Deng *et al. Int J Educ Technol High Educ (2022) 19:14*
https://doi.org/10.1186/s41239-022-00321-1

International Journal of Educational Technology in Higher Education

RESEARCH ARTICLE

Open Access

Off-task social media multitasking during class: determining factors and mediating mechanism

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Abstract

Framed by social learning theory, the study examines a set of personal and social factors determining off-task social media multitasking inside university classrooms. We aim to clarify the relationships between social media multitasking and self-efficacy, intrinsic motivation, multitasking preference as well as peer distraction, and to elucidate the interactive relationships between these factors. Questionnaire data from 203 university students in China show that academic self-efficacy fully mediates the association between intrinsic motivation and off-task multitasking. Moreover, multitasking preference partially mediates the association between peer distraction and off-task multitasking during class time. The findings of the study contribute to a deeper understanding of why students multitask during class, which can inform the development of strategies for combating social media distraction and enhancing students' learning engagement.

Keywords: Multitasking, Social media, Self-efficacy, Motivation

Introduction

As digital devices and social media become indispensable to university students, many students have developed the "always-on" and "always-connected" lifestyle. Multitasking with social media notably social networking sites (SNSs) and instant messengers has become pervasive inside and outside classroom (Deng, 2020; Derounian, 2020; Junco, 2012; Kornhauser et al., 2016; Lawson & Henderson, 2015). Increasing evidence has shown that students multitasking during lectures are often involved in activities unrelated to learning, which is detrimental to their attention, learning engagement, and performance (Chen & Yan, 2016; Demirbilek & Talan, 2018; Felisoni & Godoi, 2018; Lau, 2017; May & Elder, 2018; Mendoza et al., 2018). In this study, we refer to multitasking unrelated to ongoing class activity as off-task multitasking (Deng, 2020; Wood et al., 2018).

Despite the growing research interest in the field of student's multitasking behavior, there is a lack of studies on the determinants or motives for students' multitasking (Kononova & Chiang, 2015). The limited research on the theme has shown that multitasking is a complex phenomenon subject to the influence of both internal and external factors (Gerow et al., 2010; Goel & Schnusenberg, 2019). Thus, it is imperative to scrutinize both the individual psychological needs and situational factors that influence students' multitasking behaviors (Zhang & Zhang, 2012). The present study aims to fill the research gap on the determinants of off-task multitasking following social cognitive theories (Bandura, 1986; Moskowitz, 2005) that posit that a person's behavior is jointly determined by personal characteristics and situational opportunities. We consider a set of individual-related factors (motivation, self-efficacy, and multitasking preference) and social factors (peer distraction) responsible for social media multitasking during class time. The purpose is to clarify the underlying reasons for off-task multitasking and the potential interactive relationships between the determining factors. The upcoming review of literature first presents an overview of multitasking in the educational context followed by the detailed account of each investigated variable.

Literature review

Multitasking: pervasiveness and impact on learning

As digital devices have been deeply embedded in the academic and social lives of university students, nonacademic usage of digital devices is common in classrooms. For example, Ragan et al. (2014) reported that two-thirds of laptop use during a large class were not related to class and social media were rated as the most common off-task activities. Ravizza et al. (2017) noted that students spent approximately one third of lecture time on off-task Internet activities, most of which were related to social media as well. In particular, social networking sites and instant messenger are shown to be the most popular applications among university students (Deng et al., 2019; Derounian, 2020) and the key initiators of off-task multitasking (Rosen et al., 2013). Tindell and Bohlander (2012) revealed that 92% of students text with their phones during lectures. Deng et al. (2019) reported that 92% of students acknowledged the habit of checking notifications on their phone during classes.

A substantial number of studies has shown that multitasking with digital devices, including laptops and mobile phones, remarkably affects students' learning performance. For instance, Wood et al. (2012) reported that students who multitasked with these devices during lectures underperformed their peers who were not multitasking. Likewise, Lau (2017) studied university students in Hong Kong and found that social media multitasking was detrimental to students' learning. However, when looking closer into different technological tools involved in multitasking, researchers have revealed different results. Several studies have indicated that the two most popular applications among the young population, namely social networking sites and instant messenger, are also the most distractive and detrimental to learning. For example, Kraushaar and Novak (2010) identified instant messenger as the only multitasking subcategory that was negatively correlated with students' academic performance. Similarly, Junco and Cotten (2012) reported that multitasking with Facebook and texting during study time negatively affected students' GPA. Therefore, in our study, we focus on social media multitasking given their pervasiveness among university students and negative implications for learning.

Motivation and multitasking

Motivation is a well-established psychological construct that plays a critical role in learning. Some studies on the relationship between students' motivation and multitasking have revealed the inverse relationship between the two. For instance, through a series of experiments, Ralph et al. (2021) found that those with high task-related motivation were more likely to be focused and less likely to work on task-unrelated media multitasking. Studies on motivation have distinguished between intrinsic and extrinsic sources of motivation: intrinsic motivation refers to the stimulation to engage in tasks for inherent enjoyment or interest, whereas extrinsic motivation refers to the stimulation to engage in tasks for external rewards or outcomes separable from the action itself (Ryan & Deci, 2000). Research has shown that both extrinsic and intrinsic motivation are important factors influencing students' attention and learning (Taneja et al., 2015).

