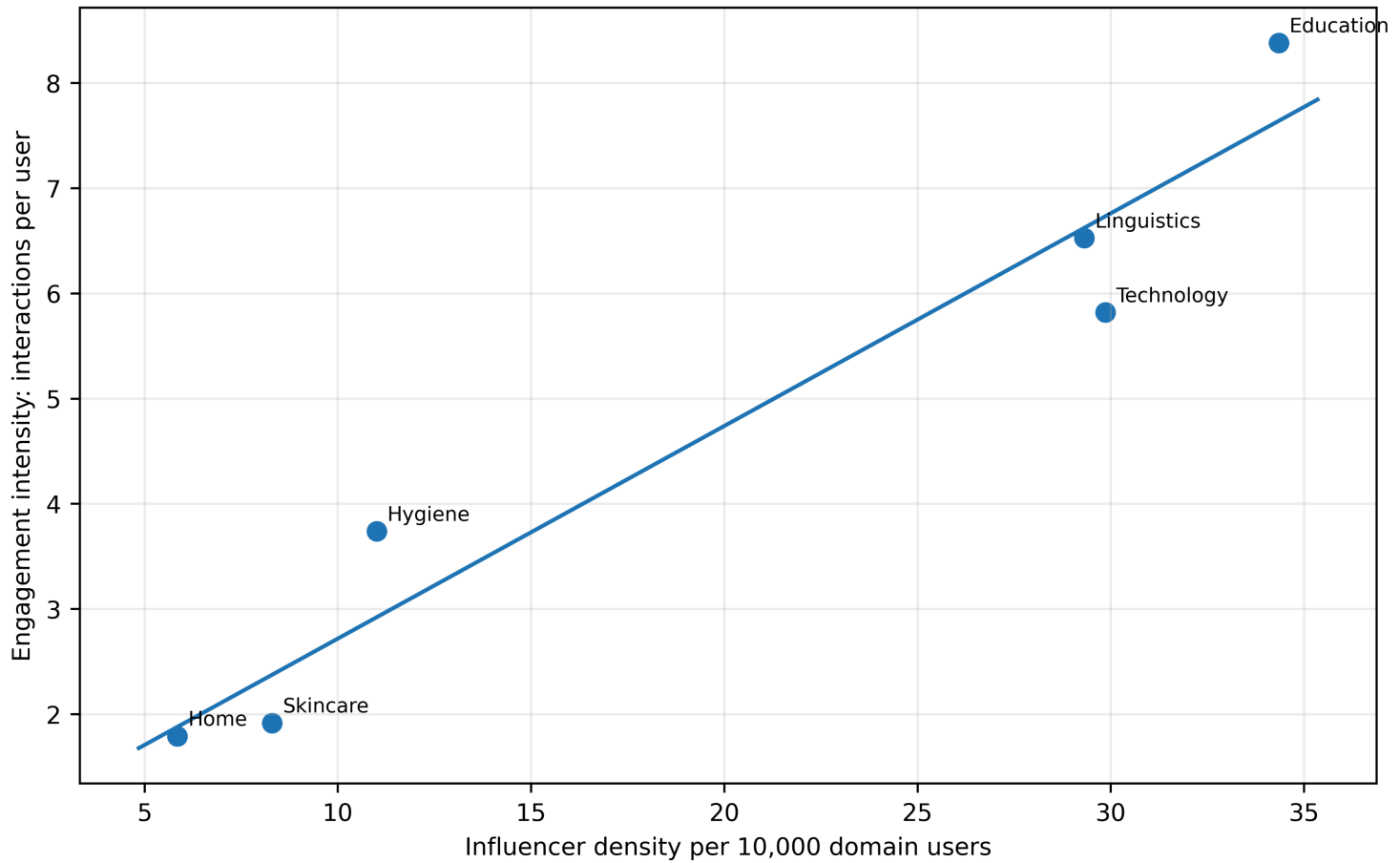


Figure 3

Influencer density and observed engagement intensity across the six SAGraph campaigns

