An Innovative Business Intelligence Modelling Approach on The Effects of Social Media Features on User Engagement

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***Abstract*— The intensity of today's social media landscape is unparalleled, with platforms that have evolved beyond basic messaging to include features such as story sharing, video content, shopping, and more. These are all in a bid to enhance user engagement. Although the effect of social media features on user engagement has been studied before, most of these studies have relied on in-person interviews, which can change the natural setting and unintentionally introduce response biases. This research adopted a different approach by utilizing observational data to analyze whether specific features influence user engagement. Data were from SEMrush and covered a time series of 2×60 points of user engagement metrics from two popular social media platforms in Indonesia: Instagram and TikTok. We retrospectively searched for credible references to determine when each feature was first introduced on these platforms. We used monthly fixed-effects regressions with robust standard errors to model the relationship between social media features and two metrics of user engagement: average visit duration and bounce rate. Our findings reveal diverse effects of features on user engagement. For instance, introducing a shopping feature increased the average visit duration of Instagram users, but conversely, a similar feature degraded the user engagement of TikTok users. Such intriguing patterns are discussed further in the paper.**

Keywords—Social Media Features, Instagram, TikTok, User Engagement, SEMRush

I. Introduction

Social media has become integral to contemporary life, enabling global connectivity and communication. Platforms like Instagram and TikTok continuously innovate, introducing features such as Live Streaming Commerce to revolutionize online sales [1]. These innovations aim to enhance User Engagement, gauged by user numbers and activity depth, encompassing cognitive, emotional, and behavioral aspects [2]. However, not all features yield desired outcomes, as engagement involves emotional and psychological responses, posing challenges for developers to assess feature relevance over time. Sustaining platform popularity requires ongoing effort beyond initial creation.

Features that no longer resonate with users may be eliminated as a result. The evaluation informs this decision of user data, trend analysis, and feature performance assessment. Research on the impact of social media features on User Engagement is limited, with only a few studies addressing this topic [3]. Most research has focused on social media content and brand engagement [4]. Previous studies have also explored factors influencing user engagement, including website design elements and personalized recommendation systems [5].

Researchers often use questionnaire surveys to study user engagement [6]. However, this method can introduce response bias due to respondents feeling overwhelmed or pressured [6]. Alternatively, some researchers utilize objective data sources like SEMRush [7] to analyze user behavior on social media platforms [8], avoiding reliance on potentially biased self-reports. [9] argue that website analysis provides more reliable insights than survey data.

User Engagement, assessed by Visit Duration and Bounce Rate from SEMRush, was studied by [10–12]. [10] found that monthly visits and acquisitions positively affected investor behavior, while high bounce rates had a negative impact. [11] observed a positive correlation between user engagement and organic traffic for logistics startups. [12] noted the significance of backlinks and referral domains for online banking services. They also found that affiliate marketing strategies increased brand-engaged customers. The bounce rate feature was analyzed by [13, 14], while [13] discovered its impact on brand engagement through video marketing analytics, cautioning against over-posting for Fintechs. [14] highlighted the influence of recommendation system design on platform engagement. [15] revealed positive associations between website product variety, visit durations, communication functionality, and shopping. So far, research on the influence of social media on user engagement and the role of time in this association still needs to be explored.

The purpose of this study is to respond to the questions of whether social media features influence user engagement and whether this influence endures over time. Insights from Instagram and TikTok are analyzed in this study so that social media developers can use them as a guide to evaluate current features and further, developing new, customized features that will enhance user engagement.

II. Literature Review

A. User Engagement and User Experience

As described by [16], engagement represents a reciprocal communication process fostering connections with an entity. According to [17], the engagement was marked by a deep dive into an activity. It also included behavioral metrics such as average time on site and bounce rate [11]. User involvement entails cognitive, temporal, affective, and behavioral engagement with a system [18]. [6, 19] emphasize the positive nature of User Engagement, reflecting users' willingness to use online applications repeatedly. Users invest attention, emotions, and time in technology to satisfy pragmatic and hedonic needs.

