

The role of self-regulated learning in modelling the relationships between learning approaches, FoMO and smartphone addiction among university students

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Smartphone addiction (SA) has become a pervasive issue among university students. Therefore, it is important to better understand the conditions under which SA develops. Previous studies indicate that fear of missing out (FoMO), a psychological barrier to behavioural self-regulation, is often associated with SA risk. In the pedagogical context, poor self-regulation may manifest as lack of self-regulated learning skills (SRLs), which may, in turn, be associated with the adoption of a superficial approach to learning tasks. Therefore, the aim of the present study was to examine and model the associations between deep and surface learning approaches, SRLs, SA and FoMO among university students. The sample comprised 687 university students, and structural equation modelling (SEM) was used to analyse the data. The results indicated that SRLs were positively associated with deep learning, and negatively associated with surface learning. It was also shown that higher SRLs were associated with lower risk of FoMO and SA. However, while SRLs may help reduce the level of SA among surface learners by helping them overcome FoMO, the same may not be said for students with a deep learning approach, whose reduced risk of SA due to higher SRLs was not explained through FoMO. Based on the findings, interventions that aim to improve SRLs appear warranted, as these may help reduce SA.

Practitioner Notes

What is already known about this topic

- Fear of missing out (FoMO) is commonly associated with smartphone addiction (SA) risk.
- Smartphone notifications disrupt the learning activities of surface learners and FoMO may be the culprit.

- FoMO is considered to be a challenge for behavioral self-regulation.

What this paper adds

- Higher levels of self-regulated learning skills (SRLSs) are associated with deeper approaches to learning.
- Although a deeper approach to learning is associated with lower SA risk, a reduction of FoMO is irrelevant in explaining this effect.
- As far as surface-learners are concerned, better SRLSs are associated with FoMO, but are not associated with lower SA risk.

Implications for practice and/or policy

- For deep learners, interventions that support the development of SRLSs are advised because these are important not only for fostering a deep approach to learning, but also for helping reduce the risk of SA.
- Further research is necessary to identify the underlying mechanism by which improved SRLSs are associated with lower SA risk among deep learners.
- Further research is necessary to identify factors other than FoMO that may be associated with SA risk among surface learners.

Introduction

The use of social media has revolutionized the ways in which people engage with one another, obtain information, and interact with their environment (Kalasi, 2014). In today's world, social media serves a vital function in helping youth socialize, communicate, study, entertain, and establish a social presence (Karaca, 2007; Kuss & Griffiths, 2017). It can even be said that the youth of today live their lives in cyberspace as much as they do in physical spaces. However, as in physical spaces, life on social networking sites is not without its risks and threats. Smartphone addiction (SA) (Sserunkuuma et al., 2022), trolling (Soares et al., 2023), and cyberbullying (Lee et al., 2023) are among the more prominent examples of potentially harmful behaviors associated with problematic social media use.

Academic literature has shown that excessive and problematic patterns of social media use exist and that these can lead to increased levels of stress and anxiety among young individuals (Kuss & Griffiths, 2011; Malaeb et al., 2021). Among the various reasons for engaging in social media in a problematic manner, the fear of missing out (FoMO) appears to

be one key reason (Przybylski et al., 2013). Therefore, the present study aimed to not only examine the relationships between SA risk and FoMO among college students, but also to approach the issue from a pedagogical perspective, guided by previous research. Therefore, the study incorporated variables such as a student's approach to learning tasks and self-regulated learning skills (SRLSs) levels, in addition to FoMO and SA in order to build a model to explain the interconnections between all these variables.

Fear of missing out from a pedagogical perspective

FoMO is a psychological phenomenon that manifests as emotions of anxiety and disturbance attributed to an individual's perception of missing the opportunity to take part in a rewarding experience or event, where friends or others are perceived to be enjoying themselves (Przybylski et al., 2013). Explanations of FoMO are typically based on the motivational Self-Determination Theory (SDT; Deci & Ryan, 1985), and in this sense, FoMO is considered to be a challenge for behavioral self-regulation due to an individual's needs for satisfaction being unmet on a situational or chronic basis (Przybylski et al., 2013). It has been reported that in modern society, individuals who experience higher levels of FoMO also frequently feel the urge to engage with their smartphones in order to stay current with new content posted on social media, especially those involving the lives of their peers and the rewarding experiences they participate in (Hadlington & Scase, 2018).

This pattern of behavior caused by FoMO has been claimed to cause specific problems particularly among youth (Alinejad et al., 2022; Wolniewicz et al., 2020). For instance, high levels of FoMO among college students have been associated with losses in academic performance, academic motivation, or an increase in attention deficit (Alinejad et al., 2022; Alt, 2015). Investigations into the cause of these problems have shown that FoMO can lead to an increased frequency of individuals checking the status of their social media accounts during study hours or lectures, consequently causing disruption (Gezgin, 2022). FoMO has also been shown to predict SA among high school students (Gezgin, 2018).

In recent years, researchers investigating the negative effects of FoMO upon academic progress have appeared to focus, among other things, on the relationship between FoMO and so-called *learning approaches*. In this context, a significant positive association has been reported between the incidence of FoMO-associated behavior during study hours and a student's adoption of a *surface approach to learning* (as opposed to a *deep approach*) (Alt & Boniel-Nissim, 2018; Rozgonjuk et al., 2018; Rozgonjuk et al., 2019). For instance,

individuals' likelihood of interrupting their progress in studying due to a smartphone notification has been shown to be an indicator not only of that person's likelihood of suffering from problematic smartphone use (Rozgonjuk et al., 2018), but also of their adoption of a surface-level approach to learning (Rozgonjuk et al., 2019). In this sense, it is important to note that a higher frequency of experiencing FoMO is related to decreased levels of self-regulation, which is another phenomenon associated with the surface learning approach (Alt & Boniel-Nissim, 2018). In the following sections, the surface and deep approaches to learning are briefly explained, followed by an overview of the concept of self-regulation, because these appear to be crucial theories for constructing a model depicting the mechanism of how FoMO – and SA associated with it – negatively affects academic performance among college students.

Deep and surface learning

Deep and surface approaches to learning are fueled by intrinsic and extrinsic motivation, respectively (Cano, 2007). Students with a deep approach to learning are expected to display behavior hinting at meaningful interactions with the instructional material. They are expected to exert effort in internalizing subject matter, linking knowledge structures, and applying skills acquired during a course to real world contexts (Biggs, 1987). In other words, common patterns exhibited by deep learners include diligent attempts at understanding underlying concepts, linking together new and old information, running critical analyses or evaluations of subject matter, and using time effectively during studies (Draper, 2009; Marton & Säljö, 2005).

On the other hand, the surface approach to learning is associated with rote and superficial learning. Surface learners potentially skip out on mental tasks required for internalizing underlying concepts and typically aim to exert only the minimum amount of effort necessary to avoid failure in a course (Biggs, 1989; Cano, 2007; Draper, 2009). This may also mean that as they adopt a surface learning approach, students not only tend to simply memorize information and strive only to pass their exams, but also display a lack of course participation or motivation (Biggs, 1989; Cano, 2007). Naturally, existing literature on academic performance suggests that, students with a deep learning approach, which is fueled by intrinsic motivation, tend to show greater academic success, whereas those who employ a surface approach tend to fail more often (Lavasani et al., 2010; Liem et al., 2008). Therefore, it is important for students to adopt a deep learning approach in order to facilitate learning retention and academic performance. One of the primary factors that influences the adoption of such beneficial learning approaches is a student's skill in self-regulated learning.

