JURNAL STUDI KOMUNIKASI

Volume 9 **Ed 1, March 2025** **Page 261 - 280**

Study on content-audience alignment: Instagram influencers' engagement strategies

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How to Cite This Article: Maskan, O. & Herdiansyah, H. (2025). Study on content-audience alignment: Instagram influencers' engagement strategies. *Jurnal Studi Komunikasi*, 9(1). doi: 10.25139/jsk.v9i1.9110
Received: 02-10-2024, Revision: 25-01-2025, Acceptance: 04-03-2025, Published: 26-03-2025

Abstract In the era of digital communications, social media influencers significantly shape consumer behaviour and engagement. This study investigated the impact of an influencer's role as an opinion leader and the perceived information quality on Instagram audience engagement intentions, mediated by perceived fit with personal interests. Engagement intentions were operationalised through respondents' willingness to follow the influencer's advice, interact with content, and recommend the influencer to others. Data were collected via a structured online survey based on a sample of 500 followers of an educational influencer. Path analysis using SPSS revealed that opinion leadership and information quality significantly enhanced engagement intentions, which amplified these effects when mediated by perceived influencer-audience alignment. This study builds upon existing literature, such as the two-step flow model, perceived quality of information, and self-congruity, by addressing gaps in their application and relevance to the dynamic environment of social media influencer marketing. While limited to a single educational influencer, the findings offer insights for influencers and marketers to showcase credibility, deliver quality content, and align with audience interests to improve engagement. Future research should expand to include diverse influencers and audience demographics across multiple platforms to enhance the generalisability and applicability of findings.

Keywords: audience engagement intentions; influencer-audience alignment; social media influencers; opinion leadership

INTRODUCTION

The rapid rise of social media and the popularity of Instagram has created such conditions that users' creations, distribution, and consumption of content are virtually omnipresent (Ho & Ito, 2019), leading to new communication patterns (Peng et al., 2018; Evans, 2019). Audiences act as both consumers and promoters of ideas and brands through social media (Lamberton & Stephen, 2016). Interestingly, studies suggest that consumers tend to have blind faith in materials shared on social media, influencing their engagement intentions and decision-making processes (Shareef et al., 2020).

In relation, audiences' engagement intentions refer to the strength of a person's willingness to follow the advice given to them, recommend it to others, and maintain interaction in the future (Casaló et al., 2020). In a study commissioned by Instagram, 66% of Indonesian users agreed that they would consider purchasing a product or service seen on Instagram, 78% of them reported having purchased those products and services, and 90% of them reported having used Instagram to communicate with a business (IPSOS, 2018).

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ISSN: 2549-7294 (Print), 2549-7626 (Online)

Due to the scalability and speed of internet diffusion, some contributors manage to attract mass audiences, create their fandoms, and become a source of advice for their fans; thus gaining the term influencers. A recent survey found that up to 81% of consumers today have purchased, researched or considered purchasing a product or service after seeing influencers' recommendations, with 69% trusting recommendations from influencers more than brands (Matternow, 2023). Another survey found the younger generation of consumers state that influencer posts are the number one way to get them to try a new product (IZEA Insights, 2024).

Figure 1. Consumer's trust in influencers
Source: Matternow (2023)

Influencer marketing has become a central focus in advertising, with brands increasingly leveraging social media influencers to promote their ideas, products, and services (Ki et al., 2020; De Veirman et al., 2017). This shift has led to the rapid growth of the influencer market, which analysts predict will reach USD 24 billion by 2024 (Dencheva, 2023).

The concept of 'opinion leaders' was first introduced by Katz and Lazarsfeld in 1957, who proposed that opinion leaders compile information from the media and then disseminate it to other people through word-of-mouth, known as the 'Two-step Flow Model of Communication'. However, in the age of modern influencers, this definition overlooks the dynamic, reciprocal nature of modern influencer-follower relationships (Godey et al., 2016).

In social media contexts, influencers don't simply disseminate information; they also engage in interactive dialogue that shapes their followers' perceptions and behaviours (Wang & Fikis, 2019). Moreover, while traditional opinion leadership emphasises one-way communication, social media platforms enable influencers to act as receivers and disseminators of information, complicating the simplistic notion of influence.

Additionally, the algorithm-driven nature of social media amplifies popularity over credibility, complicating the boundaries between genuine influence and paid advertisement (Wang & Fikis, 2019). While influencer marketing offers effective brand promotion (Ki et al., 2020; De Veirman et al., 2017), it also risks market saturation and consumer fatigue due to over-commercialised content.

Every opinion leader can be considered an influencer, but not all influencers are recognised as opinion leaders. An influencer is seen as an opinion leader when their audience perceives them as a trusted source of advice, whether for product recommendations or guidance on attitudes and behaviours (Casaló et al., 2009; Thakur et al., 2016). Therefore, understanding how an influencer's perceived opinion leadership affects audience engagement is crucial.

In addition to source credibility, the quality of the information itself plays a significant role in how influencers impact audiences' behaviour within mass communication (Balaban, 2020; Shah et al., 2023). The quality of the information being delivered is considered an extremely significant element influencing others' decision-making processes (Maltz, 2000; Price, 2008). Furthermore, a meta-analysis by Han and Balabanis (2024) supports that informativeness of content has a positive impact on engagement intentions, highlighting the importance of detailed and accurate information in shaping consumer behaviour.

Perceived quality of information (PQI), referring to the value given by the audience to the message sent, can be affected by three dimensions: the perceived relevance, perceived reliability, and perceived enjoyability of the information (Nicolaou & McKnight, 2006; Koohikamali & Sidorova, 2017; Balaban, 2020). How people perceive a message depends on

the quality they believe it possesses (Greer, 2003). High quality information is thus seen to be more compelling than information of lower perceived quality (Ohanian, 1990; Xiao et al., 2018). Customers turn to social media platforms to find important sources of information on a wide range of topics, products, or services (IPSOS, 2018). According to Alalwan (2018: 72-73), content's informativeness is the second most vital factor in predicting customer purchase intentions significantly. This suggests that social media advertisements that exhibit a high level of quality can be considered more valuable and efficient from the customer's perspective, which could lead to positive intentions and actions (Alalwan, 2018: 69; Jiménez-Castillo, 2019).

Current studies by Casaló et al. (2020) and Han et al. (2024) indicate a significant impact of an influencer's opinion leadership on audience engagement intentions. The opinion leadership exhibited by Instagram influencers is strongly influenced by the perceived originality, credibility, and uniqueness of their persona, which in turn favourably affects the audience's intentions to continue engaging with the influencer's account, to recommend the account, and to follow the advice being given (Casaló, 2020). Similar findings also suggest the significant influence of opinion leadership on purchase intentions and engagement, illustrating a robust correlation between the two (Han and Balabanis, 2024).

The engagement intentions of audiences are also greatly influenced by the quality of information or content provided by opinion leaders on Instagram (Wang & Chuan-Chuan Lin, 2011; Chen & Chang, 2018). Followers are more likely to be impacted and to act on the information if they perceive it as good quality (Wang & Chuan-Chuan Lin, 2011; Chen & Chang, 2018). Moreover, according to Jiménez-Castillo & Sánchez-Fernández (2019) and De Veirman & Hudders (2020), the information quality of content influences followers' tendency to buy from brands.

