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Does Excessive Influencer Advertising Reduce Brand Trust Among University-Aged Consumers?

Shuyu Zhang

Abstract:

The use of influencer marketing will be among the most effective methods of contemporary digital marketing, particularly among the younger generation of consumers spending most of their time on social media. Despite the influencer advertising strategy being effective in brand promotion, a series of concerns have risen to the fore with the excess consumption of the influencer advertising strategy potentially leading to decline in consumer trust due to advert fatigue and commercialisation. The paper looks at the relationship between influencer advertising strength and brand trust among consumers of their university age. The quantitative secondary data approach means that the research analyses almost 150,000 instances of influencer marketing campaigns in different social media. The behavioural proxy (brand trust) is the engagement rate and advertising exposure and intensity is determined by the number of days to carry out the campaign and the number of engagements per day. The two regression equations are one linear regression equation which examines the direct relations as well as nonlinear regression equation which examines weakening returns using inverted-U relation. The findings indicate that the impact of advertisement is dependent on the extent of the influencer advertising positively on the engagement rates, yet the marginal returns decline with the increasing exposure. The findings do not show a strong negative wear-out effect but rather show that advertising saturation leads to diminishing returns rather than a diminishing level of trust. These findings depict the necessity to strike the balance between the frequency of the advertisement and authenticity and relevance of the content to reach the Generation Z audiences. The study contributes to the body of knowledge concerning the effectiveness of influencer marketing and provides reasonable implications to the brands that strive to maintain consumer confidence and ensure the largest engagement in the highly competitive digital environment.

Keywords: Influencer marketing; Brand trust; Advertising saturation; Social media engagement; Generation Z.

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1. Introduction

Influencer marketing is the idea that has made one of the most significant shifts in digital advertising that took place during the past decade. Influencer marketing involves the involvement of the individual as opposed to the traditional channels of advertisement through corporate message via televisions, print or banner advertisements. The message marketer has already amassed huge amounts of online followers, and has acquired perceived credibility herself. Influencers can incorporate branded content into Instagram, Tik Tok, YouTube, and Twitter posts with no inconvenience based on a lifestyle, tutorials, reviews and entertainment content. The fact that the practice is popular on a global scale suggests its commercial value as the influencer marketing business is estimated to be 21 billion dollars as of 2023 to demonstrate how it can be the main promotional tool in the contemporary economy (Statista, 2024).

The fact that influencer marketing can integrate both commercial and perceived authenticity appeals makes it compelling. Influencers establish parasocial relationship with their followers more frequently than once since even though the relationship between the audience and the influencer is mediated and unidirectional, audiences have a personal attachment to the influencer. This dynamic can be reduced to minimize psychological resistance to advertising and increase the rate of message acceptance, respectively. The recommendations provided by influencers are seen in the majority of cases as the word of mouth rather than the brand promotion, compared to the classic ads. As a result, influencer marketing is traditionally associated with higher engagement rates, more brand memory and purchase intentions.

The consumer market that is highly appealing to the influencer-based campaigns is university-aged consumers, generally speaking of individuals in the range of 18 to 24 years old. Their level of social media penetration is very high, and this segment dedicates considerable amounts of time on digital formats. It has been reported that over 90 percent of people in this age group are followers of at least one influencer and a significant number of them are subscribers of several creators on various platforms (Morning Consult, 2023). Other than the high response rates, this group is a strategic one since early adoption of the brand in the university years could lead to lifelong customer loyalty. Because of this, influencer campaigns have become more popular promotion budgets involving young adults.

The fast adoption of influencer marketing, however, has raised concerns about the issue of over-commercialization and the loss of authenticity. Since brands are lining up to compete in saturated online spaces, influencers often take part in various paid deals in brief periods of time. Sponsored posts, discount codes, affiliate links, and product placements can be repeated several times in the feed of a follower. This repetition can cause advertising fatigue, build more skepticism and perceived reduced smattering of sincerity. The level of persuasion that comes with the authenticity of the influencers can be reduced when the promotion frequency is too high.

The element of brand trust is one of the fundamental concepts of the marketing theory and consumer behavior study. Trust is a belief on the reliability, honesty and capability of a brand by a consumer to provide promised value. Brand trust leads to a low perceived risk, higher likelihood of buying the product and long-term loyalty. In the case of younger consumers with a high level of digital literacy and used to seeing sponsored content, perceptions of authenticity might be especially relevant in generating trust accounts. When influencer advertising is seen as financially driven as opposed to being sincere, reviving trust could become difficult regardless of the warmth of engagement rates.

Meanwhile, other theoretical viewpoints propose that familiarity and perceived credibility can get stronger by repetition and exposure. The mere exposure effect is the hypotheses that repeated contact with a stimulus can positively evaluate, at least to a certain extent. Therefore, the dependence between advertising force and trust is not always negative but nonlinear, which could be characterized by decreasing returns, as opposed to negative ones. Engagement rate is used as a behavioral proxy of trust using secondary campaign-level data, campaign duration and campaign intensity are the measures of exposure to advertisements.

2. Literature Review

2.1 Influencer Marketing and Consumer Psychology

The concept of influencer marketing is built on the idea of psychological processes that goes beyond the conventional advertising methods. Primarily early and seminal theory of parasocial relations, initially introduced by Horton and Wohl, explains the process through which the audiences of media engage in relationship formation on one-sided, yet emotionally meaningful relationships with media personalities (Lotun, 2022). Within the framework of social media, such parasocial relationships are even stronger: the followers experience a personal connection to influencers that post apparently intimate and every-day content, and their recommendations are perceived as befriending peers, rather than corporations, marketing products. This sense of psychological proximity is what raises the persuasion as it makes the person committing it not to be viewed as a stranger marketer, but rather as a source of opinion that people can relate to. Recent studies have confirmed this influence with regard to online spaces, such that consumers, even young adults, often use the opinions of the influencer to create product attitudes (Migkos, 2025).

The cause behind this phenomenon is Source Credibility Theory that postulates that any form of trust and persuasion on the part of any communicator is based on the perceived expertise and sincerity (Filieri et al., 2023). Perceived to use products and support them in an authentic manner, influencers are recognized to be more credible sources that increase the persuasive effect of their messages as well as consumer responses to the brand promoted. In fact, the research conducted in the field of influencer marketing shows that authenticity and seemingly honesty are important predictors of consumer engagement and purchase intentions (Gohil, 2025). Skepticism is a possibility as noted in psychological models like the Persuasion Knowledge Model despite its advantages. In this model, consumers create mental constructs to detect and withstand persuasion; when consumers are aware of such an attempt to persuade them, they might respond at a higher level of skepticism and less trust. This detection is becoming quite prevalent in the digital age of literacy, particularly among consumers in the university age bracket who spend most of their lives in the social media space.

Generation Z in that regard has been demonstrated to distinguish authentic and highly commercialized content, and in some cases, prefers content created by micro-influencers or ordinary users instead of large-scale celebrity promotion (Ben, 2025). The psychological complexity of the credibility of the digital age is also brought up in recent literature. Influencer authenticity does not simply pertain to the factual trustworthiness but also emotional appeal and consistency of the storyline (Ebulueme, & Vijayakumar, 2024). Research takes a further step to highlight that influencers should be genuine, rather than strategic, whenever it comes to their product or values associations because followers are more inclined to follow influencers when they are authentic, though this is often less effective when influencers engage in sponsored activities on a regular basis or announce this information improperly (Rajput, 2024).

2.2 Brand Trust

Brand trust is one of the cornerstone concepts in consumer behavior that is given as a confidence of a consumer that a brand will behave in a reliable way, honestly and in the interest of the consumer. Trust minimizes how risky the decision can be and is a major indicator of loyalty and long-term involvement. Contemporary studies attest to the idea that trust is no less important in the realm of the internet environment, yet there are specific triggers of its emergence as far as influencer marketing is concerned (Ki et al., 2023). Sharing relatable content and showing an example of using the product in a real-life case make influencers humanize a brand and make it closer and more trustful to the followers. The results of a study carried out by various markets in 2025 identified the role of the authenticity and engagement of influencers to mediate the impact of marketing on brand trust in the case of the most affected Generation Z and Millennial consumers, with credibility and transparency being the most potent predictors of trust (Khanali & Moeini, 2025).

