

Digital Influence Beyond Reach: Early Consumer Conversation and Subsequent Product Engagement on TikTok

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Research Article

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Abstract

Social-media engagement is commonly evaluated through views, likes, and comments, yet these metrics reveal little about whether consumer attention is directed toward the advertised product. This study examines how early TikTok attention develops into qualified product conversation in the context of Värna, a functional-nutrition brand in Vietnam. Using 198 TikTok posts from 149 creators and 2,775 top-level comments, consumer responses were decomposed into product-relevant, functional-health, sensory, purchase/action, question, and off-topic engagement. A temporally ordered design then used information observed within the first 0–3 hours to predict subsequent sensory-product engagement during 3–24 hours. The results reveal a clear reach–relevance divergence: creator reach was positively associated with views, likes, and raw comments, but negatively associated with product-relevant comment share. Although interaction volume declined rapidly after posting, product-relevant and sensory discussion became relatively more prominent during the early conversation window. Out-of-time prediction further showed that early interaction volume substantially improved performance beyond post content, while qualified semantic signals provided additional predictive information, yielding a final PR-AUC of .952 and ROC-AUC of .963. These findings show that digital influence cannot be inferred from reaction volume alone. Instead, the direction and semantic quality of early consumer conversation provide distinct information about subsequent product experience, supporting more adaptive and product-focused advertising analytics.

JEL Classification: M31, M37, C53.

1. INTRODUCTION

In one social media post, a high number of engagement may be achieved without any considerable value creation related to the items advertised. A study by Yang et. al (2024) investigated a sample of 2,685 TikTok influencer ads and noted that likes, comments and share counts showed no relation to the change in the sales of the advertised brands ($p = -.008$, $-.020$ and $-.007$ respectively; all $p > .70$). In their larger sample including 19,636 influencer videos, it was confirmed that standard engagement indicators are not a good measure of sales effectiveness. The issue is therefore not just one of whether consumers will engage but one of with what those engagements are associated.

The problem of measurement is pronounced in influencer marketing in particular since influencers are promoting not only goods but also their personalities. Yang and colleagues (2024) refer to this problem as a potential gap between the influencers' desire for engagement and advertisers' desire for product results. Klostermann et al. (2026), while analyzing 3480 advertising posts written by 555 influencers promoting 15 brands, found that posts with lower product importance tend to accumulate more engagement, while posts with higher product importance receive more product-focused engagement. Importantly, product engagement turned out to be four times stronger in relation to brand engagement than generic engagement. More generally, Pan et al. (2025), synthesizing 1531 effect sizes collected from 251 publications, showed that influencer effectiveness varied significantly depending on the type of

outcome, post characteristics, follower characteristics, platform, and product type rather than being expressed in one engagement metric. Liu and Zhao (2025) showed that informing about the sponsorship increased persuasion recognition and brand awareness but decreased the credibility level.

The differentiation is important in functional nutrition, as consumers need to determine not only whether a product grabs attention, but what it offers and how it can be experienced. According to Grunert (2010), the key characteristics through which consumers assess functional foods include the flavor and sensory properties, healthfulness, ease of use, and being natural. Grunert emphasizes the possible trade-offs between perceived benefits of healthiness and sensory characteristics. In line with this distinction, Pan et al. (2025) have shown that informational value is a more significant predictor of attitudes and behavior in case of functional products than self-expressive brands. Sensory information can also produce informative outcomes: Cascio Rizzo et al. (2023) demonstrated that sensory information informs buyers and raises their willingness to purchase, using social media posts to support findings from experiments. Hence, a comment about the creator's appearance and a comment questioning whether the nutritional drink is too sweet are not simply different subjects, where the latter demonstrates that more progress in consumer learning and evaluation took place.

Vietnam is a particularly interesting place to study this transition due to the interaction of demographic, nutritional, and digital aspects. The Vietnam General Statistics Office (2025) reported that in 2024 there were about 14.2 million people aged 60 years or older in Vietnam, which is 2.8 million higher than in 2019. By 2030 this population will be close to 18 million. Kemp (2025) mentioned that TikTok's advertising capabilities indicated that in late 2025 approximately 76.1 million people aged 18 years and older will be users in Vietnam, which is equal to 88.8% of the total number of Internet users in the country. Health consumption is also highly digitalized; according to Doan, Vu, Nguyen, Nguyen, et al. (2024), 97.2% out of 1,070 Vietnamese interviewees searched for health information online, and 52.8% bought drugs and/or functional food online. According to the second survey of Doan, Vu, Nguyen, and Dinh (2024) involving 1,305 Vietnamese respondents, 45.1% utilized online purchase of functional food while 77.5% were planning to buy drugs or functional food using the Internet in the future. Feedback and evaluations provided by other users are some of the factors that were mentioned by buyers. Thus, Vietnam is characterized by the growing relevance of adult nutrition and the intensive application of the Internet in the health information-seeking behavior of its population.

In this particular respect, Värna serves as a practically insightful case rather than just a valid example of branding. According to its website, NutiFood (n.d.) positioned the Värna brand as “a full solution for the nutrition of Vietnamese adults.” The brand architecture distinguished the functions of the different variants of the Värna range. Specifically, Värna Complete focuses on recovery and musculoskeletal continuity and prevents problems with the cardiovascular system and memory; Värna Diabetes focuses on blood-glucose control; Värna Colostrum deals with immunity, health of bones and muscles, digestion, and cardiovascular support. Investigating the brand variants at the same time provides both stability of brand ownership and core brand identity and significant differences in meeting health needs, product offerings, brand strategy, and consumer behavior. Hence, it minimizes the problem of the difference

between brands in terms of notability, reputation, history, and positioning, while keeping significant differences in the context of the brand.

Yet, existing investigations remain incomplete in an important area of this process. The authors Yang et al. (2024) have proven that engagement relevant to the product is a better predictor of sales than the number of likes, comments, or shares. Klostermann et al. (2026) distinguished comments connected to the product from post-engagements and concluded that the former correlates with brand engagements better than the latter. Cascio Rizzo et al. (2023) showed that using sensory language made by influencers can signal product usage and the authenticity of the product. These studies stress the role of product-focused communication and sensory information. Nevertheless, they mostly analyze what companies do in their postings and how consumers react to such information. There is little data on the consumer side of the process in that it is unclear whether social talk happens before discussion about the product, especially regarding functional food, and whether the context of the first discussion contains useful information that goes beyond the number of the posts.

The issue is solved by indicating early observation proactively and consumer response afterward. We forecast consumers' discussion about sensory products during 3–24 hours after the post through information from the messages and their comments during the first 0–3 hours of posting. Instead of relying on total early engagement, we apply separate predictors that refer to the semantics of the post, the volume and timing of early interaction, the category of post, and differences in posts' previous experience regarding its historical context and networking. To evaluate success, we use a chronological holdout that allows to forecast later posts by the observations done previously.

