

Reach and Engagement as Predictors of Instagram Influence Scores: Implications for Digital Public Relations

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Abstract: This study investigates the relationship between audience reach and consolidated audience engagement with the Influence Scores of top influencers on Instagram, and explores the implications of these relationships for data-informed influencer evaluation for digital PR. A quantitative, cross-sectional design was applied to secondary data from 200 profiles contained in the Top Instagram Influencers Data (Cleaned) dataset. As the three measures were highly intercorrelated, the Average Likes, 60-Day Engagement Rate, and New Post Average Likes were standardized and averaged to create an Engagement Index. A multiple linear regression was then utilized to predict the Influence Score provided by the dataset from follower count and the Engagement Index. There was moderate correlation between follower count and Influence Score ($r = .368$); and strong intercorrelation among the engagement indicators ($r = .845-.869$). In the regression model, follower count significantly predicted Influence Score ($B = 4.602 \times 10^{-8}$, $t = 5.670$, $p < .001$), whereas the Engagement Index was not statistically significant ($B = -0.689$, $t = -1.078$, $p = .283$). The overall model was significant, $F(2,197) = 16.074$, $p < .001$, explaining 14.0% of the variance. Findings suggest that audience reach is correlated with the Influence Score from the data provider, and that consolidated engagement does not add a significant predictive value. These findings should be interpreted as evidence relevant to influencer screening rather than as direct evidence of public-relations effectiveness.

Keywords: Influencer Marketing; Digital Public Relations; Instagram; Audience Reach; Audience Engagement; Social Media Analytics.

Type: Research paper



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1. Introduction

Digital platforms have revolutionized the way organizations engage with their stakeholders, handle stakeholder visibility, and respond to public discussion. More and more, the public relations activities are conducted via social-media platforms which can facilitate the exchange of information and direct access to the target audience in a timely manner (Wolf & Archer, 2018). In this context, social-media influencers are important communication intermediaries, as they combine credibility with high reach and familiarity, and their content is believed to be in-depth and of high value (Borchers & Enke, 2021; Gammarano et al., 2025; Melnychuk et al., 2024).

Thus, influencer marketing is not just about the short-term promotion of products. Beyond that, influencers can help organisations spread a message, target specific online communities and aid larger communication goals. But their value comes with the evaluation of influencer performance. Some of the most popular metrics are number of followers, average likes, engagement rate, and recent-post performance. Likes and engagement rates indicate actual audience interaction, while followers are a good indicator of potential audience reach.

The previous studies on influencer marketing have focused on the purchase intentions of consumers, the reaction of the brand, the credibility of the endorsement, and the results of the advertising, and have been carried out by surveys, experiments, or case studies (Haenlein et al., 2020; Melnychuk et al., 2024; Vrontis et al., 2021). In contrast, less work has been conducted on the relationship between reach and engagement, and an influencer-performance score together, using archival platform data. This reduces the data managers must choose and measure influencers from tangible performance indicators.

To address this gap, the study analyzes secondary data from 200 most popular Instagram profiles that are part of the Top Instagram Influencers Data (Cleaned). It tests if follower count and a combined variable of audience engagement is correlated with and predictive of the Influence Score provided with the data sets. Importantly, the study does not directly measure digital-public-relations effectiveness. Instead, it examines profile-level indicators that may assist communication managers in the preliminary screening and evaluation of potential influencers. Rather, indicators at the profile level that can help communication managers screen and evaluate potential influencers are considered. The implications for DPR are therefore managerial and interpretive – the findings could be used to make decisions about who to select for their influencer relations program, but they do not claim that higher Influence Scores lead to higher stakeholder trust, reputation, relationship quality, or communication effectiveness.

