Fear of missing out is associated with disrupted activities from receiving smartphone notifications and surface learning in college students

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Abstract

Digital technologies, such as smartphones and tablets, can be useful in academic settings by allowing browsing for additional information, organizing the study process online, and facilitating communication between peers and instructors. On the other hand, several recent studies have shown that digital technology use can, in some circumstances, be negatively related to academic outcomes for some individuals. Fear of missing out (FOMO) could be one of these factors causing individual differences in how frequently people receive and react to interruptive notifications (INs). The aim of this study was to investigate how FOMO, the frequency of receiving INs, and stopping current activities due to INs, is associated with a surface approach to learning. Three hundred and sixteen U.S. university students responded to a web survey that included items regarding experiencing FOMO, the frequency of receiving INs and daily activity disruptions due to INs, and surface learning. Results showed that FOMO was associated with daily disrupted activities due to INs and surface learning, but not the frequency of receiving INs. Mediation analysis showed that the association between FOMO and surface learning was mediated by the frequency of daily disrupted activities due to INs. However, the nature of the sample somewhat restricts the generalizability of these results. The findings, their implications, and future directions are discussed.

Keywords: fear of missing out; FOMO; interruptive notifications; pop-up notifications; surface approach to learning

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1. Introduction

In addition to providing improved means for entertainment and social communication, digital technologies, such as the Internet, computers, and smartphones, may improve productivity in educational contexts. Browsing for additional information, and the possibility to discuss study materials with peers over social networking sites (SNSs), may help increase student engagement and learning in some situations (Lester & Perini, 2010). However, the ubiquity of these technologies, both inside and outside of the classroom, may actually interfere with learning for certain students. Indeed (excessive) use of digital technologies can be associated with poorer academic outcomes (Felisoni & Godoi, 2018; Kates, Wu, & Coryn, 2018; Lepp, Barkley, & Karpinski, 2015; Rozgonjuk & Täht, 2017; Wammes et al., 2019). As a result, there is a critical need to examine factors that link the use of digital devices and reduced academic achievement, both to determine which types of students might be most at risk, and to identify ways to mitigate this risk. In response, this paper investigates whether students who are fearful of missing out on social information are more inclined to interrupt their daily activities to attend to smartphone notifications, and whether this inclination is related to use of less effective learning strategies. We have posed three hypotheses (see section 4. Aims and hypotheses), outlining the expected relationships based on previous empirical findings and theoretical frameworks, discussed below. Although a convenience sample of students from a single U.S. university is used, the findings could be at least partially applicable to college students in general.

2. Literature review

One of the key attitudinal constructs relevant to academic achievement is the thoroughness and mindfulness of students' learning processes. Among the better known constructs in this area are deep and surface approaches to learning (Asikainen & Gijbels, 2017; Marton & Säljö, 1976). While the former involves learning material so that it is fully understood, the latter could be characterized as a superficial and instrumental approach, which is typically incentivized by external factors such as grades (Biggs, Kember, & Leung, 2001; Dolmans, Loyens, Marcq, & Gijbels, 2016). Adopting a deep approach to learning is beneficial, as it facilitates critical thinking, creativity, synthesis of information, curiosity, and helps in associating one's life experiences with learned materials (Chin & Brown, 2000; Hoeksema, 1995; Rogaten, Moneta, & Spada, 2013; Warburton, 2003). On the contrary, students who use surface learning approaches tend to put minimal effort into studying, and commonly learn only obligatory materials, isolated facts, details, and examples without attempting to synthesize the information (Biggs et al., 2001; Rogaten et al., 2013). Unsurprisingly, deep approaches to learning are associated with better academic outcomes, while surface approaches are related to poorer academic outcomes (Arquero, Fernández-Polvillo, Hassall, & Joyce, 2015; Heikkilä & Lonka, 2006; Salamonson et al., 2013).

Although there is growing potential in applying digital devices to classroom work, there has been scant research investigating the link between use of digital devices and deep and surface learning approaches. Given the established association between lower academic outcomes and surface learning, coupled with the increasing ubiquity of digital devices in classrooms, this is arguably an important area of inquiry. Of the few studies conducted thus far, results have demonstrated that surface learning is positively correlated with (excessive) smartphone and Internet use (Alt & Boniel-Nissim, 2018a; Loredo, de Souza Matos, da Silva Ezequiel, Lucchetti, & Lucchetti, 2018; Rozgonjuk, Saal, & Täht, 2018). Furthermore, it has been proposed that this relationship may be driven by SNS use (Rozgonjuk, Saal, et al., 2018), and fear of missing out (Alt & Boniel-Nissim, 2018a).