The research article has three major contributions. First, it redefines social media engagement as a multi-layered consumer reaction process, comparing general attention with product-relevant engagement such as effective health engagement, experience engagement, and behavioral engagement. Moreover, it analyzes the trade-off between brand reach and relevance, investigating whether high reach leads necessarily to greater product conversations. Lastly, the study demonstrates the incremental importance of early conversational quality in predicting product conversations, checking whether semantic cues of the message can provide better predictions in comparison with the content and the total engagement volume. Machine learning is used as a methodological tool for measuring information value rather than as a contribution of the article.

RQ1. How does creator reach relate differently to overall social-media attention and product-relevant consumer engagement within a functional-nutrition brand?

RQ2. How does consumer conversation evolve from general attention toward product-relevant and sensory product discussion after posting?

RQ3. To what extent do qualified early interaction signals improve out-of-time prediction of subsequent sensory product engagement beyond content and engagement volume alone?

The rest of the study goes as follows: Section 2 explains the differences between the post, product, and sensory involvement concepts and reviews the research already done in influencer marketing and functional nutrition. Section 3 explains the Värna TikTok data, the engagement categorization, time structures, and prediction models. In Section 4 we provide the results of the reach-relevance, temporal, and out-of-time predictions. Sections 5 and 6 present theoretical and managerial contributions of the study, discuss its limitations and directions for future research.

2. RELATED WORK

2.1 Product-Directed Engagement in Influencer Marketing

The figures obtained in influencer marketing research have used like scores, shares, and comments in order to measure campaign engagement. However, those overall metrics are more about the number of involvement than the focus of attention, and this is crucial. Influencer content reflects that there is a consumer, some entertainment features, and a promoted item. The authors Yang et al. (2024) found out that the TikTok ads can foster considerable engagement although the origin of that engagement is very limited, and successful engagement with products is much better predictor of sales.

Following this logic, Klostermann et al. (2026) distinguished the engagement of posts from the engagement with product. By using 3,480 posts of endorsements, the authors showed that a higher salience of products can lead to lower engagement of posts and higher engagement of products, though engagement with products is better predictor of the involvement with brands.

In this regard, the study examines whether consumer reactions are aimed at product itself instead of just the post. The importance of this distinction is especially prominent in functional nutrition, where consumers' talk about products might be indicative of their health needs, sensory experiences, as well as the reactions leading to purchases.

2.2 Functional-Nutrition Influencer Marketing

Functional-food products are different from many regular products, as their acceptance is based on perceived health benefits as well as experience in using them. According to Grunert (2010), taste and other sensory aspects, healthiness, convenience, and naturalness are the main dimensions in functional-food evaluation. Siró et al. (2008) also pointed out that consumer acceptance is very important for the market viability of functional foods. Subsequently, different reviews stressed the multidimensionality of this problem: Plasek and Temesi (2019) argued that credibility of health influence is one of the most important aspects in the willingness to purchase any functional foods, Baker et al. (2022) summarized factors influencing functional-food acceptance based on different characteristics of a product.

Research on social media suggests that these meanings concerning health and products are being increasingly conveyed by means of influencers. Ng et al. (2025) analyzed 1,036 instances of ads on the digital market dealing with baby formula and reported that both influencer and company practices

including sharing of parental experiences and star endorsements were correlated with interaction through social media. In turn, Dupuis et al. (2025) showed that branded food and drink products were widely used by TikTok influencers with little clues regarding the presence of commercial ties behind these messages. In the area of health products directly, Park et al. (2026) demonstrated that TikTok influencers in their ads for gut health supplements made use of such strategies as health claims and e soft-sell framing techniques, and even though these influencers typically possessed fewer qualifications than other specialists, their posts generated more likes and saves than competitor posts. Lemmens et al. (2026) reached similar conclusions regarding posts of influencers on plant-based milk.

Accordingly, these studies reveal that functional-nutrition communications encompass claims about health, credibility of the source, and personal experience with the product. However, the majority of existing studies focus primarily on likes, comments, or shares that make it impossible to analyze what people talk about when discussing health relevance, sensory impressions, or their intentions to buy a product.

2.3 Sensory Language and Product Experience

Sensory information is particularly important for products whose key attributes cannot be fully evaluated before consumption. Krishna (2012) showed that cues related to taste, smell, texture, sight, and sound could shape product perception, judgment, and behavior by engaging consumers' senses. This role is especially salient for food and beverages: analyzing 393,568 consumer food reviews, Reed et al. (2019) found that taste-related language appeared more frequently than references to price, nutrition, texture, smell, or service. Sensory language therefore provides more than descriptive detail; it can reveal which aspects of actual consumption become salient to consumers.

The latest investigations in the sphere of digital marketing have come to confirm the notion that sensory language provides both informational and persuasive functions. In the research paper of Cascio Rizzo et al. (2023), it was demonstrated that sensory language in social media posts of an influencer increases engagement and purchase intention due to product usage being more obvious, as well as a higher level of perceived authenticity. The same outcomes were achieved in the study of Chen et al. (2026) who came to the conclusion in their research of live commerce that sensory words in the description of the offering increase the likelihood of purchase because of the creation of mental images and authenticity perception, with this aspect being different depending on the type of product. It is also necessary to point out that the results of consumer reviews include sensory experience as well: for instance, Hallikainen et al. (2025) discovered that sensory indicators in online grocery reviews served as indicators of consumer experience, and Yao and Chen (2025) found out that sensory verbs made consumers believe that the review was helpful.

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2.4 Early Social Signals and Subsequent Consumer Response

A great deal of research has established that early social-media activity holds vital clues about subsequent performance. Szabó and Huberman (2010) provided evidence that one could predict sustained success on Digg and YouTube based on early patterns of usage. Pinto et al. (2013) made a similar observation: the early distribution of views increased the chances of successful prediction of YouTube popularity. Cheng et al. (2014) went beyond measurement of volume, discovering that any predictions of Facebook cascade growth become more successful with the addition of early reshares, especially those that facilitated temporal and structural readings. Other works by Wu et al. (2016) and Shang et al. (2021) confirmed the link between temporal patterns and successful predictions of social media popularity in general.

Nonetheless, this literature primarily classifies the future result as characterised by the size of the post for instance, total views or reshares or size of cascade. The recent literature on cascade prediction still highlights the previous diffusion amount, network structure and temporal dynamics as predictors for such popularity in the future. All this is undoubtedly effective in estimating reach in general terms but does not provide any insights whether early interactions offer some information about the type of consumer reaction to the post in question later.