Perceived fit with personal interests, defined as the alignment between content and a person's values, interests, and personality, fosters a stronger psychological connection between audiences and influencers (Belanche et al., 2014; Casaló, 2020; Kim & Kim, 2020). When audiences perceive congruence between their self-concept and the influencer's persona, their engagement intentions increase (Graeff, 1996; Beerli et al., 2007; Bekk et al., 2016). Research highlights that this perceived fit enhances fan-influencer relationships and positively impacts attitudes toward brands and behavioural intentions on social media (Shan et al., 2019).

Despite the importance of influencers in shaping audience behaviour, empirical research has yet to comprehensively examine how an influencer's opinion leadership and the quality of the information they provide impacts audiences' engagement intentions, particularly when mediated by the perceived fit with personal interests (Casaló, 2020; Vrontis et al., 2021; Han et al., 2024).

Previous studies have largely overlooked the mediating role of perceived fit with personal interests, leaving a critical gap in understanding the key mechanisms that drive successful influencer marketing in an era shaped by algorithmic personalisation and targeted content strategies. Therefore, the novelty of this research lies in its emphasis on the mediating role of perceived fit with personal interests. This study aims to build on established theories such as the two-step flow model, perceived quality of information (PQI), and self-congruity to introduce a novel approach to understanding influencer-audience dynamics in the modern age. The findings will provide insightful knowledge for influencers and marketers alike, with the goal of utilising social media platforms to create content that resonates with audiences and improve positive audiences' behavioural outcomes. Therefore, to achieve this purpose, the study addressed the following research questions: 1) Is there a significant influence of opinion leadership towards the perceived fit with personal interests? 2) Is there a significant influence of information quality towards the perceived fit with personal interests? 3) Is there a significant influence of opinion leadership towards engagement intentions? 4) Is there a significant influence of information quality towards engagement intentions? 5) Is there a significant influence of the perceived fit with personal interests towards engagement intentions? 6) Is there a significant indirect influence of opinion leadership towards engagement intentions, mediated by the perceived fit with personal interests? 7) Is there a significant indirect influence of information quality towards engagement intentions, mediated by the perceived fit with personal interests?

METHODOLOGY

This study employed a quantitative causal-comparative method within the positivist paradigm, aiming to examine cause-and-effect relationships between research variables. The variables include: a) Independent Variables: (1) Opinion Leadership (X1), reflecting the influencer's ability to shape audience opinions through credibility and expertise; and (2) Perceived Quality of Information (X2), indicating audience evaluations of content relevance, clarity, and usefulness. Intervening Variable: Perceived Fit with Personal Interests (Y), representing how well the content aligns with audience values and preferences. b) Dependent Variable: Engagement Intentions (Z), which measures the audience's likelihood to interact with, recommend, or act upon the influencer's content.

Each variable is measured using a Likert-type scale, where higher scores indicate stronger perceptions of the respective constructs. For example, higher scores on the Opinion Leadership scale signify greater trust in the influencer's authority. In comparison, higher scores on the Engagement Intentions scale reflect a stronger willingness to interact and follow recommendations. This method enables rigorous statistical analysis to test direct and indirect effects, providing insights into how opinion leadership and information quality drive engagement through personal interest alignment (See Figure 2).

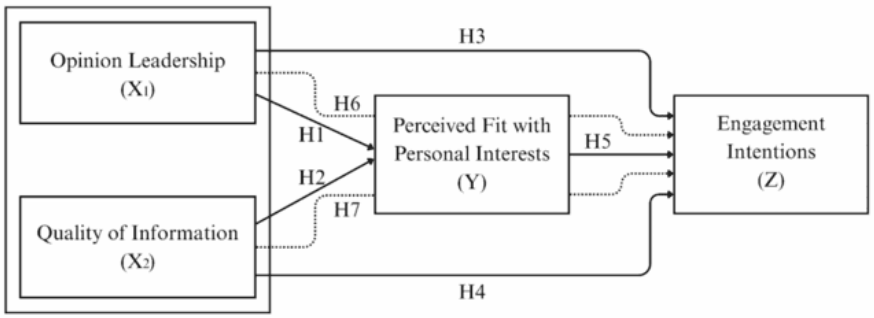

Figure 2. Theoretical framework
Source: developed by the researcher, 2024

Path Analysis tests the following hypotheses regarding direct and indirect effects among variables. For direct effects: H1 posits that X1 affects Y, H2 proposes that X2 affects Y, H3 proposes that X1 affects Z, H4 proposes that X2 affects Z, and H5 proposes that Y affects Z. For indirect effects: H6 proposes that Y mediates the effect of X1 on Z, and H7 proposes that Y mediates the effect of X2 on Z. This analysis provides insights into the causal pathways and the mediating role of Y.

The population for this research encompasses the Instagram audience of Peachy Liv, an Indonesian influencer with a following of 230.000 and more than 60 million total viewers. The influencer was chosen based on McCracken's (1989) criteria for an opinion leader: be regarded as an expert on a subject, product, or service; regularly and significantly participate in an online community; or be viewed as having excellent taste by other users when making decisions or purchases. The influencer is regarded as an expert in lifelong education, self-development, and social issues. Peachy Liv's audience comprises 13-17 and 18-24 age groups, collectively making up most of her Instagram audience.

The focus on Peachy Liv's Instagram audience provides a valuable opportunity for an in-depth analysis, as she is a prominent influencer among young people. However, using her audience as the study population has limitations, particularly regarding the generalizability of the results. This limitation emphasises the importance of interpreting the findings within the context of Peachy Liv's specific audience demographics and the characteristics of the Instagram platform.

This research has concentrated on the population on Instagram due to its prominence as a leading platform for information dissemination and brand marketing. It has the quickest rate of growth (Djafarova & Rushworth, 2017) as the main application where influencers build their careers (Evans et al., 2017). Furthermore, Instagram is particularly favoured by the Gen Z and millennial demographics, presenting a prominent opportunity to explore strategies to utilise social media influence effectively.

Due to the large population size, this study employed a convenience sampling method, which allowed respondents to be selected based on their accessibility and availability. This approach is advantageous in large-scale research where reaching every potential participant is impractical. While convenience sampling lacks the randomness of other techniques, it remains effective for gathering data efficiently, especially when studying social media audiences. The target age range for the research sample includes the 13-17 and 18-24 age groups, prioritising the most active and engaged demographic segments to enhance the efficiency and relevance of the findings (Kozinets, 2010).

To accurately represent the target audience, the researcher applied two filters during respondent selection. The first filter focused on age classification, selecting only teens (13–17 years) and young adults (18–24 years), based on Instagram's analytics categories. This ensured the study captured insights from the influencer's primary audience while maintaining demographic relevance. The second filter assessed familiarity with Peachy Liv's content, excluding respondents unfamiliar with the influencer to ensure meaningful feedback on engagement patterns. Additionally, respondents provided personal information, including gender and frequency of engagement, enabling analysis of engagement trends across different demographics and interaction levels.

Hair et al. (2014) suggests that the sample size be four or five times the total number of research items used in the study. Given that there are 98 items, multiplying by four yields a recommended sample size of 392. However, the sample size achieved is 500 respondents, which exceeds the minimum requirement and strengthens the robustness of the findings. Sekaran & Bougie (2016) stated that a sample size ranging from more than 30 to less than 500 respondents is suitable for most research.

