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Demystifying the Link between Social Media Addiction and Sharing without Verification: The Role of Absentmindedness and Wellbeing

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Abstract:

We use salience and dual-system theories as the lens to investigate how (via which intervening mechanism) and when (under what condition(s)) social media addiction impacts unverified information sharing. Based on results from analyzing data from 234 social media users, we found that social media addiction augments unverified information sharing, and that absentmindedness partially mediates this relationship. Furthermore, we establish that wellbeing status buffers the harmful impact of social media addiction on unverified information sharing and absentmindedness.

Keywords: Social Media Addiction, Unverified Information Sharing, Absentmindedness, Wellbeing Status, Salience Theory, Dual-system Theory

Andreas Eckhardt was the accepting senior editor for this paper.

1 Introduction

The advent of social media has drastically transformed the way people share information (Moqbel & Nah, 2017). Despite an increase in how many people rely on social media as their primary news and information source (Suciu, 2019), the medium remains highly susceptible to (and has emerged as a fertile ground for) unverified information and its dissemination in large part because social media allows people to rapidly share information with minimal to no repercussions (Khan & Idris, 2019).

In 2022, WhatsApp had over two billion users (Dixon, 2022) and solidified its position as the world's third-most popular social media platform behind Facebook and YouTube (Chaffey, 2022). If one focuses on the Middle East region, WhatsApp represents the most widely used social media platform (Gull et al., 2019). In Qatar, for example, WhatsApp remains by far the most popular social media platform with seven out of ten Qataris using it (Dennis et al., 2019). One can attribute this preference to the perception among Arab nationals that WhatsApp safeguards their privacy better than other social media platforms (Dennis et al., 2019).

Social media platforms provide a convenient avenue for people to communicate and share information with their loved ones and acquaintances. However, this convenience comes with a potential drawback: the information may be unverified. For instance, numerous unverified claims have circulated on social media linking vaccines to autism, which led some parents to delay or entirely refuse vaccination for their children despite recommendations from medical experts (Jang et al., 2019). While many blame unverified information for misleading voters and election tampering in the West, in India, false information about child kidnappings that spread on social media triggered mass beatings and resulted in at least three deaths (Samuels, 2020). Unverified information on social media has also contributed to recent election results and health crises as well as endangered individuals' safety and lives (Pulido et al., 2020). Despite the evident risks associated with sharing unverified information, we lack an understanding of the magnitude of the problem since scholars have yet to comprehensively investigate its scope (Allcott et al., 2019).

Several organizations, such as the World Health Organization (WHO, 2022), have called for interventions to combat the spread of unverified information on social media. The first step to developing such interventions involves understanding why and how social media use leads to unverified information sharing. Indeed, rising concerns about unverified information sharing on social media have prompted a surge of research on the topic (Adnan et al., 2021; Apuke & Omar, 2021a, 2021b; Bermes, 2021; Herrero-Diz et al., 2020; Islam et al., 2020; Laato et al., 2020; Lu et al., 2022; Tai et al., 2022) that has mainly focused on motivational predictors such as altruism, information overload, trust in information, and fear of missing out. While limited research has identified a direct link between social media use and unverified information sharing (Adnan et al., 2021; Alshare et al., 2023; Apuke et al., 2022), these studies have failed to theoretically explain how and when this relationship holds. In particular, the current literature lacks a theoretical framework and empirical evidence that explain the underlying conditions and intervening mechanisms that underpin the relationship between social media use (e.g., addictive use) and unverified information sharing. As such, we do not comprehensively understand the behavior as well as ways to combat it. To more thoroughly understand the underlying mechanism that social media addiction plays in unverified information sharing, we identify factors that modify (i.e., moderate) and mediate the impact of social media addiction on unverified information sharing. We focus on identifying mechanisms that reduce the harmful effects of addictive behavior based on the rationale that people can find it challenging to cease such behavior altogether.

To narrow these research gaps and to help explain the link between social media addiction and unverified information sharing, we base our theoretical framework on the dual-system (also known as dual-process) theory (Kahneman, 2011; Wason & Evans, 1974) and salience theory (Bordalo et al., 2012). At its core, dual-system theory posits that two information-processing systems control human cognition: System 1 for quick, automatic, and effortless cognition, and System 2 for slow, analytical, and cognitively demanding thought processes. People frequently consume and exchange information on social media with others in their network. When addicted to social media, people tend not to make conscious judgments, which creates a condition wherein they spend little time and effort verifying information that they share. On the other hand, salience theory builds on four core principles: salience (i.e., the more attention people pay to information, the more they will give weight or importance to them in later decisions), attention (i.e., when people selectively concentrate on certain salient aspects of their environment while ignoring others), context (i.e., the situation that influences which attributes people perceive as salient), and decision making (i.e., when people select a course of action among several alternatives based on the salience of the information available to them in the given context) (Bordalo et al., 2012). The theoretical framework section will present more details on these principles.

Our research makes several contributions. From a research contribution perspective, our study extends the prior literature (Khan & Idris, 2019; Laato et al., 2020; Talwar et al., 2019) by theoretically identifying social media addiction as another primary antecedent of unverified information sharing on social media. Furthermore, our study contributes to the emerging body of knowledge about unverified information sharing and technology addiction by providing empirical evidence and theoretical explanations for how (via which intervening mechanism) and when (under which condition(s)) social media addiction impacts unverified information sharing. In particular, we introduce attention (absentmindedness) as an intervening mechanism through which social media addiction affects unverified information sharing. Furthermore, we present wellbeing status as a moderating factor that explains the impact of social media addiction on unverified information sharing and absentmindedness. Specifically, we posit that wellbeing helps overcome social media addictive harm by restoring users' attention and cognitive capacity (System 2), which allows them to make better decisions when verifying information before sharing. Furthermore, our findings offer significant implications for intervening in and preventing unverified information sharing. Our study contributes to practice by suggesting ways for social media providers, individual users, and government organizations to develop evidence-based interventions to combat false or unverified information sharing.