Social media personalities are increasingly incorporating products into their content in such a way that appears to be natural and reflects their own personal identity, consumers feel endorsements are honest reviews and not paid placements. This fuels the trust into the brand as such - an aspect that is especially relevant in the environment of younger adults, who require a transparent nature. The studies also indicate that, compared to advertising companies, the credibility of an influencer can be more effective than traditional brand messaging to influence the trust of an audience who is already skeptical of heavyweight corporate brand conversation, yet vulnerable to the influencer voice (Oranusi, 2025). Nevertheless, too much commercialization i.e. the use of sponsorships time and time again without the relevancy to a situation can violate trust. High digital literacy and critical discernment in gen Z ensure that they are able to note when content is motivated by monetary profit and not it is being used in a genuine way, and this can work against brand perceptions (Liventsova et al., 2024). Instead, brands have a two-fold task of ensuring promotional reach is balanced by networking with genuine influencers in whom the values of the target population are reflected.

2.3 Advertising Saturation and Wear-Out Effect.

Advertising saturation is defined as the stage where recurring exposure to the promotional messages no longer causes positive results on the consumer but, rather, the promotional messages can result in negative consumer reactions. The wear-out effect is an effect that was initially theorized during previous advertising research in which it was hypothesized that excessive repetition has the potential of being irritating and inducing message fatigue, which decreases the total effectiveness of the entire cam-

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paign (Bograkou, & Kontopoulou, 2025). This effect may be magnified in the realm of the digital and social media since users are constantly being bombarded with large amounts of content, including numerous sponsored posts by the same influencer or brand.

The advertising traffic is especially thick in terms of the users of generation Z who are some of the most active social media users. Modern day coverage points out that today, younger people are bombarded with thousands of adverts on a daily basis, which make it more probable that adverts will become background noise or annoying instead of persuading. Such saturation can undermine the perceived authenticity of the endorsements of the influencers, and it can even make people distrustful in case they experience the bombardment by commercials that seem to have no substance and worth (Barbosa, & Real de Oliveira, 2026).

Recent studies about the impacts of influencer marketing validate these fears, as they indicate that moderate exposure to the influencer content may increase engagement and intentions to purchase, while the frequency of high frequency but less authenticity of the content may decrease perceptions of credibility and diminish trust (Lashari, 2025). In the overly saturated digital world, consumers are looking increasingly at content that seems natural and familiar, and might resort to user-generated content or word-of-mouth discussion over sponsored messaging. In the meantime, the tendency, including the so-called de-influencing, where users warn people against buying hyped products, is also indicative of a much more general distrust of overexposed marketing and the reaction of the audience to the commercial densification of such platforms as TikTok.

2.4 Empirical Findings

A large body of literature reveals that the moderate exposure to influencers delivers some positive effects on trust and purchasing intentions. Recent research findings on the application of influencer marketing demonstrate that trustworthiness and perceptions have a positive relationship with quality of content, authenticity, and transparency, and engagement is highly interconnected with perceived trust (Migkos, 2025). A qualitative research report on consumer feelings about trust and authenticity in 2025 points out that being overburdened with commercials may undermine consumer trust. Repeated paid-based collaborations will be viewed with skepticism as consumers increasingly become conscious of branded content and are aware of the financial gain of the influencer. The research carried out particularly on Generation Z supports the importance of genuineness and openness.

In studies conducted across the varied population settings, it can be seen that influencer credibility has a strong relationship with brand trust in gen z consumers, despite the fact that they might discount the old methods of advertising. These findings are per the understanding that the digital natives are largely reliant on the peer-like suggestiveness and that the target audience needs the genuine tethering between the influencer and the advertised brand. In the meantime, the facts show that in some situations, brand recall and familiarity can be enhanced through repeated exposure and increase upward the trust and buying habits. This subtle evidence represented is to indicate that there is as much negative aspect to the positive correlation between advertising and trust as there can be a positive aspect or otherwise depending on quality of message, platform rules and consumer anticipations.

3. Methodology

The research assumes a quantitative approach to secondary data analysis to examine the connection between excessive influencer advertising and brand trust among consumers of university age. The analysis of Secondary data is appropriate to this study since it will enable the researcher to reuse vast existing data that contains real-life metrics of festival influencer campaigns in terms of engagement level, time span of the campaign, and coverage. This method compares to primary data collection since it would involve surveying the university students directly on their trust perceptions (which would be limited in time and ethics) but this method makes use of behavioral proxies based on the real campaign interactions in the key social media platforms. This is a common method used in marketing research where direct measures of a subjective construct have to be considered based on observable results.

The data is collected based on a big influencer marketing warehouse containing 150,000 campaign observations that were conducted on various platforms. Such variables included the duration of campaigns to be carried out, engagements, perceived reach, and the types of influencers. Instead of unique survey responses, these data are aggregated results of the influencer content performance, and thus the engagement rate as the ratio of engagements over estimated reach is a proxy variable of a desired consumer response to influencers content. In earlier studies, the association between higher levels of engagement and positive attitudes to consumers and perceived authenticity and trust in content has been demonstrated since credibility and trustworthiness are powerful predictors of engagement behaviors (Pan et al., 2025).

3.1 Research Design and Rationale

The study design is ex post facto quantitative analysis by regression modelling to investigate effective relations in functionalities between advertising intensity and engagement results. The design suited well since it considered the observations of already existing campaign data wherein the experimental manipulation to study (intensity of campaigns and duration) has already taken place and the researcher merely observes the associations, and not dictate the treatments. Observational designs of this nature are prevalent in the analysis of secondary data in marketing science, when the outcomes of real-world observations are studied in large numbers to identify observations of patterns that would not be easily feasible to accomplish experimentally.

Operationally defined key dependent variables and independent variables were applied before analysis. The log-transformed engagement rate is a dependent variable that aids in normalization of skewed distribution, thereafter making linear modelling possible. The independent variables will be a bag of log campaign and log engagements per day that is the length and intensity of the campaign respectively. Other control variables are categorical measures of platform, influencer type, and campaign type which correct structural differences in contexts of campaigns and thus could otherwise bias the findings.

The statistical analysis and data processing were done in Python due to the fact that the programming environment enables significant data to be analysed effectively using statistical and data science packages. Jupyter Notebook was used as the interactive environment in which the Python code was run, enabling the process of data cleaning, regression modelling and visualisation to be practically performed in a workflow that could be replicated.

3.2 Regression Models

3.2.1 Model 1 – Linear Effects Model

The initial model calculates the extent to which advertising intensity (duration and engagements per day) predicts the shifts in the engagement rate when holding other variables (campaign characteristics) constant. The equation may be formulated as follows:

$$ln(1+\text{EngagementRate}) = \beta_0 + \beta_1 ln\left(\text{Duration}\right) + \beta_2 ln\left(\text{EngagementsperDay}\right) + \sum \beta_i \text{Controls} + ?$$

With this model, it is possible to test the relationship as to whether higher advertising exposure increases or decreases the quality of engagement, with a linear relationship assumed. Using log-based transformation of duration and intensity will minimize skew and will process the predictors in terms of percentage change that is common in the marketing regression analysis using secondary campaign data.