In this context, the current study builds upon the framework of popularity prediction to introduce the prediction of response quality. Instead of investigating the relationship between initial engagement and the likelihood of further interaction, it examines whether the semantic richness of comments referring to specific products and sensory details during the first hours is helpful for the prediction of future product engagement in terms of sensory interaction.

2.5 Research Gap

Prior research established four relevant insights: product-directed engagement can be more informative than generic post engagement (Yang et al., 2024; Klostermann et al., 2026); functional-nutrition products are evaluated through health and sensory dimensions (Grunert, 2010; Plasek & Temesi, 2019); sensory language can signal product use and authenticity (Cascio Rizzo et al., 2023); and early social activity can predict later popularity when temporal and structural signals are considered (Szabó & Huberman, 2010; Cheng et al., 2014).

However, these streams are still separate from one another. Research seldom examines how consumer dialogue travels from broader engagement to product discussions with a sensory twist. Sensory research is usually concerned with how influencers or marketing materials communicate senses. On the

other hand, predictive studies mostly focus on how many individuals will hear or engage with a particular product instead of examining the nature of their future interactions with it. Therefore, the current paper attempts to investigate whether the semantic quality of early consumer conversation has the ability to predict his/her future sensory engagement with a product.

3. DATA AND METHODS

3.1 Case Selection, Data Collection, and Sample Construction

Värna was considered a diagnostic single-brand rather than a standard that represents the Vietnamese nutrition market. Keeping the target brand stable helped decrease the variation across brands in terms of ownership, initial reputation, and positioning while maintaining variation in terms of the product line, reach of creator, content of message, and reaction of consumers.

Data was obtained using two Apify TikTok scraping workflows. On 31 August 2026, the following nine phrases containing 'Värna' were entered into the TikTok search engine for prompting: #suavarna, #varna, sũa Varna, Varna Life, Varna Diabetes, Varna Complete, Varna Colostrum, Varna Nutifood, and #varnalife. As a result, there were 1,338 suggested records. Search membership served only for high-recall retrieval process, which included checking captions, hashtags, context of the creator, and explicit product references to eliminate duplicates or items that were not related to the brand name like the word "Varna" used in geographic terms. The result of this screening process was 462 validated posts with Värna name. There also were 12 more doubtful cases that were not included in the comment group.

On September 1, 2026, a set of valid post URLs was collected using the TikTok Comments scraper with a limit of 120 comments. The comments generated a total of 206 posts from which it was possible to get a total of 3,653 comments. In order to deal with the effects of samples censored on the right due to the limit, eight posts for which the search data showed that they had more than 120 comments were left out. Thus the consideration set contained 198 posts with a total of 2,775 comments from 2,388 distinct commentors and 149 content creators. Since the comment sets comprised only posts that ended up generating comments in the comment file, any conclusions based on the findings made should include only Värna posts which had generated comments.

Table 1
TikTok Data Collection and Sample-Construction Procedure

Stage	n	Decision / output
Värna-query candidate records	1,338	High-recall retrieval from nine Värna search strings
Verified Värna posts	462	Brand/product evidence + Vietnam-context screening
Posts with returned comments	206	3,653 observed top-level comments
Excluded by > 120-comment QC rule	8	Reduced potential outcome censoring
Primary analytical cohort	198	Used for descriptive and predictive analyses
Top-level comments	2,775	Temporal and semantic analysis
Unique commenters	2,388	De-duplicated commenter IDs
Unique creators	149	Within-brand creator variation
<i>Note.</i> Search strings were used for candidate retrieval rather than final inclusion. Twelve uncertain Värna cases were set aside. Replies were disabled. Source: Authors' own work.		

3.2 Qualified Engagement Reformulation

Based on the difference in terms of product-directed and post engagement (Yang et al., 2024; Klostermann et al., 2026), the comments received got a redefinition as nonexclusive response categories: product-related, functional-health, sensory, purchase/action, question/inquiry, and irrelevant. Overlapping of categories was allowed as a comment could simultaneously state a question regarding relevance of the product, sensory experience, or purchasing activity.

The device of sensory engagement deals with the product-related vocabulary about taste, sweetness, smell, richness, or ease of drinking (Cascio Rizzo et al., 2023). Also, the needs/health dimension of functional-health captures need-state/suitability features such as diabetes or blood sugar, lactose intolerance, nutrition of older people, and recovery processes or related matters. Meanwhile, purchase and action category includes information about the price, where to buy, ordering, performed selling actions/clicking as well. The coding process used original Vietnamese text with accents to avoid false matches.

Table 2
Illustrative Reformulation From Raw TikTok Comments to Qualified Engagement

Observed comment	Reformulated dimensions
“Sữa này uống có bị ngọt k” [Is this milk too sweet?]	Product-relevant; Sensory; Question
“Người tiểu đường có uống được không chị” [Can people with diabetes drink this?]	Product-relevant; Functional-health; Question
“Sữa mua ở đâu vậy chị” [Where can I buy this milk?]	Product-relevant; Purchase/action; Question
“Đẹp quá” [So beautiful]	Off-topic / creator-focused
<i>Note.</i> Examples are anonymized verbatim comments from the analytical dataset; English glosses were added by the authors. Labels are nonexclusive. Source: Authors’ own work.	

$$\text{ProductShare}_i = n_i(\text{product-relevant comments}) / n_i(\text{all comments}) \quad (1)$$

The current semantic labels are transparent rule-based measures rather than a human-coded gold standard. They should therefore be interpreted as operational measures pending blinded manual validation with inter-coder agreement and class-specific accuracy statistics.

3.3 Temporal Reformulation and Predictor Blocks

Every message was transformed into two distinct windows. Only information known from the original period of 0–3 hours was considered for making predictions, while the main result indicated whether there had been at least one sensory-product comment in the period > 3–24 hours. Some metrics were important for analysis but could be used only for descriptive reasons, as they contained data collected later than 3 hours.

$$Y_i = 1[n_{i,\text{sensory}}(> 3-24 \text{ h}) \geq 1] \quad (2)$$

Predictors were added in a cumulative fashion to determine the additional value of each. In model M0, there were 12 static features from the post/content needed; M1 introduced the first two dynamic features - the volume and timing; M2 extended the model by four qualified product and sensory semantics features to a total of 51 features; M3 added another four history/network-lite variables, making the total 55 features. The nesting of the models enabled the determination of how much consumers reacted early from what they were talking about at the beginning.

$$M_0 \subset M_1 \subset M_2 \subset M_3 \quad (3)$$

3.4 Model Development and Out-of-Time Evaluation

There were 138 training posts, 30 validation posts, and 30 future test posts in chronological order. The chosen model and threshold were determined from earlier training and validation periods, while the test labels were not employed in the fitting. ExtraTrees was used as a nonlinear classifier; it is effective for capturing nonlinearity and interactions through the use of random tree ensembles (Geurts et al., 2006).