Self-regulated learning skills

Self-regulated learning has been defined as a process through which students actively try planning, monitoring, and evaluating their own learning objectives, as well as adjusting their own cognitive or behavioral strategies, in order to maximize their learning outcomes (Zimmerman, 1989). Self-regulated learning encompasses the phases of planning, monitoring, control, and action (reaction/reflection) in each of the four areas for regulation: cognitive, motivational, behavioral, and contextual (Pintrich, 2000). In other words, a self-regulated learner is a metacognitively, motivationally, contextually, and behaviorally active participant in their own learning (Kim et al., 2020; Zimmerman, 1990). This self-regulation involves metacognitive strategies such as planning, monitoring, and modifying one's cognition (Zimmerman & Martinez-Pons, 1986; 1988); strategies that provide control and management of their efforts on academic tasks (Pintrich & De Groot, 1990); and cognitive strategies such as repetition, elaboration, and organization, which involve understanding, learning, and remembering materials (Zimmerman & Martinez-Pons, 1986; 1988). Considering that activities such as comprehending, planning how to approach a particular learning task, or evaluating one's progress towards the completion of a task are carried out by metacognition, it is thought that metacognition, in particular, plays a critical role in successful learning (Stanton et al., 2021). However, in general, knowledge and awareness of cognitive and metacognitive strategies are not enough to increase students' achievement, as they also need to be motivated to actually use these strategies and to regulate their own cognition and effort (Ortega-Torres et al., 2020; Pintrich & De Groot, 1990).

Research suggests that SRLSs can indicate deep learning, but their effectiveness varies. For instance, highlighting, a cognitive type of self-regulated learning strategy, may not be effective alone. However, combining it with metacognitive self-regulation training has been shown to improve learning outcomes (Leopold & Leutner, 2015). Similarly, knowledge mapping and visualizing strategies, when paired with self-regulation, have been shown to enhance text comprehension (Leopold & Leutner, 2015). Although the use of demanding cognitive and metacognitive strategies may result in a heavy cognitive load on the student, these come naturally with intrinsic motivation, while superficial strategies are associated with extrinsic motivation (Young, 2005). Therefore, by enabling classroom environments that promote autonomy, competence, and task mastery orientation, the adoption of SRLSs may increase alongside increasing intrinsic motivation (Evans et al., 2024; Young, 2005).

However, a distinction between different types of SRLSs may not always be clear-cut, as demonstrated in a study with Ecuadorian students by Yaguarema et al. (2022), who, while examining the factor structure of a self-report questionnaire that assessed deep learning, found that basic SRLSs may overlap with strategies in the visual elaboration, or social self-regulation domains. Overall, the effectiveness of SRLSs depends on their specific nature and implementation. In his review of international research on deep learning, Rhem (1995) lists four characteristics of deep learning, which are repeated in McKay and Kember (1997). These features are (a) a well-structured knowledge base that emphasizes concepts, integration of knowledge, and accumulated experience; (b) an appropriate level of motivation emphasizing a sense of ownership of the course material and intrinsic motivation; (c) student activity associated with active rather than passive learning; and (d) interaction with others, including student-instructor and student-student relationships (Rhem, 1995; McKay & Kember, 1997).

In the context of the four characteristics of deep learning, the contribution of metacognitive, motivational, and behavioral constituents of self-regulated learning appears to be important for deep learning to occur. In simpler terms, self-regulated learning may enable students to participate effectively in deep learning processes. Poor motivation and a lack of active participation in a course, however, would inhibit the activation of SRLSs, even if the student possesses knowledge of these skills. In this respect, while the theoretical basis between self-regulated learning and deep learning is built upon metacognitive strategies, high intrinsic motivation, increased awareness, and collaboration are indispensable in the application dimension. From this, it can be concluded that possession of a well-rounded set of SRLSs may contribute to a student's development of a deep learning approach.

In this sense, specific connections may be drawn between self-regulated learning and deep learning under the following categories: (i) *metacognition and deep learning* – metacognitive skills, which are an important aspect of SRL, enable students to monitor and reflect upon their own understanding of subject matter. This self-awareness encourages deeper interaction with the subject matter and more thorough investigation of connections between concepts, therefore promoting deep learning; (ii) *motivation and deep learning* – deep learning students may be those who possess intrinsic motivation (Xie, King & Luo, 2023) while those who employ SRLSs may also be those who are genuinely interested in the learning tasks at hand (Virtanen, Nevgi & Niemi, 2015; Lai et al., 2024). Intrinsic motivation may encourage deep learning, since it renders students more likely to actually spend more time and effort in order to internalize course content and not just memorize facts; and (iii) *strategic action and*

deep learning – self-regulating students employ strategies such as time management, optimization of study techniques, and/or seeking out feedback. These, once again, may enable students to allocate more time and effort which lead to deeper understanding and a stance for critical thinking.

The potential role of self-regulated learning skills in mitigating smartphone addiction risk

A glance at the literature over the past decade shows that there is an increasing number of studies focusing on the relationship between SRLSs and the use of digital devices in the classroom or during study hours. Wei et al. (2012) highlighted that students with SRLSs not only show less likelihood of texting one another during a course, but also exhibit greater attention spans during learning activities. On the other hand, Chaklader and Bohlander (2009) reported that an increased frequency of texting during lectures negatively affects meaningful learning.

Anthony et al. (2020) listed a number of self-regulation components that a student may employ under the categories of (i) cognitive engagement, (ii) metacognitive knowledge, (iii) resource management, and (iv) motivational beliefs. It may be inferred that some of these strategies may indeed help a student avoid distraction due to smartphone alerts during classroom hours or study time. For instance, a student who can make better use of metacognitive knowledge strategies may possess awareness of the notion of being distracted, which may help in deciding to take action. Strategies in the resource management category, such as those involving adjustments to time and study environment, can help students optimize these parameters to minimize harmful effects caused by student-owned smartphones at school settings, which UNESCO (2023) groups under the category of digital technology that is distracting, instead of helpful.

Fear of missing out as a potential mediator between self-regulated learning skills and smartphone addiction risk

The way that SRLSs facilitate learning may also be due to the way these skills help students cope with the digital distractors around them. The final component of self-regulation, motivational beliefs, includes aspects such as goal orientation and task value that may translate into a willingness to use digital devices for productive purposes only (Adesope et al., 2015; Mädamürk et al., 2021; Pahljina-Reinić et al., 2024). For instance, a student with mastery goals, especially *task goals* – indicating a desire to correctly carry out the task at hand – might employ a deeper approach to learning and would likely be less affected by distractors. Students with

performance avoidance goals may suffer from unwanted effects including but not limited to a surface approach to learning and frequent distractions (Daumiller et al., 2023), which may include a desire to use digitally connected devices for various reasons, including FoMO. Therefore, although there are many listed reasons for being distracted by digital devices during lectures or study hours (Gezgin & Sarsar, 2020; Sumuer et al., 2018; Taneja et al., 2015), researchers have concluded that helping adolescents foster and apply SRLSs may help them reduce their FoMO levels, which, in turn, may help combat problematic use of digital devices during learning activities.

