

# Exploring the Dynamics of Less Frequent Social Media Usage

**Anh Ta**

College of Business Administration  
University of Nebraska Omaha  
Omaha, Nebraska, USA  
Email: ata@unomaha.edu

**Quynh N. Nguyen**

School of Business  
Stockton University  
Galloway, New Jersey, USA

**Steve Schulz**

College of Business Administration  
University of Nebraska Omaha  
Omaha, Nebraska, USA

**Linh Le**

College of Business Administration  
University of Nebraska Omaha  
Omaha, Nebraska, USA

## Abstract

This study addresses a significant gap in Information Systems (IS) research by examining Less Frequent Use (LFU) and discontinuation of IS products, particularly in the context of Social Media (SM) platforms. Previous research has emphasized adoption and continued use, leaving later lifecycle stages underexplored. Building upon the Stimulus-Organism-Response (S-O-R) framework, this study proposes a novel LFU model to explore key determinants, including perceived influencer disengagement, loss of interest, negative news exposure, addiction realization, and distrust, which contribute to reduced SM usage and the intention to discontinue. Empirical testing of the LFU model reveals that influencer disengagement reduces user interest, leading to less frequent usage and potential discontinuation. Additionally, negative news exposure fosters distrust, diminishing user engagement and leading to discontinuation intent. The results of post hoc analyses provide a comprehensive view of the model for different subsamples, considering variables such as gender, usage frequency, and the number of social media platforms used. The findings have both theoretical and practical implications, offering insights into SM user retention strategies. We also introduce the Integrated Technology Life Cycle framework, which clarifies overlooked stages such as intermittent discontinuance and less frequent use, and outlines directions for future research across diverse technological contexts.

**Keywords:** Less Frequent Use (LFU) Model, IS Discontinuance, Stimulus-Organism-Response Framework, Structural Equation Modeling, Integrated Technology Life Cycle.

## 1 Introduction

In the field of Information System (IS) research, scholars have extensively examined user behaviour across various stages of an IS product life cycle. Considerable attention has been given to studying the adoption phase (Davis et al., 1989; Ajzen, 1991; Rogers, 1995) as well as the continued usage stages of IS products/services (Bhattacharjee, 2001; Bhattacharjee & Lin, 2015; Rezvani, 2017). However, despite the prevalence of IS discontinuation, the research community has paid relatively little attention to it, focusing primarily on organizational-level discontinuation (Furneaux & Wade, 2011; Mehrizi et al., 2019; Soliman & Rinta-Kahila, 2020). Few studies have investigated the later stages of IS usage, particularly at the individual level, where users begin to engage with systems less frequently.

While Vaghefi and Tulu (2019) briefly mentioned "limited use" in the context of health apps, describing intermittent user engagement despite perceived usefulness, and Islam et al. (2022) highlighted technology exhaustion as a factor for decreasing use during the Covid-19 pandemic, research remains scarce on the determinants of less frequent use. Additionally, Osatuyi and Turel (2020) explored factors such as realization, addiction, and peer influence as contributors to the intention to reduce use. More recently, Ye et al. (2023) argued that usage reduction represents a distinct form of discontinuous usage and called for further research in this emerging area.

Recent scholarship has increasingly examined the nuances of social media user engagement and disengagement. For instance, a systematic review by Bastrygina (2023) highlights that consumers engage with social media influencers due to factors such as brand placement, influencer credibility, and social influence. Ooi et al (2023) introduced the concept of influencer credibility, suggesting that mobile convenience and influencer credibility are crucial for influencer marketing effectiveness. While these studies offer valuable insights, few have examined the interplay between influencer behaviour and individual user motivations for reduced platform use. This study addresses this gap by focusing on perceived influencer disengagement and loss of interest—constructs that remain underexplored but are increasingly relevant in the context of declining platform stickiness. By integrating these perspectives, our study seeks to provide a more holistic view of social media disengagement.

Unlike traditional IS research, which largely emphasizes adoption and continuance, this study addresses a critical gap by examining the determinants of less frequent use and discontinuation. By exploring these later-stage behaviours through a novel integration of established theories, we contribute both deeper theoretical understanding and actionable insights for platforms aiming to mitigate user churn. Specifically, in the context of Social Media (SM) usage, this research identifies and differentiates between two distinct types of reduced usage, contributing to a new understanding of user behaviour in the later stages of IS engagement. This model offers fresh insights into these often-overlooked phases of the IS lifecycle, with a focus on social media platforms.

To further clarify the research gap, the study visualizes different stages of IS lifecycle in the Integrated Technology Life Cycle (ITLC) in Figure 1. This framework is conceptualized from various life cycle theories, in Figure 2, such as the technology life cycle (Sood & Tellis, 2005),

product life cycle theory (Dean, 1950; Levitt, 1965; Vernon, 1966), product evolutionary cycle (Tellis et al., 1981), and industry life cycle model (Klepper, 1997), which generally neglect the later stages of less frequent use and discontinuation.

From a practical standpoint, understanding IS continuance is critical for firms to remain competitive, but equally important is the need to investigate the factors driving "less frequent use." Research shows that increasing customer retention by just 5% can lower operating costs by 18% and increase profits by 25% to 95% (Crego & Schiffrin, 1995; Reichheld, 2001; Gallo, 2014). However, less frequent use has been relatively understudied, often conflated with discontinuance. Yet, most IS products and services inevitably enter this phase. This research seeks to fill that gap by examining the dynamics of lower-frequency use in social media contexts and their implications for sustaining active user communities.

It is also important to note that while some manufacturers deliberately shorten product life cycles through strategies like planned obsolescence (Bulow, 1986), this approach is less applicable in the social media (SM) context. The SM market is neither a monopoly nor an oligopoly, and the incentive for planned obsolescence is theoretically low. As both a product (in terms of the platform) and a service (through its functionalities and user experiences), social media platforms offer a unique context for studying the factors driving less frequent use.

This study seeks to address two primary research questions:

- What factors influence less frequent use in the context of SM?
- What factors impact user intention to discontinue using an information system in the context of SM?

Building on the Stimulus-Organism-Response (S-O-R) framework (Mehrabian & Russell, 1974), we propose the Less Frequent Use (LFU) model, which identifies perceived influencer disengagement, loss of interest, negative news exposure, realization of addiction, and distrust as the primary factors driving less frequent social media usage. In this model, the stimuli or environmental triggers include perceived influencer disengagement and negative news exposure. Perceived influencer disengagement and negative news exposure are conceptualized as external stimuli based on Social Influence Theory and Agenda-Setting Theory, respectively, capturing how users' perceptions of their environment shape emotional and cognitive responses.

The organism, representing emotional and cognitive states, encompasses loss of interest, distrust, and the realization of addiction. Loss of interest, distrusting beliefs, and realization of addiction reflect internal organismic states within the S-O-R framework, aligned with evolving understandings of user burnout and disengagement. These constructs were selected over traditional factors like user satisfaction or content quality because the latter primarily drive adoption and continuance, whereas our focus is on explaining reduction and withdrawal behaviours that emerge in later IS lifecycle stages.

The response, or avoidance behaviour, is reflected in reduced social media use (in terms of activity or time) and the intention to discontinue. Also, given the complexity of user engagement and trust on social media platforms, we employ an integrative framework that draws on four key theoretical domains. The technology acceptance model provides the basis for understanding the technical drivers of engagement and disengagement. Social influence theories and parasocial interaction theory help explain how influencers impact user behaviour. Finally, agenda-setting and framing theories offer insight into how media narratives shape public trust toward platforms. The proposed model was empirically tested using survey data.

In the next section, we review the theoretical underpinnings that shape the conceptual foundation of our model. We then introduce our hypotheses, which are directly embedded within the overall research approach by drawing on the S-O-R framework and supported through an integration of established IS and communication theories. After discussing the development of hypotheses for studying less frequent use in the context of social media, we present the research model, outline the research methodology, and present the analysis and results. Finally, we conclude by discussing the theoretical and practical implications of our findings.

## 2 Literature Review

### 2.1 Integrated Technology Life Cycle (ITLC) Framework

Life cycle theories have long been used across disciplines such as marketing, management, and technology to describe stages of development, growth, and decline. Classic models—including the Product Life Cycle (PLC) (Dean, 1950; Levitt, 1965; Vernon, 1966), product evolutionary cycle (Tellis et al., 1981), industry life cycle (Klepper, 1997), and Technology Life Cycle (TLC) (Sood & Tellis, 2005)—outline stages like introduction, growth, maturity, and decline. However, they often overlook nuanced stages such as less frequent use and discontinuance, especially at the individual level. While PLC dominates literature, a database search, over the past 33 years shows only 0.63% of articles focus on Industry Life Cycle (ILC) and 1.14% on TLC, as shown in Table 1. Given technology's growing role in the industry 4.0 era, more attention to TLC is needed.

	Product Life Cycle*		Industry Life Cycle		Technology Life Cycle		Total
	Paper Count	%	Paper Count	%	Paper Count	%	
EBSCO Host Academic Complete (Academic Journals)	6260	97.9%	51	0.80%	83	1.30%	6394
EBSCO Host Business Source Complete (Magazines, Trade Publications, News Papers)	2828	99.0%	7	0.25%	22	0.77%	2857
Total	9088	98.2%	58	0.63%	105	1.14%	9251

Table 1. Number of papers for PLC, ILC, TLC (1/1/1991 to 9/8/2023) (EBSCO Host Search)

\*Different spellings of life cycle such as, lifecycle and "life-cycle," are considered.

Conceptualized from previous life cycle theories and IS literature, the Integrated Technology Life Cycle (ITLC) framework is introduced to addresses the fragmented understanding of the technology life cycle (TLC) in both organizational and individual contexts. Unlike traditional macro-level approaches, this framework adopts a micro-level perspective, providing a more granular exploration of the stages of TLC. The ITLC framework defines four key stages: Adoption, Usage, Termination, and Post-Adoption, offering detailed insights and examples for each, as depicted in Figure 1 and Table 2.

In the adoption stage, users encounter activities such as resistance, compliance, appropriation, and implementation. These activities range from resisting new technologies (Rivard & Lapointe, 2012; Gerhart & Ogbanufe, 2022) to appropriating systems for unintended purposes (Mudambi et al., 2016), ultimately leading to initial acceptance (Davis et al., 1989; Venkatesh et al., 2003).

Stages	Activities	Definition	Organizational level (Examples)	Individual level (Examples)
Adoption	Resist or workaround	Not to use or create new routines to avoid using the technology	Ferneley & Sobrepez (2006); Rivard & Lapointe (2012); Polites & Karahanna (2012)	Gerhart & Ogbanufe (2022)
Adoption/ Usage	Comply	Use the system under command without acting in the best interest, such as not revealing system issues	Marakas & Hornik (1996); Ferneley and Sobrepez (2006)	
	Appropriation	Use the technology in new ways or for different intended purposes	Orlikowski (1992); Button et al. (2003); Petrides et al. (2004); Kobayashi et al. (2005); Ferneley & Sobrepez (2006)	Mudambi et al. (2016); Kirk et al. (2015)
	Implementation and Adoption	Develop intention to use an IS	Davis (1989); Venkatesh et al. (2023)	Venkatesh & Agarwal (2006)
Usage	Continuance	Develop intention to use an IS continuously	Bhattacharjee (2001)	Ta & Prybutok (2018); Tam et al. (2020)
	Less frequent use	Use the technology but not as much as before		<b>This study</b>
Termination	Replacement or switching	Develop intention to switch to alternatives	Furneaux & Wade (2017) ; Xiao et al. (2020)	Xu et al. (2014); Msaed et al. (2017)
	Discontinuance	Develop intention to stop using an IS	Furneaux and Wade (2011); Recker (2016); Mehrizi et al. (2019)	Maier et al. (2015); Turel (2015); Zhao et al. (2020)
Post-Termination	Intermittent Discontinuance	Stop using an IS for a period of time but ultimately restart using it afterward		Shen et al. (2018); Zhou et al. (2018); Margaret (2020)

Table 2. Stages and Activities in the Integrated Technology Life Cycle Framework

The usage stage builds on the concept of continuance by introducing less frequent use, highlighting the need to understand decreasing user engagement over time. While continuance has been widely studied (e.g., Bhattacharjee, 2001; Ta & Prybutok, 2018; Tam et al., 2020), less frequent use, where users engage with technology less often, has received less attention. This phase may arise from changes in user needs, competing technologies, or shifts in relevance, making it essential for IS providers to address this behaviour in order to retain users.

The termination stage examines the cessation of technology use, whether through replacement or complete discontinuance. Users may transition to alternative solutions or abandon a system entirely due to dissatisfaction or advancements in technology (Furneaux & Wade, 2011; Maier et al., 2015; Recker, 2016; Msaed et al., 2017; Xiao et al., 2020). At the individual level, this stage is crucial for understanding the factors that drive users away from technology, yet it remains underexplored in IS research. Finally, the post-adoption stage introduces the concept of intermittent discontinuance, where users temporarily stop and later resume using a technology. This cyclical behaviour, although rarely addressed in current literature, is particularly relevant in IS contexts like social media, where users may deactivate and reactivate accounts or create new profiles for specific purposes (Shen et al., 2018). Understanding this non-linear relationship between users and technology further enriches our comprehension of the technology life cycle, highlighting the evolving nature of user engagement.

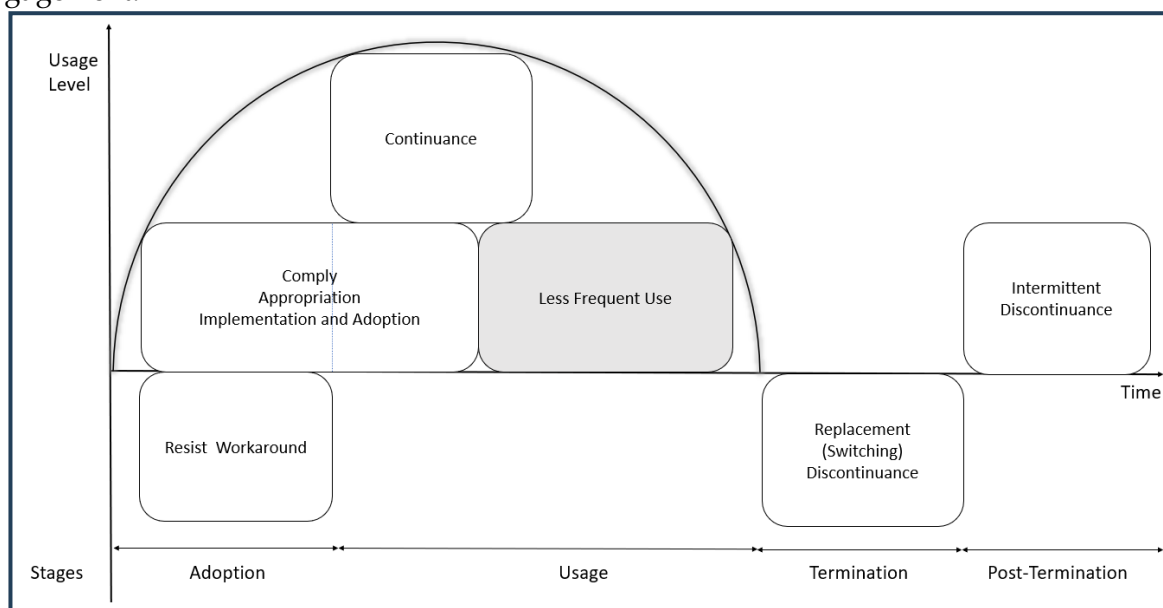


Figure 1: Integrated Technology Life Cycle (ITLC) Framework

In short, the ITLC Framework offers a new perspective on the full lifecycle of a technology, highlighting which stages have been widely studied and which require more attention from researchers. It identifies the gap in understanding less frequent use behaviour and explains why it has been overlooked in the past—previous lifecycle frameworks have not emphasized this stage.