The primary discriminating metric was PR-AUC, given that the positive class was imbalanced; precision-recall metrics are most useful in such instances (Saito & Rehmsmeier, 2015). ROC-AUC, F1, precision, recall, and the Brier score were presented for informational purposes. Other types of thresholds and product-, purchasing-, and health-related implications were assessed as alternatives and not used in the retrospective search for the easiest target.

4. RESULTS

4.1 Engagement Composition: The Measurement Gap Is Observable in the Data

In Table 3, we see that 1182 out of 2775 comments (42.6%) were found to follow the product-relevant condition. The sensory experience comments accounted for 502 cases (18.1% of total), while purchase/action received 195 comments (7.0%), functional/health comments got 172 comments (6.2%), and questions/inquiries got 191 comments (6.9%). The majority of comments were in the Vietnamese language (79%), while 97.3% of respondents had their region listed as Vietnam.

What is important is that 42.6% is not a number that can be judged as being high or low; the main point that can be made about it is that it indicates how the platform scored all types of comments that have different manners of responding in one particular indicator. More than half of all comments that were obtained scored negatively, while those comments that involve references to the product became a kind of sub-group with different features: sensory, health, purchase, inquiry.

Table 3
Sample Composition and Qualified Engagement

Measure	n	%
Posts in primary analytical cohort	198	—
Top-level comments	2,775	100.0
Unique commenters	2,388	—
Vietnamese-language comments	2,192	79.0
Comments from VN-region accounts	2,700	97.3
Product-relevant comments	1,182	42.6
Sensory-experience comments	502	18.1
Purchase/action comments	195	7.0
Functional-health comments	172	6.2
Question/inquiry comments	191	6.9
<i>Note.</i> Semantic subcategories are nonexclusive and therefore do not sum to 100%. Source: Authors' calculations from the TikTok dataset.		

4.2 Creator Reach and Product Relevance: Scale Does Not Guarantee Product Focus

Table 4 and Fig. 2 provide answers regarding RQ1. The amount of followers of the creator has a positive correlation with views (Spearman's $\rho = .552$), likes ($\rho = .621$), and current raw comments ($\rho = .411$), all $p < .001$. On the contrary, the amount of followers is negatively correlated to product-relevant share ($\rho = -.219$, $p = .002$). The sensory share is also negatively correlated but does not pass the classical significance threshold ($\rho = -.128$, $p = .071$), while the purchase/action share is practically unrelated to follower count ($\rho = .053$, $p = .459$).

The quartile distribution clarifies the interpretation. The relationship is not monotonous on the lower end- the second quartile has more relations to the product than the first quartile- but for the higher-reach creators the divergence becomes evident; namely, the highest follower quartile generated significantly higher amount of comments, while having the lowest average value of product relevance. Thus, supporting the conclusion of reach-relevance divergence, not supporting the statement that “big creators dampen relevance.” The size of creator and product-events discussion are the two different dimensions; reach is directly related to attention level but is not a perfect indicator of the topic of this attention.

Table 4
Associations Between Creator Reach and Engagement Outcomes

Outcome	Spearman's ρ	p
Views	.552	< .001
Likes	.621	< .001
Raw comments	.411	< .001
Product-relevant share	-.219	.002
Sensory share	-.128	.071
Purchase/action share	.053	.459

Note. N = 198 posts. Crawl-time platform totals were used only for descriptive reach analysis, not as prospective predictors. Source: Authors' calculations.

4.3 Temporal Evolution: Attention Decays Faster Than Product Meaning

RQ2 is addressed in Table 5 and Fig. 3. There was a strong initial volume of engagement: the first hour resulted in 410 comments (2.07 comments per post per hour) but this fell to 0.79 in hours 1–3 and continued to decline thereafter. The channels of the conversation evolved differently. The share of product-related comments rose from 43.9% in the first hour to 52.9% in hours 1–3 ($z = 2.39$, $p = .017$), while the share of sensory comments increased from 22.7% to 34.3% ($z = 3.45$, $p < .001$).

Therefore, the findings point to two temporal dynamics: intensity of reactions peaked in the beginning while the share of product-related and sensory information gained over time. This is important, but it does not imply that consumers are continuously learning in an orderly fashion. It shows that temporal decoupling exists on aggregate level.

Table 5
Temporal Composition of Engagement During the First 24 Hours

Window	Comments	Comments/Post/Hour	Product %	Sensory %
0–1 h	410	2.071	43.9	22.7
1–3 h	312	0.788	52.9	34.3
3–6 h	221	0.372	52.5	23.5
6–12 h	234	0.197	50.9	28.2
12–24 h	402	0.169	48.8	18.9

Note. The prospective feature window ends at 3 hours. Percentages are calculated within each time window. Source: Authors' calculations.

4.4 Incremental Prediction: Early Meaning Adds Information Beyond Early Volume

The significance of Table 6 as well as Fig. 4 lies in supporting the central argument of RQ3. Content did not generalize well to the time period under consideration (ROC-AUC .366; PR-AUC .367). Considering early volume and time has helped improve the results (ROC-AUC .889; PR-AUC .854). After qualified semantics have been added in the model, there was an increase in efficiency levels (ROC-AUC .954; PR-AUC .943), and the Brier score has become lower than it was in the first case (.168 → .128). Meanwhile, the history/network-lite block affected the model performance very slightly and made the Brier score even worse (.131).

The results of blockwise comparison suggest that most of the predictive information was provided by the early activity volume. Although qualified semantics was responsible for only .089 of PR-AUC increment, given that both volume and timing were already known, the additional complexity of history network made no difference during applying the model on the test data.

Addressing the selected M3 specification on the training and validation data, the holdout sample of 30 posts secured the ROC-AUC score of .963 and the PR-AUC score of .952. Using the validation threshold of .32, we obtained a recall of 1.000, precision of .545, F1 of .706, and Brier of .134. The high recall in combination with moderate precision shows that the current model is best viewed as an early detection device rather than a highly efficient automatic rule.

Table 6
Out-of-Time Predictive Performance and Feature-Set Ablation

Specification	Features	ROC-AUC	PR-AUC	F1	Brier
M0 Content	12	.366	.367	.286	.269
M1 + Early volume/timing	26	.889	.854	.727	.168
M2 + Qualified semantics	51	.954	.943	.686	.128
M3 + History/network-lite	55	.954	.943	.800	.131
Final refit: selected M3	55	.963	.952	.706	.134
Note. Ablation rows use validation-selected thresholds. The final row is M3 refit on training + validation before evaluation on the same chronological holdout. Source: Authors' calculations.					