3.2.2 Model 2 – Nonlinear “Inverted-U” Model

Model 2 requires testing more K tests because the structure of the relationship between the predictors is nonlinear, i.e. diminishing returns (or even negative effects at extreme levels) on the engagement rate:

$$ln(1+\text{EngagementRate}) = \beta_0 + \beta_1 ln\left(\text{Duration}\right) + \beta_2 ln(\text{Duration})^2 + \beta_3 ln(\text{EngagementsperDay}) + \beta_4 ln(\text{EngagementsperDay})^2 + \sum \beta_i \text{Controls} + ?$$

The inclusion of squared terms enables the detection of curvature: a positive linear term accompanied by a negative squared term suggests increasing engagement up to a threshold, followed by diminishing returns. This shape is more or less accurate so as to capture a theoretical concept of advertising wear-out / saturation effect where further exposure might yield less marginal gains or even negative ones, which is consistent with the logic behind marketing-mix modelling with a falling advertising effectiveness as reach becomes saturated.

3.3 Limitations and Ethical Considerations

The very existence of campaign metrics in the analysis of secondary data means that it as a necessity prevents the interpretation of such a psychological construct as trust since the engagement rate is on an indirect proxy. Moreover, demographic data about age groups in the university is not provided in the dataset, which means that the target population will be determined with caution. Among the moral issues are how to use and reference secondary sources rather than direct human subjects research that renders the process of obtaining new ethical approval unnecessary. The study appreciates a few limitations that consist of the deletion of content, bias in the algorithm of platforms, and the inability to express problems, such as the quality of message or authenticity of influencers, which cannot be monitored. Having such a methodologically sound study design of a combination of descriptive and regression analysis, the research will provide sound and evidence-based research on the perceived linkage of influencer advertisement intensity with the engagement outcome which is commonly perceived in the marketing field as a sign of trust.

4. Data Analysis and Findings

4.1 Dataset Overview and Variable Construction

The data includes 150,000 campaign-based observations,

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which gives an adequate research ground to investigate the connection between the advertising intensity and the engagement quality. Engagement rate was operationalized with the engagements compared to the estimated reach, and it is a behavioral measure of brand trust. The duration of the campaign is exposure to advertising and engagements per day are an indicator of advertising intensity. The Excessiveness Index is an index developed by standardizing variables of log length, and log intensity to indicate campaigns where there is long exposure with high interaction density. With this composite measure, it is possible to identify the 20% of campaigns that are the most common which could be considered as too much influencer advertising.

Table 1: Variable Definitions and Operationalization

Variable	Definition	Role in Analysis
Engagement Rate	Engagements ÷ Estimated Reach	Proxy for Brand Trust
Campaign Duration	Length of campaign in days	Proxy for Advertising Exposure
Engagements per Day	Engagements ÷ Duration	Advertising Intensity
Excessiveness Index	Standardised duration + intensity	Excessive Advertising Indicator

4.2 Descriptive Statistics

The descriptive statistics in Table 2 shows that the duration of the campaign is averaged at 14.98 days with a median of 15 days, implying that the campaign length was evenly distributed among the sample. The average of engagements is 50,065, and the estimated reach is 500,240, both almost equal to their corresponding median, which means that there is a relatively funnel-shaped distribution of raw campaign metrics. The mean and the median of product sales are 2,497 and 2,501 respectively and has indicated that the sales output remains steady between campaigns.

Table 2: Descriptive Statistics of Key Variables

	campaign_duration_days	engagements	estimated_reach	product_sales	engagement_rate	engagements_per_day	sales_per_reach	excessiveness_index
count	150000.000000	150000.000000	150000.000000	150000.000000	150000.000000	150000.000000	150000.000000	1.500000e+05
mean	14.976127	50065.296107	500239.634920	2497.730433	0.339736	6836.359621	0.016804	-2.919383e-16
std	8.358356	28847.302798	288003.388219	1443.222587	1.747477	11698.110414	0.082969	4.176851e-01
min	1.000000	100.000000	1002.000000	0.000000	0.000102	3.846154	0.000000	-2.743787e+00
25%	8.000000	25060.500000	251439.500000	1248.000000	0.050149	1676.190000	0.002511	-1.995635e-01
50%	15.000000	50100.500000	500073.500000	2501.000000	0.100153	3344.057566	0.004990	9.643706e-02
75%	22.000000	75045.250000	750016.750000	3746.000000	0.200121	6506.116667	0.009914	3.057567e-01
max	29.000000	99999.000000	999992.000000	4999.000000	97.892611	99996.000000	3.644250	5.778747e-01

Engagement rate, on the other hand, has a significant right-skewness. Despite the average rate of engagement being 0.3397, the median is lower at 0.1002, meaning that a small percentage of the campaigns produce disproportionate high engagement rates. The mean is smaller than the standard deviation of 1.7475 and the top figure of 97.89 proves the existence of extreme outliers. Sales per reach are also rather disseminated, with the maximum value of 3.64 even though the average is 0.0168. The Excessiveness Index is all zero because it was going to be because it is standardised and the dispersion is moderate.

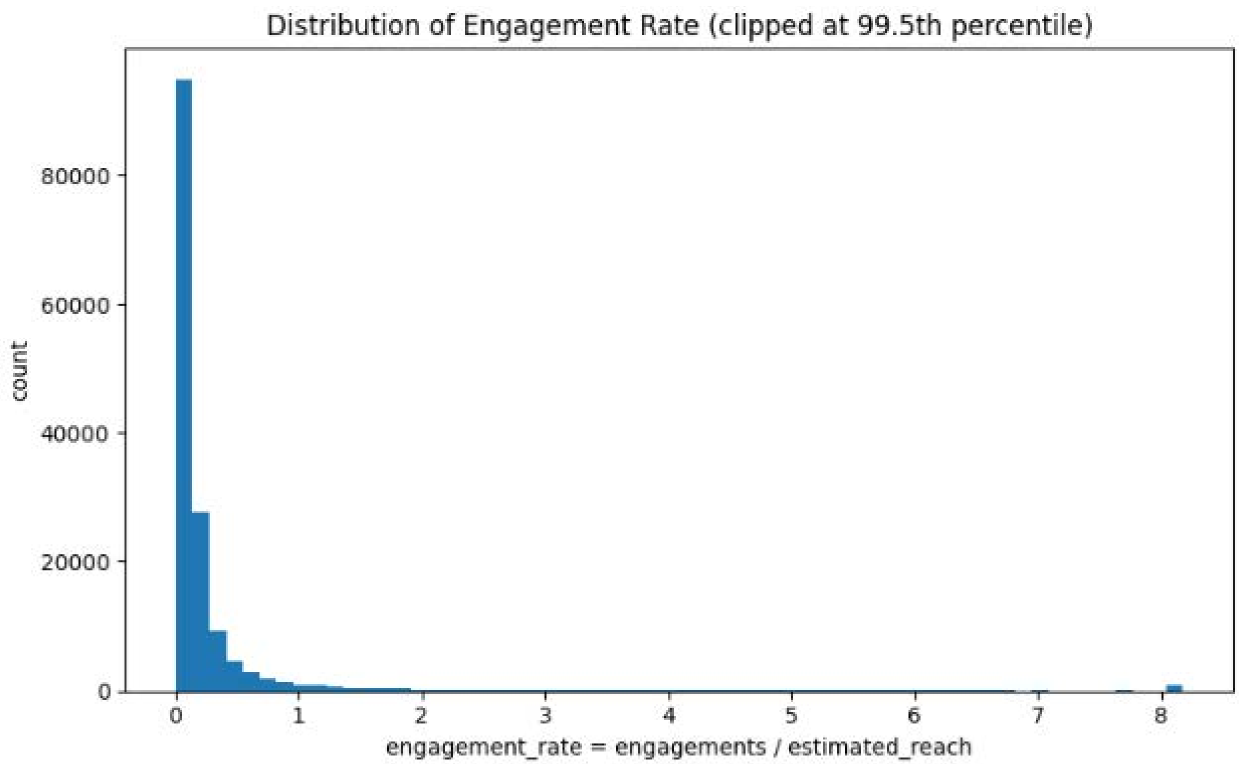

Figure 1: Distribution of Engagement Rate

The visual confirmation of the skewed nature of the engagement rate is provided in Figure 1. Most of the observations are concentrated around zero, and their right tail is long with large values. After cutting off at the 99.5 th percentile, much dispersibility is still observed. The trend explains the use of logarithmic transformation when using the regression modelling that follows.