## 2.2 The Stimulus-Organism-Response (S-O-R) Framework

The new proposed ITLC framework shows the need to find the interrelationship and the antecedents of less frequent use and discontinuance, which has not been studied in the literature. The stimulus-organism-response (S-O-R) framework (Mehrabian & Russell, 1974) was used to develop the less frequent use model in this paper. The SOR framework has been successfully employed in numerous IS studies (e.g., Benlian, 2015; Li, 2019; Behl & Pereira, 2021; Perez-Vega et al., 2021; Li et al., 2023), demonstrating its effectiveness in explaining user behaviours and interactions within digital environments. This precedes its suitability and potential in providing insightful analyses into the phenomena of social media discontinuance and less frequent use, which are central to this research. This framework is designed to

understand the dynamics between environmental stimuli and individual responses, perfectly mirroring the research's focus on exploring the external factors, such as Perceived Influencer Disengagement and Negative News Exposure, that influence users' engagement with information systems.

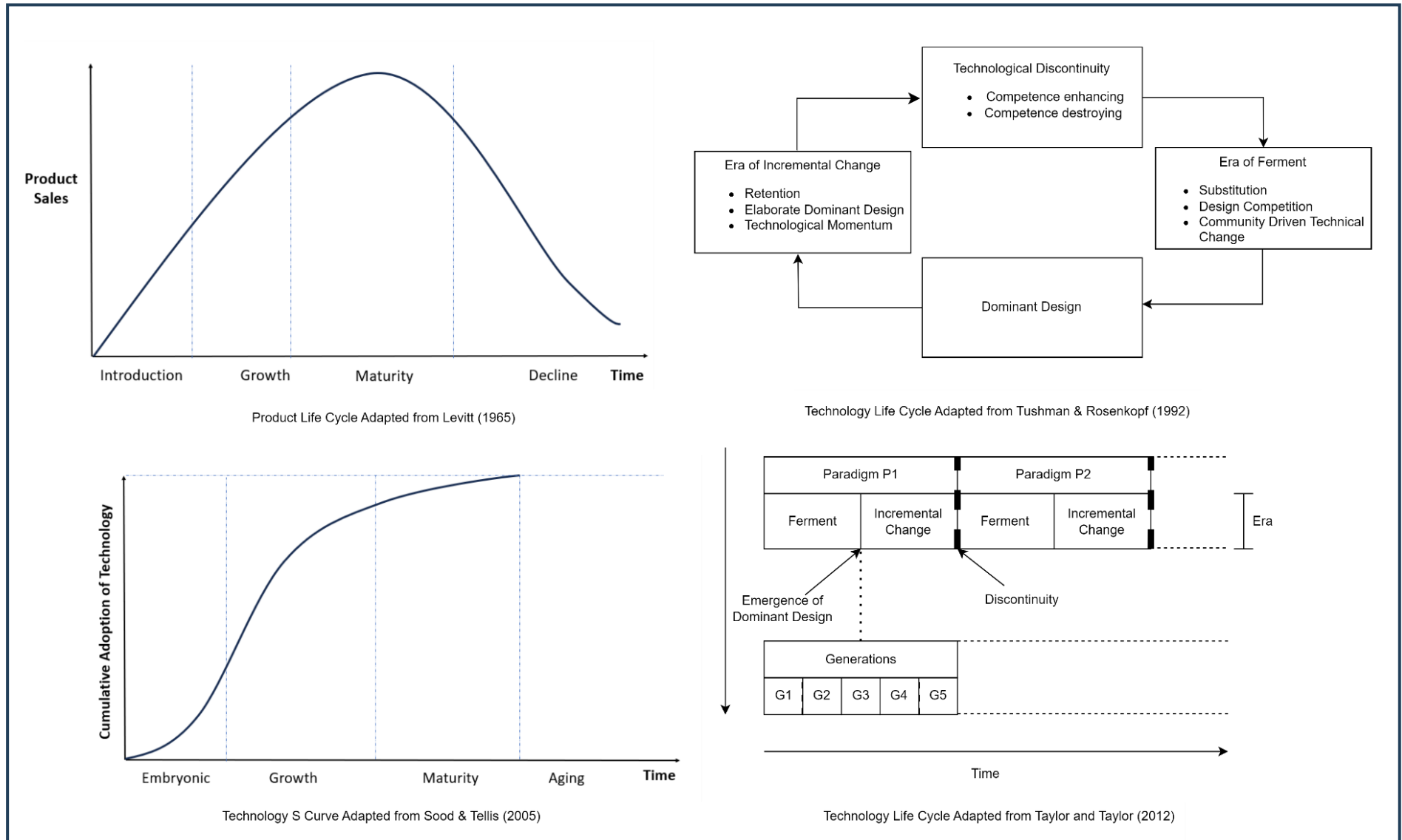


Figure 2. Popular Product/Technology Life Cycle Models



Recent transformations in the social media industry, including the rise of algorithm-driven content curation, short-form video platforms (e.g. TikTok), and ephemeral features, such as Stories and Reels, necessitate a nuanced application of traditional IS behaviour models. The S-O-R framework remains especially relevant as it captures the emotionally charged, rapidly shifting nature of user-platform interactions. For instance, parasocial interactions with influencers are more salient than ever, as users increasingly engage with media personas over personal networks. Additionally, the real-time amplification of negative news across digital channels influences public trust and prompts greater self-awareness regarding social media addiction. These evolving platform features and user experiences underscore the importance of applying and extending established theories to fit today's technological and behavioural realities.

The model's focus on the internal states of the organism, including constructs such as loss of interest, distrusting beliefs, and realization of addiction, aligns seamlessly with the research objectives to dissect the cognitive and emotional underpinnings behind user disengagement. The constructs referenced in the stimulus and organism components above will be thoroughly defined and explored during the hypothesis development section. The application of the S-O-R framework theoretically enhances the newly proposed model by providing a structured way to analyse the nuanced shifts in user engagement. It helps in understanding how users' perceptions and emotional states triggered by external stimuli translate into behavioural outcomes like reduced usage or complete discontinuance.

### **3 Hypothesis Development – Social Media Less Frequent Use Model**

#### **3.1 Perceived Influencer Disengagement**

The social influence theories (Deutsch & Gerard, 1955; Venkatesh & Brown, 2001; Graf-Vlachy et al., 2018) and parasocial interaction theory (Horton & Wohl, 1956) offered insights into how influencers affect people's actions and beliefs. These frameworks posit that influencers can shape others' actions and mindsets through different routes and that people are inclined to emulate behaviours or attitudes observed in their peers or influential figures. SM influencers, also known as content creators on SM networks, possess a substantial base of followers (De Veirman et al., 2017). They are widely regarded as experts within specific industries and have established reputations for their knowledge on various topics, including lifestyle, photography, healthcare, and beauty (Audrezet et al., 2020). With the increasing significance of SM in our daily lives, more individuals are utilizing these platforms to connect with friends and family, stay informed with the latest news, express opinions familiar acquaintances and even strangers, and follow celebrities or influencers (Statista, 2021a). The influencer marketing industry is projected to reach approximately \$21.1 billion in 2023 (Geyser, 2023). SM influencers produce diverse forms of content, such as product reviews, tutorials, and fashion or lifestyle-related materials, which they share through posts, videos, and livestreams on platforms such as Instagram or TikTok.

While some well-known celebrities who utilize social media sites (SMS) also act as SM influencers, it is important to note that not all SM influencers are celebrities. SM influencers typically engage with their followers, listen to their requests, and create valuable content to retain and attract more followers. Research conducted by Morning Consult (2019) revealed that 72% of Gen Z and Millennial SM users follow more than one influencer. Furthermore, a

study on YouTube influencers by O'Neil-Hart and Blumenstein (2016) demonstrated that 70% of teenage YouTube subscribers identified more with YouTube creators than traditional celebrities, and 4 out of 10 millennial subscribers claimed that their favourite creators understood them better than their friends.

Adobe Communications (2022) conducted a survey of 1,000 Gen Z individuals in the UK, indicating that approximately 67% of participants reported being positively influenced and inspired by public figures such as Harry Styles, Zendaya, and David Bowie. Casaló et al. (2020) proposed that influencers are a new type of opinion leaders who share similar values and ideas with their followers, thereby fostering close relationships. Dhanesh and Duthler (2019) suggested that SM influencers establish and maintain relationships with their followers through personal branding, exerting influence over their attitudes and behaviours. Additionally, Masuda et al. (2022) examined the role of parasocial relationships in influencer marketing, comparing these relationships with other factors such as trustworthiness and perceived expertise. Their findings suggest that parasocial relationships, driven by personal attributes like attitude homophily and physical and social attractiveness, have a greater impact on purchase intentions than other factors.

Therefore, the para-social relationship between SM users and influencers can significantly impact SM usage. In this study, we define perceived influencer disengagement as the extent to which a user perceives a decline in the level of activity and engagement of influencers on SMS. Loss of interest measures the extent to which a user's motivation and engagement with an information system decreases over time. We propose that when social influencers reduce the frequency of content updates on a specific SM platform, become inactive, or transition to different SMS, it diminishes the available content for their followers to consume. Consequently, this decrease in content availability contributes to a reduction in the level of engagement between individuals and a specific SM platform. Based on these premises, we propose the following hypothesis:

**H1:** *Perceived influencer disengagement positively influences loss of interest in social media use.*

### **3.2 Loss of Interest**

The technology acceptance model (Davis, 1989) emphasizes the significance of perceived usefulness and perceived ease of use in shaping users' acceptance and adoption of technology. However, as time progresses, various factors can contribute to a decline in perceived usefulness or ease of use, leading to a loss of interest and eventual disengagement. O'Brien and Toms (2008) discussed various factors contributing to disengagement while using diverse applications, including video games, educational tools, online shopping platforms, and web search engines. Disengagement stemmed from a combination of internal factors such as loss of interest or time pressures, and external factors including distractions, lack of novelty, and usability issues with the technology.

Intention to discontinue refers to an individual's conscious decision to terminate or cease engagement with an IS (Vaghefi et al., 2020). Previously published studies on IS usage have demonstrated that loss of interest is one of the primary reasons users discontinue their use of an IT system. For instance, Krebs and Duncan (2015) conducted research on the usage of mobile health apps among U.S. users and found that loss of interest is the second most common reason for discontinuation. Fukuoka et al. (2011) also identified loss of interest over time as one of the potential barriers for users to continue using a mobile virtual community, a

social support tool aimed at improving healthy behaviour among overweight and sedentary adults. They found that participants who lost interest no longer valued the messages they received and might delete them without reading. Bardus et al. (2021) explored the use of mobile and wearable technology among university student-athletes and similarly discovered loss of interest as the top reason for users to abandon wearable fitness devices. Ming and Chan (2022) showed that users who use Facebook, Instagram, and Twitter less frequently, consider them “boring” apps, and instead, they spend more time on newer SM apps such as TikTok, Douyin, or BeReal.

In this study, “Less frequent use (Activities)” and “Less frequent use (Time)” are defined as distinct constructs. “Less frequent use (Activities)” refers to the reduction in the number of activities a user engages in on a social media site, such as posting new content or reacting to others’ news feed, while “Less frequent use (Time)” refers to the decrease in the time spent on a SMS. The distinction between these constructs is essential given the prevalence of passive users or the silent majority in social media platforms (Mai et al., 2018). Further discussion on this will be presented in a subsequent section. We anticipate that when a user starts losing interest in a SMS, it can lead to various scenarios: they may decrease their SM activities (Less frequent use (Activities)), such as posting new content or reacting to others’ news feed less often; they may spend less time on that SM site (Less frequent use (Time)); or they may ultimately discontinue using the SMS altogether. Thus, we propose the following hypotheses:

**H2a:** *Loss of interest positively influences less frequent use (activities).*

**H2b:** *Loss of interest positively influences less frequent use (time).*

**H2c:** *Loss of interest positively influences intention to discontinue.*

The relationship between perceived influencer disengagement, loss of interest, and the resulting decrease in activity and time spent on the platform aligns with the S-O-R framework (Mehrabian & Russell, 1974). According to the framework, perceived influencer disengagement functions as a critical stimulus. When users observe that the influencers they follow are less active or engaged, this external factor serves as a trigger that initiates a series of internal cognitive and emotional responses. In the organism phase of the S-O-R framework, this stimulus leads to a cognitive and emotional shift within users. Specifically, the perceived decline in influencer engagement leads to a loss of interest in the platform. Users may begin to feel less connected and less satisfied with the content on the platform, as the presence and activity of influencers often play a significant role in shaping user engagement and overall experience. As users’ interest declines, there is a decrease in both the frequency of activities and the time spent on the platform in the response phase. Users may reduce their participation in various activities, such as posting content, liking or commenting on posts, or interacting with other users. Additionally, they may spend less overall time on the platform, as the diminished interest reduces their motivation to engage with the social media environment. In some cases, users may decide to discontinue their use altogether.

### 3.3 Negative News Exposure

Lewicki et al. (1998) introduced the definition of trust as the degree of confidence and positive expectations toward a product, while distrust was defined as the degree of confidence and negative expectations. Previously published studies (e.g., Tang et al., 2014; Mcknight & Chervany, 2001; Lewicki et al., 1998; Rotter, 1980) have emphasized the importance of considering trust and distrust as distinct constructs in psychology and other disciplines.

McKnight & Chervany (2001) highlighted different types of distrust, including distrusting intentions, distrust-related behaviours, distrusting beliefs, institution-based distrust, and disposition to distrust. In the context of this research, we focus on the construct of distrustful beliefs, which aligns with our proposed model. Distrusting beliefs refer to the degree of confidence and negative expectations an individual holds towards a SM site. In other words, this construct measures the extent to which users believe that a SM provider is not motivated to act in their best interest and that their personal information is at high risk or inadequately protected by the provider.