4.5 What Information Did the Selected Model Use?

The Fig. 5 exhibits a complementary perspective of the fitted model, despite not being a causal one. The maximum influence of Extra Trees assigned to the following features includes the discussion surrounding the product in the first 3 hours (0.085), early sensory involvement (0.074), sensory discussion in the first 3 hours (0.069), early product discussion in general (0.054), and when the last

early interaction performed (0.053). Hence, it is likely that the majority of important variables are around product relevance, sensory content, and interaction persistence rather than static post characteristics, which is the case of feature ranking in this case being consistent but comparatively less reasonable than the ablation evidence analysis. The reason for that is the fact that impurity-based importance does not show direction or causal relationships as far as its use is concerned here.

4.6 Robustness, Alternative Outcomes, and Model Boundary

According to Table 7, the results display outcome specificity, not consistently effective. Under the established comparison method, sensory level ≥ 1 received score ROC-AUC of .949 and PR-AUC of .939. The stricter sensory level ≥ 2 still showed good discriminative ability (ROC-AUC = .864) but the level of recall fell to .125. The product-based variables key outcome ≥ 1 and ≥ 2 achieved PR-AUC values of .840 and .801 respectively; while purchase behavior/outcome ≥ 1 achieved ROC-AUC of .904 but only PR-AUC of .524, and functional health variable ≥ 1 performed unstably (PR-AUC = .345).

Such comparisons bring additional support to the interpretation of key outcome without showing that one and the same approach performs equally well across all variables. Sensory ≥ 1 links theoretical significance of the variable related to the product with sufficient frequency of occurrence for stable classification in the current case. In a count regression scenario, the results were less stable (the best validation $R^2 = .634$; out-of-time test $R^2 = .247$), thus further supporting the choice of the binary outcome of interest sensory level.

In summary, the evidence responds to the research queries sequentially. RQ1 proves that creator reach connects strongly with attention, but only partially with product relevance. RQ2 proves that while the amount of attention received and the composition of the conversation develop independently. RQ3 underlines the fact that qualified early semantics offer out-of-time predictive information which does not depend on the content of the post and the volume of early interactions. Nevertheless, these conclusions are still limited since they are based on a single-brand, comment-active group and the current principles of semantic measurement which should be validated separately before publication.

Table 7
Predictive Performance Across Alternative Outcome Definitions

Outcome	ROC-AUC	PR-AUC	F1	Precision	Recall
Sensory ≥ 1	.949	.939	.706	.545	1.000
Sensory ≥ 2	.864	.777	.222	1.000	.125
Product-relevant ≥ 1	.777	.840	.667	.500	1.000
Product-relevant ≥ 2	.847	.801	.667	.583	.778
Purchase/action ≥ 1	.904	.524	.348	.211	1.000
Functional-health ≥ 1	.702	.345	.429	.300	.750
Health or purchase ≥ 1	.789	.566	.600	.462	.857
<i>Note.</i> Alternative-outcome comparisons use the common comparison model rather than the final train + validation refit. Source: Authors' calculations.					

5. Discussion and Implications

The results taken together lead to the understanding that digital influence involves more than only the ability to elicit observable reactions. Three trends for the TikTok sample of Värna can be identified: first, creator reach is related to attention scale but not proportional growth of product- focused conversations; second, consumer conversations evolve from the semantic perspective even when the interaction process decreases; finally, the quality of conversations contributes extra predictive value apart from static parameters and the level of engagement. Therefore, the mentioned findings help to shift the analytical focus from the amount of attention the post gains to the way how that attention transforms when consumers start interacting with the product.

The first implication relates to the interpretation of digital influence itself. The findings confirmed a positive relationship between the size of creator audience and views, likes, and number of comments per post, while the number of followers was negatively related to the share of product-related comments. However, this does not mean that creators with larger follower accounts diminish product relevance; the findings suggest that attention and product relevance are two independent types of influence. In his study, Yang et al. (2024) showed that the content created by influencers could generate engagement for various reasons, even if these reasons are not closely related to a particular product. Similarly, Klostermann et al. (2026) identified a distinction between post engagement in general and product-related engagement. However, the present paper brought this distinction to the level of user-generated conversations. The current study found that a larger audience does not guarantee that most of the conversation serves the purpose of focusing on the product. Thus, digital influence should be seen as a multi-layer phenomenon including both attention-making capacities and the ability to conduct this attention toward the product in question.

A second conclusion drawn from the temporal findings is that the consumer's reaction did not only change in magnitude but also in nature. Just after the start of the conversation, it was the first hour of chat where most of the talk occurred. In the first three hours, the amount of relevant talking changed from 43.9% to 52.9%, while sensory discussions increased from 22.7% to 34.3%. The findings of previous studies (Szabó and Huberman, 2010; Pinto et al, 2013; Cheng et al, 2014) indicate that early temporal activity can provide good management tips on popularity in the future. Instead of claiming to have discovered the universal sequence in consumer learning, the current study adds a new temporal factor to the understanding of chat dynamics. Actual conversation duration and meaning of the talk can progress in different ways. In other words, evidence indicates rapid decrease in interaction does not necessarily lead to decline in product-relevant discussions. For advertising analytics, time monitoring of chats can be improved if it considers not only activity intensity but also structure of conversations.

The results support this argument even further. The data alone does not do a very good job predicting the outcome, but adding an early number of mentions and their timing greatly increases predictive performance. Importantly, the introduction of qualified semantic constructs also boosts PR-AUC amounting to an increase from .854 to .943, while data on the history of mentions does not help improve test-AUC. The comparison described above distinguishes two types of early information. Interaction volume indicates the presence of activity while qualified semantics indicates what kind of activity is taking place. Thus, the latter provides additional information that could not be inferred from the volume data alone. The importance of features confirms the point: product talk happening in hours 1–3, early indication of the product and persistence of early interaction are among the most important features of the model. Therefore, the contribution of the study is not in the performance of ExtraTrees models, but in indicating that semantic quality is indicative of time-wise information about product-related discussions.

This conclusion has implications for social network analytics. Even though traditional SNA approaches are particularly efficient in identifying actors, ties, communities, centrality and diffusion structure, structural prominence on its own does not indicate what meaning is being communicated through such relationships. It appears that the obtained evidence indicates that advertising intelligence can benefit from the integration of the semantic layer with structural and behavioral analytics. Two posts may produce the same amount of interaction despite being substantially different in what consumers discuss when interacting in their posts: the creator, the product characteristics, health suitability, sensory experience, or purchase related actions. In this way, network reach is about the distance of influence, while conversational semantics helps understand the way the influence acts. This distinction is important for adaptive advertising because in this case, the decision-making system should know not only which nodes are highly connected or active, but also if the interaction taking place is relevant for the objective of the advertisement delivered by the advertising company. Because the current dataset did not contain a complete reply network, this study does not claim that semantic variables generally outperform centrality or network-structure measures. Rather, it identifies a complementary information layer that future full-network models can integrate with structural features.