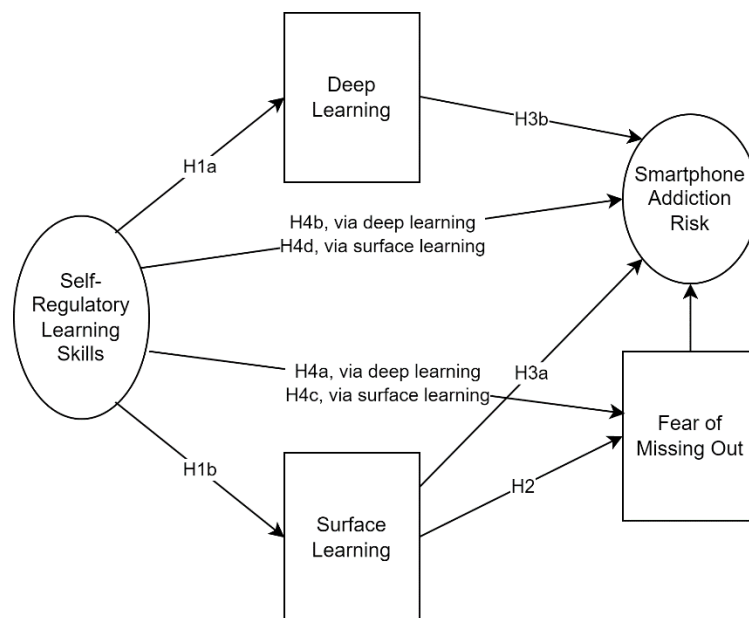
For instance, Alt and Boniel-Nissim (2018) investigated the relationship between FoMO, learning approaches, and problematic internet use among adolescents. The study focused on how surface and deep approaches to learning interact with FoMO and problematic internet use, particularly in the context of digital device use during study hours. They found that FoMO mediated the relationship between surface learning and problematic internet use, suggesting that students who adopt a surface approach are more likely to experience FoMO, which, in turn, leads to problematic internet use. Deep learning approaches did not show a significant relationship with FoMO or problematic internet use. In conclusion, it was reported that low self-regulation, inherent in surface learning, may explain this relationship, and they called for future research to further investigate the role of SRLSs in mitigating the effects of FoMO and problematic internet use. Therefore, the present study primarily addressed this gap in the literature by adding the dimension of SRLSs to the variables reported by Alt and Boniel-Nissim (2018). More specifically, the present study constructs a more exhaustive model that incorporates SRLSs alongside both deep and surface approaches to learning, in order to understand the interplay between these variables, as well as FoMO, and SA risk, among university students.

Aims and hypotheses

The aim of the study is to test the following assumptions: (a) that possession of SRLSs affects the adoption of different learning approaches, (b) that FoMO is a significant contributor to SA, and (c) that different approaches to learning also predict SA risk. In addition to these confirmatory aims, it was also deemed necessary to understand (d) whether possession of SRLSs helps students avoid FoMO and/or SA and if this mechanism works differently in students with different approaches to learning. Consequently, the hypotheses shown in Table 1 have been formulated, and a diagram showing the proposed causal model is shown in Figure 1.

Table 1*Study hypotheses*

H _#	Hypothesis
H1 _a	A higher level of SRLSs will be associated with a deeper approach to learning
H1 _b	A lower level of SRLSs will be associated with a surface approach to learning
H2	Adoption of a surface approach to learning will positively predict FoMO
H3 _a	A surface approach to learning will predict SA risk
H3 _b	A deep approach to learning will negatively predict SA risk
H4 _a	A higher level of SRLSs will be associated with lower levels of FoMO, with the deep approach to learning acting as a mediator
H4 _b	A higher level of SRLSs will be associated with lower levels of SA risk, with the deep approach to learning acting as a mediator
H4 _c	A lower level of SRLSs will be associated with higher levels of FoMO, with the surface approach to learning acting as a mediator
H4 _d	A lower level of SRLSs will be associated with higher levels of SA risk, with surface approach to learning acting as mediator

**Figure 1.** Diagram showing the proposed causal model with associated hypotheses**Materials and Methods**

Participants and procedure

A total of 687 university students, comprising 264 males (38.4%) and 423 females (61.6%), participated in the study. The participants' ages ranged from 18 to 57 years (mean=22.01 years; SD=4.09). Prior to data collection, approval for the study was granted by the Ethics Board of the first author's university. Data were collected via an online survey from volunteering participants studying in a diverse range of major departments at a Turkish university. The link to the survey was shared with students over *Microsoft Teams* classroom groups. No rewards or incentives of any kind were offered to those who completed the survey. Prior to data collection, participants were required to read and agree to the terms of exclusion and inclusion criteria, the confidentiality clauses, and statement of consent to voluntary participation.

Measures

Fear of Missing Out Scale (FoMOS). The FoMOS (Przybylski et al., 2013; Turkish version: Gökler et al., 2016) was used to assess overall levels of FoMO. It consists of 10 items rated on a five-point scale from 1 (*not true at all*) to 5 (*extremely true*). An example item is "*I fear others have more rewarding experiences than me*". The total score ranges from 10 to 50, and the higher the score, the greater the FoMO. In the present study, the Cronbach's α was 0.77.

Smartphone Addiction Scale-Short Version (SAS-SV). The SAS-SV (Kwon et al., 2013; Turkish [10-item version] Noyan et al. 2015) was used to assess smartphone addiction. It consists of 33 items rated on a six-point scale from 1 (*strongly disagree*) to 6 (*strongly agree*). The shorter 10-item version was used in the present study. An example item is "*Not being able to use my smartphone would be as painful as losing a friend*". The total score ranges from 10 to 60, and the higher the mean score, the greater the risk of SA. In the present study, the Cronbach's α was 0.87.

Revised Two Factor Study Process Questionnaire (R-SPQ-2F). The R-SPQ-2F (Biggs et al., 2001; Önder & Beşoluk, 2010) was used to assess surface or deep approaches to learning. It consists of 20 items rated on five-point scale from 1 (*never*) to 5 (*always*) and comprises two sub-scales: deep learning (10 items) and surface learning (10 items). An example item from the surface learning sub-scale is "*My aim is to pass the course while doing as little work as possible*", while an example item from the deep learning sub-scale is "*I find that at times studying gives me a feeling of deep personal satisfaction*". The total scores for both sub-scales range from 10 to 50. Higher score on the deep approach scale indicates a deeper approach to

learning, while a higher score on the surface approach scale indicates a more surface approach to learning. In the present study, the Cronbach's α for deep learning and surface learning subscales were 0.75 and 0.78, respectively.

Self-Regulated Learning Skills Scale (SRLSS). The SRLSS (developed in Turkish by Turan et al. [2009]) was used to assess self-regulated learning skills. It consists of 41 items rated on a five-point scale from 1 (*strongly disagree*) to 5 (*strongly agree*) and comprises four subscales: (a) motivation and action to learning (seven items, e.g., "*When faced with a problem, I take action to solve it*"), (b) planning and goal setting (eight items, e.g., "*I make a plan to utilize learning resources efficiently*"), (c) strategies for learning and assessment (19 items, e.g., "*I choose the most appropriate learning approach to reach my goal*") and (d) lack of self-directedness (seven items, e.g., "*I have difficulties in determining how I should study a particular subject*"). The total score ranges from 41 to 205, and higher total score indicates greater possession of overall SRLSs (with the exception of lack of self-directedness subscale, the items of which are reverse scored). For brevity purposes, subscales of the instrument are henceforth referred to as 'motivation and action to learning', 'planning and goal setting', 'strategies for learning and assessment', and 'lack of self-directedness'; and the Cronbach's α for each of the subscales were 0.84, 0.88, 0.93 and 0.79, respectively.