2 Theoretical Background and Hypothesis Development

To understand the influence of social media addiction on unverified information sharing through social media platforms, we propose a research model (see Figure 1) based on dual-system and salience theories. Dual-system theory posits that two systems govern human cognition: System 1 for rapid, automatic, and effortless thinking and System 2 for slow, analytic, and cognitively demanding thinking. For example, social media addiction and absentmindedness primarily engage the automatic, intuitive, and fast-thinking System 1, while wellbeing engages the slower, more deliberative, and reflective thinking System 2. We elaborate more in the following subsections.

Salience theory builds on four core principles—salience, attention, context, and decision making—that link the concepts in our model. Thus, in our study, salience relates to social media addiction, attention relates to absentmindedness, context relates to wellbeing status, and decision making relates to the decision to share information without verification. We elaborate on these concepts in the next subsections.

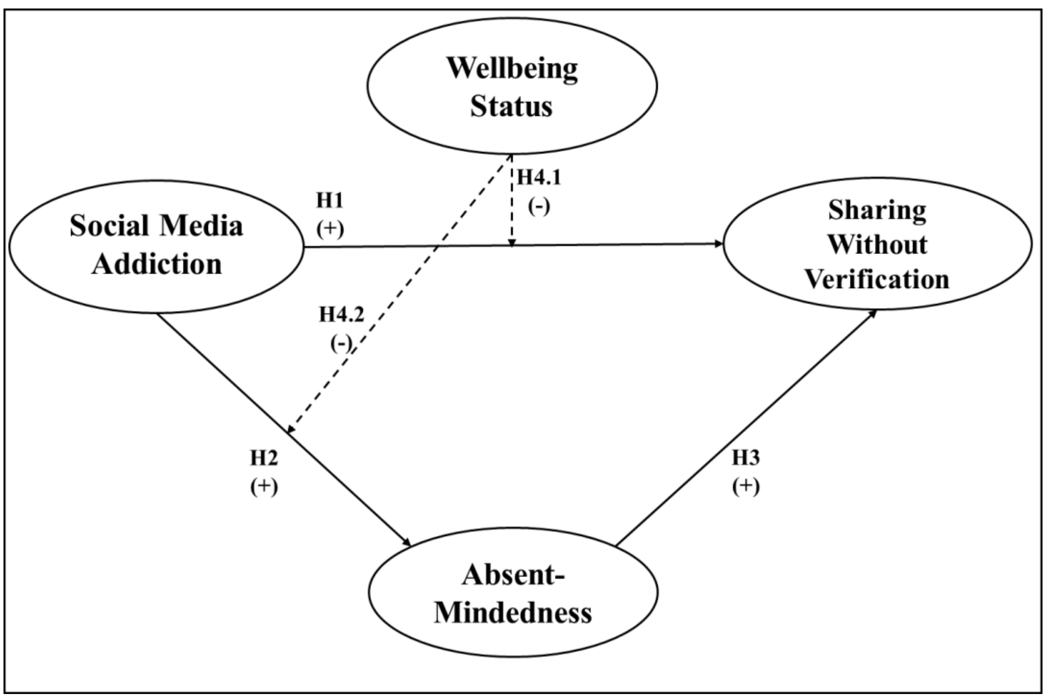

Figure 1. Model with Hypotheses

2.1 Social Media Addiction

We define social media addiction as "being overly concerned about social media, strongly motivated, and having been devoting a great amount of time and energy to use social media, to the degree that an individual's social activities, interpersonal relationships, studies or jobs, and/or health and wellbeing are impaired" (Schou Andreassen & Pallesen, 2014, p. 4054). Desires for belongingness, social activities, and relationship-building correlate with social media addiction (Kwon et al., 2016). Social media addiction represents just one among many technology-enabled addictions (Turel, 2015). Isolated and stressed individuals often seek out rewarding behaviors to assist with coping (Cheikh-Ammar, 2020; Panno et al., 2020). Using social media constitutes one such rewarding behavior since frequent posting and interaction lead to an increase in the number of social connections, content engagement, and feedback from other users (rewards). While many consider social media use harmless, excessive use can lead to addictive behaviors (Moqbel & Kock, 2018). Although recent research has offered explanations for how social media addiction develops and leads to negative consequences (He et al., 2017; Keles et al., 2020; Moqbel & Kock, 2018; Ponnusamy et al., 2020; Turel et al., 2018), the role of social media addiction in unverified information sharing has received little attention.

2.2 Dual-system Theory

Dual-system theory proposes that one can break down human cognition into two unique ways of thinking: 1) rapid, automatic, and undemanding thinking and 2) slow, analytical, and cognitively demanding thinking. Kahneman (2011) calls the two modes of thinking "System 1" and "System 2", respectively (Evans & Stanovich, 2013). The theory posits that System 1 controls the majority of our daily behavior. In contrast, System 2 comes into action only when the quick responses of System 1 fail to produce the intended results. Therefore, dual-system theory casts doubt on the widespread notion that humans constitute rational beings who always process information analytically and objectively and make judgments accordingly because many people perceive their views, opinions, and actions as objective and rational; therefore, they tend to undervalue System 1's impact on their reasoning. Kahneman (2011) demonstrates that System 1 contributes significantly to human reasoning, which one can see in the many systematic errors in judgments that people make (also known as cognitive biases). Scholars have attributed the failure to identify unverified information to the laziness that is attributed to System 1 (Mirhoseini et al., 2023; Moravec et al., 2020; Pennycook & Rand, 2019).

Dual-system theory, which suggests that social media-addicted users rely on their automatic, quick, and cognitively undemanding thoughts (System 1) when it comes to the decision to share information without verification, provides strong arguments for the hypothesized relationships between social media addiction and unverified information sharing.

2.3 Salience Theory

Salience theory depends on the context and focuses on the interplay between attention and decision making. At its core, it posits that people pay the most attention to the most salient activity when making decisions. Thus, in proposing that people substitute decision weights that favor salient payoffs or rewards (e.g., social media addictive activities) for objective choices (e.g., verifying information), the theory can help one explain the relationships between social media addiction and unverified information sharing. We draw on Bordalo et al.'s (2012) salience theory in highlighting the interplay between attention (e.g., absentmindedness) and decision, and extend the salience concept to social media addictive behavior and choices about whether to share unverified information in a risk-laden health context with regard to wellbeing status. Due to the attention component of salience theory, salient attributes receive more weight in decisions.