Positive user experiences are crucial for driving User Engagement on platforms [20]. Enhanced satisfaction and comfort increase engagement, fostering interaction and loyalty [19]. Two-way interactions between companies and users are fundamental to engagement, with activities such as content creation and liking on social media serving as indicators of brand engagement [21]. User engagement forms the foundation of interaction between companies and users, influencing behaviors such as content creation and liking on social media platforms [22]. Additionally, User Engagement focuses on interaction with online applications, reflecting users' relationship and involvement with a website [23].

B. Social Media Features

Social media features foster user interaction and establish a digital presence [24]. Alongside platforms, these features enable users to express themselves through comments, shares, and likes, thereby boosting User Engagement. The continuous development of these features reflects platforms' responsiveness to evolving trends and user preferences, emphasizing the need to enhance interaction effectiveness in the digital age. Furthermore, these features enrich the user experience by catering to diverse content consumption preferences. Platforms perceived as flexible and adaptable to user preferences create positive experiences, empowering users to explore functions aligned with their interests, ultimately enhancing engagement and satisfaction.

C. Feature Life Cycle

[25] outlined the four stages of a product's life cycle: introduction, growth, maturity, and decline. During the introduction stage, users encounter and explore new features, exemplified by Instagram's "Stories." Usage surges in the growth stage, as seen with the widespread adoption of "Stories." Features reach maturity, such as Facebook's ubiquitous "like" feature, which faces intense competition and requires strategic maintenance. Eventually, trends or technology changes prompt feature decline, leading platforms to replace or remove them with more engaging alternatives.

Different strategies are needed at each stage of a feature's life cycle. For instance, new features can spark user interest during the growth phase, while in the maturity phase, maintaining feature quality is crucial for sustaining User Engagement [17]. As new trends and technologies emerge, the perceived value of features can change, posing challenges for online communities in maintaining engagement as user experiences improve [17]. What was once innovative may become standard or outdated, highlighting the importance of understanding the Feature Life Cycle for long-term sustainability [26].

D. Evolvability

An essential aspect of social media platform development is adaptability, the capability to evolve and expand to meet users' changing needs. Platforms must introduce new features as user expectations regarding navigation and interaction shift over time. For instance, Facebook has extended its offerings beyond social groups to include gaming apps, creating new usage opportunities [27]. Furthermore, relevant and supportive communication is crucial for enhancing user engagement, as active participation significantly influences consumer purchasing behavior [22].

Increased user engagement is linked to heightened interest in system utilization. Participation involves individuals becoming subjects of involvement, while interaction experiences focus on specific entities [28]. In this framework, users are engaged subjects, while the object of engagement comprises brands, services, organizations, and their activities. Research suggests that perceiving intense involvement is crucial, elevating individuals' passion, interest, and motivation to participate.

User satisfaction, reflecting a comprehensive product or service evaluation, aims to fulfill user needs [29]. It encourages prolonged platform use and extended durations. High satisfaction cultivates user loyalty to a social media platform, while dissatisfaction may prompt users to switch to alternative products or services. Satisfied users spend more time browsing, making return visits, and prolonging their site visits.

User engagement on social media is greatly influenced by its features, with platforms that offer a wide range of features typically seeing higher engagement rates. Here is an outline of a potential correlation between user engagement and social media features:

H1: Social Media features positively affect User Engagement.

Innovative and engaging social media features may initially boost user engagement but could decline if they are not updated or become irrelevant to user preferences over time. The impact of social media features on user engagement diminishes over time, leading to the following hypotheses:

H2: Times moderate the relationship between Social Media features and User Engagement. The influence of social media features on User Engagement decreases over time.

Based on the literature review discussed the research framework can be seen in Figure 1 with Social Media features as the independent variable, User Engagement as the dependent variable, and Feature Life Cycle as the moderating variable.