Data analysis

A power analysis was conducted to determine the minimum sample size required for the structural equation model (SEM) using the method proposed by MacCallum et al. (1996). The analysis was based on the Root Mean Square Error of Approximation (RMSEA) values, with a null hypothesis RMSEA (H_0) of 0.05 (indicating close fit) and an alternative RMSEA (H_1) of 0.08 (indicating a less close fit). The analysis was conducted with 114 degrees of freedom, aiming for a power of 0.80 and an alpha level of 0.05. The results indicated that a minimum sample size of 121 participants would be necessary to achieve the desired power level. With 687 participants in the study, the sample size was sufficient to meet this requirement.

The measurement and structural models were tested accordingly using the following indicators: Root Mean Square Error of Approximation (RMSEA), Standardized Root Mean Square Residual (SRMR), Goodness of Fit Index (GFI), Comparative Fit Index (CFI), Incremental Fit Index (IFI), Tucker Lewis Index (TLI), and Normed Fit Index (NFI). RMSEA and SRMR values less than .08, and GFI, CFI, IFI, TLI, and NFI values greater than .90 have been considered to indicate an acceptable fit (Schermelleh-Engel & Moosbrugger, 2003).

Bootstrap analyses with 10,000 iterations were conducted. In order to provide additional evidence on whether the direct and indirect effects of variables within tested models were statistically significant, a 95% confidence interval was selected. Data were analyzed using IBM SPSS 25 and AMOS 24 statistical software.

Results

Descriptive statistics and correlations

Descriptive statistics, correlation coefficients, and Cronbach's α reliability coefficients for data pertaining to each of the study variables are presented in Table 2. Based on these values, data were normally distributed for each variable. Results indicated that (i) SA was positively correlated with FoMO; (ii) a deep approach to learning was negatively correlated with SA and FoMO, but positively correlated with all subscales of SRLSs; (iii) 'motivation and action to learning', 'planning and goal setting', 'strategies for learning and assessment', and 'lack of self-directedness' sub-scales were all positively correlated with one another; and (iv) a surface approach to learning was positively correlated with FoMO and SA, but negatively correlated with all sub-scales of SRLSs. Pearson correlation coefficients were calculated to assess the relationships between the variables. To control for the risk of Type I errors due to multiple comparisons, a Bonferroni correction was applied, resulting in a significance level of $\alpha=0.00139$. After applying the Bonferroni correction, all correlations remained significant.

Table 2

Descriptive statistics, correlations and Cronbach's α reliability coefficients

Variables	Mean	SD	Skew.	Kurt.	A	1	2	3	4	5	6	7	8
(1) SAS-SV	29.073	9.861	.355	-.472	.87								
(2) FoMOS	25.358	6.524	.070	-.392	.77	.493*							
(3) Deep learning	33.352	5.483	.235	.198	.75	-.170*	-.139*						
(4) Surface learning	28.936	6.559	.186	-.059	.78	.309*	.292*	-.231*					
(5) Motivation and action to learning	27.572	4.516	-.236	-.477	.84	-.132*	-.136*	.550*	-.146*				
(6) Lack of self-directedness	24.134	4.751	-.237	-.431	.79	-.288*	-.255*	.264*	-.383*	.296*			
(7) Planning and goal setting	30.288	6.009	-.253	-.239	.83	-.138*	-.149*	.535*	-.132*	.709*	.316*		
(8) Strategies for learning and assessment	70.604	12.149	-.051	-.371	.93	-.138*	-.149*	.535*	-.132*	.709*	.316*	.763*	
(9) SRLSs	152.598	22.775	-.023	-.477	.94	-.203*	-.196*	.568*	-.215*	.793*	.536*	.867*	.941*

Note. FoMOS=Fear of Missing Out Scale, SAS-SV=Smartphone Addiction Scale-Short Version, SRLSs=Self-Regulated Learning Skills, SD= Standard Deviation, Skew= Skewness, Kurt= Kurtosis, α =Cronbach's alpha, * $p<.05$.

Measurement model

Before testing the hypothesized model, the measurement model was evaluated to address problems in convergence of fitting data with the model (Preacher, 2006). In this regard, the five measures were tested separately for their measurement model. For the FoMOS, FoMO is the latent variable with 10 FoMOS items being observed variables. For the SAS-SV, smartphone addiction is the latent variable with 10 SAS-SV items being observed variables. For the R-SPQ-2F (deep learning factor), deep learning is the latent variable with 10 R-SPQ-2F items on deep learning being observed variables. For the R-SPQ-2F (surface learning factor), surface learning is the latent variable with 10 R-SPQ-2F items on surface learning being observed variables. For the SRLSS, self-regulated learning skills is the latent variable with four sub-dimensions ('motivation and action to learning', 'planning and goal setting', 'strategies for learning and assessment', 'lack of self-directedness') being observed variables. The results of the analysis showed that the factor loadings and fit indices for each measure were also good, as shown in Table 3.

Table 3

Factor loadings and fit indices for measurement models for the study's five measures

Statistics	Measures				
	FoMOS	SAS-SV	R-SPQ-2F (Deep learning)	R-SPQ-2F (Surface learning)	SRLSS
Factor loading					
Item/sub-dimension 1	.607	.430	.439	.542	.744
Item/sub-dimension 2	.617	.483	.291	.378	.395
Item/sub-dimension 3	.460	.734	.596	.284	.830
Item/sub-dimension 4	.640	.710	.665	.170	.918
Item/sub-dimension 5	.705	.527	.595	.560	--
Item/sub-dimension 6	.665	.405	.537	.709	--
Item/sub-dimension 7	.767	.502	.519	.638	--
Item/sub-dimension 8	.604	.290	.435	.518	--
Item/sub-dimension 9	.670	.204	.276	.694	--
Item/sub-dimension 10	.614	.477	.403	.603	--
Fit indices					
χ^2 (df)/p-value	190.699 (35)/<.001	184.742 (33)/<.001	157.822 (35)/<.001	93.255 (35)/<.001	4.042 (2)/.132
CFI/TLI	.967/.958	.931/.906	.924/.903	.973/.965	.998/.994
RMSEA/SRMR	.081/.076	.082/.071	.072/.073	.049/.061	.039/.025

Note. FoMOS=Fear of Missing Out Scale; SAS-SV=Smartphone Addiction Scale-Short Version; R-SPQ-2F=Revised Two Factor Study Process Questionnaire; SRLSS=Self-Regulated Learning Skills Scale; CFI=comparative fit index; TLI=Tucker-Lewis index; RMSEA=root mean square error of approximation; SRMR=standardized root mean square residual.

Structural models

Next, the explanatory roles of deep and surface learning approaches in the relationship between SRLSs and FoMO and SA were examined. In Structural Model 1, all hypotheses were tested as shown in Figure 1. However, the results showed that the direct pathways from both SRLSs to SA, and SL to SA, as well as indirect effects of deep and surface learning approaches upon SRLSs to SA, yielded statistically non-significant results ($p>.05$). The direct pathways were therefore removed from the model. The resulting model, Structural Model 2, was also tested.