Although the critical role of motivation in learning has been widely accepted, the effects of intrinsic and extrinsic motivation on multitasking are not always clear. Alt (2015) examined the relationship between motivational constructs (intrinsic motivation, extrinsic motivation, and amotivation) and social media engagement and revealed that students driven by external motivation were more likely to use social media during lectures; however, no significant relationship was found between intrinsic motivation and social media engagement. Similarly, Zhang (2015) found no relationship between students' intrinsic motivation and laptop multitasking. Nevertheless, Taneja et al. (2015) denoted that both extrinsic and intrinsic motivation are associated with students' lack of attention inside the classroom. The inconsistency in the aforementioned findings suggests that the relationship between motivation and multitasking is complex, which led us to explore the mechanism behind the relationship.

Self-efficacy, motivation, and multitasking

Scholars have long recognized that motivation and self-efficacy are inextricably connected: self-efficacy represents the belief that one can successfully execute certain behaviors to achieve specific goals, whereas motivation is related to the anticipated benefits or outcomes of the behavior (Bandura, 1986). As such, perceived efficacy not only pertains to the judgment of personal capacity but also involves the expectation of a desirable outcome. Self-efficacy has been considered an effective predictor of learning, as it helps determine the goals a person sets, efforts mobilized, and the commitment level to the goals (Bandura, 1991; Pajares, 1996; Pintrich & De Groot, 1990; Zimmerman, 2000).

Students driven by intrinsic motivation are more likely to believe they can perform well (Callahan et al., 2003; Partin et al., 2011; Wu et al., 2020). Furthermore, self-efficacy and intrinsic motivation have been shown to have a positive association with students' learning engagement (Pintrich & De Groot, 1990). In the context of classroom learning, self-efficacy is especially related to the choice of activities, meaning that students with a low sense of efficacy may tend to avoid tasks they perceive as difficult (Schunk, 1985).

There is a handful of studies that explored the relationships among motivation, self-efficacy and multitasking. For example, Calderwood et al. (2014) examined university students' multitasking during self-study time and reported that motivation in academic tasks and self-efficacy to concentrate were negatively associated with the frequency and duration of media multitasking. Similarly, Zhang (2015) examined the relationships between learning variables (e.g., motivation and self-efficacy) and multitasking with laptops during lectures and found that the students with low self-efficacy had a higher tendency to multitask. However, these studies have not explore the mediating mechanism that explains how motivation affect students' multitasking.

Preference for multitasking

Besides self-motivational factors, previous studies have revealed the role of personal preference in determining multitasking behavior. Some studies on multitasking have used the term "polychronicity" to describe the tendency or preference to simultaneously perform more than one task, which differs from multitasking as a behavioral variable (Goel & Schnusenberg, 2019). Polychronicity was originally conceptualized as shared behavior within a culture and was later used to describe individual traits or preferences (Goel & Schnusenberg, 2019). Research has identified the preference for multitasking as a significant predictor of the actual multitasking behavior (David et al., 2015; Goel & Schnusenberg, 2019; Kononova & Chiang, 2015). The preference for multitasking is also associated with people's perceptions of their competence in multitasking, which may jointly explain their multitasking behaviors (Pollard & Courage, 2017). In a learning environment, those in favor of multitasking with digital devices are more likely to bring in those devices and hence more likely to be distracted while studying (Rosen et al., 2013).

Peer influence, multitasking preference, and multitasking

Multitasking behaviors within classroom are also subject to social influence and multitasking students can negatively influence their co-present peers. Off-task multitasking behavior could exert the "spreading effect" in classroom settings (Lindroth & Bergquist, 2010). That is, the adverse effects of off-task technology use on attention and understanding could ripple out to fellow students inside the classroom (Fried, 2008; Sana et al., 2013). Correspondingly, some studies have shown that fellow students with off-task technology use were perceived as the most prominent distractor during lectures (Fried, 2008). In particular, a shared social norm, that is, an individual's belief in whether classmates and friends accept or approve of multitasking significantly predicts students' intention of (Taneja et al., 2015) and actual multitasking on course-unrelated activities (Gerow et al., 2010). That is to say, when multitasking becomes a widespread scene and commonly acceptable behavior during class time, students are more likely to multitask. However, social norm does not always lead to multitasking behaviors. Deng et al. (2019) denoted that social norm regarding multitasking did not show predictive power for in-class multitasking behaviors. This suggest that the social factor might affect multitasking behavior through mediators. In this regard, personal preferences is deemed closely connected with peer influence. Riemer et al. (2014) eloquently contended the reciprocal relationship between personal preference and social norms and highlighted the role of cultural differences. They compared two models related to attitude formation: a person-centric model, which views attitude as a personal preference, and a normative-contextual model, which emphasizes attitude as contingent on contexts and significantly shaped by social norms. In Western culture, which accentuates independence, personal preference may take precedence over social norms, whereas in many Eastern cultures that value interdependence and compliance, a person's behavior is more subject to what is socially appropriate or norms of the situation. In the context of this study, it is logical to expect that when Chinese university students see other peers multitask, their personal preference for multitasking would be reinforced. Conversely, if the social norms or rules of conduct inside the classroom are against multitasking, students may be more likely to restrain their preferences for multitasking (Lepp et al., 2019).