The agenda-setting theory (McCombs & Shaw, 1972) and framing theory (Entman, 1993) from mass communication literature suggest that the way news is presented (framing) and the importance given to certain topics (agenda-setting) can significantly influence public perception and trust towards a subject, including social media platforms (e.g., McCombs & Shaw, 1972; Entman, 1993). These theories support the idea that media plays a crucial role in shaping public opinion and understanding of various issues, including social media platforms. In other words, the media's role extends beyond merely presenting information; it actively constructs the reality perceived by the public. In the effects of negative news, particularly in relation to social media platforms, this link becomes crucial. Negative news exposure is defined as the extent to which an individual perceives that mainstream media news (such as TV news networks, newspapers, or radio) contains negative information specifically related to a SM platform. Previously published research, examining how negative news affect individual's trust (e.g., Kleinnijenhuis et al., 2006; Han et al., 2019), studied the role of the media in creating distrust towards political leaders. They found that negative news had significant effects on the level of distrust in these leaders. In recent years, the media has shed light on the darker side of SM, including privacy violations (Aten, 2019; Conger, 2020; Nuñez, 2019), cyberbullying (Anderson, 2018; Murez, 2021), and social media addiction (Morton, 2021). Han et al. (2019), conducted three experiments examining the effect of negative energy news on social trust, found that individuals demonstrate an attentional bias toward negative news. Specifically, reading negative news headlines leads to negative cognitive bias, resulting in reduced social trust. Based on these findings, we propose a hypothesis that negative news exposure about a SMS would likely lead to higher levels of distrust towards the SMS.

**H3a:** *Negative news exposure positively influences distrusting beliefs.*

### **3.4 Realization of Addiction**

SM addiction is a form of Internet addiction characterized by individuals' excessive use of SM, which interferes with their daily lives (Starcevic, 2013; Soh et al., 2022; Jabeen et al., 2023). In recent years, SM addiction has emerged as a common issue in the modern world and become a significant research topic. Individuals afflicted with SM addiction excessively concern themselves with SM, experience a strong desire to log on frequently, and spend an excessive amount of time using SMS (Schou Andreassen & Pallesen, 2014). According to a survey conducted in 2019, 40% of online users in the U.S. admitted to being addicted to SM (Statista, 2021b). Moreover, SM addiction can lead to physical health issues and increase the risk of other mental health problems such as anxiety, stress, and depression (e.g., Hawi & Samaha, 2017; Priyadarshini et al., 2020). In this study, realization of addiction is defined as the extent to which an individual becomes aware of their excessive use of SM and its impact on their daily life.

Negative news about SM such as cyberbullying, privacy issues, misinformation, and social comparison could draw users' attention to the negative consequences of their SM behaviour, prompting them to reflect on their own usage patterns and habits (Huang et al., 2023). When negative news about SM becomes prevalent in society and SM addiction is acknowledged and discussed as a problem, individuals are more likely to introspect and recognize their own excessive use in line with this prevailing social norm. Negative news stories are often emotionally charged and receive considerable public attention, shaping people's attitudes and behaviours (Kim et al., 2013). As individuals consume these news stories, they might start questioning their SM habits and recognize potential signs of addiction. Thus, we posit that negative news about a SMS could raise user awareness of detrimental aspects associated with its use, and subsequently, aid the user in recognizing their SM addiction.

**H3b:** *Negative news exposure positively influences realization of addiction.*

Moqbel and Kock (2018) showed the consequences of SM addiction such as impaired performance, task distraction, and a significant reduction in positive emotions. When users become aware of their excessive use of SMS and their negative consequences on their lives, they may gain a deeper understanding of their own behaviour. This increased self-awareness allows them to recognize the adverse effects of SM addiction, which can lead to a desire to change their behaviour and discontinue its use. They may experience a conflict between their desire to continue using SMS and the recognition of its negative impact on their well-being. Individuals may be more inclined to consider discontinuing SMS use to reduce this cognitive dissonance. The realization of addiction may act as a wake-up call, prompting individuals to prioritize their mental and emotional well-being.

Several studies (e.g., Turel, 2015; Vaghefi et al, 2020) have examined the relationship between user intention to stop using SMS and SM addiction. Vaghefi et al. (2020) found a positive association between SM addiction and cognitive dissonance, which subsequently leads to feelings of guilt and eventual discontinuance of SMS use. In another study, Turel (2015) investigated Facebook users and found that user satisfaction can directly or indirectly reduce discontinuance intentions through habit formation. However, habitual usage can also lead to the development of addiction, which is positively associated with feelings of guilt during SMS use and a reduction in one's self-efficacy to discontinue to use. These factors ultimately lead to user intentions to discontinue SMS use. Based on these findings, we propose that the realization of addiction will positively influence intention to discontinue the use of SMS.

**H4:** *Realization of Addiction positively influences Intention to Discontinue.*

### **3.5 Distrusting Beliefs**

Thielsch et al. (2018) conducted a study on trust and distrust in IS within the workplace. The findings showed that distrust in an information system led to negative outcomes, including reduced job performance and the need to seek alternative ways to complete tasks. Cheng et al. (2020) and Amrollahi (2021) explored the influence of misinformation on Facebook on users' trust, distrust, and intensity of Facebook use. The results showed that distrust had a detrimental effect on the intensity of Facebook use, leading users to feel less emotionally connected and less actively engaged in activities on the platform. Individuals who hold a distrusting belief towards SMS are more likely to approach these platforms with caution, leading to reduced engagement in various activities. They may avoid participating in potentially risky or dubious activities, such as sharing personal information, clicking on

suspicious links, or engaging with unknown individuals. Individuals, who have strong distrusting belief towards SMS, are more likely to perceive these platforms as potentially unsafe, unreliable, or untrustworthy. As a result, they may be more cautious and skeptical about their SMS usage. This heightened vigilance may lead them to limit the time spent on SMS to avoid potential risks and negative outcomes associated with these platforms. The strong distrusting belief towards SMS can also lead to the formation of intentions to discontinue SMS use to protect privacy and avoid potential risks. Thus, we propose that when a user experiences distrust toward a SM platform, they are more likely to reduce their SM activities, spend less time on the platform, and potentially form an intention to discontinue SMS use.

**H5a:** *Distrusting beliefs positively lead to Less frequent use (activities).*

**H5b:** *Distrusting beliefs positively lead to Less frequent use (time).*

**H5c:** *Distrusting beliefs positively lead to Intention to discontinue.*

The three hypotheses (H5a, H5b, and H5c) can have a cumulative effect on users' behaviour. As individuals develop distrusting beliefs towards SMS, they may start engaging in fewer activities (H5a), spend less time on these platforms (H5b), and, later, form an intention to discontinue SMS use (H5c). These interconnected behaviours reflect their cautious approach in response to their distrusting beliefs.

The S-O-R framework (Mehrabian & Russell, 1974) provides a comprehensive understanding of how external stimuli, such as negative news exposure, influence users' internal states and subsequent behaviours on SMS. Negative news acts as a stimulus, shaping users' perceptions and attitudes. When exposed to negative information about an SMS, users may develop distrust towards the platform. This exposure can also lead to heightened awareness of SM addiction during the organism phase, where users recognize the negative impact of excessive use on their lives. In the response phase, these distrusting beliefs often result in decreased platform usage, reduced activity, and in some cases, the intention to discontinue using the SMS altogether.

### **3.6 Less Frequent Use**

In the era of exponential growth in technology, staying updated with the constant stream of news and information becomes challenging without the use of SMS. Completely quitting all SMS at once is a difficult task. Drawing from Endler's (1992) reinterpretation of the theory of natural selection, which can be applied to the realm of information technology, users gradually use less the current IS platform, explore other IS alternatives, and ultimately select the best option until a new invented IS which incorporates the advantage of the past technology mixed with new technology. We contend that, prior to discontinuing the use of any information system, users undergo a phase of "Less Frequent Use", characterized by reduced interaction before they cease using it entirely. Within the SM context, two distinct types of Less Frequent Use are proposed in terms of activity and time. Regarding activities, users continue to allocate time to watch the news and connect with friends but do fewer overall activities. For instance, they will not use "like" button, "share" function, "re-tweet", or do interactions as often as before. This group of users, constituting approximately 95% of the user base on SMS and contributing around 40% of total messages, has been identified as the "silent majority" by Mai et al. (2018).

While users may curtail their use of SM for interpersonal connections with family, friends, and strangers, it's crucial to recognize that SM offers a multifaceted suite of services. It serves as a tool to access news, facilitate the sale of goods, or monitor acquaintances' activities without showing any traces. Notably, a substantial 48% of American adults derive news content from SM (Walker & Matsa, 2021). Thus, when users reduce their activities on a SM platform such as refraining from leaving comments, clicking the thumbs-up button, or sharing/retweeting preferred news items, they might still engage with other services provided by the platform. However, when these auxiliary services no longer hold sway, a gradual decrease in overall time spent on SM becomes evident, or in other words "Less Frequent Use in terms of time", is also one step closer to the eventual intent to discontinue use. Thus, we propose the following hypotheses:

**H6:** *Less frequent use (activities) positively influences Less frequent use (time).*

**H7:** *Less frequent use (time) positively influences Intention to discontinue.*

All hypotheses and the LFU model are presented in Figure 3.

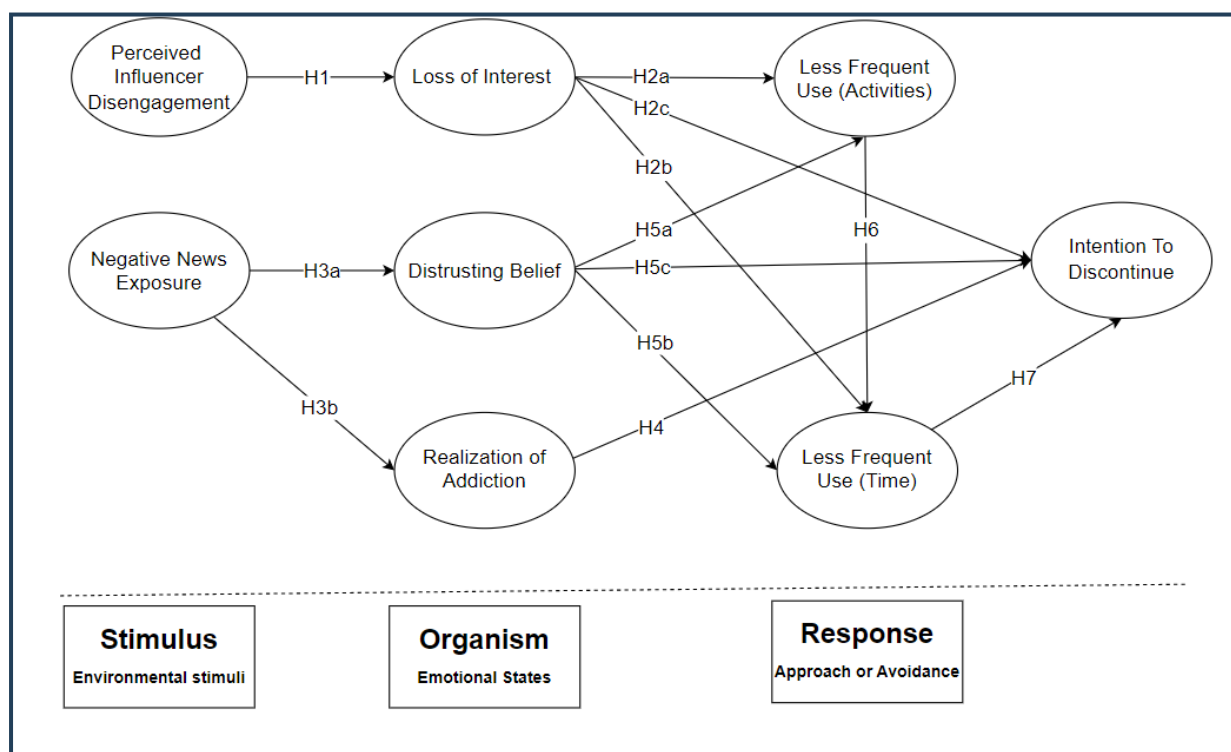


Figure 3. Social Media Less Frequent Use (LFU) Model

## 4 Research Methodology

### 4.1 Survey development

Except for the self-developed questionnaires to measure the constructs of Less Frequent Use, all other items were developed and conceptualized from existing literature to align with the context of SM usage. These items were structured using a seven-point Likert scale, ranging from "Strongly Disagree" to "Strongly Agree". The complete list of survey questionnaires is presented in Table A1 in the appendix. The survey items of the construct Realization of Addiction were conceptualized based on Paswan et al.'s (2015) study. The scale items for measuring Negative News Exposure were developed and inspired by Smith and Foxcroft

(2009) and Paswan et al. (2015). The constructs Distrusting Beliefs and Intention to Discontinue were conceptualized from McKnight and Chervany (2001) and Vaghefi et al. (2020), respectively. These measurement items were drawn from validated instruments in prior research to maintain robustness and contextual relevance. The authors developed the remaining constructs, including Perceived Influencer Disengagement, Loss of Interest, and Less Frequent Use (Time or Activities). After reviewing prior measures, the authors clarified wording and trimmed redundant items to minimize respondent fatigue.

The constructs selected for this study were based on a rigorous review of prior IS and communication literature and aligned with the unique behavioural dynamics of social media usage. Constructs such as perceived influencer disengagement and negative news exposure were developed to reflect emerging social and environmental stimuli relevant to today's social media landscape. Similarly, loss of interest, distrusting beliefs, and realization of addiction reflect internal user states highlighted in both technology discontinuance and media addiction literature. These constructs help fill notable gaps in IS research, especially regarding less frequent use and discontinuance, which have been underexplored compared to adoption and continuance behaviours. Their inclusion enables the development of a novel, context-specific framework that advances understanding of later IS lifecycle stages, particularly in consumer-driven environments.

Where applicable, we adapted existing validated scales to better align with the context of social media usage. For example, items for were conceptualized from Paswan et al. (2015). Adaptations involved modifying terminology (e.g., substituting "alcohol use" with "social media use") and integrating relevant media channels (e.g., TikTok, Instagram). All adapted items underwent expert review for clarity and contextual appropriateness, ensuring construct validity while enhancing relevance to modern digital behaviour.