2. Literature Review

2.1. Influencer Marketing

Influencer marketing is a carefully orchestrated partnership between brands and influencers who have built visibility and credibility with social-media consumers. Influencer communication is integrated within the normal content and relationship with audiences, which can lead to greater perceptions of authenticity and relevance (Chidiac & Bowden, 2023; De Veirman et al., 2019; Faisal, 2025; Vrontis et al., 2021) as compared to conventional advertising. Some of the key properties to measure the effectiveness of an influencer are size of the audience, credibility, quality of content and engagement around the content posted (Dhanesh & Duthler, 2019; Haenlein et al., 2020; Reinikainen et al., 2020).

Follower count and engagement are related, but conceptually different factors of influencers' performance. Follower count is generally seen as a reflection of possible audience reach, while likes and engagement rates reflect what can be seen when audience interacts with published content. A high number of followers do not automatically mean a high level of engagement; therefore, reach and engagement metrics can be used together to assess the performance of influencers and not solely as a measure of engagement.

New studies also reveal that influencer communication is shifting from traditional, print-based social media endorsement to a more dynamic form. Today, the main focus is on increasingly interactive and relational communication models with influencers, such as livestreaming, virtual influencers, and hyperconnected influencer environments. For instance, Buckley et al. (2025) illustrate that immediacy, interactivity, credibility and authenticity are increasingly important attributes in livestream-based influencer marketing, while Davlembayeva et al. (2025) further demonstrate that virtual-influencer effectiveness depends on combinations of relational attributes, including interactivity, credibility, warmth, relatedness, competence, empathy, uniqueness, and fairness, rather than on audience size alone. These are signs that should make people think about the difference between reach and engagement and relational qualities as they assess influencers for their organizations.

2.2. Relationships Between Influencers and Digital Public Relations

Digital public relations (DPR) is an extension of organizational communication into communication environments made up of online channels that allow stakeholders to receive, share and react to messages in real-time (Wolf & Archer, 2018) and (Tong & Chan, 2023). Influencers can serve as external communication intermediaries, bringing the organization's message to existing online communities. Their role is relevant to DPR because they can help broaden the message reach and enable a dialogue with audiences that might not be reached via an organization's-controlled channels (Borchers & Enke, 2021; Davies & Hobbs, 2020; Haenlein et al., 2020).

However, social media metrics at the profile level are not direct measures of reputation, trust, stakeholder relationships, and public relations effectiveness. Rather, these are clues to possible reach and actual interactions. Their value to DPR is thus mainly in aiding the identification, selection and performance measurement of influencers.

2.3. Reach, Engagement, and Influence Score

The effectiveness of influencer marketing in terms of consumer attitudes, the intention to purchase, endorsement credibility and brand reactions has been studied, among others, in previous research in this field. Less research has examined the relations among observable measures of audience reach and engagement and platform-based scoring of influencers relative to each other or to performance data from the past. The issue is particularly important since the indicators of engagement (such as average likes, engagement rate and likes of the last posts) can be highly intercorrelated and thus provide redundant information if used in the same regression model.

In this study, follower numbers are used as a measure of audience reach, and multiple highly intercorrelated measurements of engagement are amalgamated into a common Engagement Index. The following hypotheses are suggested:

H1: Follower count is positively associated with Instagram Influence Score.

H2: The Engagement Index is positively associated with Instagram Influence Score.

3. Research Methodology

3.1. Research Design

This study adopts a quantitative, explanatory and cross-sectional research design to examine whether observable audience-reach and engagement indicators are associated with and predict the dataset-provided Influence Score of leading Instagram profiles. The research uses a deductive approach, which involves the formulation of hypotheses based on the theories of influencer marketing, digital communication, and DPR and then the empirical testing of the formulated hypotheses using secondary data. This is a cross-section research design because the observations reflect the performance of the picture of the influencers at one moment in time. The study is based on the positivist research philosophy, which focuses on the objective measurement of phenomena, statistical analysis, and hypothesis testing to explore the relationships between digital communication indicators and influencer effectiveness.