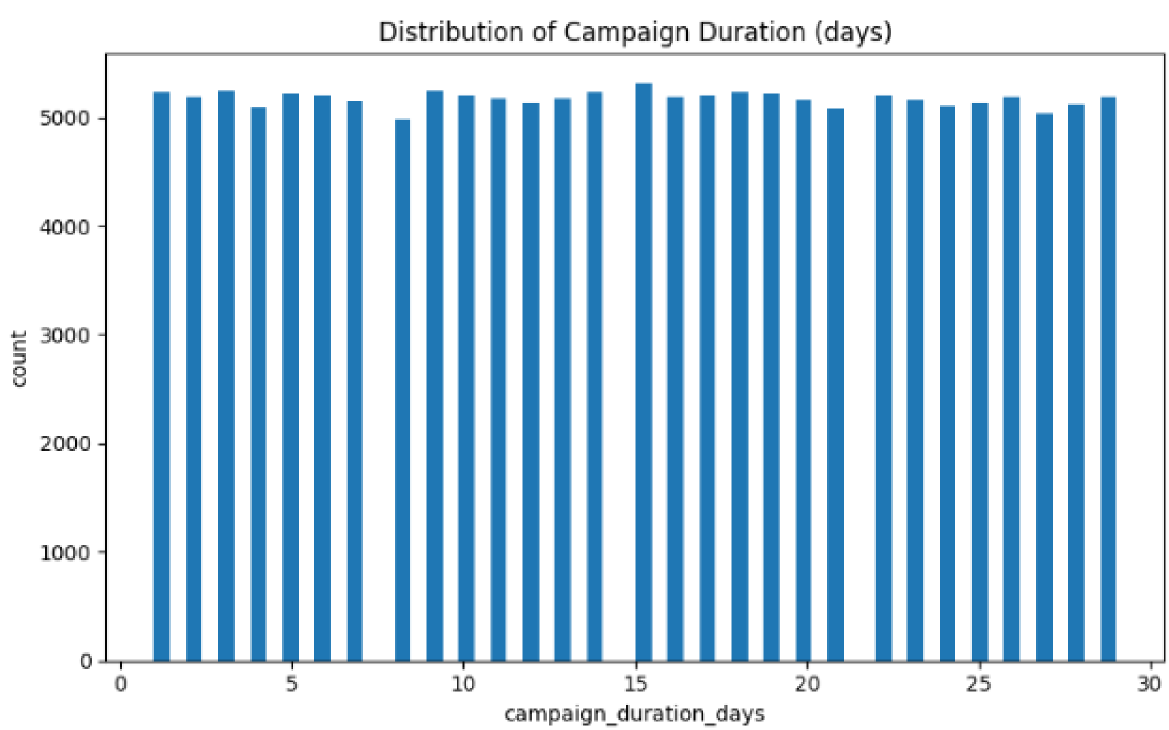

Figure 2: Distribution of Campaign Duration

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As Figure 2 demonstrates, the length of the campaign is spread quite evenly between 1 and 29 days. The lack of detachment at the long durations suggest that further effects cannot be sustained to be operated by distributional imbalance.

4.3 Engagement Rate by Campaign Duration

The scatter plot in Figure 3 does not show any apparent negative linear correlation between the campaign duration and the engagement rate. A high-density clustering can be seen at the low levels of engagement within all the lengths of staying whereas outliers can be seen on different lengths of campaigns. The lack of the decreasing trend implies that duration is not a direct diminishing factor of engagement.

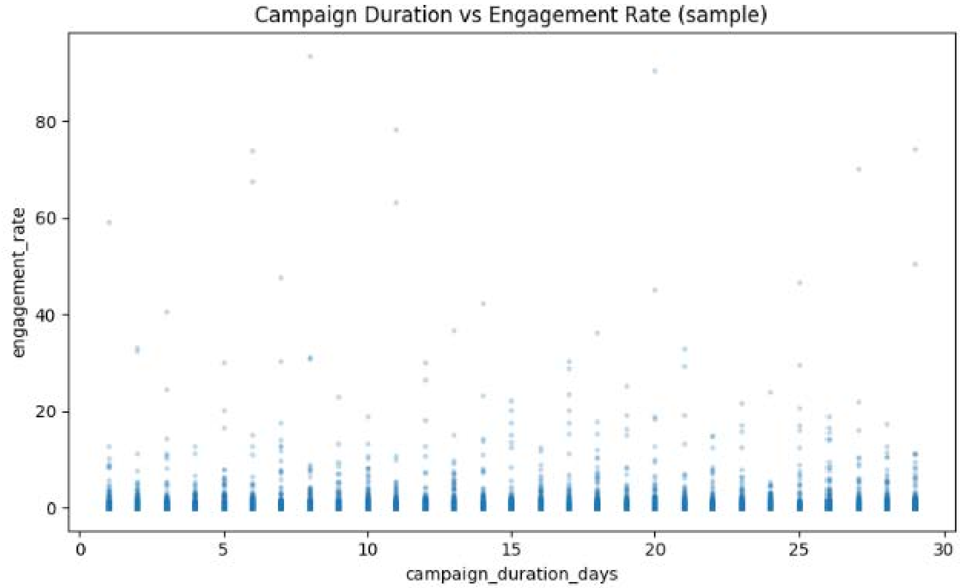

Figure 3: Campaign Duration vs Engagement Rate (Scatter Plot)

The mean engagement rate by duration decile shown in figure 4 suggests a more subtle trend. There is enhanced engagement at the initial campaign time, which peaks at the tenth month and then swings up and down as well as a minor moderation at the top deciles. It is not a downward trend but the declining overshoot along the curve is indicating a decreasing marginal return. Such findings suggest that longer campaigns do not necessarily lower the engagement, but the advantages of longer time seem to fade away with time.

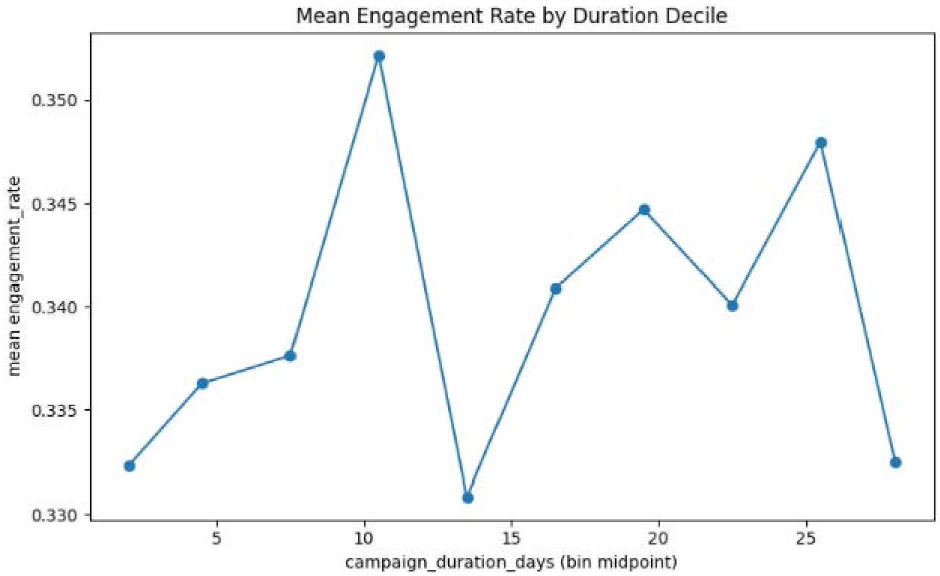

Figure 4: Mean Engagement Rate by Duration Decile

4.4 Platform-Level Differences

As shown at Figure 5, it can be concluded that the median engagement rates are generally similar on Instagram, YouTube, Tik Tok, and Twitter. The interquartile ranges are also large in size, and there is no platform with systematically greater engagement. Diversity is still strong in each category of platforms. These results are suggestive of the idea that platform does not significantly change the engagement/exposure relationship in this dataset.