Fear of missing out, or FOMO, has been defined as “a pervasive apprehension that others might be having rewarding experiences from which one is absent”, and is viewed as a trait-like dispositional characteristic. (Przybylski, Murayama, DeHaan, & Gladwell, 2013, p. 1841). Contemporary digital technologies provide ubiquitous access to SNS, where users’ social circles continuously display and update their experiences, often in real-time. Thus, FOMO could be easily driven by this constant news feed, and potentially compel users to engage in more frequent technology use. Several recent studies have demonstrated a relatively strong link between FOMO and problematic smartphone and Internet use (Alt & Boniel-Nissim, 2018a, 2018b; Elhai, Levine, Dvorak, & Hall, 2016; Gezgin, 2018; Wolniewicz, Tiamiyu, Weeks, & Elhai, 2018).

However, few studies have thus far investigated the role of interruptive notifications (IN), also known as pop-up or push notifications, in the relationship between surface learning and levels of FOMO. These notifications are information-based alerts sent to a user to provide real-time updates relating to an event or other information, such as a new chat message, system update/alert, etc. (Paul, Komlodi, & Lutters, 2015). Because the function of INs is to immediately draw the smartphone user’s attention to inform them of updated content or actions, they have the potential to disrupt user attention while performing a task or are engaged in an activity – such as studying. While there have not been many studies investigating the distracting role of INs, some initial results indicate that they are associated with detrimental effects on work performance (Bailey & Konstan, 2006) and attention, potentially resulting in hyperactivity symptoms (Kushlev, Proulx, & Dunn, 2016; Stothart, Mitchum, & Yehnert, 2015). Therefore, we propose that there is value in investigating the interplay between INs, FOMO, and adopting a surface approach to learning.

3. Theory

Self-determination theory (SDT; Ryan & Deci, 2000) is a commonly used theoretical framework to conceptualize FOMO (Alt, 2015; Przybylski et al., 2013). SDT focuses on human motivation and innate needs, and it differentiates between intrinsic and extrinsic motivation. While the latter is characterized by the tendency to engage in activities associated with external reward (e.g., working for pay), intrinsic motivation is associated with activities that provide intrinsic rewards, such as internal satisfaction and enjoyment (e.g., playing videogames because they are fun). Relevant to FOMO, one pivotal driver of intrinsic motivation is social relatedness, or the need for socialization and human connection. Experiencing negative affect due to one's unmet social relatedness needs could be viewed as FOMO within the SDT framework (Elhai, Levine, et al., 2018; Przybylski et al., 2013). In other words, those who experience more FOMO have higher unmet social relatedness needs. In order to meet these unmet needs, these individuals may engage in more technology use to be "up-to-date" with their social network.

However, because being attentive to one's social network requires attention and concentration, it may be cognitively demanding and disruptive. Cognitive psychological theories may be helpful in conceptualizing the role of INs in the potential FOMO-surface approach to learning relationship. According to the Threaded Cognition Model (TCM; Salvucci & Taatgen, 2008), different cognitive tasks are associated with separate cognitive, perceptual, and motor resource "threads". Because some resources, such as attention and working memory, are finite, conducting multiple simultaneous tasks (or switching between tasks) that require the same thread may lead to disruption and poorer performance of either one or both tasks. For example, when cognitive resources are being used for a learning related task (e.g., studying for a test), INs competing for cognitive resources may interfere with and disrupt performance on that task. Therefore, when individuals are inclined to prefer IN content over the learning related task, and they receive a high frequency of INs, they may necessarily need to adopt a surface learning approach to compensate for the decreased cognitive resources they have available. TCM has been adopted in recent interruptions-related research (Örün & Akbulut, 2019; Wilson, Farrell, Visser, & Loft, 2018), and provides a useful theoretical framework for the present study.

4. Aims and hypotheses

The main goal of this study is to fill the gap in research by investigating INs in the relationship between FOMO and surface learning. We posed the following hypotheses:

H1: FOMO is positively related to interruptive notification frequency (H1a) and disrupted daily activities due to notifications (H1b). People who have higher levels of FOMO may logically prefer receiving more INs, and to want to react to them immediately. It is possible that, in an attempt to stay constantly updated, individuals with higher levels of FOMO may turn on or activate more INs than individuals with lower levels of FOMO. As such, these individuals may receive a higher frequency of INs. Furthermore, because information contained within INs may involve social relatedness needs (e.g., notifications about text messages, updates and SNS, etc.), individuals with higher levels of FOMO may more likely attend to those INs. Furthermore, this may lead these individuals to stop a task at hand in order to react to the displayed IN.