Research gap

Although previous research has revealed a set of individual and social factors influencing students' multitasking, it remains unclear whether and how these factors interact with each other and influence multitasking behaviors. There is scant research on the links between motivational constructs, self-efficacy, and off-task multitasking (Zhang, 2015). Particularly, little effort has been made to clarify the extent to which these learning variables, such as self-efficacy, can explain the links (Alghamdi et al., 2020). Moreover, according to the self-efficacy theory, people's behavior, personal factors, and environmental factors "all operate as interacting determinants of each other" (Bandura, 1986, p. 18). Therefore, this study aims to disentangle the complex relationships between social media multitasking and a set of self-motivational (motivation, self-efficacy, multitasking preference) and social factors. In particular, we explore the possible mediating role of self-efficacy and multitasking preference in explaining how motivation and peer influence could predict social media multitasking.

Methods

Research site and participants

With class as a cluster, we recruited first-year students from different majors attending compulsory programming courses in a large comprehensive university in Eastern mainland China. The study has been approved by Research Ethics Committee (REC) and informed consent was obtained prior to the start of data collection. The students were recruited from one specific course because the variables of interest (self-efficacy, motivation, and multitasking) are domain-specific, meaning that they may vary among different courses or subjects (Bandura, 1991; Zimmerman, 2000). When taking the questionnaire, the students were asked to answer the questions based on their perceptions of and behaviors in the programming course. Furthermore, given that the course was compulsory for all freshmen, we had access to students from various departments, such as the School of Mechanical and Power Engineering, and the School of Information Science and Engineering. The students were invited to complete the online questionnaire at the end of the class, so that they could recall their classroom behaviors more effectively. A total of 257 students filled out the questionnaire. After screening, 54 responses were excluded in the final analysis due to missing data, which resulted in 203 valid responses. The final data set included 163 male students (80%) and 40 female students (20%). This gender ratio was similar to the overall gender compositions of the involved schools.

Research model and hypotheses development

Considering the inconsistent findings in the field, we conducted a preliminary test to explore the potential relationship between the proposed variables. The zero-order

Table 1 Descriptive data and results of correlation analysis

Variables	M	SD	1	2	3	4	5	6
1. Intrinsic motivation	4.82	1.35	–	0.520**	0.696**	− 0.014	0.065	− 0.155*
2. Extrinsic motivation	5.42	1.12		–	0.441*	− 0.09	0.131*	− 0.029
3. Self-efficacy	4.24	1.30			–	0.036	− 0.008	− 0.263**
4. Multitasking preference	3.80	1.41				–	0.141*	0.287**
5. Peer distraction	4.37	1.57					–	0.205**
6. Social media multitasking	2.54	0.74						–

*$p < 0.05$; **$p < 0.01$

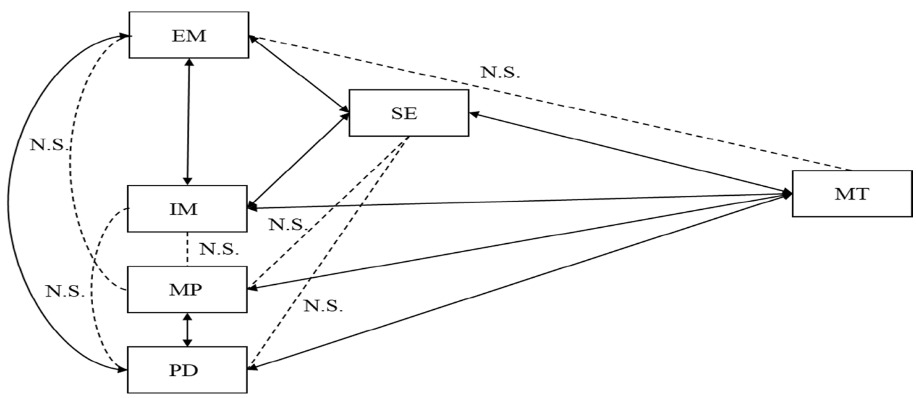

Fig. 1 Hypothesized model. *EM* external motivation,*IM* internal motivation, *SE* self-efficacy, *MP* multitasking preference, *PD*peer distraction, *MT* off-task socialmedia multitasking

correlations analysis (Table 1) reveals that except for extrinsic motivation, all of the variables showed significant relationships with social media multitasking. Figure 1 provides a visual display of the correlational relationships among the variables with the unbroken lines and bi-directional arrows signifying an interactive relationship and the dotted lines implying no relationship between the variables on both ends. For instance, no significant link has been found between extrinsic motivation and media multitasking, between intrinsic motivation and peer distraction, or between intrinsic motivation and multitasking preference.

Based on the preliminary analysis and related literature, we constructed the research model consisting of two clusters (as shown in Fig. 2). Extrinsic motivation was excluded as it showed no correlations with the dependent variable—social media multitasking. The first cluster of the model includes internal motivation, self-efficacy, and social media multitasking. In this respect, considerable work has revealed the positive correlation between students' motivation and self-efficacy (Callahan et al., 2003; Partin et al., 2011; Wu et al., 2020). There is also a small body of scholarly work exploring the linkage between self-efficacy and students' multitasking which noted the negative association between the two. That is to say, those with high self-efficacy are more likely to be focused and less likely to multitask on activities unrelated to learning (Calderwood et al., 2014; Zhang, 2015) As such, we put forward the following hypothesis:

H1 Intrinsic motivation directly and positively predicts academic self-efficacy.