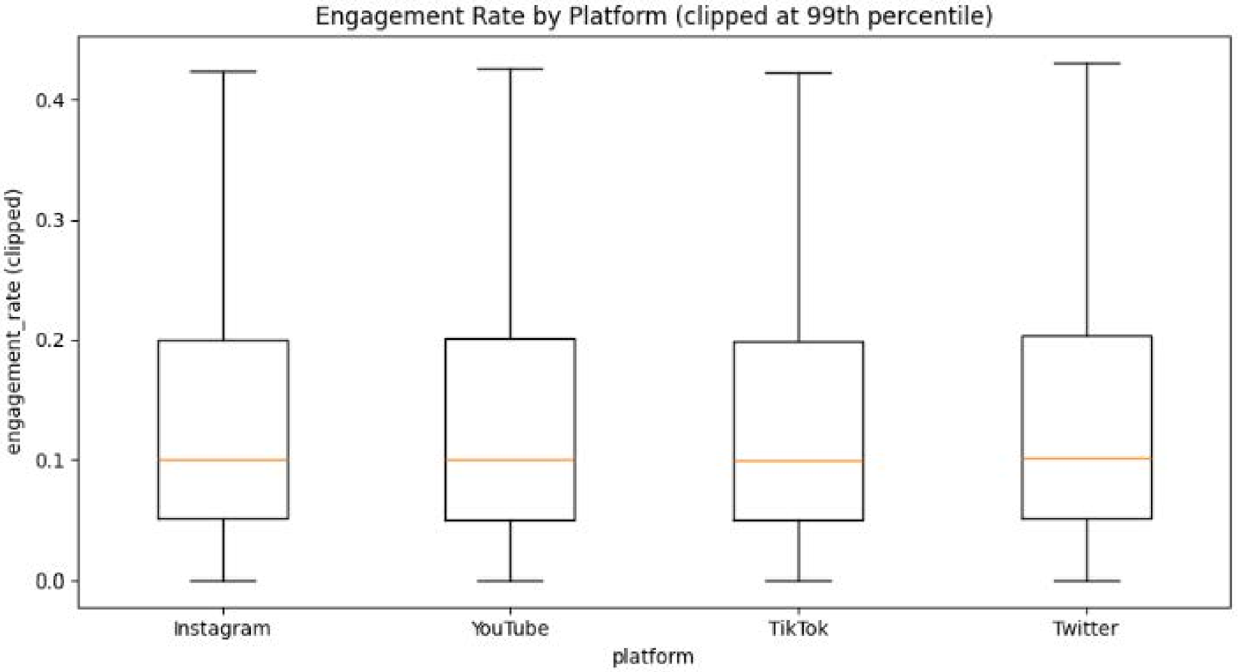

Figure 5: Engagement Rate by Platform (Boxplot)

4.5 Excessive vs Non-Excessive Campaign Comparison

Table 3 provides a comparison between campaigns that are excessive and the ones that are not excessive, being in the 20% of the Excessiveness Index. The excessive group has an excessively high group engagement of 0.5552 to 0.2859 in the non-excessive group. There are also significant differences in median engagements of 0.1661 and 0.0825 respectively. There is an increase in the standard deviation of excessive campaigns and so there is a wider variation in performance.

Table 3: Engagement Rate by Excessiveness Group

Excessive Group	Mean	Median	Std. Deviation	Count
Excessive (Top 20%)	0.555232	0.166143	2.471108	30,000
Not Excessive (Bottom 80%)	0.285862	0.082462	1.508653	120,000

It is graphically verified that over campaigning show more average engagement rates 6. Descriptively, this result goes against the hypothesis that intensive influencer advertising decreases trust. Rather, exposure and intensity show positive correlation with engagement that is observed. Descriptive comparisons, however, do not consider the possibility of confounding factors and thus require that regression analysis is carried out.

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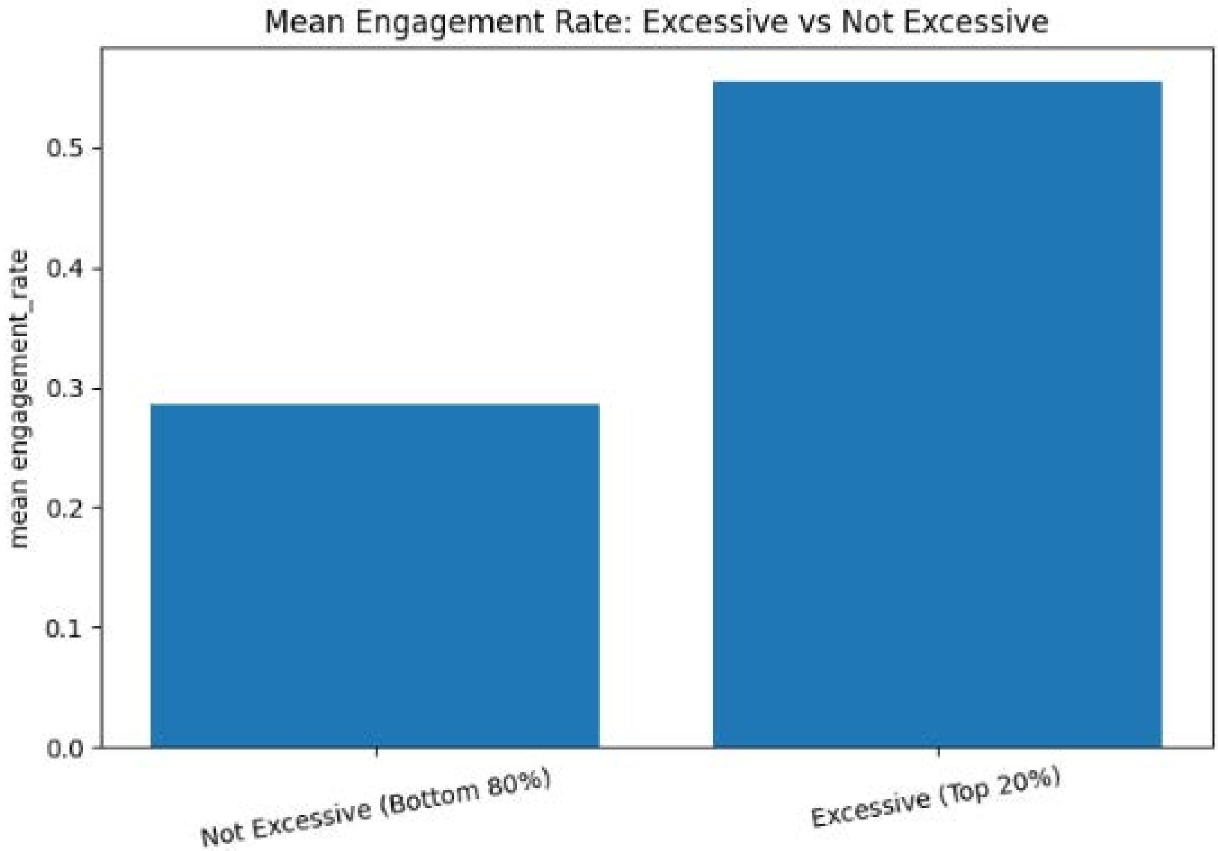

Figure 6: Mean Engagement Rate – Excessive vs Not Excessive

4.6 Correlation Analysis

The correlation table, shown in Table 4 indicates that campaign duration and engagement rate are almost linear with having a coefficient of 0.0017. The engagements per day are positively correlated with engagement rate with a weak positive correlation of 0.0364. The Excessiveness Index has a small positive correlation with the engagement rate of 0.0896. These associations are of statistically insignificant magnitude.