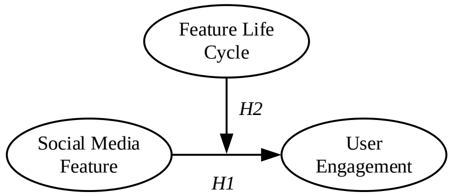

Fig. 1. Research Framework

III. Research Methodology

This study used data from SEMrush, an American public company whose services are in the online visibility management and content marketing SaaS platforms [7]. We gathered 5 years span of user engagement metrics of social media, starting from January 2019 to December 2023. We thoroughly cleaned the data to ensure it was accurate and consistent. Our focus is on Instagram and TikTok, the two most popular social media in Indonesia. Therefore, there were 2×60 monthly time series points included in the data.

The dependent variables are two user engagement metrics: the average time visit in seconds [10–12, 15, 30] and the bounce rate [10–14]. These variables measure how strongly users were tied to the social media they accessed. A higher average time visit signals stronger user engagement [6]. The opposite applies to the bounce rate: the percentage of users that end their visit without further interactions.

The independent variables comprise two features from each social media platform: Instagram (reels and shopping) and TikTok (story and shopping). These variables are represented as dummies, with a value of "0" indicating the absence of the feature at the corresponding monthly time point and "1" indicating its presence. Credible information sources were consulted when assigning the binomial value for these dummies, and a table listing this information is available from the authors upon request. However, the binomial design complicates the assessment of the effects of the story feature for Instagram and the video feature for TikTok, as these features were introduced before and remained available throughout the 5-year data span analyzed. Additionally, the time variable was coded as the month count for the period, ranging from "1" for January 2019 to "60" for December 2023.

We investigated the hypotheses by using monthly fixed-effects regressions. To be conservative in rejecting the null hypotheses and also, to reduce estimation bias because of possible heteroskedasticity, we applied robust standard errors. The equation could be written as follows:

$$Y_t = b_0+b_1F_1+b_2F_2+b_3t+b_4(F_1 \times t)+b_5(F_2 \times t)+b_6month+e_t \quad (1)$$

Y_t are user engagement metrics at time t (average visit duration in seconds and bounce rate), F_1 is a dummy for feature 1, F_2 is a dummy for feature 2, and month is a vector matrix for monthly fixed-effects. The constant b_0 apprehends user engagement because of other factors aside from those variables in the model. The coefficients b_1, b_2, and b_3 are the main effects. These coefficients capture the average effects of feature 1, feature 2, and time t on user engagement. Our interest is in b_1 and b_2, which test the effects of social media features on user engagement (*H1*). Interactions effect b_4 and b_5 record moderating effects of time t on the relationship between social media features and user engagement (*H2*). STATA 18 is used for conducting the statistical analyses.

IV. Result and Discussion

A. Results

Table 1 provides descriptive statistics of user engagement metrics on Instagram and TikTok. These statistics cover a five-year comparison of the average visit duration (in seconds) and bounce rate of the two social media platforms. The overall 5–years average showed striking differences in average visit duration. While Instagram users spent nearly 17 minutes (1,002 seconds) each time they visited the platform, TikTok users only spent less than 12 minutes (695 seconds) (*p-val.* < 0.001). The average visit duration and bounce rate gaps between the two platforms vary each year, but it seems that during the peak of the COVID-19 pandemic 2020–2021, the gaps were smaller (*p-val.* = 0.082 in 2020 and *p-val.* = 0.142 in 2021). These smaller gaps might contribute to insignificant five-year average differences in the bounce rate of Instagram vs. TikTok (*p-val.* = 0.247). An interesting pattern is that TikTok users' average visit duration peaked at the tip of the COVID-19 pandemic in 2021 and tripled that of average visit duration in 2019 (2019 = 314 seconds vs. 2021 = 915 seconds). However, this trend did not last long, as the number considerably shrank but remained double in 2023 compared to the base year of 2019 (2023 = 686 seconds). The bounce rate of users on these two platforms was over 50%, except for Instagram in 2019 (0.437) and 2020 (0.480).