H2: FOMO is positively correlated with surface learning. This hypothesis is confirmative, based on previous research which associated higher levels of FOMO with surface learning (Alt & Boniel-Nissim, 2018a).

H3: *The frequency of disrupted daily activities due to notifications mediate the relationship between FOMO and surface learning.* This hypothesis stems from TCM. Assuming that people who experience higher levels of FOMO also receive and engage with more INs, they may be prone to multi-tasking and task-switching. Because this behavior may disrupt other tasks that involve cognitive resources (e.g., studying), individuals with higher levels of FOMO may also be more likely to adopt surface learning approaches.

5. Methods

5.1. Sample, procedure, and measures

Participants were 316 psychology undergraduate students from a Midwestern American university (M_{age} = 19.21, SD_{age} = 1.74; 66.8% were female) who completed a web survey administered through the psychology department's research platform. Data collection took place from September 2018 to February 2019. This study was approved by the university's Institutional Review Board.

The majority of participants identified as Caucasian (n = 238; 75.3%), African American (n = 60; 19.0%), Asian (n = 15; 4.7%), and Hispanic (n = 15; 4.7%); designations were not mutually exclusive. Most participants also reported working, either part-time (n = 164; 51.9%) or full-time (n = 32, 10.1%).

The web survey consisted of the following questionnaires:

Socio-demographics items asking about age, sex, and other relevant demographics.

The Fear of Missing Out (FoMO) scale (Przybylski et al., 2013) is a 10-item measure reflecting apprehension of missing out on experiences involving one's friends and their rewarding experiences. The scale is uni-dimensional and item ratings vary from 1 = *not at all true of me* to 5 = *extremely true of me*. The measure has shown good internal consistency and is positively related with SNS engagement, and negatively related with life satisfaction. Cronbach's alpha for our effective sample is .89.

The Surface approach to learning subscale from the **Revised Study Process Questionnaire** (R-SPQ-2F; Biggs et al., 2001) is a 10-item scale reflecting a student's surface learning approach. Items are measured on a 5-point scale (1 = *never or only rarely true of* me to 5 = *always or almost always true of me*). The scale could be treated as onedimensional. Alternatively, two subscales involve learning due to fear of failure ("surface motive") and rote learning ("surface strategy"); Cronbach's alphas are adequate for these subscales (Biggs et al., 2001), and the total scale (Martinelli & Raykov, 2017). For this study, the alphas for the subscales are .75 and .73, respectively, and .86 for the uni-dimensional scale.

IN frequency scale is a 10-item self-report scale that measures frequency of receiving different types of pop-up notifications on one's smartphone (or smartwatch). INs were defined to participants as follows: "Pop-up notifications are information alerts that intend to actively draw your attention in order to inform you of a new event or information, such as a new chat message, system update/alert, etc. They appear prominently on-screen as a pop-up alert or banner in the foreground; not just as a number indicator in the background." This measure was adapted from the Smartphone Use Frequency Scale (Elhai et al., 2016) (SUFS), and smartphone features listed in SUFS were used to ask about notifications from these features. Some examples include pop-up notifications from voice/video call, texting/instant messaging, and system updates/alerts. The scale ranges from 1 = *never* to 6 = *very often*. Internal consistency of the effective sample was .76.

Daily activity disruptions from INs is a 20-item list of leisure and work related activities based on previous work (Kahneman, Krueger, Schkade, Schwarz, & Stone, 2004; Kushlev et al., 2016). Participants were asked "How often do you stop or pause the following activities when you receive a pop-up notification on your smartphone (or smartwatch)?". They were then presented with the list of activities (Paul et al., 2015). Based on the frequency of disruption occurrence, ratings ranged from 1 = *never* to 6 = *very often*. Sample activities include intimate relations, eating, exercising, and working for pay. It has previously been found that more IN-related disruptions correlated with hyperactivity symptoms (Kushlev et al., 2016). Internal consistency in our study was .91.

5.2. Analysis

For our analyses, we used R version 3.5.2 (R Core Team, 2019) for descriptive and correlational analyses, and Mplus version 8 (Muthén & Muthén, 1998-2019) for measurement models using confirmatory factor analysis (CFA), and structural equation modeling (SEM). The few instances of missing data were imputed using the *mice* package (van Buuren & Groothuis-Oudshoorn, 2011) in R.