Table 4: Correlation Matrix

	campaign_duration_days	engagements_per_day	excessiveness_index	engagement_rate	sales_per_reach
campaign_duration_days	1.000000	-0.535067	0.384702	0.001739	0.003814
engagements_per_day	-0.535067	1.000000	-0.033194	0.036444	-0.001900
excessiveness_index	0.384702	-0.033194	1.000000	0.089590	-0.000511
engagement_rate	0.001739	0.036444	0.089590	1.000000	0.708354
sales_per_reach	0.003814	-0.001900	-0.000511	0.708354	1.000000

The positive relationship between the engagement rate and sales per reach is strong, 0.7084, which proves the economic significance of engagement and its close association with sales efficiency. On the whole, we cannot find correlation evidence proving the assumption that too much advertising decreases the quality of engagement.

4.7 Regression Analysis

According to the linear regression findings shown in Table 5 log duration as well as log engagement per day are related to log engagement rate. The log duration coefficient is 0.0874 and is significant with the likelihood that the coefficient of the log engagement per day is also 0.0856 and significant. These findings indicate that campaign duration and intensity are positively correlated with engagement after dominating platform and category of influencer, and type of campaigns. The approximated 6.9% of explained variance of engagement rate suggests that the model has low explanatory power.

Table 5: Linear Regression Results – Advertising Intensity and Engagement Rate (Model 1)

OLS Regression Results

Dep. Variable:	log_engagement_rate	R-squared:	0.069
Model:	OLS	Adj. R-squared:	0.069
Method:	Least Squares	F-statistic:	1240.
Date:	Mon, 02 Mar 2026	Prob (F-statistic):	0.00
Time:	11:39:45	Log-Likelihood:	-35349.
No. Observations:	150000	AIC:	7.073e+04
Df Residuals:	149984	BIC:	7.089e+04
Df Model:	15		
Covariance Type:	HC3		

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	-0.7224	0.007	-101.441	0.000	-0.736	-0.708
C(platform)[T.TikTok]	-0.0004	0.002	-0.184	0.854	-0.005	0.004
C(platform)[T.Twitter]	0.0054	0.003	1.886	0.059	-0.000	0.011
C(platform)[T.YouTube]	0.0010	0.002	0.511	0.610	-0.003	0.005
C(influencer_category)[T.Fashion]	0.0042	0.003	1.427	0.153	-0.002	0.010
C(influencer_category)[T.Fitness]	0.0012	0.003	0.410	0.682	-0.005	0.007
C(influencer_category)[T.Food]	0.0034	0.003	1.164	0.244	-0.002	0.009
C(influencer_category)[T.Gaming]	0.0031	0.003	1.091	0.275	-0.002	0.009
C(influencer_category)[T.Tech]	0.0027	0.003	0.937	0.349	-0.003	0.008
C(influencer_category)[T.Travel]	0.0034	0.003	1.154	0.249	-0.002	0.009
C(campaign_type)[T.Event Promotion]	0.0003	0.002	0.131	0.896	-0.005	0.005
C(campaign_type)[T.Giveaway]	0.0023	0.003	0.924	0.355	-0.003	0.007
C(campaign_type)[T.Product Launch]	-0.0009	0.002	-0.382	0.703	-0.006	0.004
C(campaign_type)[T.Seasonal Sale]	0.0025	0.003	0.983	0.326	-0.002	0.007
log_duration	0.0874	0.001	77.779	0.000	0.085	0.090
log_eng_per_day	0.0856	0.001	136.224	0.000	0.084	0.087

In Table 6, the nonlinear regression model provides squaring terms to examine the presence or absence of diminishing returns. The coefficient of log duration is positive that is 0.1623, whereas the squared term that is negative and statistically significant is +0.0117. This combination implies the reversed-U type of relationship, whereby there is an increase in engagement with the duration until a certain point and thereafter the marginal gains decrease. The same can be seen with engagement intensity and it has a negative linear term and a positive squared term which is indicative of non-linear dynamics. The fit of the model is a bit better, and the R^2 increases to 0.074.

Table 6: Nonlinear Regression Model (Inverted-U Test) (Model 2)

OLS Regression Results

Dep. Variable:	log_engagement_rate	R-squared:	0.074
Model:	OLS	Adj. R-squared:	0.074
Method:	Least Squares	F-statistic:	1411.
Date:	Mon, 02 Mar 2026	Prob (F-statistic):	0.00
Time:	11:39:47	Log-Likelihood:	-34884.
No. Observations:	150000	AIC:	6.980e+04
Df Residuals:	149982	BIC:	6.998e+04
Df Model:	17		
Covariance Type:	HC3		

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	-0.2959	0.011	-27.980	0.000	-0.317	-0.275
C(platform)[T.TikTok]	-0.0003	0.002	-0.131	0.896	-0.005	0.004
C(platform)[T.Twitter]	0.0051	0.003	1.794	0.073	-0.000	0.011
C(platform)[T.YouTube]	0.0011	0.002	0.562	0.574	-0.003	0.005
C(influencer_category)[T.Fashion]	0.0042	0.003	1.435	0.151	-0.002	0.010
C(influencer_category)[T.Fitness]	0.0014	0.003	0.482	0.630	-0.004	0.007
C(influencer_category)[T.Food]	0.0032	0.003	1.109	0.267	-0.002	0.009
C(influencer_category)[T.Gaming]	0.0029	0.003	1.009	0.313	-0.003	0.008
C(influencer_category)[T.Tech]	0.0026	0.003	0.904	0.366	-0.003	0.008
C(influencer_category)[T.Travel]	0.0037	0.003	1.263	0.206	-0.002	0.010
C(campaign_type)[T.Event Promotion]	0.0001	0.002	0.046	0.963	-0.005	0.005
C(campaign_type)[T.Giveaway]	0.0019	0.003	0.740	0.459	-0.003	0.007
C(campaign_type)[T.Product Launch]	-0.0011	0.002	-0.436	0.663	-0.006	0.004
C(campaign_type)[T.Seasonal Sale]	0.0023	0.003	0.901	0.368	-0.003	0.007
log_duration	0.1623	0.004	39.551	0.000	0.154	0.170
log_duration_sq	-0.0117	0.001	-12.048	0.000	-0.014	-0.010
log_eng_per_day	-0.0690	0.003	-20.448	0.000	-0.076	-0.062
log_eng_per_day_sq	0.0107	0.000	42.108	0.000	0.010	0.011

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Figure 7 represents the estimated correlation between duration of campaign and engagement rate keeping other factors constant. The curve ascends rapidly at the beginning duration and gradually levels off with increase in duration. A steep fall is not seen in the range of observation, so it is a case of diminishing returns and is not the case of collapse in engagement.