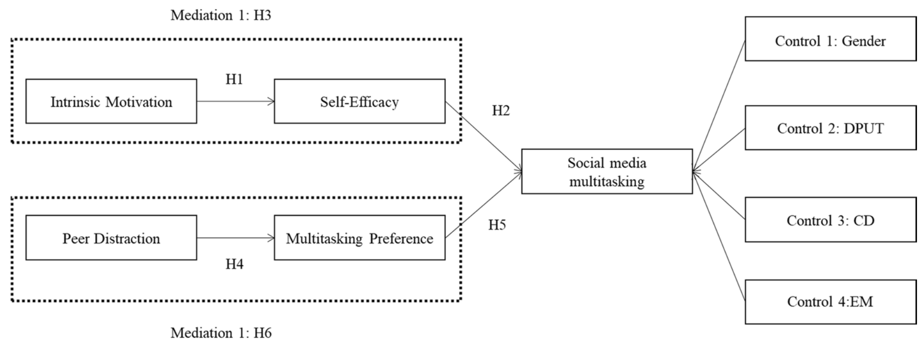

Fig. 2 Research model and hypotheses

H2 Learning self-efficacy directly and negatively predicts off-task social media multitasking.

Furthermore, we explored the mediating mechanism behind the variables. Self-efficacy has been widely studied by the researchers in the field education who have recognize that it played a mediating role amid students' attitude or skills and learning performance (Bandura & Schunk, 1981). However, there is very limited studies examining the the mediation mechanism that might affect the relationship between motivation and students' multitasking. As one of such studies, Hong et al. (2017) noted that intrinsic motivation in learning predicted self-efficacy, which in turn predicted the level of flow experience. The state of flow denote the state of task immersion, which is considered the opposite of multitasking that involves abandoning a task in pursuit of a new one (Adler & Benbunan-Fich, 2013). Therefore, we hypothesized that self-efficacy will serve as a mediator between the relationship between motivation and multitasking.

H3 Self-efficacy mediates the effects of intrinsic learning motivation on off-task social media multitasking.

The second cluster of the model includes multitasking preference, peer distraction, and social media multitasking. In this respect, there are a rich body of empirical work showing multitasking preference could predict actual multitasking behavior (David et al., 2015; Goel & Schnusenberg, 2019; Kononova & Chiang, 2015). Moreover, personal preference of multitasking is subject to the influence of social norms of conduct inside classroom (Lepp et al., 2019). As such, the following hypothesis are put forth:

H4 Peer distraction directly and positively predicts multitasking preference.

H5 Multitasking preference directly and positively predicts off-task social media multitasking.

Moreover, we sought to explore the mediating role of multitasking preference in the relationship between peer influence and social media multitasking. The literature on peer influence and social learning perspectives espouse that the mechanism of peer influence is complex and personal charateristics and attitude play an important role in the process (Bandura, 1986; Brechwald & Prinstein, 2011). In the context of our study, it is assumed that peer influence does not directly predict students' multitasking behavior, but through individual students' personal preferences for multitasking.

H6 Multitasking preference mediates the effects of peer distraction on off-task social media multitasking.

Furthermore, three control variables, namely gender, daily phone use time (DPUT), and course difficulty levels (CD), were included in the model because previous research has indicated that they could affect individuals' media multitasking. For instance, female students were found to be more distractible than male students (Kanai et al., 2011) and more likely to report their multitasking behavior (Jeong & Fishbein, 2007). In the current analysis, gender was dummy-coded (1 = female and 2 = male). Several studies have also identified the daily habit of technology or phone use as a significant determinant of multitasking behavior (Chen et al., 2021; Wei & Wang, 2010); and the difficulty level of the course material could trigger multitasking as well (Adler & Benbunan-Fich, 2015). Additionally, intrinsic motivation and extrinsic motivation are the two primary types of motivated academic behavior (Cokley & Kevin, 2003), and they are often jointly used for measuring motivational variables (Lin et al., 2003; Sansone & Harackiewicz, 2000). Therefore, although extrinsic motivation (EM) showed no significant linear relationship with social medie multitasking, it was introduced into the research model as a control variable.

Measurements

The questionnaire began with some general questions about the students' personal information and daily digital device usage. We asked the respondents to estimate how much time they spent on digital devices in general, and on social networking sites and instant messenger in specific. The rest of the questionnaire consisted of measurement items adapted from established scales to fit our research context. All items were measured on a 7-point Likert-type scale ranging from 1 (strongly disagree) to 7 (strongly agree). The items for external motivation (EM), internal motivation (IM), and self-efficacy (SE) were adapted from the work by Zhang (2015). As presented in Table 2, there are three items for internal motivation, six items for self-efficacy, and two items for external motivation. Two items measuring the students' multitasking preference were borrowed from the study by David et al. (2015). There were also two items measuring peer distraction during lectures, which were adapted from the work of Gerow et al. (2010). The dependent variable, that is, off-task social media multitasking, was measured on a 5-point semantic scale anchored from 1 (never) to 5 (frequent). The scales were adapted based on interviews with two students to ensure the items were more in line with students' experience and behaviors. Finally, to ensure the face validity of the measurement items we adopted the forward-and-backward translation method and consulted two other experts in the field.