3.2. Data Source and Sampling

The raw data used for this study is from Top Instagram Influencers Data (Cleaned) which can be found on Kaggle and is provided by S. Jha (2022). The archived dataset includes 200 of Instagram's most popular profiles and their data consisting of Influence Score, followers, posting activity, average likes, 60-Day Engagement Rate, New Post Average Likes, total likes and country. According to the Kaggle repository, the data was made public several years prior to this study, but the exact dates that the profile metrics of Instagram were recorded is not reported by the source. The data cannot be interpreted as current performance data of Instagram, and the results are therefore based on archival data and should be considered as a cross-sectional snapshot.

The study adopted a complete enumeration approach and analyzed all profiles of influencers in the analyzed secondary data for the period under study. The data is a representative sample of the top performers on Instagram; however,

not all of the Instagram influencers are represented. So, the results only really apply to account profiles that have a large following of influencers.

3.3. Data Collection

This study uses secondary data that are available in the public Kaggle repository. The data includes details about the Instagram influencers, like their influence score, followers, total posts, average likes, 60-day engagement rate, new post average likes, and country of origin. The data was cleaned for duplicates, missing data, inconsistent data, and data formatting before analysis. Values given in abbreviated notation (e.g., “m” for millions, “b” for billions, and percentages) were translated into numerical values for statistical analysis.

The missing proportion was relatively small (0.5%) with regards to the variable ‘60-Day Engagement Rate’, as noted by Data Quality Assessment. Missing values were minimal and thus mean value was imputed to replace the missing value such that 200 influencer profiles were analyzed descriptively, correlational, and regressively. The dataset is freely available and de-identified; thus, there are no ethical considerations concerning the confidentiality of the participants.

3.4. Variable Measurement

The operational definitions for the study variables are included in Table 1. The digital communication practices for which the indicators are followers, average likes, engagement rate, and new post average likes are practices that reflect audience interaction and the effectiveness of the communication. The Influence Score used in this study is simply the quantitative dependent variable provided by the archived data set. It cannot be used as an indicator of the effectiveness of public-relations efforts, stakeholder trust, organizational reputation or campaign results.

Table 1: Measurement of Research Variables

Variable	Type	Measurement
Followers	Independent	Total number of Instagram followers
Average Likes	Independent	Average number of likes received per post
60-Day Engagement Rate	Independent	Percentage of audience engagement during the previous 60 days
New Post Average Likes	Independent	Average likes received on recent posts
Influence Score	Dependent	Dataset-provided composite score used to rank or characterize influencer prominence; its underlying construction and external validity are not independently established in this study

3.5. Multicollinearity Diagnostics

To check for the presence of multicollinearity among the independent variables of the multiple linear regression model, Pearson correlation, tolerance, and Variance Inflation Factor (VIF) were employed. The initial analysis on correlation indicates a very high positive correlation between average likes, engagement rate, and new post average likes, implying that there is multicollinearity among the variables.

To substantiate this problem, tolerance and VIF statistics were taken. Those variables with tolerance < 0.20 or VIF > 5 were deemed to represent an undesirable degree of multicollinearity. The results of the diagnostic tests showed that the three variables related to engagement had high values of VIF, which were above the threshold to be considered acceptable.

To overcome this problem, the three engagement variables were standardized and then combined into one composite variable referred to as the 'Engagement Index.' This index is a measure of the overall degree of audience engagement and is free from multicollinearity and will make the regression estimates more stable. The revised regression model thus had only two predictors: Followers and Engagement Index.

3.6. Model for Analysis

This study uses multiple linear regression (MLR) to analyze the effect of digital communication practices on the effectiveness of influencers. Multiple linear regression is used because it takes multiple independent variables into consideration for a single dependent variable and holds constant the influence of the other independent variables. The regression model is expressed as Equation (1 & 2):

$$IS_i = \beta_0 + \beta_1 FOL_i + \beta_2 EI_i + \varepsilon_i \quad (1)$$

Where IS_i represents the Influence Score of influencers i , FOL_i represents the number of followers, EI_i represents the Engagement Index, β_0 is the intercept, β_1 and β_2 are the regression coefficients, and ε_i is the error term.