The unconventional approach has allowed the author to shift the research from post-event assessments to pre-event analytics. By differentiating the 0–3 hour window of observation from the 3–24 hour timeframe of outcomes, it became possible to assess whether the knowledge of the events taking place at the outset could help making decisions before the resolution of the conversation. The outcome of the research achieved a ROC-AUC of .963 and PR-AUC of .952, yet it is not only these coefficient figures that matter, as the metrics of the functioning of the final model are of importance. The recall of the model accounted for 1.000, whereas the precision equalled .545. Thus, the final model ought to be seen as a mechanism of pre-event screening instead of being regarded as a fully-fledged advertising allocation tool. Its significance is derived from being able to flag early-interacting posts to be analyzed further, not from its possibilities of reallocating funds automatically.

For advertising managers, the results suggest to them that campaign dashboards should not mix scale metrics and qualified engagement metrics. Although views, followers, and raw comments are still relevant measures of reach, they should also be reinforced with other relevant measures such as product-tied share, sensory discussion, functional-health discussion, and purchase/action indicators. The three initial hours can now be seen as diagnostic window which will give advertisers an opportunity to see not just the comment flow but how the discussion is focused on the product. It offers practical logic in terms of portfolio management, which can result in people identifying those posts which had simultaneously great level of attention and good product relevance; those posts that had high level of attention but were not very relevant for the product will be referred to the need for increased product importance or message alteration; posts with low attention and good qualified engagement will be supported by targeted ads; and posts low on both measures will not be entertained. Therefore, what is of great importance in general terms is that managers should not abandon conventional engagement measures but distinguish between the reach of the message and its relevance.

6. Conclusion

According to this study, social media engagement cannot be looked at in isolation as an indicator of digital impact. In the case of Värna on TikTok, creator's reach increased engagement, but it did not correspond to an increase in product-affiliated conversation. In addition, the characteristics of consumer conversations changed with time, while qualified semantic signals made it possible to predict the outcomes of the study better than static content and traditional engagement metrics. Thus, the main significance of this research is not the prediction algorithm but the fact that the quality and direction of early consumer conversations provide information stemming from engagement metrics.

The implications of these results should be viewed through the lenses of certain limitations. First, the study used one type of functional-nutrition brand. Thus, the detected concentration-reach association may not apply to different brands, categories, or channels. Secondly, the resulting historical testing set consisted of only 30 posts, which means that the estimates may be rather imprecise. Thirdly, the analysis only involved comments without replies since reply-level interactions could not provide necessary conditions for making full use of network measures like centrality, communities, and diffusion

pathways. Finally, the present semantic labels were developed based on a rules-based approach and require confirmation before being able to claim something about their reliability.

Consequently, there are three main areas to focus on for further research. Future studies should test this framework using more substantial cross-platform datasets to see if the gap between reach and relevance is still present in various markets and media. The inclusion of complete replying and interaction networks would enrich harmonization with structural social network analysis metrics of sociometry (e.g., centrality, clustering, diffusion). Moreover, the use of the validated (or supervised) semantic models should strengthen measurement of the audience engagement in terms of product and sensory-related engagement.

Declarations

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DATA AVAILABILITY

The data that support the findings of this study are publicly available.

DECLARATIONS

The authors declare no competing interests.

DECLARATION OF AI ASSISTANCE

AI tools were used only to support language refinement and interface visualization. All analytical procedures, interpretations, and conclusions were developed and verified by the authors.

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Figures

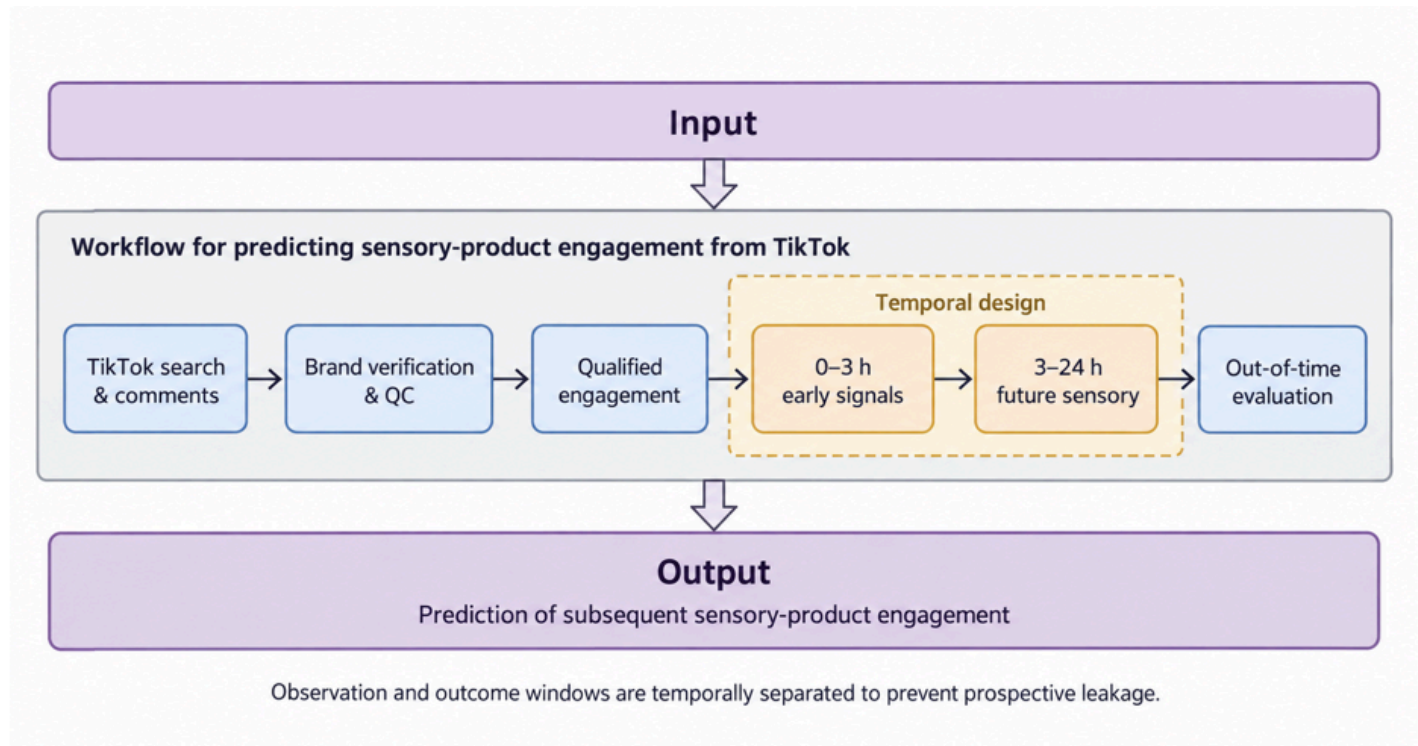


Figure 1

Analytical Workflow From TikTok Retrieval to Future Sensory Engagement

Note. The 0–3-hour observation window and the >3–24-hour outcome window are temporally separated to prevent prospective leakage. Source: Authors’ own work.