Self-constructed research scales adapted from previous researchers were used as the primary data (Sekaran & Bougie, 2016). Rating questions were used to allow for a variety of possible answers. The Likert scale is used because it is simpler to construct, more dependable, and capable of producing more data than any other technique (Joshi, 2015). It is a closed-ended question with five response categories: strongly agree, agree, neutral, disagree, and strongly disagree. Subsequently, an interval scale was employed as the measuring tool to ensure that variations within question items have a consistent interpretation (Bacon-Shone, 2013). The research scale is then distributed online to Peachy Liv's audiences on Instagram.

In the last research stage, data analysis was done using several statistical methods to describe data and discover the relationship between variables. Data analysis methods used in this research are Descriptive Analysis, Validity & Reliability Test, Classical Assumption Test, and Path Analysis. Descriptive analysis defines and summarises data collected from respondents' characteristics in order to provide a description (Sekaran & Bougie, 2016). Validity testing was conducted to ensure the instrument accurately measured relevant results (Messick, 1989), while reliability testing was done to confirm the consistency of responses across repeated measurements (Sekaran & Bougie, 2016).

Before conducting path analysis, three classical assumption tests needed to be fulfilled, particularly the normality, heteroscedasticity, and multicollinearity tests (Field, 2013). The normality test determines whether or not the data is normally distributed, the heteroscedasticity test determines whether or not the variances of the errors are equal across all levels of the independent variables, and the multicollinearity test checks whether two or more independent variables are highly correlated with each other, which can make it difficult to determine their individual effects on the dependent variable (Gujarati & Porter, 2009). If multicollinearity is detected, its severity will be assessed using variance inflation factors (VIFs), and corrective actions such as variable transformation or removal of highly correlated predictors will be considered to improve model stability.

Path Analysis is a sophisticated statistical technique used to investigate causal linkages between a group of variables in a conceptual model. Researchers begin by estimating the model's parameters using statistical methods such as regression analysis. The key parameters include path coefficients, which indicate the direction and intensity of interactions between variables. Once the parameters are estimated, the model assesses how well it fits the data. This is done using fit indices like RMSEA, CFI, and TLI, as well as the chi-square test. Acceptable fit indices and non-significant chi-square values indicate that the model accurately captures the data.

After the model assessment, the researchers proceeded to hypothesis testing to ascertain the significance of the estimated path coefficients. They examine the statistical significance of the independent variables' direct and indirect impacts on the dependent variables. Non-significant path coefficients suggest that specific linkages may not exist, while significant coefficients confirm the proposed relationships. Lastly, researchers compute the total effects, including direct and indirect effects, to understand how the independent factors influence the dependent variables (Wright, S., 1934). The limitations section will provide further discussion to address the methodology's limitations, including the focus on a single influencer, convenience sampling, cultural considerations, and ethical concerns regarding participants.

RESULTS AND DISCUSSION

Descriptive Analysis, Validity, and Reliability Test

The target respondents of the survey are young people from Indonesia, aged 13 to 24, who have seen and interacted with Peachy Liv's content. 5 of the 511 initial responders did not fit into the (18 - 24) and (13 - 17) age categories; hence, their responses were not included (See Figure 3). Then, six more could not meet the criteria of being familiar with the influencer's content. Through this process, 500 respondents met all the sample requirements. A descriptive analysis then illustrated the percentages of the remaining respondents' characteristics to form the basis for interpreting the subsequent analytical findings and ensuring the validity of the research results (Sekaran & Bougie, 2016).

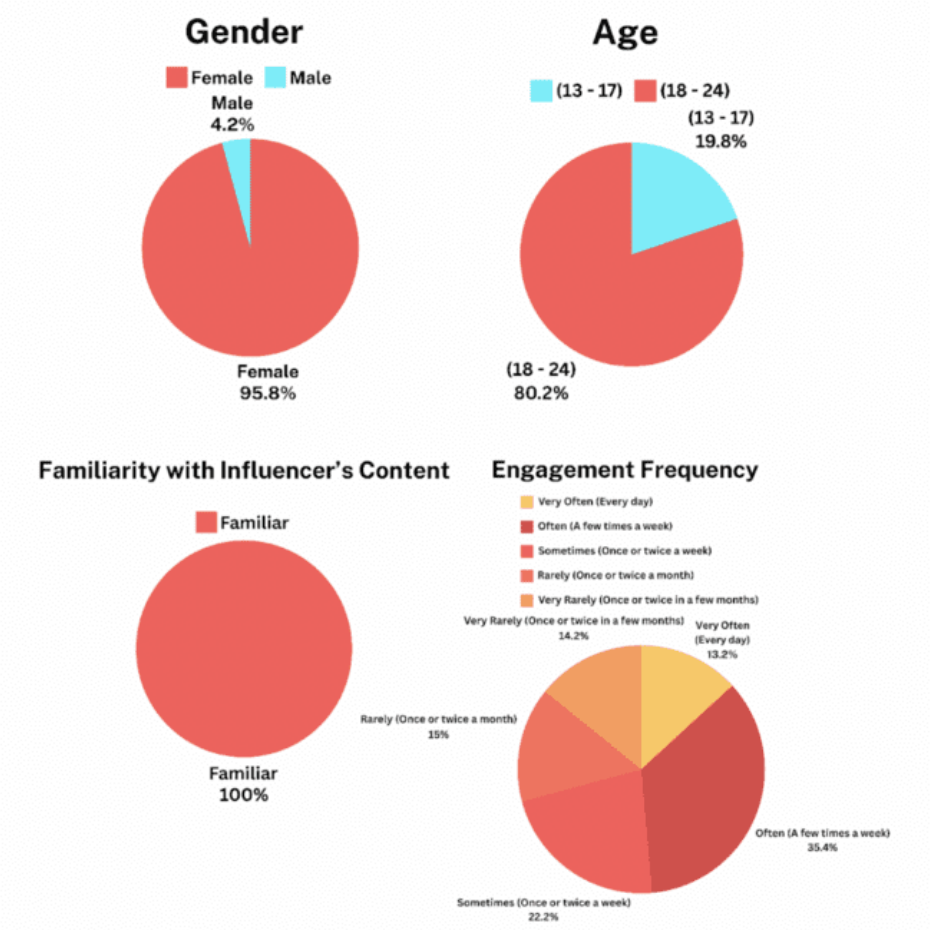

Figure 3. Descriptive analysis
Source: processed by author, 2024

Descriptive statistics are essential for evaluating the quality of the data (Trochim, 2001; Hinton, 2014). As seen in Table 1, a moderate level of variability in respondents' judgments of opinion leadership is shown by the opinion leadership mean score of 99.86 with a standard deviation (SD) of 10.318. The mean score for the perceived quality of information is 114.07, with

a standard deviation of 12.585. This indicates a comparatively higher central tendency and a moderate dispersion surrounding the mean. A somewhat larger variability than the other variables is shown by the perceived fit with personal interests, with a mean of 111.65 and an SD of 14.060. This might point to a wider variety of perceptions about the perceived fit with personal interests. Lastly, the engagement intention variable has a moderate variability among respondents, with a mean of 96.46 and an SD of 13.041.