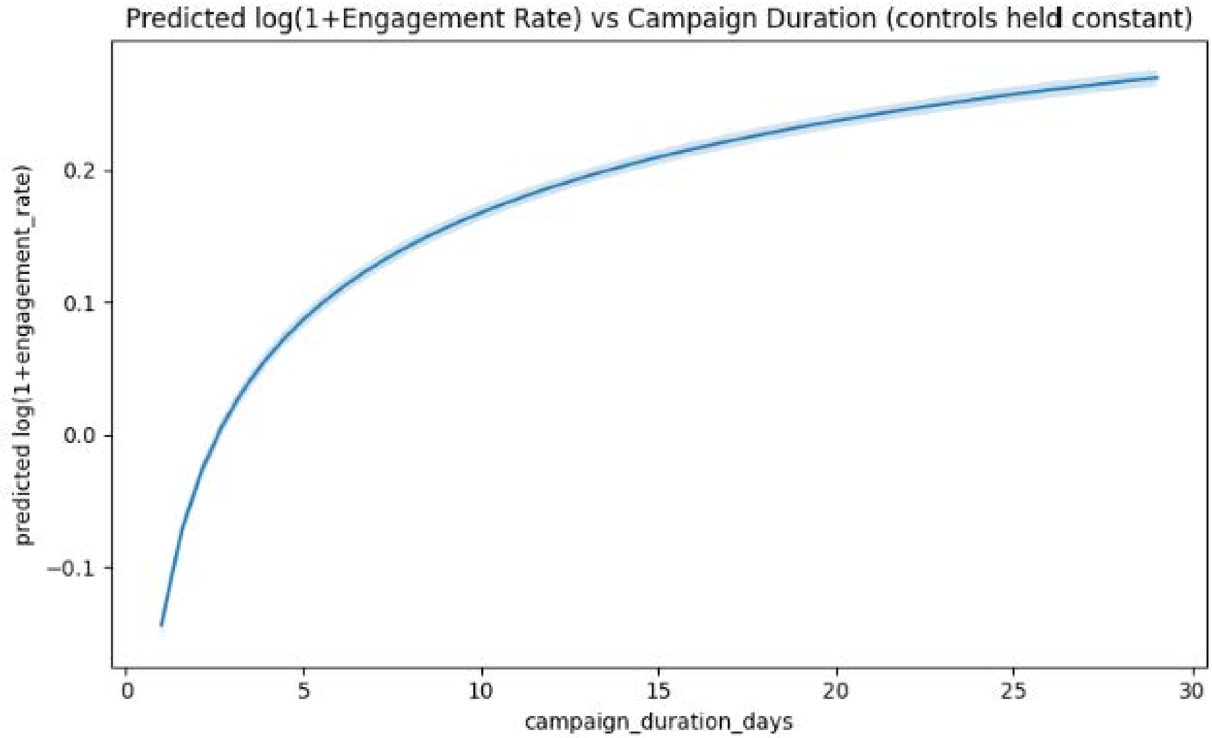

Figure 7: Predicted Engagement Rate vs Campaign Duration (Marginal Effects Plot)

4.8 Platform-Specific Regression Results

Table 7 consists of platform-specific regressions. On Instagram, Youtube, Tik Tok, and Twitter, the coefficient of the log time is positive and the coefficient of the square is negative, and the consistent inverted-U trends are taken into consideration. The values of R2 are between 0.0709 and 0.0755 that show that the explanatory power is similar regardless of the platform. Tik Tok shows a bit higher intensity sensitivity, but the differences are not very significant. The regularities of nonlinear patterns across mediums imply that the effects of advertising time look structural time features independent of social media conditions.

Table 7: Platform-Specific Regression Coefficients

	platform	n	log_duration	log_duration_sq	log_eng_per_day	log_eng_per_day_sq	R2
0	Instagram	59819	0.162290	-0.012379	-0.064753	0.010375	0.075330
1	YouTube	45139	0.159852	-0.010813	-0.073780	0.011075	0.074587
2	TikTok	29984	0.166148	-0.012214	-0.077528	0.011377	0.075507
3	Twitter	15058	0.161326	-0.010521	-0.055073	0.009861	0.070868

5. Conclusion

The results of the study experience suggest that the overall effect of excessive influencer advertising on brand trust does not necessarily occur because of the engagement proxies in the studied dataset. Whereas the conventional advertising wear out theory holds that excessive exposure may induce adverse behavioral reactions among the consumers, both descriptive and inferential data show an alternative and nonlinear association between the intensity of influencer advertising and the quality of engagement. The rate of engagement is more likely to increase with length and intensity of campaign, although the marginal rates decrease not at a full straight line, but in the form of an inverted-U. It implies that a further exposure would bring the less marginally good response, instead of creating a sudden decline in consumer responsiveness.

These findings are consistent with the current literature that found the consumers of the generation Z to respond favourably to influencer content provided they uphold a perceived authenticity, credibility and conformity to their values. The relations of authenticity and trust established as positive in the previous research indicate that the level of advertising intensity can be maintained in case the content of influencers is effective and eager. Besides, the recent sensitivity of Gen Z to inauthentic content proves the relevance of quality and not quantity of influencer and sponsorships. On a more practical note, instead of telling the brands to limit the amount of exposure to the influencers, the research indicates that including authenticity, content relevancy, and aligning with consumers will prove more effective to establish long-term trust among younger consumers.

6. Evaluation

Looking back into the research process yields key findings including the strengths as well as the limitations of this study. The ability to utilize a massive secondary data set which allowed conducting a large-scale quantitative influencer campaign analysis is one of the core strengths. The size of the sample offered statistical strength to identify the existence of minor trends in the data and prevented the bias on outcomes because of small samples exception. Moreover, the combination of descriptive and inferential approaches made the analysis process more enriched with the possibility to explore both general patterns and complex nonlinear consequences. The combination of various models such as the linear and nonlinear regressions was also found particularly useful in determining that the intensity of advertising does not have consistent effects on decreasing engagement as they would have been ignored with more simplistic methods.

The dataset does not consist of direct indicators of brand trust and lacks demographic indicators that the respondents are of university age. Applying engagement rate as a proxy of trust, although it can be justified through the marketing literature, places an interpretative burden; engagement behaviour is not necessarily trust, particularly in the digital context in which likes and shares can be motivated by curiosity and not trust. It is strengths to these kinds of behavioural proxies that would be enhanced with primary survey research data that directly measures perceptions of trust, authenticity and advertising fatigue.

Even though it presented congruent nonlinear tendencies, causality cannot be even imagined, as it is an observational design. It has confounding variables, such as quality of content, readability of the narrative and influencer credibility, which might likely have an impact on the results of engagement but could not be comprehensively described in the dataset. Inclusion of increased rich metadata on content characteristics would contribute to explanatory power on a subsequent model. The methodology of the study was also acceptable with regard to the choice of control and transformation. Categorical controls were required to help isolate skewed distributions and adjustments of logs were required so that an effort could be made in trying to manage the skewed data which meant that statistical work on large real-world data demands strong manipulation. It was demonstrated that the provided methodology is informative and can be useful in regard to describing the areas to be reviewed, particularly, in the domain of measurement validity and causal inferences.

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Appendix

Primary Data Table (First 20 Rows)

campaign_id	platform	influencer_category	campaign_type	start_date	engagements	estimated_reach	product_sales	campaign_duration	end_date
CAMP100000	TikTok	Fitness	Giveaway	1/1/2022 0:00	79900	1892	2834	14	1/15/2022 0:00
CAMP100001	YouTube	Food	Product Launch	1/2/2022 0:00	47985	437228	165	13	1/15/2022 0:00
CAMP100002	TikTok	Travel	Brand Awareness	1/3/2022 0:00	13875	982513	2539	5	1/8/2022 0:00
CAMP100003	YouTube	Food	Brand Awareness	1/4/2022 0:00	41200	213400	100	20	1/24/2022 0:00
CAMP100004	Instagram	Food	Giveaway	1/5/2022 0:00	96998	42501	550	28	2/2/2022 0:00
CAMP100005	Twitter	Beauty	Brand Awareness	1/6/2022 0:00	76687	443289	2338	27	2/2/2022 0:00
CAMP100006	TikTok	Tech	Seasonal Sale	1/7/2022 0:00	8878	116825	1027	17	1/24/2022 0:00
CAMP100007	TikTok	Gaming	Brand Awareness	1/8/2022 0:00	74092	644094	121	13	1/21/2022 0:00
CAMP100008	Instagram	Travel	Event Promotion	1/9/2022 0:00	84035	66087	3405	14	1/23/2022 0:00
CAMP100009	YouTube	Food	Event Promotion	1/10/2022 0:00	74906	258767	1149	1	1/11/2022 0:00
CAMP100010	Instagram	Tech	Event Promotion	1/11/2022 0:00	15117	926004	2657	18	1/29/2022 0:00
CAMP100011	Twitter	Fitness	Seasonal Sale	1/12/2022 0:00	87945	992541	2901	7	1/19/2022 0:00
CAMP100012	YouTube	Travel	Product Launch	1/13/2022 0:00	59591	343970	1906	19	2/1/2022 0:00
CAMP100013	TikTok	Fashion	Product Launch	1/14/2022 0:00	71678	696891	2935	9	1/23/2022 0:00
CAMP100014	YouTube	Tech	Product Launch	1/15/2022 0:00	65588	420535	279	21	2/5/2022 0:00
CAMP100015	Instagram	Tech	Seasonal Sale	1/16/2022 0:00	51368	905867	2297	23	2/8/2022 0:00
CAMP100016	YouTube	Gaming	Brand Awareness	1/17/2022 0:00	14300	719281	3530	11	1/28/2022 0:00
CAMP100017	Instagram	Fitness	Giveaway	1/18/2022 0:00	66262	130779	4080	25	2/12/2022 0:00
CAMP100018	TikTok	Food	Brand Awareness	1/19/2022 0:00	5542	362628	1083	18	2/6/2022 0:00