Table 2 Measurement items

Constructs	Items	Mean	SD	Loadings	CR	AVE
Internal motivation	IM1: One of the reasons that I take classes is because I want to learn new things	5.09	1.56	0.895	0.921	0.796
	IM2: My favorite class is the one makes me engage my brain	4.97	1.45	0.862		
	IM3: One of the reasons that I take classes because I like the programming course	4.43	1.56	0.919		
External motivation	EM1: Academic performance is important for me	5.48	1.30	0.804	0.852	0.742
	EM2: What I learned in this course is helpful to my career	5.38	1.25	0.916		
Self-efficacy	SE1: I am sure I can understand the content of this course	4.52	1.48	0.847	0.957	0.787
	SE2: I feel that I have good methods of learning	4.62	1.41	0.871		
	SE3: I am sure I can successfully complete the assignments and tasks assigned by the teacher	4.34	1.50	0.933		
	SE4: I believe I can get a good score in this course	4.22	1.41	0.913		
	SE5: Compared with my classmates, I performed better	4.12	1.49	0.891		
	SE6: Compared with my classmates, I feel myself know more about the subject	3.65	1.55	0.864		
Multitasking preference	MP1: I try to multitask whenever possible	3.70	1.60	0.860	0.844	0.730
	MP2: I lose track of time when multitasking	3.88	1.70	0.849		
Peer distraction	PD1: I would be distracted when people around me are using digital devices for non-class related purposes	4.29	1.66	0.945	0.937	0.881
	PD2: I would be distracted by my friends around me who are using digital devices for non-class related purposes	4.44	1.71	0.933		
Off-task social media multitasking	MT1: How often do you check instant messengers during class time?	2.60	0.87	0.793	0.826	0.704
	MT2: How often do you browse social networking sites during class time?	2.49	0.89	0.883		

Data analysis

Partial Least Square Sructural Equation Modeling (PLS-SEM) was used to validate the measures and test the research model. The reason for adopting PLS method lies in its two characteristics: First, PLS is often used for exploratory purpose (Fornell & Bookstein, 1982). Second, it imposes minimal restrictions on measurement scales, sample, size and residual distributions (Chin et al., 2003). Moreover, SmartPLS is a variance-based SEM that is preferred over a covariance-based SEM like AMOS or LISREL since it is less sensitive to the sample size smaller than 300 (Chin, 1998; Henseler et al., 2009). Therefore, it is considered especially suitable for analyzing the data of the current study with a relatively small sample size (N = 203). The analysis of the data with PLS-SEM can be accomplished by conducting two main assessment, namely the Measurement Model and the Structural model (Hair et al., 2017). SMARTPLS 3.0 was used to run confirmatory factor analysis (CFA), and to verify the internal consistency, reliability, and validity of the research model.

Common method bias

Before data analysis, Harman's single-factor test was first conducted to examine the common method bias (Podsakoff, 2003). All the measurement items were examined with an principal component analysis that took the emergence of one factor as evidence of common method bias. The results of unrotated factor analysis showed that five factors emerged and accounted for 71.19% of the total variance. The first principal factor explained 37.41% of the variance, indicating that common method bias was not a concern in this study.

Results

Descriptive and demographic information

First, descriptive statistical analysis was conducted with SPSS and the data showed that mobile phones were the most used devices in the daily lives of the university students. On average, the students spent 6.6 h on mobile phones (SD = 3.24) and 2.07 h on computers (SD = 2.07). Their off-task multitasking behaviors during lectures were rated on a 4-point Likert scale ranging from 1 (never) to 4 (frequently). The students reported an average of 2.6 (SD = 0.87) for instant messenger and 2.49 (SD = 0.89) for social networking sites (Table 2). For the other variables measured on a 7-point Likert scale, the students reported medium levels of intrinsic motivation with mean values of 4.43–5.09 (SD: 1.45–1.56), self-efficacy with mean values of 3.65–4.62 (SD: 1.41–1.55), and peer distraction with mean values of 4.29–4.44 (SD: 1.66–1.71). On average, the preference for multitasking was slightly lower with mean values of 3.70–3.88 (SD: 1.6–1.7).

Measurement model

Several measures were taken to ensure the reliability and validity of the instruments. First, the Cronbach's alpha was computed which yielded alpha coefficient values ranging from 0.586 to 0.946. Although the value of off-task media multitasking (0.586) fell slightly below the benchmark of 0.6, it was considered acceptable for a scale with only two items (Swailes, & McIntyre-Bhatty, 2002; Spiliotopoulou, 2009). Then, the reliability, convergent validity, and discriminant validity were estimated according to the guidelines developed by Fornell and Larker (1981) and Gefen and Straub (2005). The reliability, as evaluated based on composite reliability (CR), was satisfactory for all measures. As presented in Table 2, the CR values all exceeded the threshold of 0.7 (Fornell & Larker, 1981), demonstrating the adequate reliability of the measures.

Third, the convergent validity was assessed on the basis of the average variance extracted (AVE) and factor loadings of the constructs. The convergent validity of a latent variable is acceptable if its AVE score is higher than 0.5 and the factor loadings are greater than 0.7. According to Table 2, both the AVE and factor loadings for each construct were higher than the corresponding thresholds, demonstrating that the convergent validity of the measurements was satisfactory.