Table 1. Descriptive statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Opinion Leadership (X1)	500	49	115	99.86	10.318
Perceived Quality of Information (X2)	500	60	130	114.07	12.585
Perceived Fit with Personal Interests (Y)	500	58	130	111.65	14.060
Engagement Intentions (Z)	500	49	115	96.46	13.041
Valid N (listwise)	500				

Source: processed by author, 2024

Table 2. Blueprint after eliminated items

Variables	Items Number	Total Items
Opinion Leadership (X1)	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23	23
Perceived Quality of Information (X2)	24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49	26
Perceived Fit with Personal Interests (Y)	50, 51, 52, 53, 54 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75	26
Engagement Intentions (Z)	76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98	23

Source: processed by author, 2024

Validity testing was conducted to ensure the instrument accurately measured relevant results (Messick, 1989), while reliability testing was done to confirm the consistency of responses across repeated measurements (Sekaran & Bougie, 2016). According to the Pearson correlation coefficients, items with a correlation above the R Table value of 0.329 (at a 5% significance level) are regarded as valid. The value of this R Table is based on N = 36 pilot responders. The validity of each variable has been confirmed by the Pearson correlation coefficients for all items, which are higher than the 0.329 criterion (See Tables 2 and 3).

Table 3. Reliability test after eliminated items

Variables	Cronbach's Alpha	N of Items	Remarks
Opinion Leadership (X1)	0.905	23	RELIABLE
Perceived Quality of Information (X2)	0.943	26	RELIABLE
Perceived Fit with Personal Interests (Y)	0.920	26	RELIABLE
Engagement Intentions (Z)	0.929	23	RELIABLE

Source: processed by author, 2024

In terms of item reliability, Opinion Leadership, Perceived Quality of Information, Perceived Fit with Personal Interests, and Engagement Intentions had Cronbach's Alpha values of 0.905, 0.943, 0.920, and 0.929, respectively, which are all significantly higher than the generally recognised reliability threshold of 0.7 (Streiner, 2003). According to these findings,

there is a strong correlation between the items in each construct, indicating that the same underlying concept is being consistently measured.

Classical Assumption Test

First, the normality test (Figure 4) shows that the model's residuals have a normal distribution. With the majority of the residuals grouped in the centre and tapering off evenly on both sides, the histogram displays a symmetrical distribution (Field, 2013). The standard deviation is near to one (0.998) and the mean is around zero (1.57E-15), all of which are in line with the characteristics of a normal distribution (Ghozali, 2013).

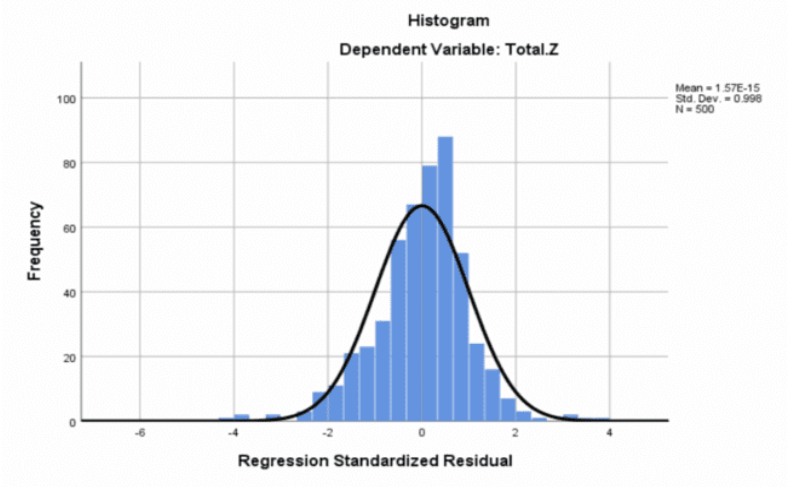

Figure 4. Normality test
Source: SPSS, 2024

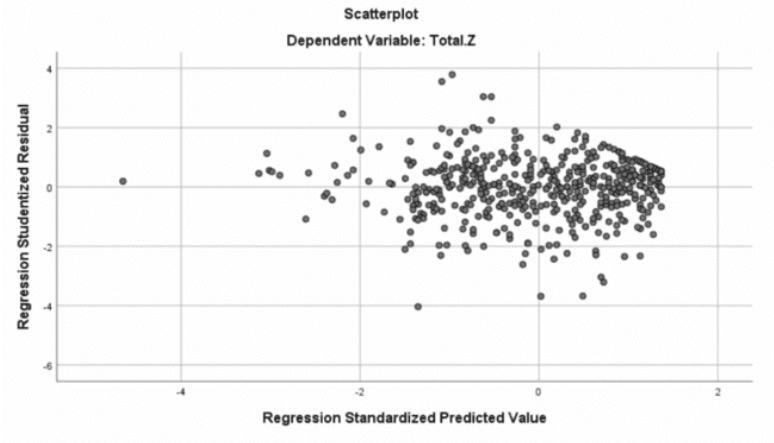

Figure 5. Heteroscedasticity test
Source: SPSS, 2024

Secondly, the heteroscedasticity test shows variance consistency within the same regression model (Field, 2013). In Figure 5, the scatterplot for the dependent variable shows homoscedasticity, with the dots distributed randomly around the horizontal axis and no discernible pattern or funnel shape (Ghozali, 2013). Hence, the assumption is met for the study, guaranteeing the objectivity and efficiency of the regression coefficients.

Table 4. Multicollinearity test

Model	Collinearity Tolerance	Statistics VIF
Opinion Leadership (X1)	.249	4.022
Perceived Quality of Information (X2)	.249	4.022

a. Dependant Variable: Engagement Intentions (Z)

Source: processed by author, 2024

Thirdly, the multicollinearity test (Table 4) shows the degree of correlation between independent variables in a regression model. Opinion leadership and perceived quality information show a tolerance value of 0.249 and a VIF value of 4.022. These findings, which have tolerance values nearing 1 and VIF values much below 10.00, are well within acceptable bounds (Santoso, 2010; Field, 2013). This suggests that the independent variables do not exhibit severe multicollinearity.

Path Analysis

Most importantly, the structural model's conclusions are shown in the Path Analysis results section, which also looks at the connections between the independent variables (IVs), the intervening variable, and the dependent variable (DV). Through the use of the intervening variable, this approach enabled us to understand the direct as well as indirect impacts of the independent variables on the dependent variable (Wright, S., 1934). Deeper knowledge of the underlying processes and routes by which the independent factors affect the dependent variable may be obtained by analysing these interactions, which also sheds light on the study's hypotheses (Table 5).

Table 5. Coefficients of X1 & X2 against Y

Model	Unstandardised Beta	Standardised Coefficients Beta	Sig.
Opinion Leadership (X1)	.174	.130	.003
Perceived Quality of Information (X2)	.853	.764	.000

a. Dependent Variable: Perceived Fit with Personal Interests (Y)

Source: processed by author, 2024

There is a significant influence of Opinion Leadership on the Perceived Fit with Personal Interests (H1)

The first hypothesis's analysis looks at how Opinion Leadership affects Perceived Fit with Personal Interests, as seen in Table 5. This impact is considered statistically significant given that Opinion Leadership's significance (Sig.) value is less than the predetermined 0.05 threshold (0.003). This indicates that the impact of Opinion Leadership on the Perceived Fit with Personal Interests is statistically significant.