Psychologists consider salience an important attentional mechanism that enables individuals to focus their limited cognitive resources on a pertinent subset of the available information (Bordalo et al., 2013b). Taylor and Thompson (1982) defined salience as "the phenomenon that, when one's attention is differentially directed to one portion of the environment rather than to others, the information contained in that portion will receive disproportionate weighting in subsequent judgments" (p. 175). Asset pricing and judicial decisions represent just two areas where researchers have applied salience theory (Bordalo et al., 2012, 2013a, 2015; Cosemans & Frehen, 2021).

2.4 Social Media Addiction and Sharing Without Verification Behavior

We argue that social media addiction can impair one’s ability to process information and make decisions because it demands cognitive effort and attention (e.g., attending to social media notifications and posts) and can preoccupy and distract users from verifying the information they share. According to evidence from cognitive load memory, multimedia (e.g., social media) overloads individuals’ working memory, which reduces their cognitive capacity (Mayer & Moreno, 2003; Turel & Qahri-Saremi, 2016). Thus, when irrelevant stimuli (e.g., addiction to using WhatsApp) overload one’s working memory, the deeper cognitive processing required to judge or verify information diminishes.

Based on salience theory, we also argue that individuals focus their attention on the addictive attributes of social media use that they consider more salient than evaluating messages. Furthermore, those addicted to social media become accustomed to rapidly skimming through fragmented pieces of information (e.g., task switching or media multitasking), which leads them to form a shallow cognition pattern and an inability to engage in deep information processing (Jiang et al., 2016). Evidence shows that heavy media multitaskers (e.g., addicted social media users) perform less effectively than people who do not multitask in volitionally allocating attentive cognition and filtering irrelevant stimuli from their environment (Ophir et al., 2009). In other words, addicted users develop a habit whereby they scan a piece of information and then quickly shift to new pieces of information rather than focusing on a single piece of information for a sufficient period. Building on the preceding discourse and adopting a systems theory perspective, we argue that social media addiction can diminish reflective and deliberative System 2 thinking—a necessary component for verifying information prior to disseminating it. Consequently, we can infer that addicted social media users may develop shallow and broad cognitive patterns in processing information, which may distract them from verifying the information they intend to share across social media platforms.

We argue that individuals choose to draw their cognitive efforts and attention to the addictive attributes of social media use (Turel et al., 2014, 2011) that they consider more important than evaluating the messages due to attentional bias (Franken et al., 2005). Attentional bias refers to the exaggerated attention that people give to addiction-related cues at the expense of other (neutral) cues (e.g., a depressed individual may focus on negative over positive situations). Evidence suggests that addictive behaviors increase brain activation in regions involved in salience (i.e., posterior regions of the medial orbitofrontal cortex and ventral striatum) (Noël et al., 2013; Wilcox et al., 2011). Therefore, social media addictive behavior restricts people’s attention to only rewarding stimuli, such as social media-induced pleasure, and draws them away from making decisions or skeptically evaluating information.

We believe that, when addicted to social media, people tend to share content quickly and less consciously to fulfill an urge. In line with dual-system theory, we argue that we can attribute unverified information sharing to an imbalance between System 1 and System 2 thinking (Mirhoseini et al., 2023; Moravec et al., 2020; Pennycook & Rand, 2019). Social media addiction primarily engages System 1 thinking, leading to problematic social media use (Turel & Qahri-Saremi, 2016). When addicted to social media, people often engage in impulsive behaviors without fully considering the consequences. Thus, we propose the following hypothesis:

H1: Social media addiction increases unverified information sharing.

2.5 Social Media Addiction and Absentmindedness

Absentmindedness refers to being “inattentive to ongoing activity, to lose track of current aims (i.e., lose awareness), and to become distracted from intended thought or action by salient but ‘currently’ irrelevant stimuli” (Manly et al., 1999, p. 661). Based on this definition, we decided to measure absentmindedness as a second-order construct that comprises three first-order constructs: inattentiveness, unawareness, and distraction. Based on the attentional bias concept, we believe addictive social media use constitutes irrelevant stimuli that divert attention and awareness from other activities (e.g., evaluating messages before sharing them through social media). In particular, social media’s notification features, such as signals and sounds, and numerous information streams (e.g., regarding events, gossip, and news) may exhaust addicted users’ cognitive capacity and distract their attention from other important tasks (Cain & Mitroff, 2011). Evidence has shown that the dynamic and complex nature of information in social media burdens people’s ability to filter information, which may impair their attention (Van Knippenberg et al., 2015).

Evidence from psychological and neurological research has shown that addiction engenders cognitive deficits because the brain regions and processes that trigger addiction overlap expansively with important cognitive functions, such as attention, that play a critical role in decision processing (Gould, 2010). Hence, addiction alters normal brain structure and function and produces cognitive shifts that encourage people to acquire maladaptive and absentminded behaviors. Furthermore, addiction-induced dopamine does not only make individuals feel good but also identifies salient phenomena—the important things one needs to pay attention to in order to survive, such as alerts about pleasure, food, danger, and pain (Ungless, 2004; Volkow et al., 2005). When addicted individuals use social media, their dopamine level rises steeply due to pleasure as if to say "Hey! Pay attention to this!" because it feels good. Addicted social media users' brains have mistakenly learned that they need to pay attention to social media and ignore other non-addictive social media-related aspects of life. Therefore, as the concept of attentional bias indicates (Franken et al., 2005; Nikolaidou et al., 2019), social media addictive behavior confines attention to only rewarding stimuli, such as addictive social media-induced pleasure (i.e., positively reinforcing stimuli that can prompt positive hedonic reactions), which augments absentmindedness for other activities (e.g., evaluating the authenticity of information before sharing it). By confining attention to only rewarding stimuli, social media addictive behavior depletes individuals' attention and awareness while distracting them from other activities (Xie et al., 2021), which increases absentmindedness behavior. Thus, social media addiction leads to greater absentmindedness. Therefore, we propose the following hypothesis:

H2: Social media addiction increases absentmindedness.