## **4.2 Data Collection**

The data were collected at several large public universities in the United States of America by using a Qualtrics online survey. Participants were recruited via official email announcements and learning management system postings in multiple undergraduate and graduate courses at two large U.S. public universities. To ensure data quality, the survey included attention-check questions, and only responses that passed these checks and completed all major sections were retained. Students voluntarily participated and were offered extra course credit as an incentive, following Institutional Review Board (IRB) approval. The participants responded to questions about their use of SMS such as the number of SM used, frequency of SM use, and intention to discontinue using a specific SM platform. The student sample is appropriate for this research because most SM users are adults under 30 (Pew Research, 2021). The survey instruments were carefully reviewed and adjusted based on feedback from academic professors in the field. After being verified by the institutional review board (IRB), the survey was distributed to college students from two public universities in the Midwestern and East Coast of the United States. The students will receive extra credits after completing the survey. Invitations were sent to 1056 students, both undergraduate and graduate. Among 840 received surveys (response rate of 79.54%), 245 incomplete or invalid responses were eliminated, resulting in 595 valid responses used for the analysis. Demographic Table 3 shows that the sample population comprises 53.3% males and 46.6% females. The majority of the sample population (38.3%) falls within the age bracket of 18 to 21 years, while the lowest proportion (5.9%) falls within the age bracket of 40 years and above. The number of SMS used shows that



the majority of the sample population (53.8%) has used between 7 and 9 SMS. The highest proportion of the sample population (37.1%) uses SM for 1-3 hours a day, while the second highest proportion (34.1%) uses SM for 3-5 hours a day. According to Figure 4, users often use SM for activities such as watching random videos, messaging a friend, sharing documents, photos, or videos, but rarely use it to search for new friends or play games.

We addressed non-response bias by comparing early (90%) and late (10%) responses, finding no significant differences via an independent t-test (Karahanna et al., 1999). While the sample includes a relatively balanced gender distribution (53.3% male, 46.6% female), it is important to acknowledge the slight overrepresentation of male participants. Prior research suggests gender differences in social media usage patterns and trust-related perceptions (Nguyen et al., 2019). To address this, we conducted post hoc analysis across gender subgroups (see Table 7), which revealed nuanced differences in path significance, particularly in how distrusting beliefs influence usage behaviour. These findings reinforce the need for continued gender-sensitive investigation but also demonstrate the robustness of our model across subsamples.

Variable	Sample	Percentage
<b>Gender</b>		
Male	317	53.3%
Female	277	46.6%
<b>Age (years)</b>		
18-21	228	38.3%
22-25	196	32.9%
26-30	64	10.8%
31-40	72	12.1%
40 and above	35	5.9%
<b>Number of SMs have ever used</b>		
1-3	33	5.5%
4-6	142	23.9%
7-9	320	53.8%
10-12	97	16.3%
>12	3	0.5%
<b>Frequency of SM used</b>		
More than 5 hours a day	81	13.6%
3-5 Hours a day	203	34.1%
1-3 hours a day	221	37.1%
less than 1 hour a day	62	10.4%
A few minutes a day	13	2.2%
Two or three times a week	7	1.2%
Once a week	4	0.7%
Once a month	4	0.7%

*Table 3. Demographic Profile*

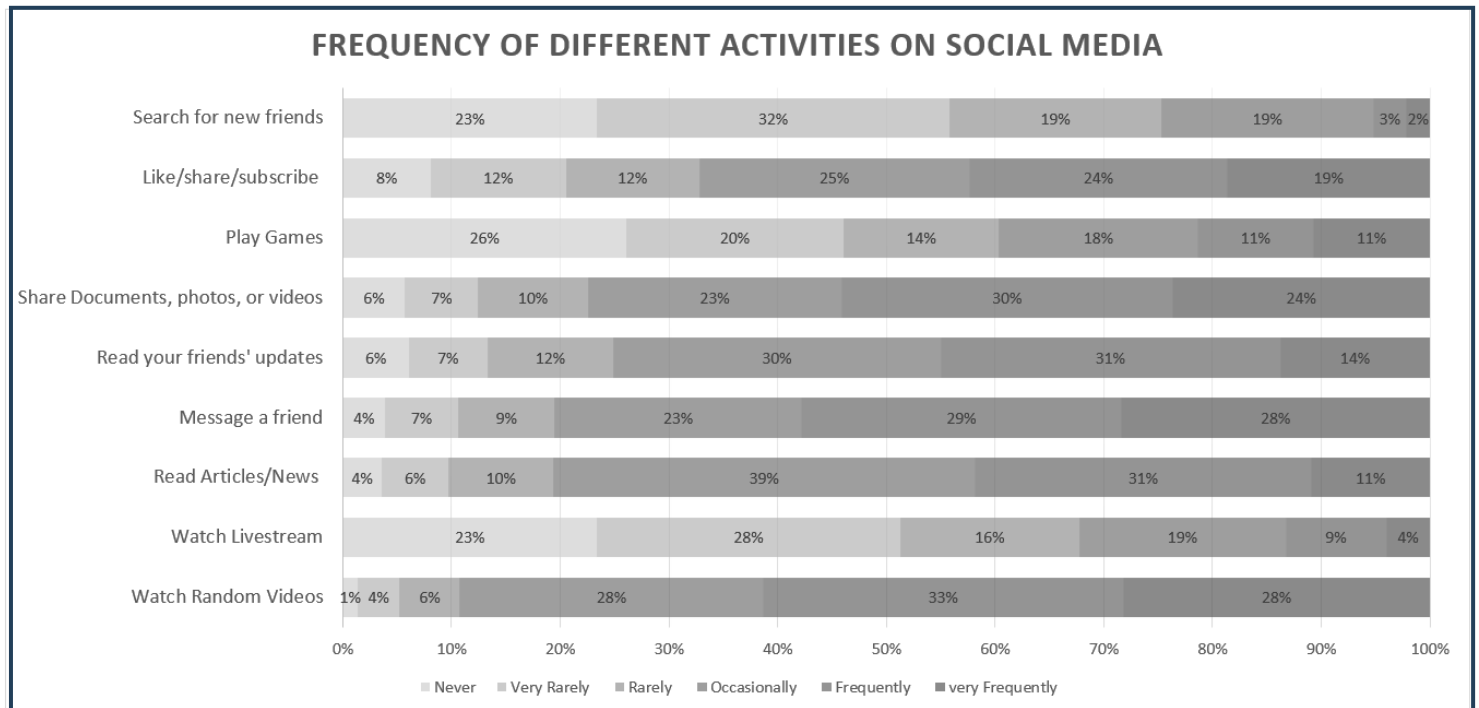


Figure 4. Frequency of Different Activities in Social Media

### 4.3 Model Assessment: Reliability and Validity Tests

				Construct							
Construct	CA	CR	AVE	DB	ID	LFU(A)	LFU(T)	LI	NNE	PID	RA
DB	0.93	0.95	0.82	0.908							
ID	0.93	0.95	0.87	0.43	0.934						
LFU(A)	0.73	0.88	0.79	0.274	0.245	0.887					
LFU(T)	0.87	0.92	0.73	0.225	0.374	0.404	0.854				
LI	0.79	0.88	0.7	0.383	0.653	0.395	0.512	0.838			
NNE	0.96	0.97	0.93	0.439	0.234	0.181	0.081	0.178	0.962		
PID	0.92	0.94	0.8	0.161	0.123	0.233	0.168	0.315	0.293	0.896	
RA	0.8	0.86	0.61	0.095	0.175	0.073	0.143	0.065	0.131	0.053	0.782

CA: Cronbach's Alpha, AVE: Average Variance Extracted, CR: Composite Reliability, Bold numbers on the diagonal are the square root of the AVE, and off-diagonal elements are correlations among constructs. DB: Distrusting Beliefs; ID: Intention to Discontinue; LFU(A): Less frequent use; LFU(T): Less frequent use (Time); LI: Loss of Interest; NNE: Negative News Exposure; PID: Perceived Influencer Disengagement; RA: Realization of Addiction.

Table 4. Construct Correlations, Consistency, and Reliability

Several metrics are used to assess the measurement scales of the eight constructs in the proposed model. To determine convergent and discriminant validity, the outer loadings of the indicators and the average variance extracted (AVE) were examined. Based on the analysis of loadings and cross-loadings, one item was removed from the Less frequent use (Activities) construct because its loading was less than 0.7. The 2-item construct Less frequent use (Activities) is still considered reliable because these items exhibit a strong correlation with each

other ( $r > .70$ ) and demonstrate a relatively weak correlation with other variables (Yong & Pearce, 2013; Worthington & Whittaker, 2006). Although the 3-item construct is recommended, for the construct Less frequent use (Activities) which is new, narrowly defined, and developed by the authors, several studies (Bergkvist & Rossiter, 2007; Drolet & Morrison 2001; Wanous, Reichers, & Hudy, 1997) suggested that more than one item measure considered adequate. After removing the low-loading LFU indicator, the remaining two items retained acceptable internal consistency (Cronbach's  $\alpha = .73$ ) and strong composite reliability (CR = .88). Discriminant validity was supported by the Fornell-Larcker criterion.

Constructs	DB	ID	LFI(A)	LFU(T)	LI	NNE	PID	RA
DB1	0.872							
DB2	0.949							
DB3	0.851							
DB4	0.831							
ID1		0.943						
ID2		0.910						
ID3		0.830						
LFU(A)1			0.725					
LFU(A)2			0.783					
LFU(T)1				0.854				
LFU(T)2				0.929				
LFU(T)3				0.817				
LFU(T)4				0.688				
LI1					0.827			
LI2					0.716			
LI3					0.862			
NNE1						0.937		
NNE2						0.940		
NNE3						0.949		
PID1							0.911	
PID2							0.936	
PID3							0.887	
PID4							0.699	
RA1								0.712
RA2								0.744
RA3								0.727
RA4								0.804

DB: Distrusting Beliefs; ID: Intention to Discontinue; LFU(A): Less frequent use; LFU(T): Less frequent use (Time); LI: Loss of Interest; NNE: Negative News Exposure; PID: Perceived Influencer Disengagement; RA: Realization of Addiction. The cross-loading values lower than 0.4 are left blank.

Table 5. Outer Loading Matrix

Thus, the reduced LFU item set continues to adequately represent less frequent social media activity engagement. Dropping the item had a minimal impact on measurement quality and no material impact on our conclusions, with all reliability and validity indices remaining

within acceptable thresholds and the signs, magnitudes, and significance of structural paths essentially unchanged. Additionally, the square roots of the AVEs are greater than the inter-construct correlations, indicating adequate discriminant validity (Fornell & Larker, 1981). The reliability of constructs was evaluated through the use of Composite Reliability (CR) and Cronbach's alpha (CA). The values of CRs and CAs for all constructs exceeded the recommended threshold of 0.7 (Hair et al., 2021). These results confirm the satisfactory reliability of the measurement scales. The results are shown in Tables 4 and 5.

## 5 Results

### 5.1 Structural Equation Model

In this study, the Covariance-Based Structural Equation Modelling (CB-SEM) was used to examine the proposed integrated model. Structural Equation Modelling (SEM) is a multifaceted approach utilized across various scientific disciplines (Byrne, 2016; Schumacker & Lomax, 2010). CB-SEM represents a specific statistical technique for estimating and testing structural equation models (Hair et al., 2018; Kline, 2023). This method employs a statistical framework to assess the correlations between dependent and independent variables and the latent structures underlying them. The analysis was conducted using SmartPLS 4.0.

The fit indices, with their respective threshold values in parentheses, are as follows: Chi-square = 723, degrees of freedom = 338, GFI = 0.88 ( $\geq 0.90$ ), AGFI = 0.89 ( $\geq 0.90$ ), RMSEA = 0.055 ( $\leq 0.06$ ), NFI = 0.904 ( $\geq 0.9$ ), TLI = 0.94 ( $\geq 0.95$ ), and CFI = 0.95 ( $\geq 0.95$ ) (Lohmoller, 1989; Hu & Bentler, 1999; Gefen et al., 2011; Gegen et al., 2000). Absolute fit indices were slightly below the  $\geq 0.90$  guideline (GFI 0.88; AGFI 0.89) and the incremental fit index TLI (Tucker-Lewis Index) is "marginally below" the  $\geq 0.95$  benchmark, a common outcome in parameter-rich models and not evidence of poor fit (Hu & Bentler, 1999; Marsh et al., 2004). Root Mean Square Error of Approximation (RMSEA) = 0.055 meets the close-fit guideline of  $\leq 0.06$ . Other incremental fit indices indicated acceptable to good comparative fit: NFI = 0.904 exceeds the  $\geq 0.90$  threshold and CFI = 0.95 meets the  $\geq 0.95$  criterion. These values indicate an acceptable model fit, as most are equal or very close to their cutoff values. In terms of the coefficients of determination ( $R^2$  results), the model explains 48.1%, 25.2%, and 11.6% of the variance in intention to discontinue, less frequent use (Time), and less frequent use (Activities), respectively. All hypotheses, with the exception of H5b, are supported at the 0.001 level or at the 0.01 level (for hypothesis 7). The findings are depicted in Table 6.

The  $f^2$  effect sizes in our structural model range from 0.002 to 0.243, spanning negligible to medium magnitudes using the conventional 0.02, 0.15, 0.35 benchmarks for small, medium, and large, respectively (Cohen, 1988). The  $f^2$  pattern shows that Intention to Discontinue is primarily shaped by Loss of Interest ( $f^2 = 0.243$ , medium) and Distrusting Belief ( $f^2 = 0.070$ , small). Less Frequently Use (Time) is influenced by Loss of Interest ( $f^2 = 0.132$ , approaching medium) and by Less Frequently Use (Activities) ( $f^2 = 0.051$ , small), indicating that reductions in activities translate into reduced time. Less Frequently Use (Activities) is shaped by both Loss of Interest ( $f^2 = 0.063$ , small) and Distrusting Belief ( $f^2 = 0.021$ , small). Although the direct link Less Frequently Use (Time)  $\rightarrow$  Intention to Discontinue is small and not statistically significant in this sample ( $p = 0.211$ ,  $f^2 = 0.022$ ), Less Frequently Use (Activities) and Less Frequently Use (Time) remain important behavioural outcomes that reflect how attitudinal shifts manifest at the usage level.

Path	Path Coefficient	P values	Effect size (f2)
Distrusting Belief -> Intention to Discontinue	0.248	0.000	0.070
Distrusting Belief -> Less Frequently Use (Activities)	0.142	0.000	0.021
Distrusting Belief -> Less Frequently Use (Time)	0.01	0.659	0.002
Less Frequently Use (Activities) -> Less Frequently Use (Time)	0.172	0.000	0.051
Less Frequently Use (Time) -> Intention to Discontinue	0.098	0.211	0.022
Loss of Interest -> Intention to Discontinue	0.696	0.000	0.243
Loss of Interest -> Less Frequently Use (Activities)	0.256	0.000	0.063
Loss of Interest -> Less Frequently Use (Time)	0.232	0.000	0.132
Negative News Recall -> Distrusting Belief	0.427	0.000	0.209
Negative News Recall -> Realization of Addiction	0.097	0.006	0.012
Realization of Addiction -> Intention to Discontinue	0.261	0.000	0.048
Social Influencer Disengagement -> Loss of Interest	0.182	0.000	0.077
**: $p < 0.001$ ; * $p < 0.01$			
Note: Chi-square = 723, degrees of freedom = 338, GFI = 0.88, AGFI = 0.89, PGFI = 0.73, RMSEA = 0.055, NFI = 0.904, TLI = 0.94, and CFI = 0.95			

Table 6. *Structural Equation Model Results*

To evaluate and strengthen the model's robustness and statistical rigor, we used two procedures to detect common method bias (Gefen et al., 2011). First, Harman's single-factor test loaded all indicators onto one factor, and the leading factor explained 38 percent of the variance, which is below the 50 percent benchmark and therefore indicates no common method bias (Harman, 1976). Second, a full collinearity assessment produced Variance Inflation Factors (VIF) for every latent construct; all VIFs for both independent and dependent constructs were below the conservative 3.3 cutoff, again indicating no common method bias (Kock, 2015; Kock & Lynn, 2012). Beyond these diagnostics, we tested robustness through alternative specifications. We reran the model using Partial Least Square Structural Equation (PLS-SEM) and PLSc, which were used and supported in similar research areas (e.g., Prybutok et al., 2020, Aldossari et al., 2023) and obtained identical signs and significance levels for the hypothesized paths. Results were stable across these alternatives, so our conclusions do not depend on a particular modelling choice.