As a result, the null hypothesis (H0: $\beta 1 = 0$) is rejected. Rather, the alternative hypothesis (H1: $\beta 1 \neq 0$) is accepted, which proposes that Opinion Leadership has a significant impact on Perceived Fit with Personal Interests. The strong correlation indicates that the audience's perception of Peachy Liv's Opinion Leadership rises in tandem with the content's perceived relevance to their own interests.

Additionally, Opinion Leadership's unstandardised beta value (β) is 0.174. This number shows that the Perceived Fit with Personal Interests rises by 0.174 units with every unit increase in Opinion Leadership. An unstandardised beta of 1 would indicate a flawless one-to-one relationship between the independent and dependent variables, and this is the most desirable value. The unstandardised beta value of 0.174 in this instance is significantly far from 1, indicating that although Opinion Leadership helps improve perceived fit, its impact is rather modest. This suggests that the perceived fit with personal interests may be influenced by other factors as well, and that Opinion Leadership may not be the primary driver of it.

This result validates the importance of opinion leaders in influencing audiences' perceptions and lends credence to the concept that good Opinion Leadership may, to some extent, increase audiences' perceptions of the content aligning well with their interests (Belanche et al., 2021). This relationship is essential to comprehending how opinion leaders can mold the perception of content relevance, increasing audience engagement by aligning their messaging with audiences' beliefs and interests (Casaló et al, 2020.)

Nonetheless, a number of theoretical frameworks provide an explanation for the modest amplitude of the beta value. Opinion leaders serve largely as middlemen between the public and mass media, according to Katz and Lazarsfeld's 1955 two-step flow of communication model. This suggests that, despite their influence, opinion leaders' effects are only one aspect

of a larger interaction between audience characteristics and media effects. Furthermore, the idea of selective exposure (Klapper, 1960) may lessen the direct influence of opinion leaders even more since people prefer to read things that already support their preexisting opinions and interests, which lessens the influence opinion leaders have on altering the alignment.

The modest amplitude of the beta value also suggests that there could be more factors involved in perceived fit with personal interests than just Opinion Leadership. Subsequent investigations have to consider other factors, which may either interact with or mediate the impact of Opinion Leadership on Perceived Fit with Personal Interests.

There is a significant influence of the Perceived Quality of Information on the Perceived Fit with Personal Interests (H2)

The second hypothesis's analysis looks at the how Perceived Quality of Information affects Perceived Fit with Personal Interests, as seen in Table 5. As the significance (Sig.) value for Perceived Quality of Information is less than the predetermined 0.05 threshold, at 0.000, it is considered statistically significant. This indicates that respondents' perceptions of how well the material fits with their own interests are significantly influenced by the perceived quality of the information. Consequently, the null hypothesis (H0: $\beta 2 = 0$) is rejected. Rather, the alternative hypothesis is accepted (H2: $\beta 2 \neq 0$), which proposes that the Perceived Quality of Information significantly influences the Perceived Fit with Personal Interests.

Moreover, Perceived Quality of Information has an unstandardised beta value (β) of 0.853. This number shows that the perceived match with personal interests rises by 0.853 units for every unit increase in the perceived quality of the information. An unstandardised beta of 1 would indicate a flawless one-to-one relationship between the independent and dependent variables, and this is the most desirable value. The unstandardised beta value in this instance, which is 0.853, is very near to 1, indicating that the Perceived Fit with Personal Interests is significantly influenced by the Perceived Quality of Information

The significant impact may be explained by a number of theoretical frameworks. Information processing theory, which posits that people are more likely to take in and use information that they believe to be high-quality—that is, accurate, dependable, and pertinent to their needs—can be used to theoretically explain this outcome (Wathen & Burkell, 2002). The cognitive and emotive demands of the audience are likely to be satisfied by high-quality information, which increases the content's applicability and personal relevance and improves the perception of its alignment with the audience's interests (See Table 6).

To further comprehend these results, Fishbein and Ajzen's (1975) expectancy-value theory offers a helpful framework. According to this concept, people assess the expected results of interacting with information based on how valuable they believe it to be. High-quality information makes people anticipate positive outcomes, leading to a greater perceived fit with their interests, as they expect the information to be more helpful and directly beneficial to them. Furthermore, the results are consistent with the media richness theory (Daft & Lengel, 1986), which proposes that a medium's richness—measured by its ability to alter understanding within a time interval—is essential to successfully transmitting complex ideas. Richer material usually has more depth, which enables more detailed and nuanced communication that closely matches the needs and interests of the audience.

Table 6. Model summary of hypotheses 1 & 2

Model	R	R Square
	.879	.772

a. Predictors: (Constant), Perceived Quality of Information (X2), Opinion Leadership (X1)

Source: processed by author, 2024

The findings indicate that a greater Perceived Quality of Information substantially impacts the Perceived Fit with Personal Interests. This shows that the quality of information plays a crucial role in determining how well the content is believed to fit with the audience's personal interests. This result aligns with other recent studies that suggest audiences perceive content as being more closely aligned with their interests and needs when influencers provide distinctive, original, and highly informative content (Balaban, 2020; Shah et al., 2023; Han et al., 2024). Influencers may greatly improve how well their content connects with and fulfils their audience's

individual interests by ensuring it contains high-quality information. In addition to increasing engagement, this strategy may increase audience loyalty and satisfaction (Lee et al., 2012; Casaló et al., 2020).

The Model Summary table explains the regression model's overall fit and the independent variables' combined impact on the dependent variable. According to the table's R Square value of 0.772, Opinion Leadership and Perceived Quality of Information combined account for 77.2% of the variation in Perceived Fit with Personal Interests. This high R Square value shows a robust model fit, which suggests that the independent variables play a major role in predicting the dependent variable.

The remaining 22.8% of Engagement Intention's variation is explained by additional variables not examined in this investigation. This finding highlights the significant influence that Perceived Quality of Information and Opinion Leadership have on Perceived Fit with Personal Interests. It also emphasises how crucial it is to investigate other factors that might improve the model's ability to explain the phenomena in future studies (Figure 6).

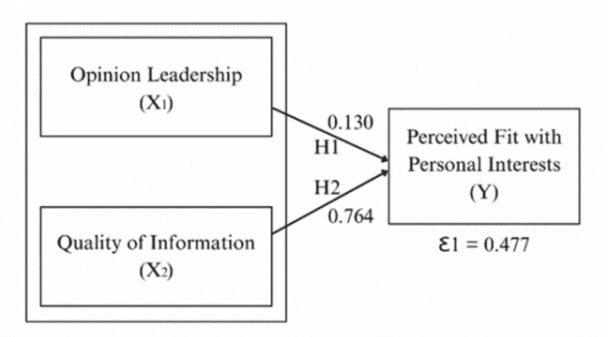

Figure 6. ε value of the R Square for hypotheses 1 & 2
Source: developed by the researcher, 2024

Table 7. Coefficients of X1, X2, and Y against Z

Model	Unstandardised Beta	Standardised Coefficients Beta	Sig.
Opinion Leadership (X1)	.218	.173	.000
Perceived Quality of Information (X2)	.161	.154	.010
Perceived Fit with Personal Interests (Y)	.532	.569	.000

a. Dependent Variable: Engagement Intentions (Z)

Source: processed by author. 2024

There is a significant influence of the Opinion Leadership on Engagement Intentions (H3)

The third hypothesis's path analysis looks at how Opinion Leadership affects Engagement Intentions, as seen in Table 7. Since Opinion Leadership's significance (Sig.) value is 0.000—well below the 0.05 threshold—it may be concluded that this impact is statistically significant. Consequently, the null hypothesis (H0: $\beta 3 = 0$) is rejected. Instead, the alternative hypothesis (H3: $\beta 3 \neq 0$) is accepted, which proposes that Opinion Leadership has a significant impact on Engagement Intentions.