Firstly, we conducted a series of CFAs for each scale subsequently used in SEM (see Figure 1). All item-level data were treated as ordinal, using probit loadings and a polychoric covariance matrix; we used weighted least squares estimation with a mean- and variance-adjusted chi-square, or WLSMV (DiStefano & Morgan, 2014). All scales were modeled as uni-dimensional.

Using SEM, surface learning was treated as the outcome, FOMO as the predictor of surface learning, and IN-related daily disruptions frequency as the mediator between those two variables. Additionally, frequency of INs was a covariate of activity disruptions frequency; participants' age and sex were treated as covariates of surface learning. Age and sex covariation was fixed to zero. We used the same methods for model parameter estimation as in CFAs.

Common benchmarks to assess goodness of fit in both CFA and SEM were implemented: the comparative fit index (CFI > .95), Tucker-Lewis Index (TLI > .95), and root mean square error of approximation (RMSEA < .06) (Hu & Bentler, 1999).

Mediation, or the indirect effect, was tested by computing cross-products of direct path coefficients. The Delta method with 1000 non-parametric bootstrapped replications was used for estimating the standard error for the mediation effect (Hayes, 2017).

6. Results

Descriptive statistics and correlations are presented in Table 1.

Table 1.

Descriptive statistics and correlations between key variables.

	M	SD	Min	Max	1	2	3	4
1. FOMO	22.59	8.57	10	50	-			
2. Surface	24.7	7.69	10	49	.173*	-		
3. INF	34.92	7.91	10	57	.041	.050	-	
4. DAD-IN	66.60	17.66	20	120	.377***	.192*	.287***	-
Age	19.21	1.74	18	30	.006	.153	-.012	-.025
Sex	-	-	-	-	-.008	-.097	.113	.082

Notes. N = 316. α = Cronbach's alpha. FOMO = fear of missing out; Surface = surface approach to learning; INF = interruptive notification frequency; DAD-IN = daily activity disruptions from interruptive notifications. * $p < .05$, ** $p < .05$, *** $p < .001$.

Bivariate results show that FOMO had a positive correlation with surface learning (small effect) and with IN-related activity disruptions (medium effect). Surface learning was also positively correlated with IN-related activity disruptions (small effect). Although frequency of receiving INs was associated with IN-related activity disruptions (small effect), frequency of receiving INs did not correlate with other variables. Age and sex did not have a statistically significant relationship with other measures.

We then tested measurement models for FOMO, surface learning, and IN-related scales. The initial, uni-dimensional FOMO model did not result in a good fit, MLR $\chi^2(35, N = 316) = 598.518$, $p < .001$, CFI = .876, TLI = .840, RMSEA = .226 (90% CI: .210 to .242). However, modification indices suggested including a covariation between two item pairs: a) "I fear others have more rewarding experiences than me" and "I fear my friends have more rewarding experiences than me", and b) "It bothers me when I miss an opportunity to meet up with friends" and "When I miss out on a planned get-together it bothers me". The two items within each pair are extremely conceptually similar. Therefore, we included residual covariances of these two item pairs in the FOMO CFA model. The resulting model fit improved: WLSMV χ^2(33, N = 316) = 155.527, $p < .001$, CFI = .973, TLI = .963, RMSEA = .108 (90% CI: .092 to .126). Standardized factor loadings for this model ranged from .607 to .894.

We next modeled surface learning as uni-dimensional. This model did not demonstrate good fit, WLSMV χ^2(35, N = 316) = 282.018, $p < .001$, CFI = .898, TLI = .869, RMSEA = .149 (90% CI: .134 to .166). Finally, poor model fit was also observed for IN frequency scale, WLSMV χ^2(35, N = 316) = 323.116, $p < .001$, CFI = .768, TLI = .701, RMSEA = .161 (90% CI: .146 to .178), and IN-related daily disruptions, WLSMV χ^2(170, N = 316) = 1391.587, $p < .001$, CFI = .800, TLI = .776, RMSEA = .151 (90% CI: .144 to .158). The sums of these scales were modeled as observed variables in SEM.

Subsequently, the full SEM model, depicted in Figure 1, was tested. The model showed good fit, WLSMV χ^2(86, N = 316) = 183.775, $p < .001$, CFI = .980, TLI = .976, RMSEA = .060 (90% CI: .048 to .072). Figure 1 includes standardized path coefficients. It can be observed that FOMO is not significantly associated with surface learning in multivariate analysis. However, IN-related daily disruptions are positively associated with FOMO and surface learning, and IN frequency predicts daily disruptions. Participants' age was positively correlated to surface approach to learning, but sex did not predict that variable.