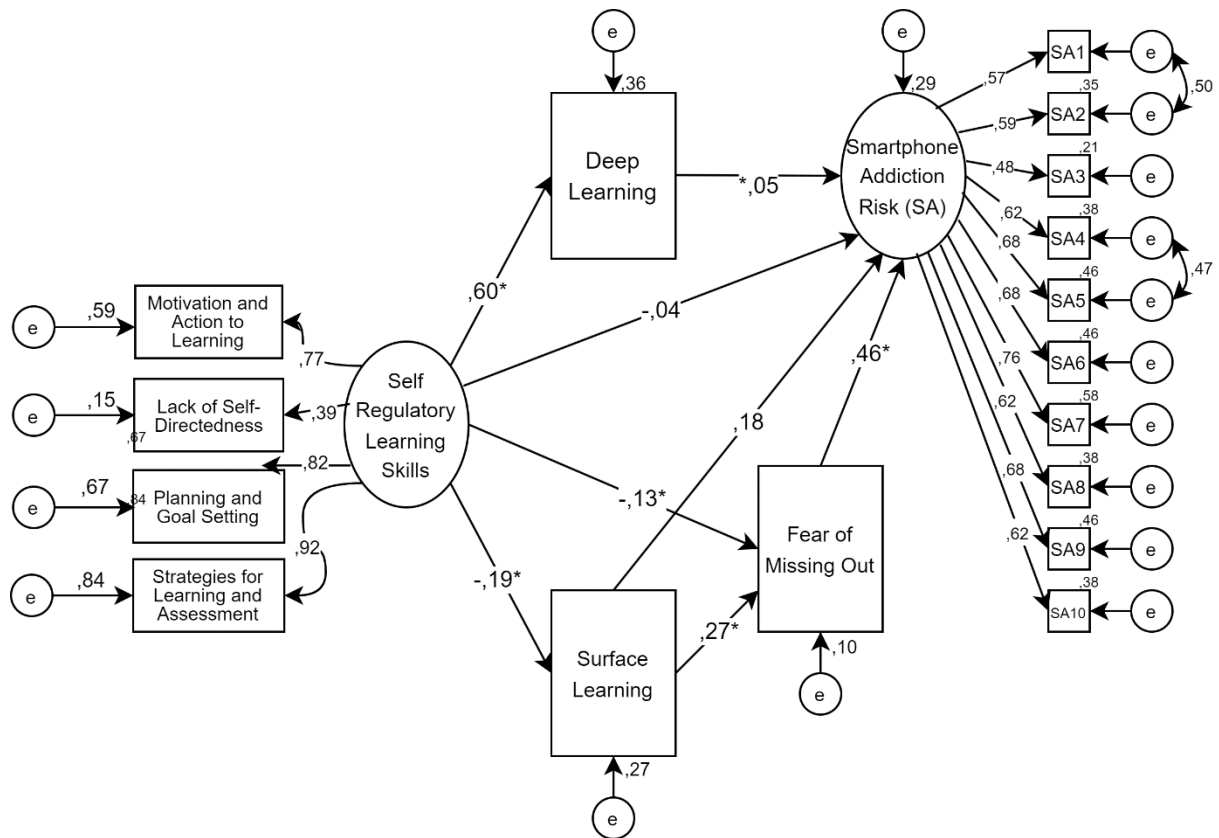
Results showed that although the goodness of fit values of Model 1 were better, Model 2 also met the goodness of fit criteria and all pathways yielded statistically significant results. For the purpose of the study, Structural Model 2, shown in Figure 3, was considered better in explaining the relationships and was therefore used for hypotheses testing. Fit indices for the two structural models are shown in Table 4. Information on average variance extracted and variance inflation factor for the studied measures are shown in Table 5.

Table 4

Fit indices for the two structural models

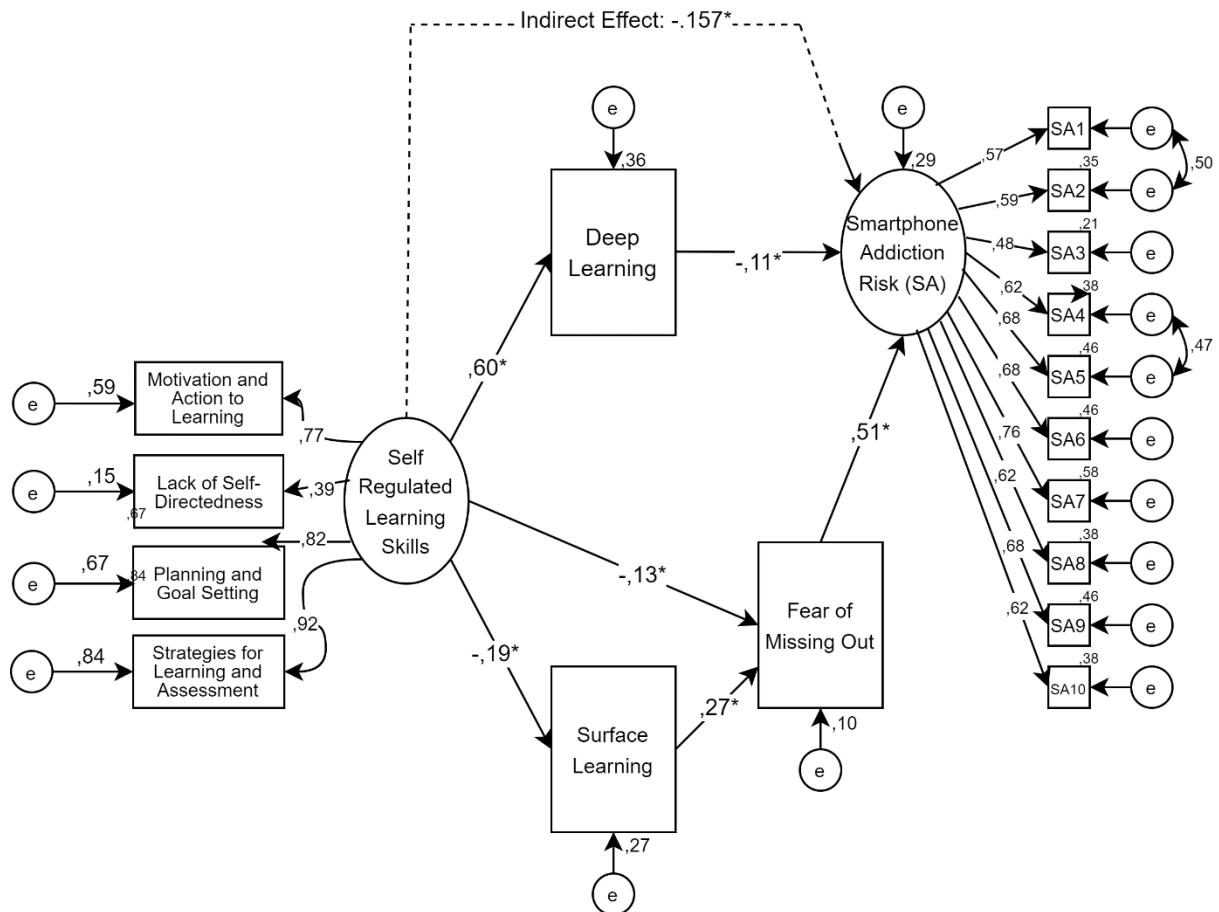
Models	χ^2	DF	SRMR	RMSEA [90% CI]	GFI	CFI	IFI	AIC	ECVI
Structural Model 1	506.863	112	.066	.072 [.065-.078]	.920	.916	.917	588.863	.858 [.762-.966]
Structural Model 2	529.740	114	.073	.073 [.067-.079]	.916	.912	.912	607.740	.886 [.787-.996]

Note. χ^2 =chi-square, df= degrees of freedom, SRMR=standardized root mean square residual, RMSEA=root mean square error of approximation, GFI= goodness of fit index, CFI=comparative fit index, IFI=incremental fit index, AIC=Akaike information criterion, ECVI=expected cross validation index. Structural model 1 contains the following paths: self-regulated learning skills→deep learning→smartphone addiction (Path 1), self-regulated learning skills→smartphone addiction (Path 2), self-regulated learning skills→fear of missing out→smartphone addiction (Path 3), self-regulated learning skills→surface learning→smartphone addiction (Path 4), self-regulated learning skills→surface learning→fear of missing out→smartphone addiction (Path 5). Structural model 2 contains Paths 1, 3, and 5, but does not contain Paths 2 and 4.