2.6 Absentmindedness and Sharing Information without Verification Behavior

We argue that absentmindedness depletes individuals' cognitive resources needed to verify the information before sharing it through social media. Absentmindedness involves being neither aware nor paying attention to a task while performing it, such as solving a problem (Brown & Ryan, 2003) or judging the authenticity of a message. In other words, when absentminded, people perform activities (e.g., assessing a message's authenticity) without much consideration because the mind wanders or goes entirely blank (Brown & Ryan, 2003; Smallwood & Schooler, 2006). In this situation, the decision-making components of attention shift away from the main task, which leads people to fail when attempting to carry out such a task. Cognitive studies have long established that attention complications severely impede an individual's cognitive abilities (e.g., Gardony et al., 2015). In other words, when alternative stimuli hijack people's attention, they tend to share information automatically without verification. Based on dual-system theory, we contend that System 1's quick, automatic, and cognitively undemanding thinking overtakes System 2, which could have helped people spend the effort to verify the authenticity of information before sharing it on social media. Therefore, absentmindedness reflects people's inability to acquire cognitive resources that they could use to enhance their judgment and decision making. Thus, we posit the following hypothesis:

H3: Absentmindedness increases unverified information sharing.

2.7 Wellbeing Status Moderation Effect

Wellbeing encompasses the degree to which an individual believes their life is going well (Diener et al., 2018, 2010). Wellbeing correlates with psychological, physiological, and social advantages (Ryff, 2014). Moreover, research has linked wellbeing to technology addictions such as Internet use (Whang et al., 2003). However, such findings have been controversial as research has found that Internet use can also reduce depression and loneliness (McKenna & Bargh, 2000; Whang et al., 2003). Research has also demonstrated the converse relationship in which Internet addiction negatively influences wellbeing (Cardak, 2013). However, research further suggests that increasing wellbeing may decrease Internet addiction (Cardak, 2013). Contrary to prior research, we investigate the role of wellbeing status in buffering or moderating the impact of social media addiction on unverified information sharing and absentmindedness.

Drawing on dual-system theory, we contend that individuals with high wellbeing levels, particularly health-conscious social media users, will be more inclined to prioritize primary goals such as assessing the authenticity of health information. Consequently, their cognitive processes will tend to engage in slow, deliberate, and analytical thinking (System 2) rather than succumb to addictive behaviors that encourage quick, automatic, and cognitively undemanding thinking (System 1). The constant demand that social media places on addicted users drains their cognitive capacity, impairs their ability to reason and judge correctly, and leads them to resort to quick and automatic System 1 thinking. However, social media users must be able to trigger System 2 to think clearly and make competent decisions regarding verifying information before sharing it.

In accordance with the tenets of dual-system theory, whether people engage in System 2 depends on whether System 1 can generate the desired outcomes through its rapid response mechanisms (Kahneman, 2011). Consequently, we posit that System 2 activates when the responses elicited from System 1, driven by social media addiction and absentmindedness, prove inadequate in yielding desired outcomes (in particular, abstaining from sharing unverified information). Hence, we posit that, by engaging System 2 thinking, wellbeing can have a negative moderation effect on the impact of social media addiction on unverified information sharing and absentmindedness. We contend that higher wellbeing levels weaken the impact of social media addiction on unverified information sharing and absentmindedness. In essence, in situations with elevated wellbeing levels, individuals are less susceptible to impulsive tendencies driven by System 1 thinking, which allows them to control such impulses to a certain degree and reduce how much impact System 1's quick, automatic, and cognitively undemanding thoughts have on their decisions related to sharing unverified information. Additionally, through the attention restoration theory lens (Gill et al., 2018), we believe that people can overcome social media's addictive harm. In particular, we believe that improved wellbeing can restore their cognitive capacity, which can help them activate System 2 thinking that enables them to make more effective decisions, such as verifying information's authenticity before sharing it.

Evidence suggests that greater wellbeing substantially correlates with competent decision-making capability (Páez-Gallego et al., 2020). Specifically, mentally healthy social media users are less likely to experience adverse impacts from the effects of social media addiction on unverified information sharing and absentmindedness. In other words, having a high wellbeing status helps mitigate the harmful effects of social media addiction on 1) unverified information sharing and 2) absentmindedness. Therefore, we posit the following hypotheses:

H4.1: Wellbeing status weakens the effect of social media addiction on unverified information sharing.

H4.2: Wellbeing status weakens the effect of social media addiction on absentmindedness.

Our discussion above indicates an indirect route from social media addiction to unverified information sharing. Specifically, social media addiction not only discourages users from making any effort to verify information or news before sharing it but also hinders their ability to acquire attention-cognitive resources (by increasing absentmindedness) that could have helped them improve their decision-making ability to not share content without verifying it.

3 Research Method

3.1 Research Design and Data Collection

We used a cross-sectional anonymous self-reported questionnaire to collect data, a common approach in the information systems (IS) literature (Lowry et al., 2016; Moqbel et al., 2022). Therefore, we used a dataset from social media users to test our research model. We have taken several measures to ensure the validity, clarity, and conciseness of the survey questions. First, to assess the content validity of the measurement instrument, we consulted an expert panel that comprised four IS faculty members and doctoral students to identify and resolve potential problems in how we phrased the questions (particularly for the new scales). We also solicited feedback from individuals of different age and gender groups. We used feedback from the expert panel to improve the content; specifically, we modified how we phrased and framed the questions, which helped reduce common method bias (Podsakoff et al., 2003).

Since we collected data in a Middle Eastern nation, a researcher who speaks Arabic natively and had studied in the United States first translated the measurement tool from English to Arabic. Another native Arabic speaker educated in the United States with a doctoral degree back-translated the survey from Arabic to English following Brislin's (1986) back-translation method. The native speakers deliberated on differences between the two versions to eliminate or minimize any unexpected alteration in meaning. We used a simple random sample to select participants in an unbiased manner. To do so, we requested to collaborate with local companies and government agencies. We contacted potential participants and provided them with a link to the online survey. Our survey contained a cover page (consent form) that stated the study's objective. Since the survey asked several sensitive questions, we assured participants that their responses would remain anonymous and confidential.

On average, the 234 individual respondents were 36.76 years old. Furthermore, 52.56 percent were female, 64.53 percent were married, 85.04 percent had at least a bachelor's degree, their average work experience was 14.21 years, and 71.37 percent held a full-time position.