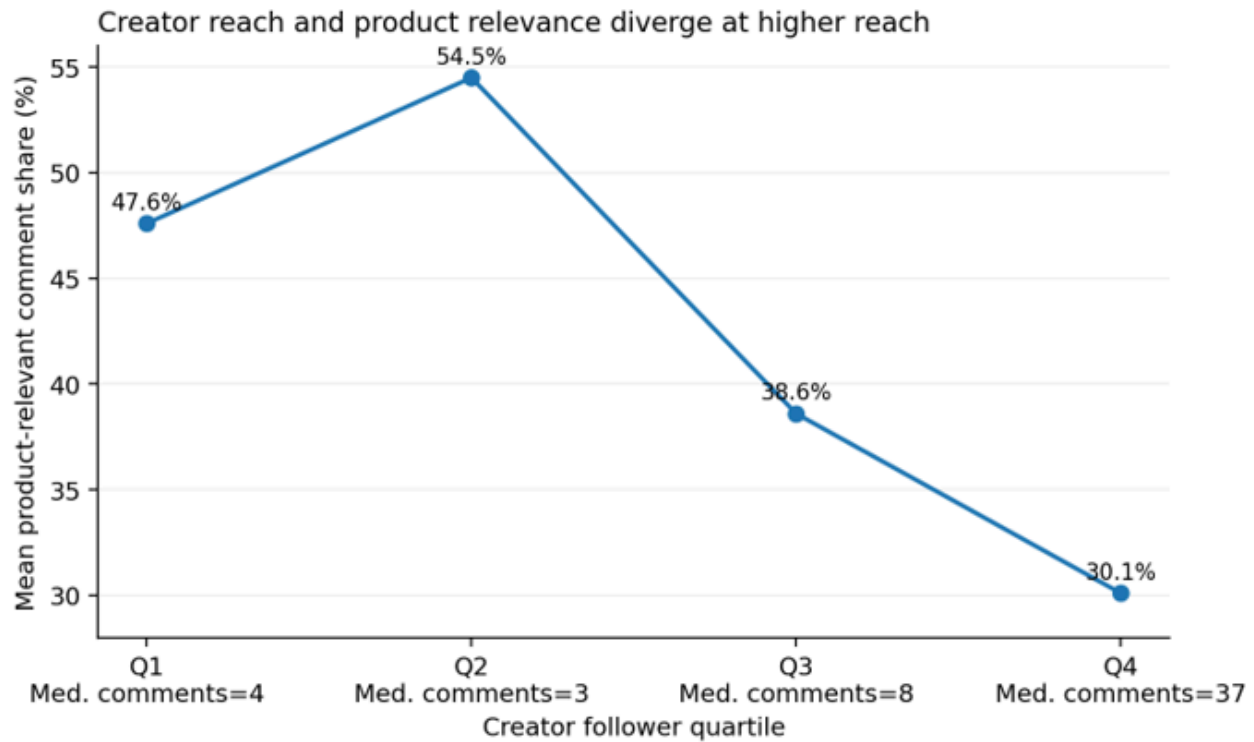


Figure 2

Creator Reach and Product Relevance Diverge at Higher Reach

Note. Follower quartiles are rank-based groups of approximately equal size. Source: Authors' calculations.

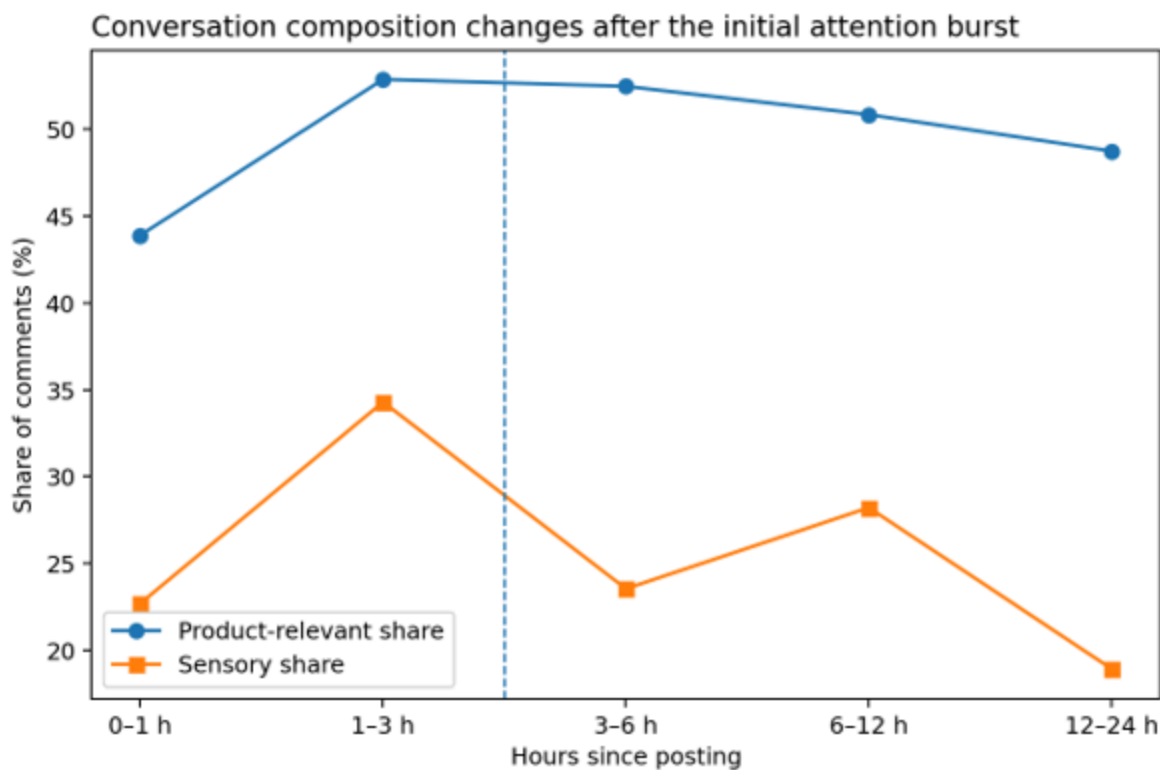


Figure 3

Conversation Composition Changes After the Initial Attention Burst

Note. The dashed line marks the 3-hour prediction cutoff. Source: Authors’ calculations.