## 5.2 Post hoc Analysis

The post hoc analysis examined the effect of gender, level of frequent use, and number of SM used in the proposed model. All hypotheses except hypotheses 3b, 5a, and 7 are supported for male subsample. For the female subsample, all hypotheses are supported except for hypothesis 5b. For users who use SMS less than 1 hour a day, the hypotheses 3b, 4, 5a, 5b, 5c, and 7 are not significant, while for those who use more than 6 hours a day, the hypotheses 2a, 3b, 4, 5a, 5b, and 5c are not significant. For users subsample who have ever used less than 5 distinct SMS, all hypotheses are supported except for hypotheses 4, 5a, 5b, 5c, and 7, while for users who used more than 10 SMS, hypotheses 3b, 5b, 5c, and 7 are not supported. All post hoc analysis results are shown in Table 7.

Group	Female		Male		<1 hour		>5 hours		< 5 SM used		> 10 SM used	
	PC	p	PC	p	PC	P	PC	P	PC	P	PC	P
DB -> ID	0.21	0.00	0.21	0.00	0.06	<b>0.51</b>	0.13	<b>0.16</b>	0.10	<b>0.22</b>	0.06	<b>0.47</b>
DB -> LFU(A)	0.23	0.00	0.07	<b>0.29</b>	0.01	<b>0.96</b>	0.08	<b>0.67</b>	0.11	<b>0.38</b>	0.20	0.04
DB -> LFU(T)	0.02	<b>0.71</b>	0.10	0.04	0.04	<b>0.59</b>	0.08	<b>0.35</b>	0.11	<b>0.17</b>	0.10	<b>0.08</b>
LFU(A) -> LFU(T)	0.22	0.00	0.21	0.00	0.23	0.01	0.25	0.03	0.33	0.00	0.28	0.01
LFU(T) -> ID	0.18	0.00	0.06	<b>0.30</b>	0.18	<b>0.31</b>	0.21	0.04	0.07	<b>0.37</b>	0.17	<b>0.10</b>
LI -> ID	0.42	0.00	0.48	0.00	0.50	0.00	0.51	0.00	0.55	0.00	0.49	0.00
LI -> LFU(A)	0.26	0.00	0.23	0.00	0.31	0.01	0.15	<b>0.32</b>	0.25	0.04	0.26	0.03
LI -> LFU(T)	0.33	0.00	0.38	0.00	0.41	0.00	0.35	0.01	0.30	0.00	0.50	0.00
NNE -> DB	0.43	0.00	0.40	0.00	0.49	0.00	0.23	0.05	0.46	0.00	0.30	0.00
NNE -> RA	0.19	0.00	0.11	<b>0.08</b>	0.10	<b>0.40</b>	0.31	<b>0.08</b>	0.28	0.05	0.15	<b>0.24</b>
PID -> LI	0.23	0.00	0.29	0.00	0.34	0.00	0.27	0.02	0.42	0.00	0.27	0.02
RA -> ID	0.17	0.00	0.20	0.00	0.15	<b>0.08</b>	0.17	<b>0.13</b>	0.16	<b>0.15</b>	0.31	0.00

DB: Distrusting Beliefs; ID: Intention to Discontinue; LFU: Less Frequent Use; A: Activities; T: Time; LI: Loss of Interest; NNE: Negative News Exposure; RA: Realization of Addiction; PID: Perceived Influencer Disengagement; SM: social media; p: p value; PC: Path coefficient

Table 7. Post hoc Analysis Results

## 6 Discussion

### 6.1 Theoretical contributions

This study contributes to technology use and discontinuance literature in several ways. The ITLC framework offers a comprehensive view of the technology life cycle stages—adoption, usage, termination, and post-termination—particularly relevant in Industry 4.0, where technology is integral to products. Unlike prior approaches that often emphasize adoption or discontinuance in isolation, the ITLC framework combines theories like Product, Industry, and Technology Life Cycles, identifying key activities at each stage. The framework also highlights underexplored phenomena such as user resistance, technology appropriation, intermittent discontinuance, and less frequent use patterns, offering valuable insights for researchers and practitioners in fields like information systems, management, and marketing.

Prior studies in the existing literature have posited several influential factors contributing to the discontinuation of IS. At an organizational level, these factors include perceived work impediment, perceived costs of system compliance (Recker, 2016), system performance, system suitability, and system supportability (Furneaux & Wade, 2010), while at an individual level, the driving factors are technology related stress creators, technology exhaustion (Maier et al., 2015), self-efficacy to discontinue, guilt feelings, technology satisfaction, and technology related habit (Turel, 2015). In line with this body of research, the present study introduces four novel drivers of IS discontinuance, including loss of interest, distrusting belief, realization of addiction, and less frequent use and explains the interconnections between various constructs within the LFU model.

In relation to RQ1, which investigates the determinants of less frequent use, the findings underscore that loss of interest, realization of addiction, and influencer disengagement are significant contributors. These results suggest that LFU is not merely a passive outcome, but a conscious response shaped by both internal realizations and external social cues. The LFU

model introduces the construct of “perceived influencer disengagement” within the context of SM. The results support that perceived influencer disengagement positively influences the loss of interest in SM use. It is more likely that when social influencers decrease their level of activity and engagement, or switch to different SMS, it may reduce the content available for their followers to consume. Consequently, this decrease in content availability results in a diminished level of engagement between individuals and a specific SM platform, ultimately leading to a decline in user interest. This study is the first to enhance our understanding of the dynamics between perceived influencer disengagement and user interest in SM use. This finding highlights the potential negative consequences of influencer disengagement and expands upon the existing understanding of social influencers' roles, which have traditionally focused on positive impacts (e.g., Hudders et al., 2021; Dinh & Lee, 2022). By uncovering the impact of influencer disengagement on user interest, the study provides insights into the factors that drive user engagement and sustain their motivation to use SMS. This understanding can inform theoretical models of user engagement and motivation, examining the specific role that influencers play in these processes.

The results provide empirical evidence that supports the hypotheses suggesting that loss of interest in SM leads to less frequent use in terms of both activities and time, as well as the intention to discontinue its use. This finding directly addresses RQ1 by identifying how declining interest serves as a precursor to less frequent use. It also connects to RQ2, which investigates what factors impact user intention to discontinue, by demonstrating that LFU is not an endpoint but a transitional stage leading toward discontinuance. Previous studies by Van der Heijden (2004), Dickinger et al. (2008), and Nguyen et al. (2018), predominantly emphasized the positive impact of perceived enjoyment on IS use or attitudes toward IS use. In contrast, this study explores the inverse relationship among loss of interest, less frequent use, and intention to discontinue. This discovery enriches our comprehension of the intricate interplay between users' interest levels, behaviours, and decision-making regarding continued platform usage or discontinuation. It underscores the pivotal role of interest as a precursor to users' intentions and the need for interventions aimed at averting disengagement and retaining users.

Addressing RQ2 more directly, the study enhances our understanding of the relationship between negative news exposure and distrusting belief within the context of SM. This novel insight expands upon the conventional concept of trust in IS research, which traditionally emphasizes factors such as system quality, information quality, and perceived usefulness as primary determinants of trust, as previously explored in McKnight et al.'s (2017) study. By introducing negative news exposure as a substantial antecedent of user distrust, this study sheds light on the mechanisms through which media narratives can exert influence over user trust.

Furthermore, the study examines the adverse effects of distrust on the intensity of SM usage. When users harbor distrust towards a SM platform, they exhibit reduced engagement in platform activities. The findings also support the hypothesis that users with a sense of distrust towards a SM platform are more likely to form intentions to discontinue their usage. This contribution advances our understanding of the behavioural consequences of distrust within the context of SMS. Distrust emerges as a significant predictor of users' intentions to discontinue their usage, potentially leading to long-term disengagement and diminished platform loyalty.

The influence of negative news exposure and perceived influencer disengagement illustrates the S-O-R sequence, whereby external stimuli (news framing and influencer behaviour) trigger internal organismic states such as loss of interest, distrust, and addiction awareness. These altered cognitive and emotional states subsequently shape user responses in the form of less frequent use and intentions to discontinue. In doing so, the findings empirically validate the S-O-R framework in the social media context, demonstrating how environmental cues can indirectly drive disengagement through their impact on users' internal evaluations and self-awareness. Our findings also extend the ITLC framework by highlighting less frequent use (LFU) as a gradual disengagement pathway, distinct from abrupt discontinuance. This distinction suggests that disengagement is not merely a binary outcome but can occur as a progressive reduction in use, thereby enhancing the ITLC framework with greater conceptual depth in the post-adoption stage.

## **6.2 Practical contribution**

This study introduces the construct of less frequent use within the ITLC framework, offering a strategic perspective for firms navigating the evolving digital product and services landscape. LFU provided valuable insights into user behaviour in response to changing technology usage patterns as it captures the transitional stage in which users do not terminate use entirely but reduce the frequency and intensity of their engagement. Recognizing this stage allows managers to intervene earlier in the disengagement process, providing actionable opportunities for sustaining user relationships before discontinuance occurs.

The findings yield several practical implications aligned with the model's core constructs. A key result related to RQ1 - which examines the factors influencing less frequent use - is that perceived influencer disengagement negatively impacts user interest in SM. This highlights the importance of fostering ongoing and meaningful interactions between influencers and users. When influencers reduce their activity, users are more likely to experience declines in interest, which can manifest as less frequent use and eventual disengagement. To address this dynamic, SMS should design mechanisms that encourage influencers to remain consistently active and produce high-quality, engaging content. For example, TikTok's top-earning influencers amassed a substantial \$55.5 million in 2021, representing a 200% increase compared to their earnings in 2020 (Brown & Freeman, 2022). Platforms could employ strategies such as establishing long-term partnerships with influencers, integrating performance tracking systems to monitor engagement levels, and implementing incentive structures tied to content regularity and audience responsiveness. Furthermore, platforms might strengthen the relational bond between influencers and users by deploying features such as personalized notifications when favoured influencers release new material. Such measures not only counteract perceived influencer disengagement but also create a more resilient content ecosystem.

This research extends our comprehension of the cognitive processes involved in addiction recognition and highlights the role of external cues, such as negative news exposure, in shaping individual self-awareness of addictive behaviours in the context of SM. Negative news can serve as an information source that sheds light on potential risks, harms, and negative aspects associated with SM use. Furthermore, the study supports the hypothesis that when individuals realize their addiction to SMS, they are more likely to develop intentions to discontinue their usage. This finding extends our understanding of the factors influencing individuals' decision-making processes regarding technology use and discontinuance. It



highlights the significance of self-reflection and awareness in shaping individuals' intentions to disengage from SMS. From a practical standpoint, several implications emerge. External cues such as media coverage can unintentionally function as digital well-being triggers; platforms and policymakers can leverage this by incorporating structured awareness interventions that help users recognize and recalibrate excessive use before it escalates to discontinuation. For example, SMS could provide personalized usage dashboards, or weekly screen-time summaries to promote self-awareness. SMS could design opt-in digital well-being tools - such as customizable limits, or "pause" modes – that enable users to monitor, manage, and reduce their technology use to promote a healthier relationship with digital devices. By normalizing conscious self-regulation, SMS can transform addiction realization into an opportunity for healthier long-term engagement rather than a pathway to discontinuance. Brands and health organizations could partner with platforms to deliver educational campaigns that frame responsible use as a form of digital literacy. These campaigns could highlight both the risks of overuse and strategies for balanced engagement, thereby empowering users to take proactive steps toward intentional usage.

Following a post hoc analysis conducted based on gender, the results indicate that there are significant differences in the relationship between distrusting beliefs and the two dependent variables, less frequent use (Time) and less frequent use (Activities), contingent upon user gender. Within the male subsample, a statistically significant relationship emerges between distrusting beliefs and less frequent use (Time), whereas the relationship between distrusting beliefs and less frequent use (Activities) does not exhibit statistical significance. This suggests that male users, who exhibit a heightened level of distrust in IS providers, are more likely to spend less time on SMS. This propensity may stem from concerns surrounding privacy, data security, or a general scepticism regarding the platform's management of user data. In contrast, among the female users, the results show that the relationship between distrusting beliefs and less frequent use (Activities) is statistically significant, while the association between distrusting beliefs and less frequent use (Time) is not significant. This suggests that female users, who show a higher level of distrust in IS providers, are more inclined to reduce their participation in various activities within the SMS. This could indicate that their lack of trust affects their motivation to participate in diverse platform activities actively. These findings signify the importance of considering gender differences when investigating the impact of distrusting beliefs on SMS usage, suggesting that males and females may have different behaviours related to trust and engagement with SMS. Factors such as privacy, data security, and perceived risks may exert differing degrees of influence on their usage behaviours. It is crucial to note that, according to the LFU model, less frequent use (Time) is directly associated with the intention to discontinue. This implies that concerns regarding distrusting beliefs have a more pronounced impact on males than females, reducing the time they spend on SM and potentially leading to their intention to discontinue its use. This result aligns with the finding from Nguyen et al. (2019) regarding gender-specific behaviours concerning trust and risk-related factors.

The post hoc analysis concerning the level of frequent use shows that the relationships between distrusting beliefs and the three constructs, including less frequent use (Activities), less frequent use (Time), and intention to discontinue are no longer statistically significant among users who use SM either less than 1 hour a day or more than 5 hours a day. For users spending less than 1 hour, it appears that their level of engagement may not be substantial enough to render distrusting beliefs a significant influence on their usage patterns. Conversely,

users spending more than 5 hours might have ingrained habits or dependencies that cause them to be less susceptible to the influence of such beliefs. It is plausible that distinct motivations come into play in these extreme usage groups, diminishing the influence of distrusting beliefs. Moreover, the paths from “Negative News Exposure to Realization of Addiction” and from “Realization of Addiction to Intention to Discontinue” are not significant for either of these groups. Users who spend minimal time (less than 1 hour) on SM might not encounter negative news or content frequently enough to impact their realization of addiction or intention to discontinue substantially.