* Indicates statistical significance at $p < .05$

Figure 2. The explanatory role of deep and surface learning role in the relationship between SRLSs and FoMO and SA (standardized estimates) – Structural Model 1



* Indicates statistical significance at $p < .05$

Figure 3. The explanatory role of deep and surface learning role in the relationship between SRLSs and FoMO and SA (standardized estimates) – Structural Model 2

Table 5

Information of variance inflation factor and average variance extracted for the studied measures

Measure	Average variance extracted	Variance inflation factor
Fear of missing out	0.250	1.116
Deep learning	0.247	1.505
Surface learning	0.294	1.145
Self-regulated learning skills	0.724	1.516
Smartphone addiction	0.410	--

The SEM analysis of Structural Model 2 indicated that, overall, SRLSs predicted deep learning ($\beta = .60$, $p < .001$) and negatively predicted surface learning ($\beta = -.19$, $p < .001$). Hypotheses H1_a

and H1_b were therefore supported. It was also shown that surface learning predicted FoMO ($\beta=.27, p<.05$), which confirmed Hypothesis H₂. Although deep learning negatively predicted SA ($\beta=-.10, p<.05$) (supporting H3_b), surface learning did not statistically significantly predict SA in Structural Model 1 ($p>.05$). Therefore, H3_a was not supported, and this pathway was removed from the final model.

The direct effect of SRLSs upon FoMO was statistically significant ($\beta=-.13, p<.001$). H4_a (that higher SRLSs would be associated with lower levels of FoMO, mediated by the deep learning approach) was not supported ($\beta=-.00, p>.05$). However, having lower SRLSs was associated with higher FoMO mediated by the surface learning approach ($\beta=-.16, p<.001$) (supporting H4_c). Hypotheses regarding the mediation effects of learning approaches in the effect of SRLSs upon SA were also examined. H4_b (that higher SRLSs would be associated with lower levels of SA risk, with the deep approach to learning acting as a mediator) was not supported. Likewise, H4_d (that SRLSs would be associated with higher SA risk mediated by the surface learning approach) was also not supported. Lastly, FoMO was shown to predict SA ($\beta=.51, p<.05$).

Bootstrap analysis showed that all the direct and indirect effects in the model were statistically significant (Table 6), and the amount of variance explained is shown in Table 7. It can be seen that SRLSs explained 3.5% of the variance in the surface learning approach (i.e., a small effect size). While there was some relationship between these variables, it was relatively modest. SRLSs explained 36.4% of the variance in the deep learning approach (i.e., medium effect size). SRLSs and surface learning together explained 10.1% of the variance in FoMO levels (i.e., a small effect size). Altogether, the independent and mediator variables (i.e., via the following paths: self-regulated learning skills→deep learning→SA risk; SRLSs→FoMO→SA risk; and SRLSs→surface learning→FoMO→SA risk) explained 28.8% of the variance in SA risk. As for indirect effects, SRLSs were shown to indirectly predict SA risk via deep learning, surface learning and FoMO ($\beta=-.157, p<.001$). Taken together, these results demonstrate the role of deep learning, surface learning, and FoMO in explaining the relationship between SRLSs and SA.

Table 6

Results of bootstrap analysis on standardized direct and indirect effects

Path	95% CI
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	Standardized coefficients	Lower	Upper
Direct effects			
Self-regulated learning skills→Deep learning	.603**	.540	.660
Self-regulated learning skills→Surface learning	-.187**	-.267	-.103
Self-regulated learning skills→Fear of missing out	-.130**	-.210	-.046
Deep Learning→Smartphone addiction	-.108*	-.188	-.027
Surface Learning→FoMO	.268**	.191	.340
FoMO→SA	.515**	.447	.575
Indirect effects			
Surface Learning→FoMO →Smartphone addiction	.138**	.094	.184
Self-regulated learning skills→Surface learning→Fear of missing out	-.050**	-.079	-.028
Self-regulated learning skills→Deep learning, Fear of missing out, Surface learning→Smartphone addiction	-.157**	-.225	-.093

Note. CI=confidence interval, * $p<.05$, ** $p<.001$

Table 7

R-squared values for the structural equation model variables

Endogenous variables	Variables that explained the endogenous variables	R^2
Surface learning	Self-regulated learning skills	0.035
Deep learning	Self-regulated learning skills	0.364
Fear of missing out	Self-regulated learning skills; Surface learning	0.101
Smartphone addiction	Deep learning, Fear of missing out	0.288

Discussion

The overarching aim of the present study was to examine the possible relationships between SRLSs level, learning approaches, FoMO, and SA among university students. SEM analysis was used to explore possible associations between the direct and indirect role of FoMO in the relationship between SRLSs level, learning approaches and SA. A list of the hypotheses of the study and whether they were supported or rejected based on the aforementioned findings is shown in Table 8.

Table 8

Study hypotheses and whether they were supported or not

H#	Hypothesis	Status
H1 _a	A higher level of SRLSs will be associated with a deeper approach to learning	Supported
H1 _b	A lower level of SRLSs will be associated with a surface approach to learning	Supported
H2	Adoption of a surface approach to learning will positively predict FoMO	Supported

H3 _a	A surface approach to learning will predict SA risk	Rejected
H3 _b	A deep approach to learning will negatively predict SA risk	Supported
H4 _a	A higher level of SRLSs will be associated with lower levels of FoMO, with the deep approach to learning acting as a mediator	Rejected
H4 _b	A higher level of SRLSs will be associated with lower levels of SA risk, with the deep approach to learning acting as a mediator	Rejected
H4 _c	A lower level of SRLSs will be associated with higher levels of FoMO with, the surface approach to learning acting as a mediator	Supported
H4 _d	A lower level of SRLSs will be associated with higher levels of SA risk, with surface approach to learning acting as mediator	Rejected

Results indicated that both H_{1a} and H_{1b} were supported, and among higher education students, the adoption of a deep or surface approach to learning was associated with higher or lower levels of SRLSs in students, respectively. In other words, a student adopting a deep learning approach was also likely to be in greater command of SRLSs, and vice versa. On the other hand, lacking SRLSs were associated with adoption of a surface learning approach. The finding obtained in the present study is consistent with the literature. For instance, among Finnish university students, Heikkilä and Lonka (2006) demonstrated that SRLSs were (i) positively associated with deep learning approaches and (ii) negatively associated with surface learning approaches.