TABLE I. DESCRIPTIVE STATISTICS OF USER ENGAGEMENT MATRICS

User Engagement	N obs.	Social Media		*p-val.*[a]
		Instagram	***TikTok***	
Average Visit Duration (in seconds)				
2019	12	912.667 (77.542)	314.083 (141.526)	<0.001
2020	12	1,061.167 (173.026)	710.167 (348.984)	0.005
2021	12	1,074.417 (125.150)	915.750 (260.109)	0.070
2022	12	1,042.833 (86.462)	853.167 (132.607)	<0.001
2023	12	920.833 (137.318)	686.417 (105.692)	<0.001
5-years avg.	60	1,002.383 (140.046)	695.917 (298.308)	<0.001
Bounce Rate				
2019	12	0.437 (0.043)	0.668 (0.066)	<0.001
2020	12	0.480 (0.027)	0.507 (0.042)	0.082
2021	12	0.562 (0.087)	0.509 (0.084)	0.142
2022	12	0.637 (0.016)	0.577 (0.048)	<0.001
2023	12	0.713 (0.023)	0.678 (0.020)	<0.001
5-years avg.	60	0.566 (0.111)	0.588 (0.093)	0.247

a. *p-val.* from t-test comparing Instagram vs TikTok user engagement metrics

TABLE II. EFFECTS OF FEATURES OF INSTAGRAM ON USER ENGAGEMENT MATRICES

	Y = avg. visit duration		Y = bounce rate	
	Coef.	***SE***	***Coef.***	***SE***
main effects				
reels	-378.234	(197.591)	0.239	(0.047)**
shopping	420.679	(152.597)**	-0.047	(0.027)
time	-7.492	(4.496)	0.006	(0.001)
interaction effects				
reels × time	13.241	(6.933)	-0.005	(0.002)**
shopping × time	-4.192	(3.311)	-0.000	(0.001)
const.	945.712	(58.209)**	0.391	(0.021)**
N	60		60	
R^2-adj.	0.587		0.951	

* *p-val.* < 0.05; ** *p-val.* < 0.01
month fixed-effects with robust standard errors; standard errors (SE) in parentheses)

The effects of Instagram features on user engagement metrics are shown in Table 2. The table consists of the main effects, that is, for features, informing the effects of video and shopping features at the month of introduction. The table shows that introducing the shopping feature in May 2020 increased users' average visit duration by 6 minutes (*coef.* = 420.679, *p-val.* < 0.01). The effects remain over time since no significant interaction effects were found (*coef.* = -4.192, SE. = 3.311). On the contrary, the video features reduced overall user engagement in terms of bounce rate. The feature increased the bounce rate by 23.9% (*p-val.* <0.01) at the time of the introduction in June 2021. Later, the bounce rate due to the video feature decreased by 0.5% each month.

Table 3 shows the effects of TikTok's features on user engagement metrics. The story features perfectly align with our hypothesis: the story feature affects user engagement (*H1*), and the effect diminishes over time (*H2*). The main effects showed that initially, the story had increased average visit duration for about 42 minutes (*coef.* = 2,501.178; *p-val.* < 0.01) and had reduced the bounce rate to 82.9% (*coef.* = -0.829; *p-val.* < 0.01). This happened in April 2022. However, the effect did not last. Each month, the story's effect flattened at a rate of 64.864 seconds (*coef.* = -64.862, *p-val.* < 0.01). The weakening effects of (the story had also been recorded in the increasing bounce rate at 2.3% each month (*coef.* = 0.023, *p-val.* < 0.01). The striking effect of the story during its introduction and how the effect diminished should be interpreted with caution because Eq.1 we used is linear and, thereby, may overestimate the actual effects of this specific feature. The shopping feature went in a different direction from the story feature. The introduction of the shopping feature in April 2021 had negatively affected user engagement in terms of average visit duration and bounce rate, completely the opposite of the shopping feature in Instagram. TikTok's shopping feature cut the average visit duration by 12.5 minutes (*coef.* = -760.835, *p-val.* < 0.05) and increased the bounce rate by 25.1% (*coef.* = 0.251, *p-val.* < 0.05). There was no interaction effect of shopping features with time on user engagement.