Additionally, the discriminant validities of the constructs were examined to ensure the separation between variables. According to the results in Table 3 and "Appendix", the discriminant validity was considered sufficient, as the square root of AVE for each construct was greater than the inter-construct correlations (Fornell & Larcker, 1981), and the loading of each indicator was greater than all of its cross-loadings (Chin, 1998). Moreover, the variance inflation factor (VIF) was also examined to determine whether multicollinearity existed in our data. The VIFs (ranging from 1.208 to 2.895) were significantly lower than the cut-off value set at 5, illustrating that there was no multicollinearity problem in this model.

Structural model

Structural equation modeling was utilized to test the independent relationships between the constructs in the main model. A bootstrap resampling procedure using 500 subsamples was performed to estimate the significance of the path coefficients (β), which quantified the strength of the relationships between two model constructs. Figure 3 presents the overall explanatory power of the main model, path coefficient, and *p*-values in the structural model. After the covariates were controlled, the model explained an overall of 17.9% of the variance in the off-task social media multitasking during lectures.

H1 states that intrinsic learning motivation positively predicts academic self-efficacy. As shown in Fig. 3 and Table 4, the results confirm this hypothesis ($\beta = 0.695$, $p < 0.001$), implying that students driven by intrinsic motivation also show higher academic self-efficacy. H2 proposes that academic self-efficacy negatively influences the extent of off-task social media multitasking behavior. As predicted, a higher academic self-efficacy could inhibit multitasking behavior ($\beta = -0.313$, $p < 0.001$); hence H2 is supported. This is to say that students with a high view of their learning competency are less inclined to use social media for tasks unrelated to learning. H4 posits that peer distraction positively influences the multitasking preference. The influence of peer influence on multitasking preference was significant ($\beta = 0.146$, $p < 0.05$), which supports H4. This indicates that when students are surrounded by multitasking peers, they are more likely to become distracted and follow suit. H5 states that multitasking preference positively influences off-task social media multitasking. As anticipated, multitasking preference was a significant predictor of off-task social media multitasking behavior ($\beta = 0.301$, $p < 0.001$); hence, H5 is supported. In other words, students who prefer to multitask are more likely

Table 3 Square root of AVE

	IM	MP	PD	MT	SE
IM	***0.892***				
MP	−0.032	***0.854***			
PD	0.064	0.148	***0.937***		
MT	−0.152	0.279	0.215	***0.839***	
SE	0.695	0.034	0.021	−0.271	***0.887***

Diagonal values in italics are square roots of AVEs

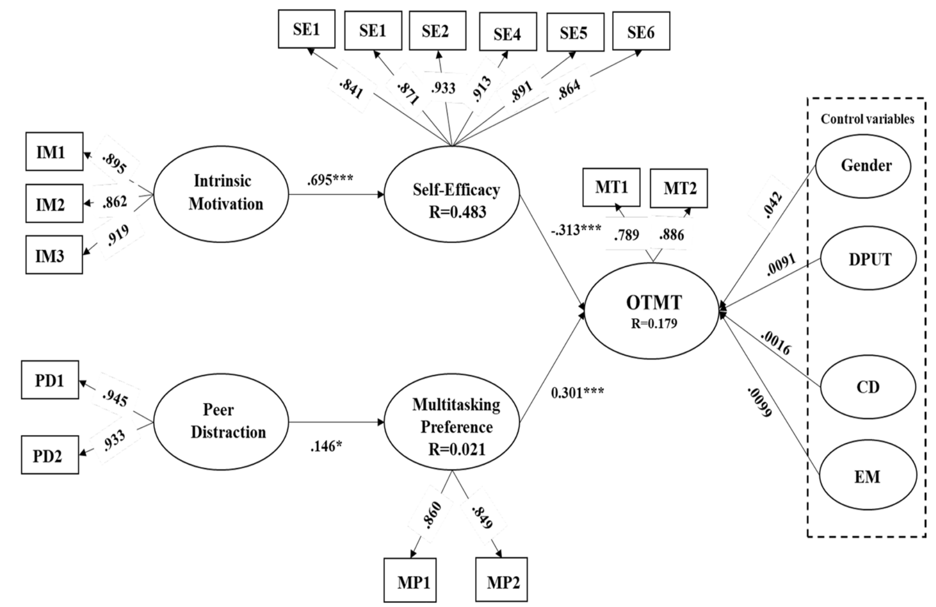

Fig. 3 Results for the main model. *$p < 0.05$; **$p < 0.00$; ***$p < 0.001$

Table 4 Results for the main model

Hypotheses	Standardized Coefficient	T-value	Supported
H1: Intrinsic motivation → Self-efficacy	0.695***	15.856	Yes
H2: Self-efficacy → Off-task multitasking	− 0.313***	3.403	Yes
H4: Peer influence → Multitasking preference	0.146*	2.024	Yes
H5: Multitasking preference → Off-task multitasking	0.301***	4.323	Yes

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

to perform off-task multitasking during class time. We also included gender, daily phone use, perceived course difficulty, and extrinsic motivation as control variables in our model. However, none of these variables had any effect on the dependent variable.