Moreover, the present study's findings showed that SRLSs explained 3% of the variance in the surface learning approach and 36% of the variance in the deep learning approach. Therefore, self-regulated learning explains very little about surface learning, while self-regulated learning is frequently associated with improving deeper learning (understanding concepts deeply, creating connections, applying information). Even if a person does not possess an adequate level of SRLSs, it still cannot be said that they will approach learning tasks superficially. Given the association between SRLSs and deep learning, educational research could try to focus on interventions that bolster self-regulation as a probable pathway to deeper engagement with learning materials, and explore whether a causal relationship exists between the two. Furthermore, the minimal explanation provided by SRLSs for surface learning suggests that other factors may be at play, indicating a need for future research to explore additional variables that influence surface learning approaches. For instance, from Biggs' (2014) perspective, it has been reported that factors such as cognitive style, personality, and values can

lead to surface learning approaches by students, and instructional design efforts need to prioritize a ‘constructive alignment’ for reducing the student tendency towards surface learning (Wang et al., 2013). It has also been shown that other variables such as higher perceived stress or negative emotions (Öhrstedt & Lindfors, 2018; Trigwell, 2012), lower expected grades (Öhrstedt & Lindfors, 2018), and course assessment methods (Beyaztas & Senemoglu, 2015) are associated with surface learning.

Results indicated that H₂ was supported and showed that higher levels of FoMO in a student may be explained by students’ adoption of a surface-level approach to learning subject matter. In support of the present study’s findings, Alt and Boniel-Nissim (2018) reported that the increase in the level of surface learning among students is associated with an increase in FoMO. Similarly, Gezgin and Türk Kurtça (2023) found a low but significant relationship between surface learning and FoMO among university students. Although the effect size was relatively small, the findings are consistent with another study showing a positive relationship between FoMO and surface learning (Rozgonjuk et al., 2019). On the other hand, the findings showed that SRLSs and surface learning together explained 9% of the variance in FoMO levels, which is a low value for predictors. Therefore, other variables that were not examined in the present study may predict FoMO should be considered in future research. For instance, impulsivity or coping with stress – the lack of which may be associated with the adoption of a surface learning approach, as indicated above – may be considered. Here, it is important to note that stress, in particular, has been shown to also be associated with problematic smartphone use severity, mediated by FoMO and smartphone use frequency (Yang et al., 2021).

According to SDT, it is thought that the basic needs of surface learners, who tend to adopt less meaningful learning strategies typically adopted by extrinsically motivated learners, such as rote memorization (Biggs, 1989; Cano, 2007), might very often not be met as much as is the case for deep learners (Deci & Ryan, 1985). A lack of the satisfaction of these basic needs (such as belonging, having social relationships, and competence) is expected to increase the level of FoMO (Przybylski et al., 2013). The fact that the surface learners cannot achieve high success in the classroom further reduces their already insufficient social relationships and belonging needs. Increasing amotivation and failure can trigger a specific sense of avoidance, and students who experience these feelings may attempt to meet these basic needs on social networking sites.

It is evident in this finding that, once again, the association between FoMO and a surface approach to learning suggest that educational interventions should not only focus on enhancing

SRLSs, but also consider addressing the psychological and social needs of students as outlined by Self-Determination Theory (SDT). This could involve fostering a more supportive learning environment that satisfies students' basic psychological needs and, at the same time, potentially reduces their reliance on surface learning strategies. While the predictive value of SRLSs and surface learning on FoMO is modest, the identification of other contributing factors, such as impulsivity and coping mechanisms, offers a pathway for further research. By expanding the focus beyond academic strategies to include psychological well-being, future educational frameworks can better support students in managing FoMO and promote more effective learning approaches.

The results indicated that H_{3a} was not supported. More specifically, results showed that a surface approach to learning had no significant direct effect on SA risk. However, in relation to indirect effects, it was found that FoMO fully mediated the path between a surface learning approach and SA risk. This suggests that being a surface learner alone does not necessarily mean an individual is prone to developing SA or that surface-level learners may be at risk of SA only insofar as they are affected by social media use-related FoMO.

The extant literature has consistently reported a positive relationship between FoMO and (i) SA and (ii) problematic smartphone use (e.g., Adelhart et al., 2018; Alinejad et al., 2022; Elhai et al., 2018; Gezgin, 2018; Li et al., 2022; Rozgonjuk et al., 2018), and the results of the present study found that students with a superficial learning strategy were associated with SA only through FoMO. The mediating role of FoMO may lead to an interpretation that surface learners problematically use social networking sites and smartphones (Li et al., 2022) to meet their basic psychological needs (Przybylski et al., 2013) and for sensation seeking (Wang et al., 2019). Rozgonjuk et al. (2018) showed that students' use of social media in school lessons completely mediated the relationship between problematic smartphone use and learning approaches. The fact that one of the driving forces of social network use is FoMO suggests that it plays a role in this mediation. In light of this information, it could be stated that educational frameworks may consider employing instructional designs that incorporate decisions or interventions for addressing FoMO, while also trying to promote deeper learning approaches that satisfy students' psychological needs in more constructive ways. Moreover, future research should explore other potential mediators and moderators in this relationship, such as individual differences in sensation seeking or coping styles, to develop more comprehensive strategies for preventing SA in students.

The results indicated that H_{3b} (that learners' adoption of a deep approach to learning would be associated with a reduced risk of SA) was supported. The risk of SA is reduced for an individual who consciously uses a smartphone and has strong SRLSs (Gezgin, 2022b) and self-efficacy (Chiu, 2014). The results obtained in the present study have shown that the SRLSs of individuals who used a deep learning strategy tended to be more developed, which was perhaps unsurprising. In addition, individuals who used a deep learning strategy heavily benefited from SRLSs in terms of learning. Based on this finding, the deep learning approach appears to carry the potential of being a protective factor against SA among university students.

The fourth set of hypotheses consisted of four sub-hypotheses (H4a to H4d). In formulating these, the intention was to see whether engaging in SRLSs helped students inhibit FoMO and/or SA, and if this mechanism worked differently among students with different approaches to learning. The decision to explore deep and surface approaches to learning as mediators was grounded in the study findings of Alt and Boniel-Nissim (2018), which highlighted the potential shared characteristic of decreased self-regulation between FoMO and surface learning.

H_{4a} posited that an increase in SRLSs would be associated with lower levels of FoMO, with the deep approach to learning acting as a mediator. Although SRLSs positively predicted the adoption of a deep learning approach and negatively predicted FoMO, H_{4a} was not supported. This suggests that in order to benefit from a reduction in FoMO due to high SRLSs, an individual does not necessarily need to be a deep learner. However, given that Alt and Boniel-Nissim (2018) emphasized the importance of fostering self-regulation to mitigate FoMO, future studies should further explore the role of deep learning in this relationship.

H_{4b} posited that an increase in SRLSs would be associated with lower levels of SA risk with the deep approach to learning acting as a mediator. However, this hypothesis was not supported due to the lack of a significant direct effect of SRLSs on SA risk. Studies in the literature report that the risk of SA increases as students' SRLSs decrease (Seong & Jin, 2012). This was also shown in terms of correlation in the present study (see Table 2). However, results of the SEM analysis failed to indicate causality and mediation. This finding should be interpreted together with the other findings showing that there are separate significant direct effects of SRLSs on adoption of deep learning, and the adoption of deep learning on SA risk.