Similarly, users who are heavily engaged (more than 5 hours) may be so deeply integrated into their daily routines that negative news exposure and addiction realization might not be as influential in their decision-making regarding discontinuation. It is conceivable that users devoting more than 5 hours a day to SM may be inundated with an excess of negative news and, as a result, have developed a certain indifference to such content. Other factors, such as social interaction, entertainment, or professional engagement may exert a more pronounced influence on the behaviour of these groups of users.

Based on the post hoc analysis of the number of SMS used, the results show that for users who have utilized fewer than five SMS, most determinants of intention to discontinue are no longer statistically significant, except for loss of interest. One possible explanation is that these individuals, having limited alternatives, exhibit less intention to discontinue the use of a specific SM platform. Their reduced array of choices may result in a decreased motivation to cease usage. Individuals who use fewer SMS may exhibit a more focused and deliberate usage pattern. The absence of statistical significance across most path coefficients may imply that these users are less influenced by external factors, such as privacy concerns or negative experiences when contemplating discontinuation. Instead, their decision to discontinue might be primarily motivated by a genuine decline in interest in the content or features offered by the platform.

Conversely, among those who have used more than 10 SMS, the relationship between negative news exposure and the realization of addiction is not significant. Users with an extensive presence across multiple SMS may have developed a heightened tolerance for negative news or content, diminishing the association between negative news exposure and the realization of addiction. These users might perceive SM as a diverse landscape, and thus, may not exclusively attribute their recognition of addiction to negative news exposure.

Upon conducting the post hoc analysis, the findings consistently underscore loss of interest as a robust determinant influencing less frequent use (Activities), less frequent use (Time), and intention to discontinue. This insight holds practical relevance for SMS seeking to enhance user retention strategies. To harness this insight effectively, SMS can prioritize the task of sustaining user engagement and fostering ongoing interest in their content. This can be achieved by continually providing novel and captivating content that aligns with users' individual interests. By adopting this approach, platforms can effectively mitigate the risk of user discontinuation arising from a loss of interest in the platform's offerings.

While the LFU model is intentionally comprehensive to reflect the complexity of user disengagement behaviours, we acknowledge that its application in practice may require simplification. For practitioners, it may be beneficial to focus on the most influential and actionable constructs, such as loss of interest, distrusting beliefs, and realization of addiction,

which emerged as consistently strong predictors across various subsamples. These core variables should be used for intervention and user engagement strategy. Future applied research could explore streamlined versions of the model tailored to specific organizational or platform contexts, enabling more accessible implementation without sacrificing theoretical grounding.

### **6.3 Limitations and Future Research**

While this study provides valuable insights into Less Frequent Use (LFU) and discontinuation of social media platforms, several limitations should be considered. The cross-sectional design limits the ability to establish causality, as user motivations and disengagement behaviours likely evolve dynamically over time. Future research could employ longitudinal panel designs or experience sampling methods to trace changes in LFU trajectories, capturing turning points such as addiction realization or influencer disengagement as they unfold. Experimental or quasi-experimental designs might also help isolate causal pathways, for instance, by manipulating exposure to negative news or influencer activity and observing its effects on perceived trust, addiction recognition, and disengagement.

Additionally, the sample, primarily university students, may not represent broader social media users, potentially limiting the generalizability of findings to other demographics. Social media use patterns, trust perceptions, and discontinuation drivers may differ across age cohorts, professions, or cultural contexts. Future research should therefore test the LFU model in more heterogeneous and representative samples, including cross-generational comparisons or cross-national surveys. Incorporating multi-group structural equation modelling could help uncover whether cultural orientations (e.g., collectivism vs. individualism) moderate the influence of influencer disengagement or news framing on user trust and disengagement behaviours.

Another limitation of this study is its primary focus on negative determinants of less frequent use and discontinuation, such as distrust, addiction, and loss of interest, without considering their interplay with positive drivers of sustained engagement. Self-determination theory (Deci & Ryan, 1985) offers one lens for understanding this dynamic, as it suggests that individuals are more likely to sustain behaviours that fulfill core psychological needs for autonomy, competence, and relatedness. Social media platforms often provide opportunities for self-expression, skill development, and social connection, which can offset disengagement pressures and reinforce ongoing participation. For example, content enjoyment or sense of community may weaken the link from privacy concerns or negativity exposure to LFU. Similarly, expectancy-value theory (Eccles & Wigfield, 2002) posits that choices are guided by individuals' expectations for success and the subjective value they place on tasks, encompassing attainment, intrinsic, and utility value, as well as perceived costs. This framework emphasizes the interplay between competence-related beliefs and task values, suggesting that users may remain engaged on social media when perceived benefits such as community, entertainment, or informational utility outweigh costs like time loss, privacy risks, or exposure to negative content. Strong positive ties can create inertia and switching costs that delay discontinuation, although accumulated negatives may reach a tipping point that triggers rapid LFU. These theoretical perspectives indicate that social media less frequent use is not simply a result of negative experiences but rather the outcome of a complex negotiation between motivational forces. Incorporating engagement constructs such as content enjoyment, sense of community, platform loyalty, or social capital into future LFU models would enrich

both their predictive power and conceptual completeness by more fully reflecting the tensions inherent in user decision-making. Future LFU models should include interaction terms between positives and negatives, nonlinear specifications to detect thresholds, and longitudinal designs to capture recovery or decay.

While the integration of diverse theoretical lenses, including the S-O-R framework, Technology Acceptance Model, Social Influence Theory, Parasocial Interaction Theory, and Framing Theory, enables a multifaceted understanding of user behaviour, we acknowledge potential challenges in harmonizing constructs from distinct domains. This theoretical pluralism, while enriching, may carry the risk of conceptual overlap or construct redundancy. However, we mitigated this risk by ensuring that each construct plays a unique role within the S-O-R structure and is operationalized with clear theoretical boundaries. We view this integrative approach as both a strength and a valuable point of departure for future refinement. Future research could use nested modelling approaches to test whether combining constructs across theories yields incremental predictive validity.

In the proposed ITLC framework, the activities of intermittent discontinuance and less frequent use are areas where research is notably lacking. Although conceptually relevant, these activities have not been investigated at the organizational level in literature. Consequently, it would be of significant value to both theoretical and practical contributions to identify and examine any instances of application, should they exist. Such findings could provide insightful contributions to understanding of technology life cycle dynamics and their implications for organizations. At the individual level, the activity "Comply," which falls within the broader Adoption and Usage stages, remains an area that has not been extensively explored in individual-level research. Investigating the role of "Comply" in the context of ITLC could offer valuable insights into user behaviour and adoption patterns. Furthermore, the applicability of the ITLC framework extends beyond the context of SM. It has the potential to inform research across various disciplines. For instance, it can be adapted for use in studies on artificial intelligence systems, such as Chat GPT or generative AI in general, and their life cycle dynamics.

Looking beyond the ITLC framework, the activity of "Intermittent Discontinuance" in the post-termination stage has garnered attention in various contexts at the individual level, such as SM (York & Turcotte, 2015), mobile short-form video (Feng et al., 2022), and smart health devices (Shen et al., 2018). A promising venue for future research involves extending the exploration of "Intermittent Discontinuance" to the organizational level to gain a more comprehensive understanding of its dynamics within different organizational settings.

The LFU model, which addresses "Less Frequent Use," can find application in various research contexts, such as E-commerce and mobile payments. Future research can delve into the implications of "Less Frequent Use" at the organizational level, offering insights into user behaviour and the strategies employed by organizations to accommodate such patterns.

In the context of SM, a noteworthy consideration is the absence of a monopoly market. As previously discussed, in a non-monopoly market, Information Systems providers may not consistently act to extend the product life cycle. Applying the LFU model in such a context could yield interesting findings. For example, the presence of prominent SM providers like Meta and Twitter being restricted in the Chinese market highlights the unique dynamics at play. In Q3 2022, approximately 81.6% of Chinese survey participants reported using WeChat

for social networking, as indicated in a study on digital usage (Statista, 2023). Therefore, future research should explore the application of the LFU model within the specific dynamics of SM in such distinct markets.

## 7 Conclusion

This study addresses a critical gap in Information Systems research by focusing on Less Frequent Use (LFU) and discontinuation of social media platforms, offering both theoretical and practical insights. Addressing RQ1 and RQ2, we explain what drives LFU and how these drivers translate into discontinuance intentions. The proposed LFU model identifies key determinants, such as perceived influencer disengagement, loss of interest, and distrust, that contribute to reduced usage and discontinuation. By incorporating the Integrated Technology Life Cycle (ITLC) framework, this research sheds light on underexplored IS lifecycle stages, particularly LFU and intermittent discontinuance. This study contributes to theory by extending the S-O-R framework to underexplored phases of IS usage, introducing novel constructs relevant to modern social media environments. The contribution is novel because it centres gradual disengagement rather than adoption or continuance and positions LFU as a distinct, theory-relevant stage within the IS lifecycle.

Practically, it provides actionable insights for social media platforms and managers seeking to proactively address user disengagement and sustain platform loyalty. While the findings are robust, limitations such as cross-sectional design, reliance on student samples, and self-reported data highlight areas for improvement in future studies. Overall, the study provides a foundation for future research to explore LFU across diverse contexts and platforms, with implications for enhancing user engagement and retention strategies. Future work should use longitudinal and experimental designs, draw on diverse non-student samples and behavioural usage data, test boundary conditions across platforms and cultures, and examine interventions that ethically reduce distrust and revive interest. These steps can build a cumulative literature of technology disengagement and underscore the broader significance of this work for IS theory and practice.

## References

- Adobe Communications (2022). The New-Era of Self Expression: How the next generation are tackling social media, creativity and authenticity. Adobe. Retrieved from <https://blog.adobe.com/en/publish/2022/07/05/new-era-of-self-expression-how-the-next-generation-are-tackling-social-media-creativity-and-authenticity>
- Ajzen, I. (1991). The theory of planned behaviour. *Organizational Behaviour and Human Decision Processes*, 50(2), 179-211. doi.org/10.1016/0749-5978(91)90020-T
- Amin, M., Rezaei, S., & Abolghasemi, M. (2014). User satisfaction with mobile websites: the impact of perceived usefulness (PU), perceived ease of use (PEOU) and trust. *Nankai Business Review International*, 5(3), 258-274. doi.org/10.1108/NBRI-01-2014-0005
- Amrollahi, A. (2021). A conceptual tool to eliminate filter bubbles in social networks. *Australasian Journal of Information Systems*, 25, 1-16. doi.org/10.3127/ajis.v25i0.2867
- Anderson, M. (2018, September 27). A Majority of Teens Have Experienced Some Form of Cyberbullying | Pew Research Center. Pew Research Center.

- <https://www.pewresearch.org/internet/2018/09/27/a-majority-of-teens-have-experienced-some-form-of-cyberbullying/>
- Aten, J. (2019, August 8). Instagram Allowed an Ad Partner to Track Millions of Users' Data, and It's a Major Privacy Problem | Inc.com. Inc. <https://www.inc.com/jason-aten/instagram-just-acknowledged-it-has-a-much-bigger-privacy-problem-than-we-thought.html>
- Audrezet, A., de Kerviler, G., & Moulard, J. G. (2020). Authenticity under threat: When social media influencers need to go beyond self-presentation. *Journal of Business Research*, 117, 557-569. doi.org/10.1016/j.jbusres.2018.07.008
- Bardus, M., Borgi, C., El-Harakeh, M., Gherbal, T., Kharroubi, S., & Fares, E. J. (2021). Exploring the Use of Mobile and Wearable Technology among University Student Athletes in Lebanon: A Cross-Sectional Study. *Sensors*, 21(13), 4472. doi.org/10.3390/s21134472
- Bastrygina, T., & Lim, W. M. (2023). Foundations of consumer engagement with social media influencers. *International Journal of Web Based Communities*, 19(2-3), 222-242. doi.org/10.1504/IJWBC.2023.131410
- Behl, A., & Pereira, V. (2021). What's behind a scratch card? Designing a mobile application using gamification to study customer loyalty: An experimental approach. *Australasian Journal of Information Systems*, 25. doi.org/10.3127/ajis.v25i0.3203
- Benlian, A. (2015). Web personalization cues and their differential effects on user assessments of website value. *Journal of Management Information Systems*, 32(1), 225-260. doi.org/10.1080/07421222.2015.1029394
- Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. *Psychological Bulletin*, 88 (3), 588-606. doi.org/10.1037/0033-2909.88.3.588
- Bergkvist, L., & Rossiter, J. R. (2007). The predictive validity of multiple-item versus single-item measures of the same constructs. *Journal of Marketing Research*, 44(2), 175-184. doi.org/10.1509/jmkr.44.2.175
- Bhattacharjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. *MIS Quarterly*, 351-370. doi.org/10.2307/3250921
- Bhattacharjee, A., & Lin, C. P. (2015). A unified model of IT continuance: three complementary perspectives and crossover effects. *European Journal of Information Systems*, 24(4), 364-373. doi.org/10.1057/ejis.2013.36
- Black S. (2022). The 46-year-old social media virgin: how people ditch Twitter, Facebook and Instagram and survive. Guardian News & Media Limited. Retrieved from <https://www.theguardian.com/media/2022/nov/12/the-46-year-old-social-media-virgin-how-people-ditch-twitter-facebook-and-instagram-and-survive>
- Brown, A. & Freeman, A. (2022). Top-Earning TikTok-ers 2022: Charli And Dixie D'Amelio And Addison Rae Expand Fame—And Paydays. Forbes. Retrieved from <https://www.forbes.com/sites/abrambrown/2022/01/07/top-earning-tiktokers-charli-dixie-damelio-addison-rae-bella-poarch-josh-richards/?sh=4353b30c3afa>