Additionally, Opinion Leadership's unstandardised beta value (β) is 0.218. This number shows that Engagement Intentions rise by 0.218 units for every unit increase in Opinion Leadership. An unstandardised beta of 1 would indicate a flawless one-to-one relationship between the independent and dependent variables, and this is the most desirable value. The unstandardised beta value of 0.218 in this instance is significantly far from 1, indicating that although Opinion Leadership affects Engagement Intentions, its impact is rather modest. This suggests that Engagement Intentions may be significantly influenced by other factors as well, and that Opinion Leadership may not be the primary driver of it (See Table 7).

The reasoning behind Opinion Leadership's modest beta value impact may be explained by a number of theoretical frameworks. According to Katz and Lazarsfeld's (1957) two-

step flow of communication model, the effect of opinion leaders is influenced by social environment and interpersonal interactions. This suggests that although opinion leaders greatly influence their followers, other things like individual interests, peer pressure, and the quality of the information they offer might dilute the effect. This study's results align with recent studies that show that although opinion leaders are essential in influencing audience behaviour, their influence is contingent on the quality and perceived relevance of their content (Casaló et al., 2020; Han et al., 2024).

The findings emphasise that Opinion Leadership has a significant influence on audiences' desire to engage on Instagram. However, the moderate unstandardised beta value indicates that audience engagement might be influenced by factors other than Opinion Leadership. Subsequent investigations have to delve into supplementary factors that might potentially interact or mediate the impact of Opinion Leadership on Engagement Intentions.

There is a significant influence of Perceived Quality of Information on Engagement Intentions (H4)

The fourth hypothesis' path analysis looks at how Engagement Intentions are impacted by the Perceived Quality of Information, as seen in Table 7. The impact of Perceived Quality of Information on Engagement Intentions is statistically significant, as indicated by the significance (Sig.) value for Perceived Quality of Information of 0.010, which is below the 0.05 threshold. Thus, the null hypothesis (H0: $\beta 4 = 0$) is rejected. Alternatively, the alternative hypothesis (H4: $\beta 4 \neq 0$) is accepted, which proposes that the Perceived Quality of Information significantly influences Engagement Intentions.

Furthermore, the Perceived Quality of Information's unstandardised beta value (β) is 0.161. According to this value, Engagement Intentions rise by 0.161 units for every unit increase in Perceived Quality of Information. An unstandardised beta of 1 would indicate a flawless one-to-one relationship between the independent and dependent variables, and this is the most desirable value. In this instance, the unstandardised beta value of 0.161 is significantly far from 1, indicating that although the Perceived Quality of Information affects Engagement Intentions, its impact is relatively modest. This suggests that engagement intentions may be significantly influenced by other factors, and that perceived quality of information may not be the primary driver of engagement.

The significant influence of Perceived Quality of Information on Engagement Intentions aligns with the media richness theory (Daft & Lengel, 1986), which proposes that because richer (i.e., better quality) media can successfully deliver more nuanced and complex information, they have a larger potential to influence audiences' behaviour. However, the modest influence also highlights that not all high-quality material leads to high engagement in the digital era, since consumers are bombarded with massive amounts of information. Users' selective exposure to content that aligns with their existing beliefs or interests (Klapper, 1960) might mitigate the impact of information quality.

This finding's practical relevance is that improving the information's quality could be a smart way to boost audience engagement. The moderate unstandardised beta value, however, indicates that audience engagement might be influenced by a variety of factors other than the Perceived Quality of Information. Subsequent investigations must delve into supplementary factors that might interact with or mediate the impact of Perceived Quality of Information on Engagement Intentions.

There is a significant influence of the Perceived Fit with Personal Interests has a significant influence on engagement intentions (H5)

The fifth hypothesis's path analysis looks at how Engagement Intentions are influenced by Perceived Fit with Personal Interests, as seen in Table 7. Since Perceived Fit with Personal Interest's significance (Sig.) value is 0.000, less than the predetermined 0.05 threshold, we may conclude that this impact is statistically significant. This indicates that Engagement Intentions are significantly impacted by Perceived Fit with Personal Interests. Thus, the null hypothesis (H0: $\beta 5 = 0$) is rejected. Instead, the alternative hypothesis (H5: $\beta 5 \neq 0$) is accepted, which proposes that Perceived Fit with Personal Interests significantly influences Engagement Intentions.

Furthermore, Perceived Fit with Personal Interests has an unstandardised beta value (β) of 0.532. According to this value, Engagement Intentions rise by 0.532 units for every unit

increase in Perceived Fit with Personal Interests. An unstandardised beta of 1 would indicate a flawless one-to-one relationship between the independent and dependent variables, which is the most desirable value. In this instance, the beta value of 0.532 means the Perceived Fit with Personal Interests has a moderate to significant influence on Engagement Intentions.

The results are theoretically consistent with the uses and gratifications theory, which proposes that people actively look for media that fulfils their needs and improves their life experiences (Katz, Blumler, & Gurevitch, 1973). Content that is well-matched to an individual's interests satisfies their basic needs for information, personal identity, integration and social interaction, or entertainment, all of which lead to engagement behaviours (Rubin, 1983).
In addition, the concept of self-congruity is also important to this relationship. According to the self-congruity theory, customers prefer companies and goods that align with their self-perception (Sirgy, 1982). When it comes to social media content, engagement is likely to rise when there is a strong perceived match between the content and the user's own interests or sense of self. This is because the user will find the information to resonate more deeply with their identity.

Furthermore, current studies in the field of influencer marketing suggest similar results. According to studies, followers are more likely to interact with influencers' content through likes, comments, and shares when they believe it aligns well with their own interests (Casaló et al., 2020; Zogaj, A., 2021). This increases the likelihood of them following the influencers' recommendations, whether it be products or behaviours (De Veirman, Cauberghe, & Hudders, 2017).

This finding implies that as the Perceived Fit with Personal Interests increases, so do the Engagement Intentions of the audience. It emphasises that, while other factors could also play a role in this connection, Perceived Fit with Personal Interests is a significant predictor of Engagement Intentions.