Mediation analysis

Mediating effects were tested using the three-step method proposed by Baron and Kenny (1986). First, a statistically significant relationship was detected between the independent variable and the dependent variables (Table 5, c). The second step was to determine a significant relationship among the independent variables and the mediators (Table 5, a). The third step looked into the effects of dependent variable on both independent variables and mediators (Table 5, c′ and b). Moreover, the mediation effects are confirmed when the relationship between the independent variables and dependent variables becomes insignificant after the inclusion of mediator in the structural model (c′), or the coefficient of the independent variable in the basic model (c) with the dependent variable is greater than the coefficient in the structural model (c′).

H3 proposes that self-efficacy mediates the effects of intrinsic motivation on off-task social media multitasking. The results of the test showed that the direct influence of

Table 5 Results of mediating effect

Path coefficient								
IV	M	DV	IV → DV	IV → M	IV + M → DV		Mediating	Indirect effect
			c	a	IV(c′)	M(b)		a × b
IM	SE	OTMT	− 0.193*	0.696***	0.046	− 0.311**	Full	− 0.216**
PI	MP	OTMT	0.235***	0.151*	0.179*	0.144*	Partial	0.179*

The significance of the indirect effect was calculated using the bootstrap percentile p-value obtained from PLS bootstrap resampling analysis

IV independent variable, *M* mediator, *DV* dependent variable

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

intrinsic motivation on off-task social media multitasking became insignificant after introducing self-efficacy to the model, demonstrating the full mediating role of self-efficacy. Hence, H3 is supported. H6 posits that multitasking preference mediates the effects of peer distraction on off-task social media multitasking. The results illustrated that the influence of peer distraction on off-task multitasking remained significant after introducing multitasking preference as the mediator. However, the direct path standardized beta changed from 0.235 to 0.179, demonstrating the partial mediating role of multitasking preference.

Discussion

Given that social media are considered the main source of distraction for students during class time, the study aims to clarify the determining factors for the use of social media for nonacademic purposes during class time. We have examined how motivation, self-efficacy, multitasking preference, and peer distraction influence multitasking behavior and the interplay among these factors. Studies on the relationship between motivation and media multitasking have shown mixed and inconsistent findings: some have shown a valid link between extrinsic motivation and multitasking (e.g., Alt, 2015), whereas others have indicated intrinsic motivation as a significant determinant of multitasking (Taneja et al., 2015). Contrary to the findings by Zhang (2015) and Alt (2015), we found a significant association between intrinsic motivation and students' off-task multitasking. That is, those who attached interest and value to the course were less likely to use social media for nonacademic purposes during class. Those who were driven by extrinsic motivation did not show such a tendency in our data.

Furthermore, our study also confirmed the predicting power of self-efficacy on students' multitasking. Substantial research has indicated that students who believe in their capability to accomplish certain learning tasks are more likely to persist on academic tasks (Pintrich & De Groot, 1990). In particular, self-efficacy governs the choices students make inside the classroom, especially regarding attention and efforts (Schunk, 1985). When students are motivated from within, they tend to feel a sense of self-efficacy toward attaining their goals, which results in more on-task behaviors (Schunk, 1985). Our data not only corroborates previous studies by confirming the predictive effect of self-efficacy on multitasking behavior (Calderwood et al., 2014; Zhang, 2015), but also clarifys the mediating role it plays between intrinsic motivation and off-task multitasking behavior. The mediation analysis indicates the indirect effect of intrinsic motivation on social media multitasking through academic self-efficacy, meaning that intrinsic motivation influences off-task social media multitasking through efficacy belief. This suggests that students with high intrinsic motivation tend to be more confident in their academic abilities and hence are less likely to succumb to social media distraction.

Besides the effects of self-motivational variables, we also explore the determining effects of students' preferences for multitasking. The results align with those of previous studies showing that multitasking preference is a significant predictor of actual multitasking behaviors (David et al., 2015; Goel & Schnusenberg, 2019; Kononova & Chiang, 2015; Srivastava et al., 2016). In other words, students who prefer to simultaneously perform more than one task are likely to actually conduct off-task multitasking.

On account that classroom is a social context, we also examine the extent to which students' off-task social media usage can be determined by their peers. The results show that the direct link from peer influence to social media multitasking is significant, so is the indirect link through multitasking preference. This finding corresponds with previous work showing the adverse effects of multitasking peers (Fried, 2008; Sana et al., 2013) and multitasking could be contagious to fellow students (Kornhauser et al., 2016).

Furthermore, we examined the interplay between peer distraction and multitasking preference. It turns out that multitasking preference partially mediates the relationship between peer distraction and off-task media multitaksing. This indicates that peer influence as a social factor has an effect on social media multitasking directly and indirectly through personal preference for multitasking. This finding supports the social learning theory in that human behavior is subject to the confluence of individual charateristics and social factors (Bandura, 1977). Instead of thoughtlessly mimic others, people modify their behaviors according to their personal characteristics such as motivation or interest (Bandura, 1978; Festl et al., 2013). As such, when students noticed peers' media multitaksing behavior, those who are in favor of multitasking might have a higher chance of performing social media multitaksing.

Conclusion

This study focuses on nonacademic-related social media multitasking inside the classroom and reveal the determining factors of this pervasive and disruptive behavior. Our model illuminates the roles of intrinsic motivation and peer influence in determining students' social media multitasking and the mediating mechanism involving self-efficacy and multitasking preferences. The results show that self-efficacy fully mediates the link between intrinsic motivation and social media multitasking and that students' preferences for multitasking partially mediate the link between peer distraction and social media multitasking.