The Engagement Index was calculated as the arithmetic mean of the standardized values of Average Likes, 60-Day Engagement Rate, and New Post Average Likes:

$$EI_i = [z(AL_i) + z(ER_i) + z(NPL_i)] / 3 \quad (2)$$

Where each standardized value is calculated as $z(X_i) = (X_i - \bar{X})/s_x$.

A statistically significant regression coefficient indicates that the respective predictor provides unique explanatory information regarding the dataset-provided Influence Score after controlling for the other predictor. Such an association should not be interpreted as evidence of causality or direct public-relations effectiveness.

3.7. Statistical Analysis

Data analysis was carried out in IBM SPSS Statistics Version 29. Data quality, outlier identification, and the translation of textual numerical values to quantitative variables for statistical analysis were performed as data preprocessing steps before hypothesis testing. Details of how missing data were treated and other preprocessing methods used are described in Section 3.3.

The statistical analysis was done in three phases. Descriptive statistics comprising the mean, standard deviation, minimum, and maximum were calculated to summarize the distributions of the study variables. The statistics give an overview of the distribution and variability of the performance indicators of influencers.

Second, Pearson correlation analysis was conducted to investigate the direction and strength of the relationships between followers, average likes, 60-day engagement rate, new post average likes, and influence score. Multicollinearity among the predictor variables was also checked using the correlation matrix.

Third, the diagnostics of multicollinearity were performed by means of tolerance and variance inflation factor (VIF). Significant multicollinearity was detected among the engagement variables: Average Likes, 60-Day Engagement Rate, and New Post Average Likes. Average Likes, 60-Day Engagement Rate, and New Post Average Likes seemed to be multicollinear because the diagnostics showed large correlations between the variables. All of these were measured on different scales, so they were first converted to a z score. The three standardized values were subsequently averaged to form a single 'Engagement Index'. This composite is an equal-weight one and it maintains the common engagement information that is present in the three-engagement information but does not simultaneously include highly correlated engagement variables in the regression model. The final regression model thus contained two predictors: Followers and the Engagement Index.

This is followed by Multiple Linear Regression (MLR) analysis, in which followers and the engagement index derived from them are used as predictor variables of the influence score. The regression analysis gave the estimated unstandardized regression coefficients (β), coefficient of determination (R^2), adjusted coefficient of determination (adjusted R^2), F statistic, t-values, and significance levels (p-values). Results were considered statistically significant at the 5% significance level ($p < 0.05$). A hypothesis was deemed to be supported if the regression coefficient was statistically significant and the direction of the regression coefficient was correct.

This integrated approach to descriptive statistics, Pearson correlation analysis, multicollinearity diagnostics, and multiple linear regression offers a holistic analysis of digital communication and its impact on the effectiveness of an influencer. This analytical framework provides a systematic basis for examining how audience reach and consolidated engagement are statistically associated with the dataset-provided Influence Score. The implications for DPR are limited to the potential use of these metrics in preliminary influencer screening and evaluation.

4. Results

4.1. Descriptive Statistics

Descriptive statistics were calculated to get an overall picture of the distribution of study variables prior to testing hypotheses (see **Table 2**). Descriptive measures are represented by the mean, standard deviation, minimum value, maximum value, skewness, and kurtosis.

Table 2: Descriptive Statistics of Study Variables

Variable	Mean	Standard Deviation	Minimum	Maximum
Influence Score	81.82	8.88	22.00	93.00
Followers	77.41 Million	73.69 Million	32.80 Million	475.80 Million
Average Likes	1.79 Million	2.19 Million	65.1 Thousand	15.40 Million
60-Day Engagement Rate (%)	1.90	3.32	0.01	26.41
New Post Average Likes	1.21 Million	1.86 Million	0	12.60 Million

The mean Influence Score was 81.82 ($SD = 8.88$), with values ranging from 22 to 93. The sampled profiles had an average of 77.41 million followers, although the high standard deviation of 73.69 million indicates substantial variation in audience size. Average likes also varied considerably, ranging from 65.1 thousand to 15.40 million. The mean 60-day engagement rate was 1.90% ($SD = 3.33$), with a maximum of 26.41%. New-post average likes ranged from zero to 12.60 million. Overall, the descriptive results indicate considerable heterogeneity in both audience reach and engagement among the sampled profiles.