TABLE III. EFFECTS OF FEATURES OF TIKTOK ON USER ENGAGEMENT MATRICES

	Y = avg. visit duration		Y = bounce rate	
	Coef.	***SE***	***Coef.***	***SE***
main effects				
story	2501.178	(475.156)**	-0.829	(0.131)**
shopping	-760.835	(294.122)*	0.251	(0.104)*
time	34.018	(5.827)**	-0.009	(0.001)**
interaction effects				
story × time	-64.862	(11.568)**	0.023	(0.003)**
shopping × time	8.778	(6.529)	-0.003	(0.002)
const.	145.099	(128.151)	0.677	(0.033)**
N	60		60	
R^2-adj.	0.617		0.726	

* *p-val.* < 0.05; ** *p-val.* < 0.01
month fixed-effects with robust standard errors; standard errors (SE) in parentheses)

B. Discussion

Main findings of this study are that social media features indeed affect user engagement. However, since the direction of the effects differ by social media, our finding only partially fits *H1*. For example, in Instagram, while the effect of the shopping feature increased user engagement, in terms of reducing the bounce rate, a similar shopping feature affected user engagement in TikTok negatively–shorten average visit duration and increased the bounce rate. This kind of variability occurred in the negative effect Instagram and the positive effect of the story in TikTok as well. Second, although we found that time negatively moderated the effect of story on user engagement of TikTok, exactly as in *H2*, such moderating effects were absent from other features we have investigated.

Our findings highlighted that the effect of social media features on user engagement may be more complex than we hypothesized before. In contrast to [19], our findings suggest that introducing new social media features only sometimes enhances user engagement. Additionally, our study uncovered an unexpected finding: the shopping feature on Instagram has demonstrated a non-traditional product lifecycle by maintaining a long-term positive effect on user engagement. This contradicts the common belief that features may lose their positive effects over time [26].

We proposed contextual might contribute to the formation of these complex relationships between social media features, time, and user engagement. Perhaps this is related to users acceptance and evolvability capacity of social media platforms. We posit the initial identity of social media platforms may form users aspiration and how they react to new features. For example, Instagram was first introduced and used by its early users as a photo sharing platform. Later on, users of Instagram have pushed the boundry of the platform creatively, utilizing its photo sharing feature as a marketing tools to promote products and services [31]. This situation may path users acceptance to a marketing–related feature such shopping. On the other hand, TikTok started as a short video sharing platform where its early users initially used the platform to share dancing activity [32], which might impact how users react to new features. While TikTok users embraced the story feature positively, they responded differently to the shopping feature, unlike their counterparts on Instagram. Besides user acceptance, the platform's adaptability could elucidate the intricate relationship patterns between social media features, time, and user engagement [27]. This adaptability may explain the sustained impact of the shopping feature on user engagement in Instagram. Continuous improvements in user experience with the shopping feature could prevent its effects on user engagement from diminishing over time.

This research has several limitations worth noting. Firstly, while we have identified complex relationships between social media features, time, and user engagement and provided context, our proposed explanations must be more specific due to a lack of data validation. Future studies could investigate factors influencing user acceptance and their role in these relationships. Secondly, our analysis may overlook factors like compelling content, which can significantly impact user engagement. The compelling content is a topic that other researchers could explore further. Thirdly, we focused solely on Instagram and TikTok, neglecting other platforms like Facebook, Twitter, and YouTube, each with unique features and impacts on user engagement. Including these platforms in future research would be valuable. Lastly, our data is limited to Indonesia, and user demographics and behaviors may vary across countries due to cultural and contextual differences. Analyzing global data and comparing results across regions would be an exciting avenue for future research.

V. Conclusion

In conclusion, our findings revealed varying effects of social media features on user engagement. Notably, the traditional product (feature) life cycle-with an assumption of diminishing effects on user engagement over time-was not universally applicable to all features that we studied. We posit that perhaps contextual plays a role in creating these findings. Such contextual may encompass social media users acceptance to new features and the platform evolvability capability to lengthen the feature life cycle. Based on these results, in order to improve and sustain user engagement, managers should carefully design social media features that align with its users aspiration. Furthermore, managers should view that managing continuous evolvability of social media features is crucial, because by doing so, social media could maintain its attractiveness over a longer period of time.

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