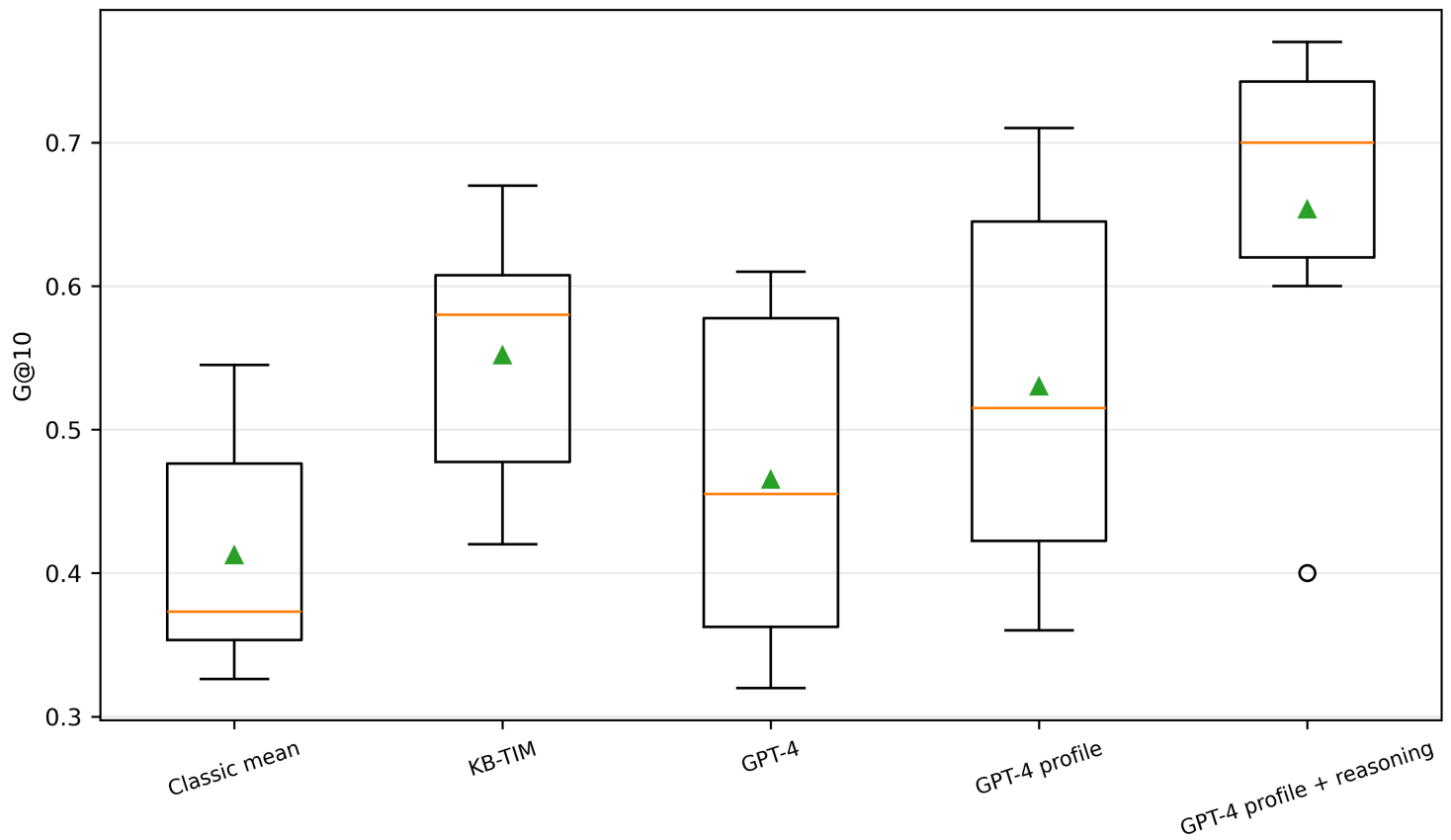


Figure 4

Distribution of G@10 across the six campaigns for major influencer-selection model families

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [AppendixA.docx](#)