It is therefore theorized by the present authors that the way the adoption of a deep learning approach reduces the risk of SA is not dependent upon SRLSs. There may be other

components or mechanisms of the deep approach to learning that explain its inhibiting effect on SA risk. For instance, high concentration, effective time management skills, and high intrinsic motivation (Draper, 2009; Marton & Saljo, 2005) associated with the deep learning approach may alleviate the lack of SRLSs in the inhibition of SA risk. Further studies are required to clarify this.

However, a significant indirect effect was found, and this suggests that engaging in SRLSs may be a protective factor against SA provided that an individual adopts a deep approach to learning. In other words, deep learners with a greater command of SRLSs may comprise a group of individuals who are effective at not being enticed and distracted by their smartphone, at least during classroom or study hours, irrespective of whether they use their smartphone in different contexts (be it the social context or process context) (Wickord & Quasier-Pohl, 2022). This, in turn, may help individuals avoid developing SA.

The results indicated that lower SRLSs were associated with higher FoMO, with the surface learning approach acting as a mediator. Therefore, H_{4c} was supported. Again, the mediation assumptions here were based on Alt and Boniel-Nissim's (2018) study, which reported that both FoMO and surface learning might share a common core characteristic of decreased levels of self-regulation. Therefore, the present study's findings appear to demonstrate the importance of self-regulation, which is thought to be an important skill to possess for not experiencing the detrimental effects of phenomena such as FoMO and surface learning. While a lack of SRLSs was a strong indicator of students' likelihood to experience FoMO, this effect was partly due to the fact that these students appeared to have adopted a surface approach to learning.

Lastly, H_{4d} posited that a decrease in SRLSs would lead to an increase in SA risk with the surface approach to learning acting as a mediator. However, this hypothesis was not supported because there was no significant direct effect of SRLSs on SA risk. Examination of the indirect effects suggested an unexpected finding. With regard to surface learners, the reduction of FoMO may help avoid the development of SA, but this may not be possible by simply increasing SRLSs.

Limitations

The findings of the present study may be limited by several factors. Firstly, from a statistical perspective, it should be noted that several of the comparative fit indices for measurement models for the study's five measures (Table 3), as well as the comparative fit

indices for both Structural Models 1 and 2 (Table 4) lay in the $.90 \leq CFI < .95$ range; which has been referred to as “indeterminate, ;gray areas; between ‘good; and 'bad’ fit” by Lai and Green (2016). Secondly, the use of a self-selecting sample introduced the potential for selection bias, because individuals who chose to participate may not have been representative of the entire population, leading to results that are not generalizable. Thirdly, the cross-sectional nature of the data restricted the ability to establish causality or examine changes over time, providing only a snapshot of the relationships at a single point in time. Fourthly, focusing solely on data from Turkey may limit the generalizability of the findings to other populations or contexts. Finally, all the data were based on self-report. Therefore, the results may be affected by social desirability and other biases (e.g., memory recall).

Implications and further research

Findings of the study have implications for educational practice. It can be inferred that focusing efforts on improving SRLSs among higher education students may lead them to adopt deep learning strategies and move away from superficial methods. Pintrich (2000) proposes a model of SRLSs and explains these through phases of planning, monitoring, control, and reflection in cognitive, affective, behavioral, and contextual domains. This model asserts that it is possible for a student to improve these skills by developing, for instance, metacognitive awareness, help-seeking behavior, or task evaluation and interest activation strategies. In this context, students that face academic hardships due to superficial approaches to learning may have a chance of actually developing intrinsic motivation or, at the very least, rationalizing their failure as an ineffective management of time and resources, rather than resorting to irrational excuses leading to self-hindrance.

Students’ awareness should also be raised regarding FoMO and SRLSs, particularly highlighting that the latter not only hold the promise of improving approaches to learning and academic performance, but help protect against SA. In order to facilitate these efforts, it is important to follow constructivist approaches in higher education institutions in order to design flexible and student-centered learning environments. This is considered necessary because SRL is an inherently constructive and self-directed process and has strong ties to constructivism (De Corte, 2019). This should be clear because constructivism does not involve the mere transfer and rote acquisition of knowledge but rather the restructuring of it. In this approach, which requires the learner to take on an active role, there is participation in the learning process through activities such as discussion, argumentation, questioning, and sharing of ideas as opposed to just reading and listening. Especially when the characteristics of students with deep

learning approach are considered, it is known that students who participate in cooperative learning, take an active role in learning, and have critical thinking skills may also be those who prefer deep learning strategies. In this respect, taking the constructivist approach as a basis in the development of teaching environments may support students' intrinsic interest (Do et al., 2023; Kingir et al., 2013), SRLSs (Kingir et al., 2013) and deep learning (Silalahi, 2021, Xiu-juan, 2008). In the context of the results of this study, by doing so it is likely that there will be a decrease in the severity or risk of SA. It is also advised to offer curriculum options appealing to individual interests and educational requirements, so as to fuel intrinsic motivation.

Lastly, educators should physically and digitally enhance the learning environments in ways that foster activities associated with deeper approaches to learning, such as collaboration, research, and problem-solving (Beausaert et al., 2013; Baldan, 2017). It has been shown that digital learning environments are particularly effective in supporting self-regulated learning by providing instructional architecture that encourages task understanding, strategy selection, and progress monitoring (Johnson & Davies, 2014). Using the internet and instant communication tools, such as forums or messaging platforms, can offer students a means of social support by facilitating peer feedback, collaborative study groups, and discussions with instructors. However, simply giving students access to internet technologies without effective instructional design, does not automatically mean it will benefit them, because studies show that while university students frequently use digital technologies, they may not consistently employ them for self-regulation in learning (Yot-Domínguez & Marcelo, 2017). As a UNESCO (2023) report notes, specific technologies may facilitate learning in specific contexts, but their efficacy diminishes when they are over-utilized or misapplied. The same report specifically posits that the use of smartphones in classrooms can interfere with the learning process.

The study also has implications in terms of recommendations for future research. Although the present findings regarding the relationship between FoMO and SA risk are not surprising and are in line with similar research in the field (Alt & Boniel-Nissim, 2018; Gezgin & Türk Kurtça, 2023; Rozgunjuk et al., 2019), specific pathways between SRLSs, the deep approach to learning, FoMO, and SA risk have not been fully explained. Consequently, future studies should be conducted to explore what other variables play a part in (as opposed to FoMO) explaining how SRLSs helps reduce SA risk among deep learners. This could be another small but important step in modelling SA risk patterns in educational settings, which may help inform decisions in taking preventive action. Finally, considering that findings of the present study are limited to a population of tertiary education students, similar studies investigating FoMO and

SA risk may be conducted among students in primary and secondary education, where SRLSs may be just as (if not more) important.

Conclusion

Although the results of the present study do not fully explain the relationships between the variables and the reasons for the effects, they do contain some important findings. As far as university students are concerned, possession of SRLSs is influential in the adoption of deep or surface approaches to learning. Higher SRLSs among surface learners translates into greater engagement by reducing levels of FoMO during study, which, in turn, likely reduces SA risk. However, the path analysis failed to find a similar pattern for deep learners. Although an increase in SRLSs is associated with a deeper approach to learning and was associated with a reduced risk of SA, this mechanism was not explained by a reduction in FoMO.

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