- Bulow, J. (1986). An economic theory of planned obsolescence. *The Quarterly Journal of Economics*, 101(4), 729-749. doi.org/10.2307/1884176
- Button, G., Mason, D., & Sharrock, W. (2003). Disempowerment and resistance in the print industry? Reactions to surveillance-capable technology. *New Technology, Work and Employment*, 18(1), 50-61. doi.org/10.1111/1468-005X.00110
- Byrne, B. M. (2016). Structural Equation Modeling with AMOS: Basic Concepts, Applications, and Programming (Multivariate Applications) (3 ed.). Routledge. doi.org/10.4324/9781315757421
- Casaló, L. V., Flavián, C., & Ibáñez-Sánchez, S. (2020). Influencers on Instagram: Antecedents and consequences of opinion leadership. *Journal of Business Research*, 117, 510-519. doi.org/10.1016/j.jbusres.2018.07.005
- Celie O'Neil-Hart, Howard Blumenstein, July 2016, Why YouTube stars are more influential than traditional celebrities <https://www.thinkwithgoogle.com/marketing-strategies/video/youtube-stars-influence>
- Cheng, Y., & Chen, Z. F. (2020). Encountering misinformation online: antecedents of trust and distrust and their impact on the intensity of Facebook use. *Online Information Review*. doi.org/10.1108/OIR-04-2020-0130
- Conger, K. (2020, August 3). F.T.C. Investigating Twitter for Potential Privacy Violations - The New York Times. The New York Times. <https://www.nytimes.com/2020/08/03/technology/ftc-twitter-privacy-violations.html>
- Crego, E. T., & Schiffrin, P. D. (1995). *Customer-centered reengineering: Remapping for total customer value*. Irwin Professional Publishing.
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 319-340. doi.org/10.2307/249008
- Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, 35(8), 982-1003. doi.org/10.1287/mnsc.35.8.982
- De Veirman, M., Cauberghe, V., & Hudders, L. (2017). Marketing through Instagram influencers: the impact of number of followers and product divergence on brand attitude. *International Journal of Advertising*, 36(5), 798-828. doi.org/10.1080/02650487.2017.1348035
- Deci, E. L., & Ryan, R. M. (1985). Intrinsic motivation and self-determination in human behaviour. New York, NY: Plenum.
- Dean, J. (1950). Pricing policies for new products. *Harvard Business Review*, 28, 45-50.
- Deutsch, M., & Gerard, H. B. (1955). A study of normative and informational social influences upon individual judgment. *The Journal of Abnormal and Social Psychology*, 51(3), 629. doi.org/10.1037/h0046408

- Dhanesh, G. S., & Duthler, G. (2019). Relationship management through social media influencers: Effects of followers' awareness of paid endorsement. *Public Relations Review*, 45(3), 101765. doi.org/10.1016/j.pubrev.2019.03.002
- Di Gangi, P. M., & Wasko, M. M. (2016). Social media engagement theory: Exploring the influence of user engagement on social media usage. *Journal of Organizational and End User Computing*, 28(2), 53-73. doi.org/10.4018/JOEUC.2016040104
- Dickinger, A., Arami, M., & Meyer, D. (2008). The role of perceived enjoyment and social norm in the adoption of technology with network externalities. *European Journal of Information Systems*, 17 (1), 4–11. doi.org/10.1057/palgrave.ejis.3000726
- Dinh, T. C. T., & Lee, Y. (2022). "I want to be as trendy as influencers" –how "fear of missing out" leads to buying intention for products endorsed by social media influencers. *Journal of Research in Interactive Marketing*, 16(3), 346-364. doi.org/10.1108/JRIM-04-2021-0127
- Drolet, A. L., & Morrison, D. G. (2001). Do we really need multiple-item measures in service research? *Journal of Service Research*, 3(3), 196-204. doi.org/10.1177/109467050133001
- Eccles, J. S., & Wigfield, A. (2002). Motivational beliefs, values, and goals. *Annual Review of Psychology*, 53, 109–132. https://doi.org/10.1146/annurev.psych.53.100901.135153
- Entman, R. M. (1993). Framing: Toward clarification of a fractured paradigm. *Journal of Communication*, 43(4), 51-58. doi.org/10.1111/j.1460-2466.1993.tb01304.x
- Feng, Y., Li, L., & Zhao, A. (2022). A cognitive-emotional model from mobile short-form video addiction to intermittent discontinuance: the moderating role of neutralization. *International Journal of Human–Computer Interaction*, 1-13. doi.org/10.1080/10447318.2022.2147714
- Ferneley, E. H., & Sobrepeerez, P. (2006). Resist, comply or workaround? An examination of different facets of user engagement with information systems. *European Journal of Information Systems*, 15(4), 345-356. doi.org/10.1057/palgrave.ejis.3000629
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18, 39–50. doi.org/10.1177/002224378101800
- Fukuoka Y, Kamitani E, Bonnet K, Lindgren T, Real-Time Social Support Through a Mobile Virtual Community to Improve Healthy Behaviour in Overweight and Sedentary Adults: A Focus Group Analysis, *J Med Internet Res* 2011;13(3). doi.org/10.2196/jmir.1770
- Furneaux, B., & Wade, M. (2010). The end of the information system life: a model of discontinuance. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems*, 41(2), 45-69. doi.org/10.2307/23042797
- Furneaux, B., & Wade, M. (2011). An exploration of organizational level information systems discontinuance intentions. *MIS Quarterly*, 573-598.
- Furneaux, B., & Wade, M. (2017). Impediments to information systems replacement: a calculus of discontinuance. *Journal of Management Information Systems*, 34(3), 902-932. doi.org/10.1080/07421222.2017.1373013



- Gallo, A. (2014). The Value of Keeping the Right Customers. *Havard Business Review*. Retrieved from <https://hbr.org/2014/10/the-value-of-keeping-the-right-customers?registration=success>
- Gefen, D., Rigdon, E. E., & Straub, D. (2011). Editor's comments: an update and extension to SEM guidelines for administrative and social science research. *MIS quarterly*, iii-xiv. doi.org/10.2307/23044042
- Gefen, D., Straub, D., & Boudreau, M. C. (2000). Structural equation modeling and regression: Guidelines for research practice. *Communications of the Association for Information Systems*, 4(1), 7. doi.org/10.17705/1CAIS.00407
- Gerhart, N., & Ogbanufe, O. (2022). Exploring smart wearables through the lens of reactance theory: Linking values, social influence, and status quo. *Computers in Human Behaviour*. doi.org/10.1016/j.chb.2021.107044
- Graf-Vlachy, L., Buhtz, K., & König, A. (2018). Social influence in technology adoption: taking stock and moving forward. *Management Review Quarterly*, 68, 37-76. doi.org/10.1007/s11301-017-0133-3
- Hair Jr, J., Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage publications. doi.org/10.1007/978-3-030-80519-7
- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2018). *Multivariate Data Analysis* (8 ed.). Cengage Learning.
- Harman, H. H. (1976). *Modern factor analysis*. University of Chicago Press.
- Han, L., Sun, R., Gao, F., Zhou, Y., & Jou, M. (2019). The effect of negative energy news on social trust and helping behaviour. *Computers in Human Behaviour*, 92, 128–138. doi.org/10.1016/j.chb.2018.11.012
- Hawi, N. S., & Samaha, M. (2017). The Relations Among Social Media Addiction, Self-Esteem, and Life Satisfaction in University Students. *Social Science Computer Review*, 35(5), 576–586. doi.org/10.1177/0894439316660340
- Horton, D., & Wohl, R. R. (1956). Mass communication and para-social interaction. *Psychiatry*, 19, 215–229. doi.org/10.1080/00332747.1956.11023049
- Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: a Multidisciplinary Journal*, 6(1), 1-55. doi.org/10.1080/10705519909540118
- Huang, Z., Palvia, P., & Mehta, N. (2023). Social media discontinuance: the salient roles of dark side and regret. *Journal of Information Technology Case and Application Research*, 25(1), 28-57. doi.org/10.1080/15228053.2023.2185059
- Hudders, L., De Jans, S., & De Veirman, M. (2021). The commercialization of social media stars: a literature review and conceptual framework on the strategic use of social media influencers. *International Journal of Advertising*, 40(3), 327-375. doi.org/10.1080/02650487.2020.1836925

- Hunt, M. G., Marx, R., Lipson, C., & Young, J. (2018). No more FOMO: Limiting social media decreases loneliness and depression. *Journal of Social and Clinical Psychology*, 37(10), 751-768. doi.org/10.1521/jscp.2018.37.10.751
- Islam, A. N., Mäntymäki, M., Laato, S., & Turel, O. (2022). Adverse consequences of emotional support seeking through social network sites in coping with stress from a global pandemic. *International Journal of Information Management*, 62, 102431. doi.org/10.1016/j.ijinfomgt.2021.102431
- Jabeen, F., Tandon, A., Azad, N., Islam, A. N., & Pereira, V. (2023). The dark side of social media platforms: A situation organism behaviour consequence approach. *Technological Forecasting and Social Change*, 186, 122104. doi.org/10.1016/j.techfore.2022.122104
- Karahanna, E., Straub, D. W., & Chervany, N. L. (1999). Information technology adoption across time: Across-sectional comparison of pre-adoption and post-adoption beliefs. *MIS Quarterly*, 23, 183–213. doi.org/10.2307/249751
- Kim, Y., Chen, H. T., & De Zúñiga, H. G. (2013). Stumbling upon news on the Internet: Effects of incidental news exposure and relative entertainment use on political engagement. *Computers in Human Behaviour*, 29(6), 2607-2614. doi.org/10.1016/j.chb.2013.06.005
- Kirk, C. P., Swain, S. D., & Gaskin, J. E. (2015). I'm proud of it: Consumer technology appropriation and psychological ownership. *Journal of Marketing Theory and Practice*, 23(2), 166-184. doi.org/10.1080/10696679.2015.1002335
- Kleinnijenhuis, J., Van Hoof, A. M. J., & Oegema, D. (2006). Negative news and the sleeper effect of distrust. *Harvard International Journal of Press/Politics*, 11(2), 86–104. doi.org/10.1177/1081180X06286417
- Klepper, S. (1997). Industry life cycles. *Industrial and Corporate Change*, 6(1), 145-182. doi.org/10.1093/icc/6.1.145
- Kline, R. B. (2023). *Principles and Practice of Structural Equation Modeling* (5 ed.). Guilford Press.
- Kobayashi, M., Fussell, S. R., Xiao, Y., & Seagull, F. J. (2005, April). Work coordination, workflow, and workarounds in a medical context. CHI'05 extended abstracts on *Human Factors in Computing Systems* (pp. 1561-1564). doi.org/10.1145/1056808.1056966
- Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration (IJEC)*, 11(4), 1–10. https://dl.acm.org/doi/10.4018/ijec.2015100101
- Kock, N., & Lynn, G. (2012). Lateral collinearity and misleading results in variance-based SEM: An illustration and recommendations. *Journal of the Association for Information Systems*, 13(7), 546–580. https://doi.org/10.17705/1jais.00302
- Krebs, P., & Duncan, D. T. (2015). Health app use among US mobile phone owners: a national survey. *JMIR mHealth and uHealth*, 3(4), e4924. doi.org/10.2196/mhealth.4924
- Kross, E., Verduyn, P., Demiralp, E., Park, J., Lee, D. S., Lin, N., ... & Ybarra, O. (2013). Facebook use predicts declines in subjective well-being in young adults. *PloS one*, 8(8), e69841. doi.org/10.1371/journal.pone.0069841

- Leonardi, P. M. (2011). When flexible routines meet flexible technologies: Affordance, constraint, and the imbrication of human and material agencies. *MIS Quarterly*, 147-167. doi.org/10.2307/23043493
- Levitt, T. (1965). Exploit the product life cycle (Vol. 43). Graduate School of Business Administration, Harvard University. Retrieved from <https://hbr.org/1965/11/exploit-the-product-life-cycle>
- Lewicki, R. J., McAllister, D. J., & Bies, R. I. (1998). Trust and distrust: New relationships and realities. *Academy of Management Review*, 23(3), 438–458. doi.org/10.2307/259288
- Li, C. Y. (2019). How social commerce constructs influence customers' social shopping intention? An empirical study of a social commerce website. *Technological Forecasting and Social Change*, 144, 282-294. doi.org/10.1016/j.techfore.2017.11.026
- Li, X., Liu, Z., Chen, Y., & Ren, A. (2023). Consumer avoidance toward message stream advertising on mobile social media: a stimulus-organism-response perspective. *Information Technology & People*. /doi.org/10.1108/ITP-11-2020-0761
- Lohmoller, J. B. (1989). *Latent variable path modeling with partial least squares*. Physica: Heidelberg. doi.org/10.1007/978-3-642-52512-4
- Mai, F., Shan, Z., Bai, Q., Wang, X., & Chiang, R. H. (2018). How does social media impact Bitcoin value? A test of the silent majority hypothesis. *Journal of Management Information Systems*, 35(1), 19-52. doi.org/10.1080/07421222.2018.1440774
- Maier, C., Laumer, S., Weinert, C., & Weitzel, T. (2015). The effects of technostress and switching stress on discontinued use of social networking services: a study of Facebook use. *Information Systems Journal*, 25(3), 275-308. doi.org/10.1111/isj.12068
- Marakas, G. M., & Hornik, S. (1996). Passive resistance misuse: overt support and covert recalcitrance in IS implementation. *European Journal of Information Systems*, 5, 208-219. doi.org/10.1057/ejis.1996.26
- Masuda, H., Han, S. H., & Lee, J. (2022). Impacts of influencer attributes on purchase intentions in social media influencer marketing: Mediating roles of characterizations. *Technological Forecasting and Social Change*, 174, 121246. doi.org/10.1016/j.techfore.2021.121246
- McCombs, M. E., & Shaw, D. L. (1972). The agenda-setting function of mass media. *Public Opinion quarterly*, 36(2), 176-187. /doi.org/10.1086/267990
- McKnight, D. H., & Chervany, N. L. (2001). Trust and Distrust Definitions: One Bite at a Time. Trust in Cyber-Societies. doi.org/10.1007/3-540-45547-7\_3
- McKnight, D. H., Lankton, N. K., Nicolaou, A., & Price, J. (2017). Distinguishing the effects of B2B information quality, system quality, and service outcome quality on trust and distrust. *The Journal of Strategic Information Systems*, 26(2), 118-141. doi.org/10.1016/j.jsis.2017.01.001
- Mehrabian, A., & Russell, J. A. (1974). *An approach to environmental psychology*. the MIT Press.
- Mehrizi, M. H. R., Modol, J. R., & Nezhad, M. Z. (2019). Intensifying to cease: Unpacking the process of information systems discontinuance. *MIS Quarterly*, 43(1), 141-165. doi.org/10.25300/MISQ/2019/13717