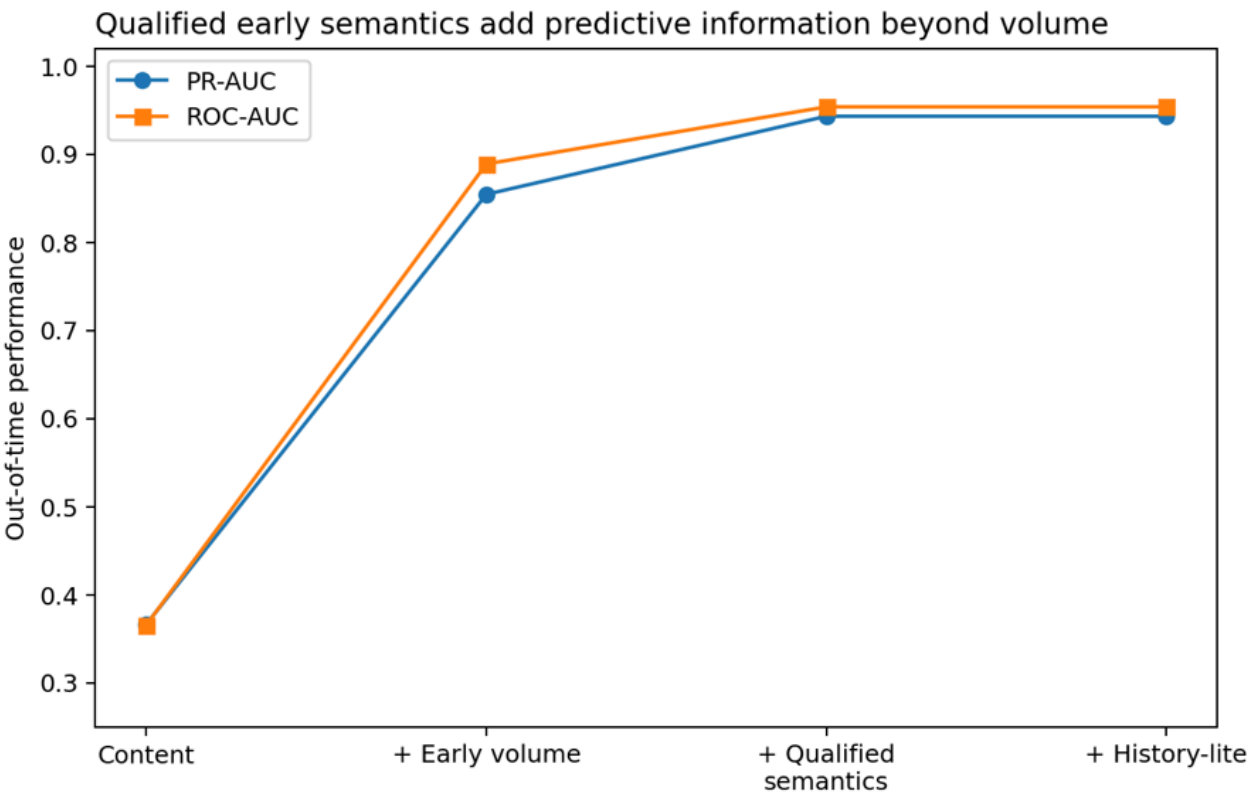


Figure 4

Qualified Early Semantics Add Predictive Information Beyond Volume

Note. Bars report chronological test ROC-AUC and PR-AUC for increasingly rich feature sets. Source: Authors’ calculations.

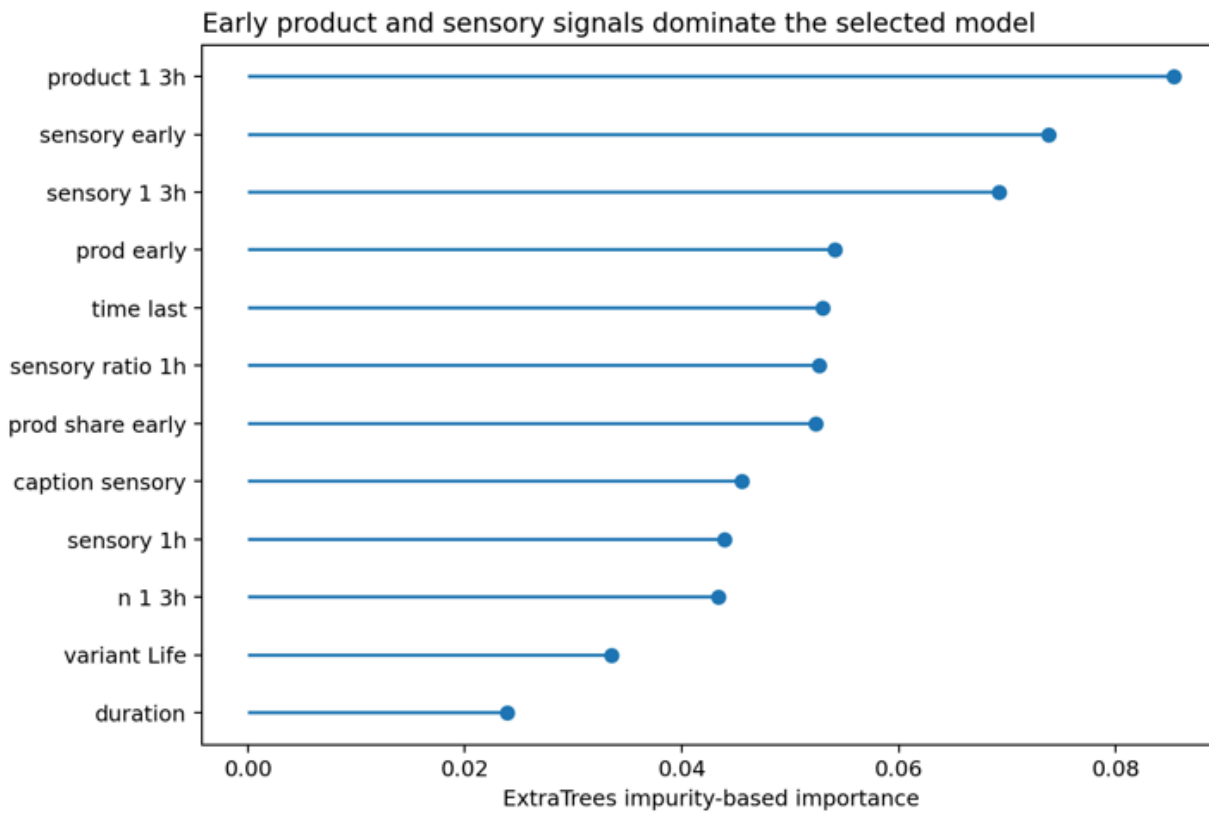


Figure 5

Early Product, Sensory, and Timing Signals Dominate the Selected Model

Note. Importance values are relative ExtraTrees impurity-based scores and do not indicate causal direction. Source: Authors' calculations.