4.2. Correlation Analysis

Pearson's correlation analysis was carried out to investigate the relationships between the study variables in terms of strength and direction before the regression analysis (see Table 3).

Table 3: Pearson Correlation Matrix

Variable	Influence Score	Followers	Average Likes	Engagement Rate	New Post Average Likes
Influence Score	1.000	0.368	0.051	-0.082	0.037
Followers	0.368	1.000	0.349	-0.101	0.301
Average Likes	0.051	0.349	1.000	0.721	0.846
Engagement Rate	-0.082	-0.101	0.721	1.000	0.868
New Post Average Likes	0.037	0.301	0.846	0.868	1.000

Follower count had a moderate positive correlation with Influence Score ($r = .368$, $p < .001$). In contrast, Average Likes ($r = .051$, $p = .469$), 60-Day Engagement Rate ($r = -.082$, $p = .249$), and New Post Average Likes ($r = .037$, $p = .607$) showed weak and statistically nonsignificant bivariate relationships with Influence Score. The three engagement indicators were positively and strongly interrelated, with correlations ranging from $r = .721$ to $r = .868$ ($p < .001$). These relationships indicate substantial overlap among the engagement measures and support the decision not to enter them simultaneously as separate predictors in the final regression model.

The multicollinearity diagnostics further supported the decision to consolidate the engagement indicators. In the initial model, VIF values were 2.80 for Followers, 3.72 for Average Likes, 10.02 for 60-Day Engagement Rate, and 11.93 for New Post Average Likes. Thus, particularly substantial multicollinearity was evident for the latter two engagement measures, while the strong correlations among all three engagement indicators also indicated considerable conceptual and statistical overlap. Their standardized values were therefore averaged to create the Engagement Index. In the final two-predictor model, the VIF values for Followers and the Engagement Index were approximately 1.04, indicating that problematic multicollinearity was no longer present.

4.3. Multiple Linear Regression Analysis

To examine whether audience reach and consolidated audience engagement predict the dataset-provided Influence Score, a multiple linear regression model was estimated using Followers and the Engagement Index as predictors. The average likes, 60-day engagement rate, and new post average likes were found to be highly intercorrelated prior to regression analysis, with the values of the variance inflation factor (VIF) being above the recommended threshold. In order to alleviate this problem, these three variables were all highly correlated and were added together to create a composite termed the "Engagement Index." To reduce the redundancy from engagement-related variables, were standardized and their means computed, which led to the creation of the Engagement Index.

Table 4: Multiple Linear Regression Results

Predictor	Unstandardized B	Standard Error	t-value	p-value	Decision
Constant	78.258	0.858	91.157	<.001	-
Followers	4.602×10^{-8}	8.12×10^{-9}	5.670	<.001	Significant
Engagement Index	-0.689	0.640	-1.078	.283	Not significant

Note: Model statistics: $R^2 = .140$; *Adjusted* $R^2 = .132$; $F(2,197) = 16.074$; $p < .001$; $N = 200$.

The multiple regression model in Table 4 was statistically significant, $F(2,197) = 16.074$, $p < .001$, and explained 14.0% of the variance in Influence Score ($R^2 = .140$; *adjusted* $R^2 = .132$). Follower count was a positive and statistically significant predictor of Influence Score ($B = 4.602 \times 10^{-8}$, $t = 5.670$, $p < .001$), thus supporting H1. Contrariwise, the Engagement Index was not found to be a significant predictor of the Influence Score with follower count controlled

($B = -0.689$, $t = -1.078$, $p = .283$), so that H2 was not supported. The results suggest that the audience reach measure when combined with the standard measure provided by the data source (Influence Score) provided additional explanatory information to the data source, while the combined engagement measure did not.