Python Code Snippets

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

# Optional (for regression)
import statsmodels.api as sm
import statsmodels.formula.api as smf

# 1) Load data
PATH = "influencer_marketing_roi_dataset.csv"
df = pd.read_csv(PATH)

print("Shape:", df.shape)
display(df.head())
print("\nColumns:", df.columns.tolist())
```

```
Shape: (150000, 10)
```

	campaign_id	platform	influencer_category	campaign_type	start_date	engagements	estimated_reach	product_sales	campaign_duration_days	end_date
0	CAMP100000	TikTok	Fitness	Giveaway	2022-01-01 00:00:00	79900	1892	2834	14	2022-01-15 00:00:00
1	CAMP100001	YouTube	Food	Product Launch	2022-01-02 00:00:00	47985	437228	165	13	2022-01-15 00:00:00
2	CAMP100002	TikTok	Travel	Brand Awareness	2022-01-03 00:00:00	13875	982513	2539	5	2022-01-08 00:00:00
3	CAMP100003	YouTube	Food	Brand Awareness	2022-01-04 00:00:00	41200	213400	100	20	2022-01-24 00:00:00
4	CAMP100004	Instagram	Food	Giveaway	2022-01-05 00:00:00	96998	42501	550	28	2022-02-02 00:00:00

```
# 2) Basic cleaning & typing
# Parse dates
df["start_date"] = pd.to_datetime(df["start_date"], errors="coerce")
df["end_date"]   = pd.to_datetime(df["end_date"], errors="coerce")

# Ensure numeric columns are numeric
num_cols = ["engagements", "estimated_reach", "product_sales", "campaign_duration_days"]
for c in num_cols:
    df[c] = pd.to_numeric(df[c], errors="coerce")

# Drop rows with critical missing values
df = df.dropna(subset=["platform", "influencer_category", "campaign_type",
                       "engagements", "estimated_reach", "campaign_duration_days"])

# Remove impossible / problematic values
df = df[df["estimated_reach"] > 0]
df = df[df["campaign_duration_days"] > 0]
df = df[df["engagements"] >= 0]
df = df[df["product_sales"].fillna(0) >= 0]

print("\nAfter cleaning shape:", df.shape)
```

```
...
After cleaning shape: (150000, 10)
```

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```
# 3) Feature engineering (EPQ variables)
# Trust proxy: engagement quality
df["engagement_rate"] = df["engagements"] / df["estimated_reach"]

# Intensity proxies:
df["engagements_per_day"] = df["engagements"] / df["campaign_duration_days"]
df["sales_per_reach"] = df["product_sales"] / df["estimated_reach"]

# A combined "exposure/intensity index" (scaled) - optional for EPQ
# Log-transform to reduce skew
df["log_duration"] = np.log(df["campaign_duration_days"])
df["log_eng_per_day"] = np.log1p(df["engagements_per_day"])  # log(1+x)

# Standardise (z-scores)
def zscore(s):
    return (s - s.mean()) / s.std(ddof=0)

df["z_log_duration"] = zscore(df["log_duration"])
df["z_log_eng_per_day"] = zscore(df["log_eng_per_day"])

# Simple composite "excessiveness index"
df["excessiveness_index"] = (df["z_log_duration"] + df["z_log_eng_per_day"]) / 2

display(df[["campaign_duration_days","engagements","estimated_reach",
            "engagement_rate","engagements_per_day","excessiveness_index"]].head())
```

	campaign_duration_days	engagements	estimated_reach	engagement_rate	engagements_per_day	excessiveness_index
0	14	79900	1892	42.230444	5707.142857	0.338146
1	13	47985	437228	0.109748	3691.153846	0.123452
2	5	13875	982513	0.014122	2775.000000	-0.560891
3	20	41200	213400	0.193065	2060.000000	0.153894
4	28	96998	42501	2.282252	3464.214286	0.558680

```
# 4) Descriptive statistics
desc = df[["campaign_duration_days","engagements","estimated_reach","product_sales",
           "engagement_rate","engagements_per_day","sales_per_reach","excessiveness_index"]].describe()
display(desc)

# Category breakdown examples
platform_counts = df["platform"].value_counts()
campaign_counts = df["campaign_type"].value_counts()
category_counts = df["influencer_category"].value_counts()

print("\nPlatform counts:\n", platform_counts.head(10))
print("\nCampaign type counts:\n", campaign_counts.head(10))
print("\nInfluencer category counts:\n", category_counts.head(10))
```

	campaign_duration_days	engagements	estimated_reach	product_sales	engagement_rate	engagements_per_day	sales_per_reach	excessiveness_index
count	150000.000000	150000.000000	150000.000000	150000.000000	150000.000000	150000.000000	150000.000000	1.500000e+05
mean	14.976127	50065.296107	500239.634920	2497.730433	0.339736	6836.359621	0.016804	-2.919383e-16
std	8.358356	28847.302798	288003.388219	1443.222587	1.747477	11698.110414	0.082969	4.176851e-01
min	1.000000	100.000000	1002.000000	0.000000	0.000102	3.846154	0.000000	-2.743787e+00
25%	8.000000	25060.500000	251439.500000	1248.000000	0.050149	1676.190000	0.002511	-1.995635e-01
50%	15.000000	50100.500000	500073.500000	2501.000000	0.100153	3344.057566	0.004990	9.643706e-02
75%	22.000000	75045.250000	750016.750000	3746.000000	0.200121	6506.116667	0.009914	3.057567e-01
max	29.000000	99999.000000	999992.000000	4999.000000	97.892611	99996.000000	3.644250	5.778747e-01

```python
# 8) Regression modelling (controls + nonlinearity)
# Goal: test whether 'excessiveness' (duration/intensity) predicts lower engagement_rate.

df["log_engagement_rate"] = np.log1p(df["engagement_rate"])

# a) Linear model with controls
# C(...) makes categorical variables
model_1 = smf.ols(
    "log_engagement_rate ~ log_duration + log_eng_per_day + C(platform) + C(influencer_category) + C(campaign_type)",
    data=df
).fit(cov_type="HC3")  # robust SEs for heteroskedasticity

print(model_1.summary())

# b) Nonlinear "too much is bad": add squared term for duration and/or intensity
df["log_duration_sq"] = df["log_duration"]**2
df["log_eng_per_day_sq"] = df["log_eng_per_day"]**2

model_2 = smf.ols(
    "log_engagement_rate ~ log_duration + log_duration_sq + log_eng_per_day + log_eng_per_day_sq"
    " + C(platform) + C(influencer_category) + C(campaign_type)",
    data=df
).fit(cov_type="HC3")

print(model_2.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:     log_engagement_rate   R-squared:                       0.069
Model:                             OLS   Adj. R-squared:                  0.069
Method:                  Least Squares   F-statistic:                     1240.
Date:                 Mon, 02 Mar 2026   Prob (F-statistic):               0.00
Time:                         11:39:45   Log-Likelihood:                -35349.
No. Observations:               150000   AIC:                         7.073e+04
Df Residuals:                   149984   BIC:                         7.089e+04
Df Model:                           15
Covariance Type:                   HC3
```