We also tested for a mediation effect where FOMO would predict IN-related daily disruptions, and that variable, in turn, predicts surface learning. The indirect effect was significant, $\beta = .066$, SE = .031, $z = 2.112$, $p = .035$.

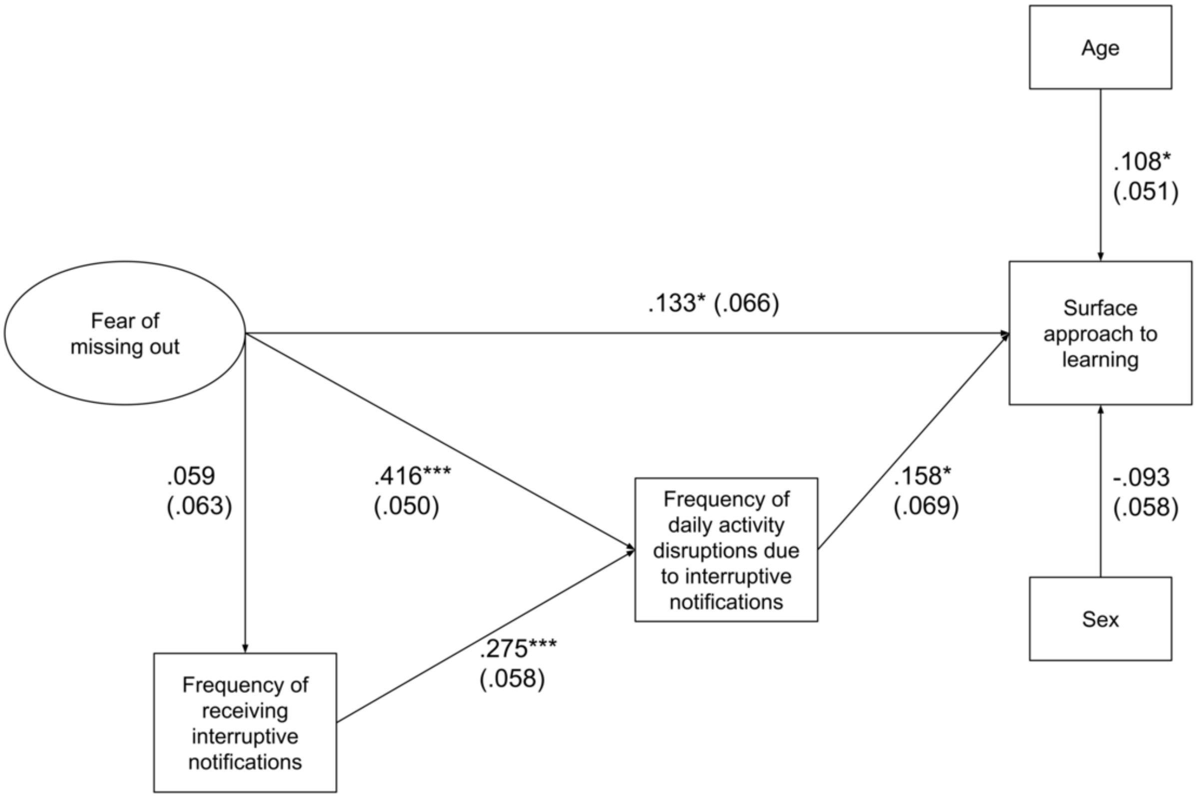

Figure 1. The results of SEM model. *Notes*. * p < .05, ** p < .05, *** p < .001.

7. Discussion

Several studies have previously demonstrated the potential negative association between digital technology use and academic outcomes (Chen & Peng, 2008; Junco, 2012; Kates et al., 2018; Lepp et al., 2015; Rozgonjuk & Täht, 2017; Wammes et al., 2019). Driven by this, recent studies have examined factors that may play a role in this relationship. Among these factors are approaches to learning, or the interplay between a student's strategic and motivational attitudes towards studying. While studies have shown that (excessive) digital technology use is associated with surface learning (Alt & Boniel-Nissim, 2018a; Loredo et al., 2018; Rozgonjuk, Saal, et al., 2018), it is not quite clear what drives that relationship. INs could, in some individuals, be a crucial element associated with poorer academic outcomes. Specifically, in this study, we believe that those individuals who experience higher levels of

FOMO could have an increased risk of receiving more INs, and interacting with them at the expense of other learning related tasks. This could thus result in adoption of surface learning approaches. Therefore, the main aim of the study was to investigate the role of INs in relation to FOMO and surface learning.