5. Discussion and Implications

Among the 200 highest-ranking Instagram profiles that were studied, the results showed that follower count (as a measure of audience reach) is significantly correlated with the dataset- provided Influence Score. After consolidating engagement, the number of followers was also statistically significant. The Engagement Index, by contrast, was found to be statistically insignificant even when controlling for the number of followers. This does not mean that engagement is not important in the process of communicating with influencers. Instead, it shows that the specific set of engagement metrics included in this de-archived data set does not vary from audience reach to forecast the source-defined Influence Score.

Additionally, Average Likes, 60-Day Engagement Rate and New Post Average Likes highly correlate with one another, further highlighting that these factors carry some redundant data. The standardized values in each of these were lumped together and not entered at the same time as separate predictors and therefore combined into an Engagement Index. As for managers, the results indicate that caution needs to be taken in using quantitative profile scores. While follower count can help initial screening, other factors like content relevance, audience authenticity, communication quality, brand–influencer fit, stakeholder sentiment, credibility and campaign-specific goals should also be taken into account during decision making for DPR partnerships.

The study adds to the field of influencer-marketing research by drawing on platform-performance data of past content, in addition to the survey perceptions and experimental responses. Yet, the analysis is predicting a data-provided Influence Score as opposed to direct consumer and/or organizational outcomes. Thus, the findings must be taken as evidence for predicting influencer scores, rather than as evidence of the relationship between follower reach/engagement and stakeholder trust, organizational reputation, and DPR effectiveness.

The results indicate that, for practitioners, follower size and single engagement measure should not be the only basis for selecting influencers. Along with audience reach, managers should consider a comprehensive list of engagement metrics and must complement them with qualitative measures such as content relevance, audience authenticity, brand–influencer fit, communication quality, campaign objectives, etc. In a DPR environment, these can be used to assist in screening and assessing influencers, but other metrics like stakeholder reaction, message credibility, sentiment, reputation, and the quality of the relationship should also be used to assess DPR outcomes.

5.1. Limitations and Future Research

There are some limitations to this study. A particularly important limitation concerns the dependent variable. Influence Score is a composite measure provided by the source of the data; the algorithm and/or the weighting method for the construction of the composite measure is not sufficiently described by the data source. It may also be the case that the variables included in the original scoring were related to the follower count or engagement measures in any way. Therefore, the regression should be interpreted with caution as a set of various statistical associations with a score defined by the source, and not as validation of variables impacting the effectiveness of influencers in the real world. Additionally, the research cannot conclude that a better PR result occurs in relation to a higher Influence Score. Future studies should confirm influencers' performance with other measures like influencer's message credibility, sentiment, influencer relationship quality, reputation, conversion, communication outcomes, or influencer's level of stakeholder engagement during the campaign.

6. Conclusion

This study examined the relationships among audience reach, consolidated audience engagement, and the Influence Scores of 200 leading Instagram profiles using archival secondary data. Follower count showed a moderate positive correlation with Influence Score and remained a statistically significant predictor in the multiple regression model. In contrast, the Engagement Index, constructed as the mean of the standardized values of Average Likes, 60-Day Engagement Rate, and New Post Average Likes, did not significantly predict Influence Score after follower count was controlled. The overall model was significant and accounted for 14.0% of the variance in Influence Score.

The results indicate that the reach of the audience adds unique explanatory information to the Influence Score in the dataset, while the various engagement measures do not add much to the prediction when aggregated to a single score. The results must still be viewed with some degree of caution as Influence Score is a composite construct created by the author of the scale and not necessarily proven in terms of its external validity. Thus, the research results cannot be interpreted as evidence of a relationship between follower count, engagement, and higher levels of public-relations effectiveness, stakeholder trust, reputation, or relationship quality. Its relevance to digital public relations is more limited in that it provides an insight to the use of archival profile metrics for initial screening and evaluation of influencers. Future research needs to use independently verified campaign and stakeholder outcomes, longitudinal data such as data spanning more than one-year, multiple social media platforms and content quality, credibility, sentiment and fit to brand measures.

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