- Ming, L. C. & Chan, R. (2022). 'The algorithm does it for you': Why social media users are ditching 'boring' Facebook and Instagram for shiny new toys. CNA. Retrieved from <https://www.channelnewsasia.com/business/elon-musk-too-much-work-my-plate-twitter-tesla-bali-g20-3069676>
- Moqbel, M., & Kock, N. (2018). Unveiling the dark side of social networking sites: Personal and work-related consequences of social networking site addiction. *Information & Management*, 55(1), 109-119. doi.org/10.1016/j.im.2017.05.001
- Morning Consult (2019). The influencer report <https://blog.hostalia.com/wp-content/uploads/2019/11/2019-influencer-report-engaging-gen-z-millennials-morning-consult-informe-blog-hostalia-hosting.pdf>
- Morton, F. M. S. (2021, June 8). Social Media Is Addictive. Do Regulators Need to Step In? | Yale Insights. Yale Insights. <https://insights.som.yale.edu/insights/social-media-is-addictive-do-regulators-need-to-step-in>
- Msaed, C., Al-Kwafi, S. O., & Ahmed, Z. U. (2017). Building a comprehensive model to investigate factors behind switching intention of high-technology products. *Journal of Product & Brand Management*, 26(2), 102-119. doi.org/10.1108/JPBPM-06-2015-0915
- Mudambi, S., Schuff, D., & Zifla, E. (2016). What's "funny" about technology adoption? Humorous appropriation of online review platforms. *Thirty Seventh International Conference on Information Systems*, Dublin 2016.
- Murez, C. (2021, April 1). Boys Who Spend Lots of Time Online More Likely to Cyberbully | Health News | US News. US News. <https://www.usnews.com/news/health-news/articles/2021-04-01/boys-who-spend-lots-of-time-online-more-likely-to-cyberbully>
- Ng, Y. M. M. (2020). Re-examining the innovation post-adoption process: The case of Twitter discontinuance. *Computers in Human Behaviour*, 103, 48-56. doi.org/10.1016/j.chb.2019.09.019
- Nguyen, Q. N., Ta, A., & Prybutok, V. (2019). An integrated model of voice-user interface continuance intention: the gender effect. *International Journal of Human-Computer Interaction*, 35(15), 1362-1377. doi.org/10.1080/10447318.2018.1525023
- Núñez, M. (2019, July 24). FTC Slaps Facebook with \$5 Billion Fine, Forces New Privacy Controls. Forbes. <https://www.forbes.com/sites/mnunez/2019/07/24/ftcs-unprecedented-slap-fines-facebook-5-billion-forces-new-privacy-controls/?sh=5a93b0d55668>
- Nunnally, J. C. (1978). Psychometric theory. New York, NYC: McGraw-Hill.
- O'Brien, H. L., & Toms, E. G. (2008). What is user engagement? A conceptual framework for defining user engagement with technology. *Journal of the American Society for Information Science and Technology*, 59(6), 938-955. doi.org/10.1002/asi.20801
- Ooi, K. B., Lee, V. H., Hew, J. J., Leong, L. Y., Tan, G. W. H., & Lim, A. F. (2023). Social media influencers: an effective marketing approach? *Journal of Business Research*, 160, 113773. doi.org/10.1016/j.jbusres.2023.113773

- Orlikowski, W. J. (1992). The duality of technology: Rethinking the concept of technology in organizations. *Organization Science*, 3(3), 398-427. doi.org/10.1287/orsc.3.3.398
- Osatuyi, B., & Turel, O. (2020). Conceptualisation and validation of system use reduction as a self-regulatory IS use behaviour. *European Journal of Information Systems*, 29(1), 44-64. doi.org/10.1080/0960085X.2019.1709575
- Paswan, A. K., Gai, L., & Jeon, S. (2015). Alcohol and college students: Reasons, realization and intention to quit. *Journal of Business Research*, 68(10), 2075-2083. doi.org/10.1016/j.jbusres.2015.03.005
- Perez-Vega, R., Kaartemo, V., Lages, C. R., Razavi, N. B., & Männistö, J. (2021). Reshaping the contexts of online customer engagement behaviour via artificial intelligence: A conceptual framework. *Journal of Business Research*, 129, 902-910. doi.org/10.1016/j.jbusres.2020.11.002
- Petrides, L. A., McClelland, S. I., & Nodine, T. R. (2004). Costs and benefits of the workaround: inventive solution or costly alternative. *International Journal of Educational Management*, 18(2), 100-108. doi.org/10.1108/09513540410522234
- Pew Research, (2021). Social Media Use in 2021. Retrieved from <https://www.pewresearch.org/internet/2021/04/07/social-media-use-in-2021/>
- Polites, G. L., & Karahanna, E. (2012). Shackled to the status quo: The inhibiting effects of incumbent system habit, switching costs, and inertia on new system acceptance. *MIS Quarterly*, 21-42. doi.org/10.2307/41410404
- Priyadarshini, C., Kumar Dubey, R., N Kumar, Y. L., & Ranjan Jha, R. (2020). Impact of a Social Media Addiction on Employees' Wellbeing and Work Productivity. *The Qualitative Report*, 25, 181-196. doi.org/10.46743/2160-3715/2020.4099
- Recker, J. (2016). Reasoning about discontinuance of information system use. *Journal of Information Technology Theory and Application (JITTA)*, 17(1),
- Reichheld, F. (2001). Prescription for cutting costs. *Harvard Business School Publishing*.
- Rezvani, A., Khosravi, P., & Dong, L. (2017). Motivating users toward continued usage of information systems: Self-determination theory perspective. *Computers in Human Behaviour*, 76, 263-275. doi.org/10.1016/j.chb.2017.07.032
- Rivard, S., & Lapointe, L. (2012). Information technology implementers' responses to user resistance: Nature and effects. *MIS Quarterly*, 897-920. doi.org/10.2307/41703485
- Rogers, E. M. (1995). *Diffusion of Innovations*, 4th Edition, The Free Press, New York.
- Rotter, J. B. (1980). Interpersonal trust, trustworthiness, and gullibility. *American Psychologist*, 35(1), 1-7. doi.org/10.1037/0003-066X.35.1.1
- Schou Andreassen, C., & Pallesen, S. (2014). Social Network Site Addiction - An Overview. *Current Pharmaceutical Design*, 20. doi.org/10.2174/13816128113199990616
- Schumacker, R. E., & Lomax, R. G. (2010). *A Beginner's Guide to Structural Equation Modeling* (3 ed.). Routledge.

- Shen, X. L., Li, Y. J., & Sun, Y. (2018). Wearable health information systems intermittent discontinuance: A revised expectation-disconfirmation model. *Industrial Management & Data Systems*, 118(3), 506-523. doi.org/10.1108/IMDS-05-2017-0222
- Smith, L. A., & Foxcroft, D. R. (2009). The effect of alcohol advertising, marketing and portrayal on drinking behaviour in young people: systematic review of prospective cohort studies. *BMC Public Health*, 9, 1-11. doi.org/10.1186/1471-2458-9-51
- Soh, F., Smith, K., & Dhillon, G. (2022). The relationship between social capital and social media addiction: The role of privacy self-efficacy. *Australasian Journal of Information Systems*, 26. doi.org/10.3127/ajis.v26i0.3367
- Soliman, W., & Rinta-Kahila, T. (2020). Toward a refined conceptualization of IS discontinuance: Reflection on the past and a way forward. *Information & Management*, 57(2), 103167. doi.org/10.1016/j.im.2019.05.002
- Sood, A., & Tellis, G. J. (2005). Technological evolution and radical innovation. *Journal of Marketing*, 69(3), 152-168. doi.org/10.1509/jmkg.69.3.152.66361
- Starcevic, V. (2013). Is Internet addiction a useful concept? In *Australian and New Zealand Journal of Psychiatry* (Vol. 47, Issue 1, pp. 16–19). SAGE Publications. Sage UK: London, England. doi.org/10.1177/0004867412461693
- Statista (2021a). Leading social media usage reasons worldwide 2021. Retrieved from <https://www.statista.com/statistics/715449/social-media-usage-reasons-worldwide>
- Statista (2021b). U.S. social media addiction by age group 2019. Statista.Com. <https://www.statista.com/statistics/1081292/social-media-addiction-by-age-usa/>
- Statista (2023). Share of internet users of the leading social media in China as of the 3rd quarter of 2022. Retrieved from <https://www.statista.com/statistics/250546/leading-social-network-sites-in-china/#statisticContainer>
- Ta, A., & Prybutok, V. (2018). A mindful product acceptance model. *Journal of Decision Systems*, 27(1), 19-36. doi.org/10.1080/12460125.2018.1479149
- Tam, C., Santos, D., & Oliveira, T. (2020). Exploring the influential factors of continuance intention to use mobile Apps: Extending the expectation confirmation model. *Information Systems Frontiers*, 22, 243-257. doi.org/10.1007/s10796-018-9864-5
- Tang, J., Hu, X., & Liu, H. (2014). Is distrust the negation of trust?: The value of distrust in social media. HT 2014 - Proceedings of the 25th ACM Conference on Hypertext and Social Media, 148–157. doi.org/10.1145/2631775.2631793
- Taylor, M., & Taylor, A. (2012). The technology life cycle: Conceptualization and managerial implications. *International Journal of Production Economics*, 140(1), 541-553. doi.org/10.1016/j.ijpe.2012.07.006
- Tellis, G. J., & Crawford, C. M. (1981). An Evolutionary Approach to Product Growth Theory. *Journal of Marketing*, 45(4), 125–132. doi.org/10.2307/1251480
- Thielsch, M. T., Meeßen, S. M., & Hertel, G. (2018). Trust and distrust in information systems at the workplace. *PeerJ*, 6, e5483. doi.org/10.7717/peerj.5483

- Turel, O. (2015). Quitting the use of a habituated hedonic information system: a theoretical model and empirical examination of Facebook users. *European Journal of Information Systems*, 24(4), 431-446. doi.org/10.1057/ejis.2014.19
- Vaghefi, I., & Tulu, B. (2019). The continued use of mobile health apps: insights from a longitudinal study. *JMIR mHealth and uHealth*, 7(8), e12983. doi.org/10.2196/12983
- Vaghefi, I., Lapointe, L., & Boudreau-Pinsonneault, C. (2017). A typology of user liability to IT addiction. *Information Systems Journal*, 27(2), 125-169. doi.org/10.1111/isj.12098
- Vaghefi, I., Qahri-Saremi, H., & Turel, O. (2020). Dealing with social networking site addiction: a cognitive-affective model of discontinuance decisions. *Internet Research*. doi.org/10.1108/INTR-10-2019-0418
- Van der Heijden, H. (2004). User acceptance of hedonic information systems. *MIS Quarterly*, 695-704. doi.org/10.2307/25148660
- Venkatesh, V., & Agarwal, R. (2006). Turning visitors into customers: A usability-centric perspective on purchase behaviour in electronic channels. *Management Science*, 52(3), 367-382. doi.org/10.1287/mnsc.1050.0442
- Venkatesh, V., & Brown, S. A. (2001). A longitudinal investigation of personal computers in homes: Adoption determinants and emerging challenges. *MIS quarterly*, 71-102. doi.org/10.2307/3250959
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 425-478. doi.org/10.2307/30036540
- Vernon, R. (1966). International Investment and International Trade in the Product Cycle. *The Quarterly Journal of Economics*, 80(2), 190-207. doi.org/10.2307/1880689
- Walker, M. and Matsa, K. E. (2021). News Consumption Across social media in 2021. Pew Research Center. Retrieved from <https://www.pewresearch.org/journalism/2021/09/20/news-consumption-across-social-media-in-2021/>
- Wanous, J. P., Reichers, A. E., & Hudy, M. J. (1997). Overall job satisfaction: how good are single-item measures? *Journal of Applied Psychology*, 82(2), 247. doi.org/10.1037/0021-9010.82.2.247
- Worthington, R. L., & Whittaker, T. A. (2006). Scale development research: A content analysis and recommendations for best practices. *The Counseling Psychologist*, 34(6), 806-838. doi.org/10.1177/0011000006288127
- Xiao, X., Sarker, S., Wright, R. T., Sarker, S., & Mariadoss, B. J. (2020). Commitment and Replacement of Existing SaaS-Delivered Applications: A Mixed-Methods Investigation. *MIS Quarterly*, 44(4). doi.org/10.25300/MISQ/2020/13216
- Xu, Y. C., Yang, Y., Cheng, Z., & Lim, J. (2014). Retaining and attracting users in social networking services: An empirical investigation of cyber migration. *The Journal of Strategic Information Systems*, 23(3), 239-253. doi.org/10.1016/j.jsis.2014.03.002
- Ye, D., Cho, D., Chen, J., & Jia, Z. (2023). Empirical investigation of the impact of overload on the discontinuous usage intentions of short video users: a stressor-strain-outcome perspective. *Online Information Review*, 47(4), 697-713. doi.org/10.1108/OIR-09-2021-0481

- Yong, A. G., & Pearce, S. (2013). A beginner's guide to factor analysis: Focusing on exploratory factor analysis. *Tutorials in Quantitative Methods for Psychology*, 9(2), 79-94. doi.org/10.20982/tqmp.09.2.p079
- York, C., & Turcotte, J. (2015). Vacationing from Facebook: Adoption, temporary discontinuance, and re adoption of an innovation. *Communication Research Reports*, 32(1), 54-62.
- Zhao, X., Tian, J., & Xue, L. (2020). Herding and software adoption: A re-examination based on post-adoption software discontinuance. *Journal of Management Information Systems*, 37(2), 484-509. doi.org/10.1080/08824096.2014.989975
- Zhou, Z., Yang, M., & Jin, X. L. (2018). Differences in the reasons of intermittent versus permanent discontinuance in social media: an exploratory study in Weibo. Conference Paper at the Hawaii International Conference on System Sciences. doi.org/10.1080/07421222.2020.1759941

## Appendix 1

Construct	Definition	Source
Perceived Influencer Disengagement	My social influencers do not use (NSMS) very often anymore. My Social Influencers do not update their content on (NSMS) as frequently as they did before. My social influencers quit using (NSMS). My Social Influencers are more active on other social media channels.	Proposed by authors
Loss of Interest	I no longer have an interest in using (NSMS). Using (NSMS) is no longer a new trend. Using (NSMS) is not fun anymore.	Proposed by authors
Less Frequent Use (times)	I don't use (NSMS) as much as I did before. I use (NSMS) less frequently. I don't spend much time on (NSMS). I will spend the time that I would have wasted using (NSMS) to do something else.	Proposed by authors
Less Frequent Use (activities)	I don't have as many activities on (NSMS) as I did before. I am less likely to like, share, repost...what I see on (NSMS) as I did before.	Proposed by authors
Intention to Discontinue	I would like to stop using (NSMS). I have often thought about stopping the use of (NSMS). I will stop using (NSMS) soon.	Conceptualized from Vaghefi et al. (2020)
Negative News Exposure	TV reports a great deal of negative news about (NSMS). Radio broadcasts include a great deal of negative news about (NSMS). Newspapers publish articles that include a great deal of negative information about (NSMS).	Conceptualized from Smith & Foxcroft (2009); Paswan et al. (2015)
Distrusting Beliefs	I don't trust (NSMS) as a social media provider. I don't think (NSMS) will protect my privacy. I am not confident that my personal information is secure on (NSMS). I think that (NSMS) will sell my private information to other organizations.	Conceptualized from McKnight & Chervany (2001)
Realization of Addiction.	I think I spent too much time on (NSMS). I have missed work or assignment deadlines because of (NSMS) use. I used (NSMS) everywhere and at any time possible. I had guilty feelings that I was addicted to (NSMS).	Conceptualized from Paswan (2015)

\*NSMS: Name of Social Media Sites

Table A1. Survey instruments



## Copyright

**Copyright** © 2025 Ta, A., Nguyen, Q. N., Schulz, S., and Le, L., This is an open-access article licensed under a [Creative Commons Attribution-Non-Commercial 4.0 Australia License](https://creativecommons.org/licenses/by-nc/4.0/), which permits non-commercial use, distribution, and reproduction in any medium, provided the original author and AJIS are credited.

doi: <https://doi.org/10.3127/ajis.v29.5549>