We posed three hypotheses. First, we expected that individuals with higher levels of FOMO would report receiving more INs (H1a) and to react more to their content, which would be reflected in frequency of disrupted daily activities (H1b). The first hypothesis was partially supported. FOMO was not associated with frequency of receiving INs, but it had a medium-sized correlation with frequency of daily activity disruptions. Furthermore, disruptions caused by INs were associated with frequency of receiving INs. This indicates that users with higher levels of FOMO may not necessarily activate more INs for their apps. This is somewhat consistent with previous literature showing that most people do not modify their IN settings, and do not pay much attention to INs while installing and setting up smartphone applications (Voit, Henze, & Weber, 2018; Westerman, Wechsung, & Möller, 2015). While individuals with higher levels of FOMO do receive INs, they tend to interact with those notifications by disrupting their current activity. These results might also be informative in media multi-tasking studies, showing that switching between or engaging in several tasks is associated with poorer academic outcomes (Hawi & Samaha, 2016; Wammes et al., 2019). Because smartphones, tablets, and laptops provide the possibility to engage in different tasks, it could be that notifications received from them may disrupt other activities – such as doing homework.

Our second hypothesis proposed that there would be a positive association between FOMO and surface learning (H2). This hypothesis was supported, albeit the effect size was rather small, and these findings are coherent with previous research (Alt & Boniel-Nissim, 2018a). Perhaps people who are more concerned about missing out on their social circle’s experiences may not fully attend to studying, and focus instead on INs which represent potential social and interpersonal experiences and opportunities. Prior work found that problematic smartphone use, a construct consistently related to FOMO (Elhai, Levine, et al., 2018; Elhai et al., 2016), is associated with surface learning, and SNS use in lectures mediates that relationship (Rozgonjuk, Saal, et al., 2018). Therefore, a potential explanation could be that individuals with higher levels of FOMO may allocate some cognitive resources to their digital devices – resources otherwise reserved for studying, congruent with TCM.

Finally, we expected that the frequency of daily disrupted activities due to INs would mediate the relationship between FOMO and surface learning (H3). This hypothesis found support from the data and could be explained by previous empirical findings and TCM. Higher FOMO scores related to more notification interactions over the activity at hand; this, in turn, may lead them to focus less on studying and to adopt more surface learning approaches. It might be that notifications from SNS could play a pivotal role here, as it has been proposed that SNS use in lectures could be an important factor in having higher levels of surface learning (Rozgonjuk, Saal, et al., 2018). It has also been shown that media multitasking is associated with poorer educational outcomes (Wammes et al., 2019), further supporting this argument. Finally, according to TCM, it could be that responding to INs (e.g., by checking them or engaging in activities related to INs) occupies cognitive resources essential to learning. However, it should be noted that effect sizes in these relationships are rather small, meaning that although there is a certain interplay between these constructs, the magnitude of those effects is small.

This study is the first to analyze the role of INs in relation to FOMO and surface learning. The main contribution of this study is demonstrating that, coherent with some previous studies and theoretical frameworks, INs can be disruptive and detrimental for studying, particularly for individuals with higher levels of FOMO. This investigation may be useful for analyzing educational processes and the role of using digital technologies in classrooms. However, some limitations with the present study ought to be addressed. First, we used a convenience sample of college students, which limits generalization of our findings to higher education. Second, we used self-reports rather than objectively measured behavioral data. Some studies have used smartphone logs and found that people's actual smartphone usage patterns may differ from self-reports (Elhai, Tiamiyu, et al., 2018; Rozgonjuk, Levine, Hall, & Elhai, 2018; Wilcockson, Ellis, & Shaw, 2018). Future studies could count the number of notifications by implementing specific apps that measure smartphone use objectively. Finally, our study was cross-sectional and, therefore, our suggested model ought to be treated with caution regarding causality. Although we treated FOMO as a predisposing factor (e.g., as a trait-like characteristic), because of the cross-sectional nature of the data we cannot rule out that direction of causality could be reversed. Furthermore, it could be that the interplay between variables could be more complex, e.g., including feedback loops. However, despite these limitations, results advance our understanding of potential ways in which digital devices may interfere with educational outcomes for particular individuals.

Acknowledgments

Authors have no competing interests to declare.

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