3.2 Measurement Instrument

To examine the theoretical model (see Figure 1), we conducted a survey using a measurement instrument that we developed based on the extant literature to increase the validity of our constructs. We adapted several measurements by modifying the words to fit the current research context. All constructs were reflective, and we measured most of them using the five-point Likert scale (see Appendix A).

We measured social media addiction by adapting items from past research (Charlton, 2002; Moqbel & Kock, 2018). We adopted the wellbeing status items from Diener et al. (2010) and the items to measure unverified information sharing from Khan and Idris (2019) (see Appendix A).

We measured absentmindedness as a second-order construct that comprised 1) two inattention-related items, 2) two unawareness-related items from the Mindful Attention Awareness Scale (MAAS) (Brown & Ryan, 2003), and 3) two distraction items (Moqbel & Kock, 2018). Following the four phases that Hinkin (1995) proposed, we constructed absentmindedness measures based on the relevant literature (Brown & Ryan, 2003; Manly et al., 1999; Moqbel & Kock, 2018). First, we defined inattentiveness, unawareness, and distraction by consulting the literature on absentmindedness (Manly et al., 1999). Second, we adjusted each dimension's wording to better align with how Manly et al. (1999) described absentmindedness using a deductive-item-generating method (Hinkin, 1995) to create two items for each dimension. Furthermore, we conducted a pilot test with students to evaluate the validity of the items. We found substantial evidence of content validity across the board. Next, we purified the instruments. We performed an exploratory component analysis and found that no item in any dimension fell below the 0.40 cutoff value that Hinkin (1995) proposed. In the final phase, we used a confirmatory factor analysis to examine the perceived effects of linked constructs, including social media addiction and unverified sharing. According to the findings, the three dimensions of absentmindedness showed acceptable fit and differentiation from other constructs. Finally, we controlled for the following potential confounding effects of variables: age, gender, education level, marital status, and employment type (i.e., full-time vs. part-time).

3.3 Data Analysis

We employed a partial least squares (PLS)-based structural equation modeling (SEM) data analysis approach (Chin, 1998; Haenlein & Kaplan, 2004) to evaluate the measurement instrument's psychometric properties. We assessed all constructs to determine their reliability, convergent validity, and discriminant validity using the WarpPLS 7.0 software (Kock, 2020). The composite reliability values of all constructs exceeded 0.7, which indicates that our measures had sufficient reliability (Chin, 1998). We conducted a confirmatory factor analysis (CFA) using WarpPLS. The CFA confirmed that every item significantly loaded on its respective construct. The factor loadings exceeded the recommended threshold of 0.5 (Hair et al., 2010; Kock, 2014), which indicates acceptable convergent validity. Table 1 shows that all constructs had satisfactory reliability and validity.

We assessed discriminant validity following the criteria that Fornell and Larcker (1981) proposed, whereby we compared the square root of the average variance extracted (AVE) with the inter-construct correlations. As Table 2 shows, the square root of the AVE of each construct exceeded its correlations with other constructs, which indicates adequate discriminant validity.

Table 1. Construct Reliability and Validity

Constructs	Item	Loading	CR	FVIF	Norm
Social Media Addiction	SMA1	(0.868)	0.897	1.339	No
	SMA2	(0.875)			
	SMA3	(0.844)			
Inattention	IA1	(0.837)	0.860	NA	No
	IA2	(0.819)			
Unawareness	UA1	(0.819)	0.864	NA	Yes
	UA2	(0.849)			
Distraction	D1	(0.975)	0.974	NA	No
	D2	(0.973)			
Unverified Information Sharing	UIS1	(0.834)	0.895	1.789	No
	UIS2	(0.883)			
	UIS3	(0.867)			
Wellbeing Status	WB1	(0.664)	0.881	1.331	Yes
	WB2	(0.611)			
	WB3	(0.664)			
	WB4	(0.688)			
	WB5	(0.752)			
	WB6	(0.800)			
	WB7	(0.713)			
	WB8	(0.653)			

Notes: All loadings and cross-loadings appear in the third, fourth, fifth, and sixth columns. All loadings, in parentheses, were significant at $p < 0.001$.
CR = composite reliability, FVIF = full collinearity variance inflation factor, Norm = normal (robust Jarque-Bera), SMA = social media addiction, IA = inattention, UA = unawareness, D = distraction, UIS = unverified information sharing, WB = wellbeing status.

Table 2. Inter-construct Correlation Matrix

	SMA	IA	UA	D	UIS	WB
SMA	(0.863)					
IA	0.129	(0.869)				
UA	0.145	0.823	(0.872)			
D	0.327	0.263	0.253	(0.974)		
UIS	0.362	0.186	0.206	0.148	(0.862)	
WB	-0.061	-0.331	-0.259	-0.062	-0.344	(0.695)

Note: Square roots of average variances extracted (AVE) appear on the diagonal within parentheses.
SMA = social media addiction, IA = inattention, UA = unawareness, D = distraction, UIS = unverified information sharing, WB = wellbeing status.

Common method bias (CMB) occurs when researchers collect data through only one method (e.g., survey). Since we collected data through the survey method, we assessed CMB using a conservative approach Kock (2015) proposed that depends on model-wide collinearity (Kock & Lynn, 2012). As recommended, all full collinearity variance inflation factors (FVIFs), which one can see in Table 1, did not exceed the threshold value (i.e., 5) (Hair et al., 2010). As such, common-method bias did not pose a threat in the study.

As Bera and Jarque (1981) and Gel and Gastwirth (2008) advised, we also measured multivariate normality (see Table 1). As Table 1 shows, some constructs did not meet the normal distribution condition and, thus, justified our decision to use PLS-based SEM.

4 Results

4.1 Hypothesis Testing Results

To test our proposed research model, we report standardized beta coefficients and the explanatory power (R^2). Figure 2 shows that we found support for all hypotheses. The model explained 28 percent of the variance in unverified information sharing and 20 percent of the variance in absentmindedness.

Social media addiction had a significant impact on unverified information sharing (β = 0.27, $p < 0.001$), which supports H1. Similarly, social media addiction significantly affected absentmindedness (β = 0.36, $p < 0.001$), which supports H2. Absentmindedness significantly affected unverified information sharing (β = 0.22, $p < 0.001$), which supports H3. Furthermore, wellbeing status significantly weakened the relationship between social media addiction and unverified information sharing (H4.1) (β = -0.14, $p < 0.05$) and weakened the relationship between social media addiction and absentmindedness (H4.2) (β = -0.20, $p < 0.001$). Figure 2 and Table 3 summarize the results.