Table 8. Model summary of hypotheses 3, 4, 5

Model	R	R Square
	.857	.735

a. Predictors: (Constant), Perceived Fit with Personal Interests (Y), Opinion Leadership (X1), Perceived Quality of Information (X2)

Source: processed by author, 2024

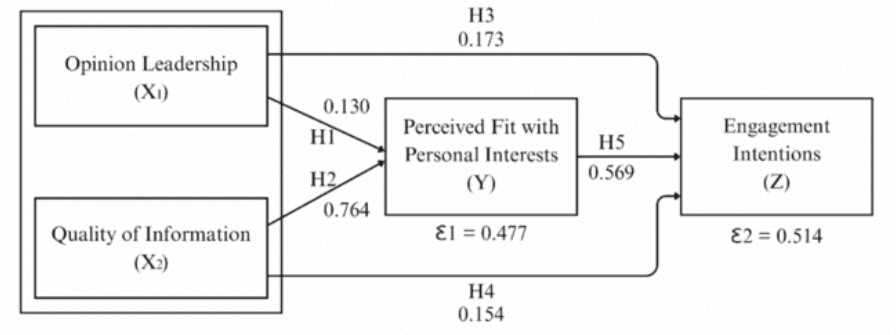

Figure 7. ε value of the R Square for hypotheses 3, 4, 5
Source: developed by the researcher, 2024

The regression model's overall fit, as well as the combined impact of the independent variables on the dependent variable, are both explained by the Model Summary table. With a R Square of 0.735, the independent variables (Opinion Leadership, Perceived Quality of Information, and Perceived Fit with Personal Interests) in this table together account for 73.5% of the variation in Engagement Intentions. This high R Square value shows a robust model fit, which suggests that the independent variables play a major role in predicting the dependent variable (Table 8)..

The remaining 26.5% of Engagement Intention's variation can be explained by other variables that were not examined in this investigation. This outcome demonstrates the significant influence that Opinion Leadership, Perceived Quality of Information, and Perceived Fit with Personal Interests have over Engagement Intentions. It also emphasises how crucial it is to

investigate other factors in future studies that might improve the model's ability to explain this relationship (Figure 7).

There is a significant indirect influence of Opinion Leadership on Engagement Intentions, mediated by the Perceived Fit with Personal Interests (H6)

To interpret the findings for the sixth hypothesis, we examine Opinion Leadership's direct and indirect effects on Engagement Intentions, with Perceived Fit with Personal Interests acting as a mediator. Opinion Leadership's direct impact on Engagement Intentions may be computed by squaring its beta value (Table 7), which is (0.173)^2 = 0.030.

The multiplication of the beta values of Opinion Leadership to Perceived Fit with Personal Interests (Table 5) and Perceived Fit with Personal Interests to Engagement Intentions (Table 7) yields the indirect influence of Opinion Leadership on Engagement Intentions through Perceived Fit with Personal Interests, which is 0.130 × 0.569 = 0.074.

Therefore, the total influence of Opinion Leadership on Engagement Intentions is the sum of the direct and indirect effects: 0.030 + 0.074 = 0.104. Based on this calculation, Engagement Intentions has an indirect effect of 0.074, larger than the direct effect of 0.030. This result indicates that the indirect influence of Opinion Leadership on Engagement Intentions through Perceived Fit with Personal Interests is far more substantial than the direct influence of Opinion Leadership on Engagement Intentions. Consequently, the null hypothesis (H0: $\beta 6 = 0$) is rejected. Instead, the alternative hypothesis (H6: $\beta 6 \neq 0$) is accepted, which proposes a significant indirect influence of Opinion Leadership on Engagement Intentions, mediated by the Perceived Fit with Personal Interests.

According to this finding, Perceived Fit with Personal Interests is a key mediating factor that amplifies the overall effect of Opinion Leadership on Engagement Intentions This emphasises the significance of taking this variable into account in the connection and indicates how, in the circumstances of the study, Perceived Fit with Personal Interests is a more effective conduit for the influence of Opinion Leadership on Engagement Intentions. This adds credence to the idea that indirect paths might cause a more significant impact, highlighting the function of mediating factors in intricate connections.

The finding that the indirect pathway exerts a stronger influence than the direct pathway is indicative of the critical role of Perceived Fit with Personal Interests as a mediator (Casaló et al., 2020; Zogaj, A., 2021). This suggests that Opinion Leadership primarily influences Engagement Intentions by enhancing how content is perceived by aligning it with audiences' interests rather than through direct persuasion or influence alone. This aligns with the mediation model theory, which posits that certain variables can have a more significant impact when they operate through intermediary mechanisms (Baron & Kenny, 1986).

The greater impact of the indirect effect emphasises the importance of content relevance to the audience. It underscores the notion that opinion leaders are most effective when they can align their messages with the interests and needs of their followers. This is consistent with the uses and gratifications theory, which proposes that individuals engage with media content to satisfy specific needs and preferences (Katz, Blumler, & Gurevitch, 1973). When opinion leaders' content meets these needs, mainly by fitting well with audiences' interests, it naturally leads to higher Engagement Intentions.

The results of Hypothesis 6 offer strong evidence that Perceived Fit with Personal Interests plays a major mediating role in the link between Opinion Leadership and Engagement Intentions. Perceived Fit with Personal Interests should be a major factor taken into account when planning and writing content, as it emphasises the significance of creating content messages that closely correspond with the interests of the target audience.

There is a significant indirect influence of the Perceived Quality of Information on Engagement Intentions, mediated by the Perceived Fit with Personal Interests (H7)

In order to interpret the findings for the seventh hypothesis, we examine Perceived Quality of Information's direct and indirect effects on Engagement Intentions, as well as Perceived Fit with Personal Interest's intervention. Perceived Quality of Information's direct impact on Engagement Intentions may be calculated by squaring its beta value (Table 7), which is (0.154)^2 = 0.024.

The multiplication of Perceived Quality of Information to Perceived Fit with Personal Interests (Table 5) and Perceived Fit with Personal Interests to Engagement Intentions (Table 7) beta

values yields the indirect influence of the Perceived Quality of Information on Engagement Intentions through Perceived Fit with Personal Interests, which is 0.764 × 0.569 = 0.435.

Therefore, 0.024 + 0.435 = 0.459 is the entire impact of Perceived Quality of Information on Engagement Intentions, which is the sum of its direct and indirect effects. According to this calculation, Perceived Quality of Information has an indirect influence on Engagement Intentions of 0.435, which is substantially larger than 0.024, the direct effect. This result indicates that the indirect influence of Perceived Quality of Information on Engagement Intentions through Perceived Fit with Personal Interests is far more substantial than the direct influence of Perceived Quality of Information on Engagement Intentions. Consequently, the null hypothesis (H0: $\beta 7 = 0$) is rejected. Instead, the alternative hypothesis (H7: $\beta 7 \neq 0$) is accepted, which proposes that there is a significant indirect influence of the Perceived Quality of Information on Engagement Intentions, mediated by the Perceived Fit with Personal Interests.

According to this finding, Perceived Fit with Personal Interests is a key mediating factor that amplifies the overall effect of Perceived Quality of Information on Engagement Intentions. This emphasises the significance of taking Perceived Fit with Personal Interests into account in the connection and indicates how, in the circumstances of the study, this variable is a more effective conduit for the influence of Perceived Quality of Information on Engagement Intentions. This adds credence to the idea that indirect paths might cause a greater impact, highlighting the function of mediating factors in intricate connections.

Perceived Fit with Personal Interests is the mediating variable behind the indirect effect, indicating that information quality has the greatest impact when it is well-aligned with the audience's demands and personal interests (Casaló et al., 2020; Ki et al., 2020; Han et al., 2024). This congruence strengthens the information's relevance and personal meaning, which heightens Engagement Intentions. This result confirms the hypothesis that information considered relevant and aligned with the audience's interests plays a major role in effective communication, not just the content's objective quality (De Vreese, 2005; Walther, 1996).