These study, first and foremost, contributes to the under-developed area in relation to the determinants of in-class multitasking. Our findings support the previous work in pinpointing self-efficacy, peer influence, and multitasking preference as significant predictors of social media multitasking. However, our work goes beyond past work by examining mediating mechanisms that may explain *how* motivation and peer influence determine students' in-class multitasking. To the best of our knowledge, there has been no study examining the mediating effects of self-efficacy and multitasking preference. In particular, no study has looked into the interplay between personal and social factors for students' multitasking. Our findings provide a more nuanced understanding regarding the interactive relationships among the determinants for multitasking which could contribute to the development of more detailed models for future work.

Limitation

One main limitation of the present study is that it relies solely on self-reported data. It can be argued that observational data or system-based usage data might provide a more objective way of measuring social media multitasking. The second limitation lies in the sample size and sampling procedure. The sample size is rather small and all the participating students are from one course which took place in a computer lab. It is plausible that students' multitasking behavior might differ in lectured-based courses. Third, although our model has shown statistically adequate fitness, a large share of the variance in off-task multitasking remains unexplained. An inferrence to be drawn is that students' in-class multitasking is a complex phenomenon subject to the influence of a wide array of factors. Within a classroom setting, other situational factors could come into play such as teacher immediacy (Wei & Wang, 2010) and technological accessibility (Calderwood et al., 2016). A more systematic and holistic approach is needed to provide a comprehensive picture of the reasons behind off-task multitasking.

Implication for research and practice

Our findings bears several implications for researchers and practitioners. The identification of self-efficacy as a strong mediator between motivation and multitasking opens new territories for further studies. Given that self-efficacy is situational and domain-specific, future work can consider other types of self-efficacy, such as multitasking self-efficacy, computer self-efficacy, and self-efficacy for self-regulation. One particular promising type of self-efficacy for further study is multitasking self-efficacy, that is, the perceived competence to simultaneously engage in multiple tasks. Interestingly, studies have shown that multitasking self-efficacy is not correlated with multitasking efficiency (Wu, 2017). That is to say people who believe in their multitasking capabilities are prone to have more attention problems, which leads to decreased learning performance. More studies are needed to further explore the roles that self-efficacy plays in affecting students' multitasking behavior and learning engagement.

Educators regard digital devices as the main contender for students' attention and engagement during lectures (Flanigan & Babchuk, 2020). The findings of this study present several important implications for practitioners, especially those in higher education sectors, on how to overcome this challenge. First, given the important role of self-efficacy in the off-task usage of social media, educators should endeavor to raise students' self-efficacy in learning and cultivate intrinsic motivation. Previous work has discussed series of strategies that teachers can use to boost students' efficacy beliefs, such as verbal encouragement, effort attributional feedback, and modeling (see Schunk, 1985).

Second, consistent with previous work that identified social norms as a stimulator for off-task multitasking behaviors (Taneja et al., 2015), our study reveals the need to establish clear policies and set codes of conduct for digital device usage inside classroom. When students see off-task device use inside the classroom as acceptable or social norm, they are more likely to divert their attention from on-task activities. Therefore, instructors should strive to cultivate a social norm against off-task multitasking inside classroom. The guidelines on appropriate use of devices should be explicitly explicated in the syllabus and discuss with students at the beginning of a course. All these measures can help combat the social media distraction and contribute to a more engaging classroom experience.

Appendix

Loadings and cross-loadings.

	IM	MP	PD	SE	OTMT
IM1	***0.895***	− 0.016	0.088	0.601	− 0.076
IM2	***0.862***	− 0.059	0.068	0.609	− 0.232
IM3	***0.919***	− 0.008	0.048	0.649	− 0.128
MP1	− 0.028	***0.860***	0.101	− 0.039	0.260
MP2	− 0.024	***0.849***	0.149	0.099	0.225
PD1	0.124	0.143	***0.945***	0.098	0.113
PD2	0.013	0.130	***0.933***	− 0.066	0.229
SE1	0.618	0.001	− 0.003	***0.847***	− 0.166
SE2	0.625	0.088	0.036	***0.871***	− 0.229
SE3	0.644	0.004	0.043	***0.933***	− 0.261
SE4	0.631	0.052	0.077	***0.913***	− 0.264
SE5	0.621	− 0.005	− 0.037	***0.891***	− 0.270
SE6	0.558	0.041	− 0.009	***0.864***	− 0.251
OTMT1	− 0.084	0.240	0.236	− 0.158	***0.793***
OTMT2	− 0.178	0.239	0.086	− 0.284	***0.883***

Authors' contributions
LD made substantial contributions to the conception and design of the study, data collection and analysis, and writing of the draft. YZ contributed through conducting data collection and analysis as well as drafting the manuscript. QH contributed through conducting data collection and analysis. All authors read and approved the final manuscript.

Funding
The work is funded by Faculty Research Fund of Hong Kong Baptist University (FRG2/17-18/049).

Availability of data and materials
The datasets used during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests
The authors declare that they have no competing interests.

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Received: 27 August 2021 Accepted: 10 January 2022
Published online: 16 March 2022

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