We also controlled for the possible effect that several demographic characteristics (age, gender, education level, marital status, and employment type) could have on the dependent variables in the research model. We found that the female gender (β = -0.31, $p < 0.01$) had a significant effect on unverified information sharing, while age (β = -0.30, $p < 0.01$) had a significant effect on absentmindedness. We also controlled for how much time people spent on social media, but the result did not reach statistical significance (β = 0.09, $p > 0.05$). Hence, our results hold regardless of how much time people spend using social media.

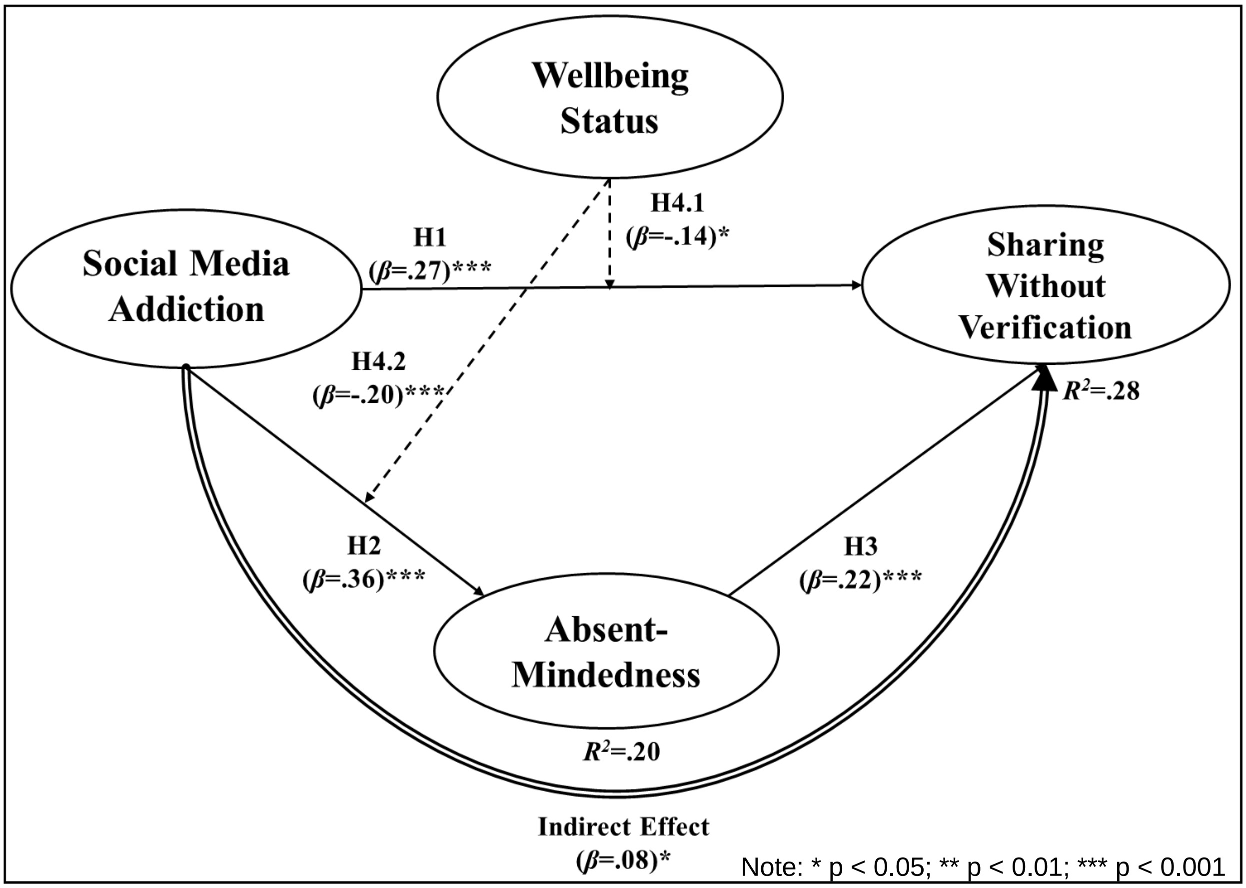

Figure 2. Model with Results

Table 3. Hypotheses Results

Hypothesis	Hypothesized relationship	Supported?
H1	Social media addiction increases unverified information sharing.	Yes
H2	Social media addiction increases absentmindedness.	Yes
H3	Absentmindedness increases unverified information sharing.	Yes
H4.1	Wellbeing status weakens the effect of social media addiction on unverified information sharing.	Yes
H4.2	Wellbeing status weakens the effect of social media addiction on absentmindedness.	Yes

We also evaluated the mediating effects of absentmindedness on the relationship between social media addiction and unverified information sharing using Preacher and Hayes' (2004) method for testing mediation. Table 4 presents the results. We found that social media addiction significantly affected absentmindedness, which, in turn, had a significant impact on unverified information sharing. Hence, absentmindedness partially mediated the relationship between social media addiction and unverified information sharing, which indicates that social media addiction impacts unverified information sharing directly and indirectly via absentmindedness.

Table 4. Analysis of Mediating Effects

Independent variable	Mediator	Dependent variable	Direct effect	Indirect effect	Total effect	Mediation
SMA	AM	UIS	0.27***	0.08*	0.35***	Partial

Note*:* SMA = social media addiction, AM = absentmindedness, UIS = unverified information sharing.
** P < 0.01; *** P < 0.001.

5 Discussion

In this study, we investigate the link between social media addiction and unverified information sharing using dual system and salience theories. Based on the empirical analysis, we found that social media addiction indeed influences unverified information sharing. In particular, we found that social media addiction increases absentmindedness as well as unverified information sharing. Overall, the theoretical research model explains a significant proportion of the variance in unverified information sharing (28%).