Moreover, the mediation result is consistent with the Selective Exposure Theory (Knobloch-Westerwick, 2015), which proposes that people are more likely to engage and interact with content that supports their preexisting ideas and interests. The robust indirect effect observed underscores the importance of targeting content to align with audience preferences, as this alignment is likely to increase the information's persuasiveness and impact on Engagement Intentions.

As demonstrated by the results of Hypothesis 7, matching the quality of content with the interests of the audience is crucial to optimising engagement. This emphasises the need for ongoing research and practical strategies that focus on enhancing the congruence between content and consumer interests to fully harness the potential of digital platforms for engaging audiences effectively.

Limitations

The primary limitation of this study arises from the fact that the data was collected from the researcher's social media audience, where the researcher also served as the influencer, which can lead to potential biases (Gelinas et al., 2017). Responses may be skewed because the most active and devoted members of the researcher's community may dominate the data (Vegetti, 2020). However, collecting data from the researcher's social media audience may offer more advantages than disadvantages if properly managed. Kozinets (2010) suggests that it can provide for a deeper understanding of engagement patterns that may not be evident in other circumstances because these audiences are more likely to contribute genuinely due to their preexisting relationship with the researcher. Nevertheless, the study's reliance on a single influencer's audience limits the generalizability of the findings, and future research should consider including multiple influencers to broaden the generalizability of the findings.

In order to minimise bias, measures were implemented to incorporate respondents with varying engagement frequencies, therefore reflecting a broader demographic than merely the most engaged demographic (Dillman, 2014). A range of involvement levels is shown by the distribution of interaction frequencies, as seen in Figure 4: 35.4% interact regularly, 22.2% occasionally, 13% very frequently, 15% seldom, and 14% very infrequently. According to Dillman (2014), increasing the representativeness and reliability of survey data requires the respondent

base to be diverse. Additionally, Fowler (2013) emphasises the value of including participants at different levels of engagement to reduce bias and maximise the authenticity of survey results. Furthermore, the potential of respondent fatigue was a concern due to the length of the survey, which included 98 research scale items. Surveys that are too long or repetitive might cause participants to get disengaged, which lowers the quality of the data that is gathered (Solanki, 2020). However, if properly managed, using a more comprehensive list of items may offer more advantages than disadvantages. DeVellis (2021) emphasises that a greater number of items can improve the precision and depth of the measured construct, provided they are relevant and well-designed. It will also provide a more comprehensive representation of the construct, which lowers the possibility of measurement error and improves the scale's capacity to identify subtle differences in responder behaviour or attitudes (DeVellis, 2021).

To minimise respondent fatigue, the survey design included favourable and unfavourable items, a method that Podsakoff et al. (2003) supported. According to Podsakoff et al., using a combination of these items might lessen the chance of response biases like Di acquiescence, which is the tendency to disagree with things regardless of content, or acquiescence, which is the tendency to agree with items regardless of content. In this research, items 2, 5, 8, 11, 14, 17, 20, 25, 28, 31, 34, 37, 42, 45, 48, 51, 56, 59, 62, 65, 68, 71, 74, 77, 80, 88, 91, 94, and 97 were the unfavourable ones. These were strategically placed to minimise acquiescence or die acquiescence biases, which is a common practice in survey design to enhance data reliability (Podsakoff et al., 2003).

Additionally, the cultural context of Indonesia, where the study was conducted, may influence the findings. Cultural values such as collectivism, power distance, and a high tendency to follow societal norms could amplify audience engagement with influencers, as noted by Hofstede (2011). These factors may make the results less generalisable to more individualistic cultures. Future research should explore whether the dynamics of influencer marketing differ in regions with contrasting cultural norms.

Furthermore, the reliance on convenience sampling further limits generalizability, as participants were primarily followers of the researcher’s account. Scholars suggest random sampling methods or quota sampling as alternative approaches to improve representativeness and reduce bias (Bryman, 2015).

Finally, including young respondents requires careful consideration of ethical guidelines related to informed consent and data protection (Steinberg, 2024). To address this, the survey was designed to ensure that all participants, including minors, were adequately informed about the study’s purpose, procedures, and their right to withdraw at any time. Furthermore, the survey minimised data collection by avoiding unnecessary demographic or personal details, ensuring that only relevant information was gathered. Data security measures were implemented in line with established ethical guidelines to protect the confidentiality and integrity of respondents’ information.

CONCLUSION

This study concludes that all hypotheses fulfil the significance value requirement, demonstrating substantial influences in all of the relationships examined. This suggests that opinion leadership (X1) and information quality (X2) have a significant impact on how audiences view how well information aligns with their interests (Y) and their intentions to engage further (Z), supporting the theories of the two-step flow model, perceived quality of information, and self-congruity.
Regarding the beta value requirement, the majority of the hypotheses show modest effects, with two exceptions that have strong effects. The two strong effects include the impact of perceived information quality (X2) on perceived fit with personal interests (Y) and the impact of perceived fit with personal interests (Y) on engagement intentions (Z). These findings suggest that high-quality content greatly enhances the alignment of material with audiences’ interests, increasing their engagement intentions.

Moreover, the study reveals that the indirect paths have a higher impact than the direct pathways, where the effects of both opinion leadership (X1) and perceived quality of information (X2) on engagement intentions (Z) are stronger when mediated by perceived fit with personal interests (Y). This highlights the critical role of personal interest alignment in mediating these relationships, suggesting that to maximise audience engagement intentions, content should not only convey strong opinion leadership and information quality, but also be tailored to the

audience's values, interests, and personality, thus contributing to a deeper understanding of influencer-audience dynamics.

This study provides a deeper understanding of how opinion leadership and perceived quality of information influence engagement intentions through the mediating role of perceived fit with personal interests. The findings highlight that while opinion leadership and information quality are significant predictors of engagement, their effects are substantially amplified when audiences perceive a strong alignment between the content and their personal interests. This underscores the importance of personalised content strategies in influencer marketing.

Furthermore, the study contributes to existing literature by demonstrating that perceived fit with personal interests is not merely a passive outcome but an active determinant of engagement. The results emphasise that influencers who consistently tailor their content to align with audience expectations and values can foster higher engagement levels, ultimately increasing trust and behavioural adherence.

Practically, these insights offer valuable implications for digital marketing strategies, emphasising the need for influencers and brands to prioritise content personalisation, credibility, and relevance. Future research should explore additional moderating or mediating factors, such as audience characteristics or content type, to further refine our understanding of audience engagement dynamics in digital spaces.

Future studies in influencer marketing and audience engagement should investigate the nuances of perceived fit with personal interests as a mediating variable in greater detail. This research has demonstrated its crucial role in magnifying the impact of perceived information quality and opinion leadership on engagement intentions. However, these findings might vary across industries, platforms, or demographics. Researchers should investigate other mediating and moderating variables as well, such as cultural factors, platform-specific features, or influencer and user personality traits, that may impact these relationships. Hence, it will help detect potential variations in audience behaviour, generalise the findings, and better understand the mechanisms that drive engagement intentions. Experimental designs, longitudinal studies, and mixed-method techniques could be used in future research to gain a more comprehensive understanding of the power of social media influencers. Additionally, expanding the study to include multiple influencers would provide broader insights into the variability of influencer effects across different contexts, platforms, or audience demographics.

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