H1 and H2 state that social media addiction increases unverified information sharing and absentmindedness, respectively, and we found support for both hypotheses. H3 indicates that absentmindedness increases unverified information sharing, which we also found support for. Finally, H4.1 and H4.2 state that wellbeing status weakens the effect of social media addiction on unverified information sharing and absentmindedness, respectively. We found support for both hypotheses.

Additional exploratory analysis indicated that gender significantly impacted unverified information sharing, suggesting that females are less likely than their male counterparts to share information without verifying it. This finding concurs with previous research that found females are less likely to share unverified information (Laato et al., 2020). Our finding that gender has a role in unverified information sharing may also relate to evidence showing that females tend to be the victims of receiving unverified information (Oates et al., 2019). Moreover, these findings suggest a probable explanation for the differences in unverified information sharing by gender. On the other hand, age as a control variable had a negative effect on absentmindedness, which suggests younger individuals are more likely to be absentminded (i.e., careless or mindless) than their older counterparts. This result concurs with the literature that has found age to relate negatively to absentmindedness (Reb et al., 2015).

People could manage their social media addiction in different ways, such as by establishing self-control mechanisms for social media usage (e.g., adhering to a certain number of hours per day for social media use) and setting a maximum number of social media visits per day. According to our findings, wellbeing represents another mechanism that can help people control the harmful effects of both social media addiction and absentmindedness. With high wellbeing levels, people can critically process and verify information before disseminating it to others via social media.

On the other hand, one may expect people with low wellbeing not to be able to make the proper judgment regarding information's quality and authenticity and then to disseminate it without verifying it. However, social media platform providers could help their users in this regard by, for example, using AI in such a way that it could assess users' health status by asking a few health-related questions or recording some bio-vital signs such as heart rate, blood pressure, or eye strain. Based on these measurement values, social media platforms could intervene by warning users and recommending that they stop using the platforms or take a break.

5.1 Research Contributions

Our study advances the IS literature on technology addiction and unverified information sharing. To date, we know little about the link between technology addiction and unverified information sharing. To our knowledge, this study represents the first effort in the IS field to investigate the link between social media addiction and unverified information sharing. We offer a theoretical explanation and empirical support for social media addiction's impact on unverified information sharing based on dual-system theory (Kahneman, 2011; Wason & Evans, 1974) and Bordalo et al.'s (2012) salience theory. Hence, we extend the prior literature (Khan & Idris, 2019; Laato et al., 2020; Talwar et al., 2019) by identifying social media addiction as another main antecedent of unverified information sharing on social media.

We highlight the interplay between System 1 and System 2 thinking and extend dual-system concepts to social media addictive behavior and information-sharing decision choices. Specifically, we argue that social media's addictive features often stimulate users to rely on System 1 (quick, automatic, and cognitively undemanding) rather than System 2 (slow, analytical, and cognitively demanding) thinking for evaluating messages that they receive before sharing them. We found that social media addiction affects unverified information sharing by depleting attention resources (which contributes to absentmindedness); in other words, social media addiction influences unverified information sharing partly through augmenting absentmindedness. Social media's features, such as signals and sounds, and the various information streams it offers (e.g., about events, rumors, and news), may tax addicted users' cognitive abilities and divert their focus from other crucial tasks. Specifically, the complex nature of information in social media strains their information-filtering function, which may hinder their attentive cognition and decision-making capacity. We believe that, in offering this novel explanation for why people share information without verifying it, we extend dual-system theory and salience theory into the IS realm and, thus, increase theoretical diversity in technology addiction research (Turel & Qahri-Saremi, 2016).

Based on our unique theoretical approach, we identified a novel link between social media addiction and unverified information sharing. In particular, we found that absentmindedness is an intervening mechanism through which social media addiction leads to negative consequences, particularly increased unverified information sharing. Furthermore, we identified wellbeing status as a significant moderating factor that fosters System 2 thinking. It modifies the relationships between social media addiction and unverified information sharing and between social media addiction and absentmindedness. We also found that wellbeing status reduces the harmful impact of social media addiction on users' unverified information sharing and absentmindedness. We attribute this finding to high wellbeing helping people overcome social media addictive harm by restoring their attention and cognitive capacity (i.e., System 2), allowing them to make better decisions (Gill et al., 2018; Kaplan & Kaplan, 1989; Páez-Gallego et al., 2020) when deciding whether to verify the information before sharing it. Then, users can assess and process social media information more accurately.

5.2 Practical Contributions

Our findings present several practical implications for policymakers, managers, software developers, and those who frequently communicate using social media. First, many policymakers recognize the challenges of disseminating accurate information and combating the increasing tendency for people to share information without verifying it. Our study reveals a link between social media addiction and unverified information sharing. Therefore, policymakers could consider introducing programs designed to reduce social media addiction. By informing policymakers and managers about the consequences of social media addiction (e.g., that it depletes attentional resources by augmenting absentmindedness and leads to increased unverified information sharing), we hope to inspire them to develop guidelines and interventions to mitigate the negative consequences of social media addiction. Policymakers and social media providers could prepare these guidelines and interventions in collaboration to ensure they are included on platforms. For example, social media providers could track visit logs and generate periodic reports on how long people spend on their platforms and the frequency of their visits.

Additionally, guidelines on the proper or appropriate usage of social media at work would include how many minutes employees are allowed to use social media and specific platform features. Also, as some interest groups share unverified information more frequently, perhaps existing training has not reached or resonated with these groups. We recommend that relevant parties develop targeted awareness campaigns and training for these groups. Hence, organizations could use our findings to train users to consume social media sustainably and avoid harms associated with social media addiction. Similarly, social media companies could play a role in curbing people's ability to spread false or unverified information by limiting the frequency with which they can do so.

Second, professionals who frequently engage in social media to promote themselves or their organizations also benefit from our findings. Unfortunately, a propensity to work with social media can often lead to addiction. However, to protect one's reputation or that of employers, these professionals benefit from being mindful of the effects of social media addiction on unverified information sharing. Such individuals can benefit from information literacy programs (e.g., Coursera's Information and Digital Literacy for University Success) to reduce their beliefs about the reliability of information on social media. Alternatively, completing fact-checking courses (e.g., Poynter's Hands-On Fact-Checking or Udemy's Fact-Checking Made Easy) may motivate people to verify information more frequently.

Third, for general social media users, we explain when and how social media addiction influences unverified information sharing. This knowledge may make social media users more self-aware of their behaviors (i.e., addictive social media use and unverified information sharing). Such awareness may help affected individuals reverse their maladaptive habits (Ladouceur, 1979). Hence, by exploring mediating and moderating mechanisms that juxtapose when and how social media addiction can fuel unverified information sharing, policymakers can devise interventions described above to mitigate the negative effects of social media addiction on unverified information sharing.

Finally, our findings provide social media platform developers insights into reducing unverified information sharing. Social media platform operators often face criticisms for not doing enough to combat the spread of unverified information (Murphy et al., 2019). Our findings suggest that social media platform operators could filter content (especially when information accuracy is a priority, such as information related to health, finances, or national security). Moreover, our findings suggest that platform operators, who are well equipped to determine potential addiction, could present notifications about reducing social media addiction through AI to generate alerting messages, a daily activity report on social media usage, and potential negative impacts on the user's health conditions. However, as such actions could hinder these platforms' revenue-growth strategy, our results suggest focusing on improving users' wellbeing by providing content and platform features such as controlling how many hours people can use such platforms, giving feedback on the health status through vital sign measures, and sharing valuable content (e.g., daily health tips). These additions could—beyond reducing addictive usage—enable social media providers to offer better services for their users, which could, in turn, increase their revenue by, for example, imposing fees on certain services or features (e.g., blue tag for Metaverse verified payments). Social media platform providers must also live up to their social responsibility toward their users and societies. Hence, from a practical perspective, policymakers, managers, healthcare professionals, and individuals must be aware of the important role of wellbeing status among addicted social media users and its likely ability to buffer or reduce the harmful effects of social media addiction on absentmindedness and unverified information sharing.

5.3 Limitations and Future Research

As with any study, our study has several limitations. First, the cross-sectional and self-reported nature of the data could limit the generalizability of our findings and the ability to infer causal relationships. Hence, future efforts should consider using a longitudinal data-collection approach. Second, we examine unintentional unverified information sharing. However, as people satisfy their addiction through increased social media engagement, it may increase the potential for them to engage in intentional unverified information sharing. Therefore, future studies should explicitly examine the effects of social media addiction on the spread of misinformation and disinformation (Hernon, 1995; Wu et al., 2019). Third, we conducted this research in a developing country. As a result, we call for researchers to conduct similar studies in developed countries and make comparisons. For instance, researchers could conduct comparative studies with other social media platforms such as X, Facebook, and TikTok. Fourth, questions about addiction, unverified information sharing, and absentmindedness may be subject to social desirability. We expect that guaranteeing anonymity and being unable to attribute individual responses helped reduce social desirability bias (Singleton & Straits, 2005). However, future studies could include the social desirability bias measure as a control variable.

6 Conclusion

In this paper, we use the dual system and salience theories as the lens to examine the link between social media addiction and unverified information sharing, the intervening mechanism (absentmindedness) through which this link occurs, and the moderating role of wellbeing status in modifying the relationships. We found that social media addiction impacted unverified information sharing and that it did so partly through augmenting absentmindedness. According to dual-system theory, addicted social media users rely on System 1 thinking and fail to evaluate messages before sharing them. Along the same reasoning and according to salience theory, addicted users focus their attention on social media's addiction-related attributes that they regard as more salient than verifying information before sharing it. In particular, we found that social media addiction significantly predicted unverified information sharing. Due to their shallow and broad cognitive patterns in processing the information and System 1 thinking's dominance, addicted social media users are less likely to make decisions to authenticate information before sharing it. Finally, based on dual-system theory and salience theory, we identified a relevant contextual factor—wellbeing status—that stimulated System 2 thinking and buffered or moderated the harmful impact of social media addiction on absentmindedness and unverified information sharing. Therefore, our findings significantly advance research on social media addiction and unverified information sharing by theoretically explaining how (through which mechanism) and when (under what condition) social media addiction impacts unverified information sharing.

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Appendix A

Table A1. Measurement Instrument

	M	SD	Items (strongly disagree / strongly agree: five-point Likert scale)	Source
Unverified information sharing	1.82	0.97	In the last 10 days, at least once I shared information about Coronavirus from WhatsApp without reading the whole article	Khan & Idris (2019)
	1.74	0.96	In the last 10 days, at least once I shared information about Coronavirus from WhatsApp without verifying its truth	
	1.68	0.89	In the last 10 days, at least once I shared information about Coronavirus that later I found out as a hoax/fake	
Social media addiction	2.57	1.09	I have made unsuccessful attempts to reduce the time I interact with my WhatsApp	Charlton (2002), Moqbel & Kock (2018)
	2.46	1.28	Arguments have sometimes arisen at home because of the time I spend on my WhatsApp	
	2.26	1.22	I think that I am addicted to WhatsApp	
Wellbeing status	4.02	0.68	I lead a purposeful and meaningful life	Diener et al. (2010)
	3.77	0.76	My social relationships are supportive and rewarding	
	3.92	074	I am engaged and interested in my daily activities	
	3.97	0.69	I actively contribute to the happiness and wellbeing of others	
	4.15	0.61	I am competent and capable in the activities that are important to me	
	4.20	0.69	I am a good person and live a good life	
	4.12	0.80	I am optimistic about my future	
	4.33	0.61	People respect me	
Construct	**M**	**SD**	**Items (almost never / almost always: five-point Likert scale)**	**Source**
Inattention	2.46	1.03	I rush through activities without being really attentive to them	Brown & Ryan (2003)
	2.31	1.13	I find myself doing things without paying attention	
Unawareness	2.59	1.07	It seems I am “running on automatic” without much awareness of what I’m doing	
	2.22	1.03	I do jobs or tasks automatically, without being aware of what I’m doing	
Construct	**M**	**SD**		**Source**
Distraction	3.95	2.73	**Items (10-point Likert scale with anchors 1= “a lot of attention” and 10 = “extremely no attention.”** How much attention are you able to pay to job tasks while using WhatsApp?	Zwarun & Hall (2014)
	3.66	2.42	**Items (10-point Likert scale with anchors 1= “extremely distracted” and 10 = “not distracted at all” (reversed))** How distracted do you feel because of WhatsApp while performing your job tasks?	

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