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Original

How smartphone addiction disrupts the positive relationship between self-regulation, self-efficacy and student engagement in distance education

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ABSTRACT

Given that students maintain a continuous connection with their smartphones in their daily lives and rely on them for participating in distance education, it becomes imperative to explore the factors associated with student engagement, considering the mediating role of smartphone addiction in distance education programs. Although extensive research has been carried out on smartphone addiction, very little is known about it in the context of distance education. This study aims to explore the relationship between student engagement, smartphone addiction, self-regulation, and self-efficacy among distance education students in online learning environments. This cross-sectional study was conducted in Türkiye. Data were collected via an online questionnaire from 1514 university students (n = 842 females, n = 672 males; M_{age} = 33.11, SD = 10.09) enrolled in various distance education programs in Turkey, specifically those undertaking synchronous online courses, through an online questionnaire distributed via e-mail. Path analysis modelling was used to test the hypothesised model. Maximum Likelihood Estimation was used as a method for estimating parameters in path analysis. The findings of this study indicate that self-regulation had a positive impact on student engagement, while smartphone addiction had a negative influence. Importantly, smartphone addiction acted as a mediating factor, weakening the relationship between self-regulation and student engagement. No significant correlation was found between general self-efficacy and smartphone addiction. These results highlight the significance of interventions focusing on self-regulation skills and promoting healthy digital habits to enhance student engagement and addressing smartphone addiction is crucial for enhancing student engagement in distance learning environments.

Cómo la adicción al teléfono inteligente altera la relación positiva entre la autorregulación, la autoeficacia y el compromiso del alumnado en un entorno de educación a distancia

Palabras clave:
Educación a distancia
Compromiso
Autorregulación
Autoeficacia
Adicción
Teléfono inteligente

RESUMEN

En la actualidad, el alumnado mantiene una conexión constante con los teléfonos inteligentes y depende de ellos para la educación a distancia. Por tanto, resulta primordial analizar los factores asociados a la participación de los estudiantes en este tipo de educación, considerando el papel adictivo que desempeñan los teléfonos inteligentes. Aunque la adicción a los teléfonos inteligentes ha sido extensamente investigada, se dispone de escasa información sobre este fenómeno en el contexto de la educación a distancia. Este estudio tiene como objetivo analizar la relación entre el compromiso de los estudiantes, la adicción

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a los teléfonos inteligentes, la autorregulación y la autoeficacia en la educación en línea. Este estudio transversal se ha llevado a cabo en Turquía. Se han recopilado datos mediante un cuestionario en línea de 1.514 estudiantes universitarios (842 mujeres y 672 hombres; M_{edad} = 33.11, *DT* = 10.09; 56% mujeres) matriculados en diversos programas de educación a distancia en Turquía, específicamente aquellos que realizan cursos en línea síncronos. Se ha utilizado un modelo de análisis de trayectorias para probar el modelo hipotetizado. Se ha empleado la Estimación de Máxima Verosimilitud como método para estimar los parámetros en el análisis de trayectorias. Es importante destacar que la adicción al teléfono inteligente ha actuado como un factor mediador, debilitando la relación entre la autorregulación y la participación del alumnado. Por tanto, no se ha encontrado una correlación significativa entre la autoeficacia general y la adicción a los teléfonos inteligentes. Estos resultados resaltan la importancia de las intervenciones centradas en las habilidades de autorregulación y la promoción de hábitos digitales saludables para mejorar la participación del alumnado y, de este modo, abordar la adicción al teléfono inteligente, mejorando así la participación del alumnado en un entorno en línea.

Introduction

Student engagement is a critical factor influencing learning outcomes in online learning environments, supported by previous studies (Bedi, 2023; Fredricks et al., 2004; Manwaring et al., 2017). With its multifaceted nature, student engagement is influenced by various factors, particularly learner characteristics that are influential from the early stages of distance education (Walker et al., 2006). Learner attributes such as self-regulation and general self-efficacy positively impact the online learning process, fostering student engagement and influencing student behaviour and motivation (Briones et al., 2023; Sun & Rueda, 2012). Furthermore, smartphone addiction, which can impact student behaviour and motivation, may also have a relationship with student engagement in online learning. Excessive and problematic smartphone use can lead to addiction, adversely affecting users' daily lives and work (Singh et al., 2023; Zhao & Lapierre, 2020). A recent systematic literature review showed that university students represent a high-risk demographic exhibiting problematic online behaviours, encompassing generalized problematic smartphone usage and specific problematic internet activities (Sánchez-Fernández & Borda-Mas, 2023). Consequently, further research is necessary to gain a better understanding of the correlation between addiction and different domains (Chen et al., 2023). Therefore, investigating the impact of smartphone addiction on psychological variables and learning outcomes in online learning environments becomes crucial. This study explores the mediating effect of smartphone addiction on the relationship between self-regulation, general self-efficacy, and student engagement in online learning environments.

Background

Empirical studies in the literature suggest that there are significant relationships between student engagement, self-regulation and self-efficacy in online learning environments and these variables interact directly or indirectly with smartphone addiction. This argument is summarized in Figure 1 based on current studies in the literature. In the following section, the study variables as seen in Figure 1 will be explained and the relationship between these variables will be revealed based on previous literature (Abbasi et al., 2021; Doo & Bonk, 2020; Fredricks et al., 2004; Jilisha et al., 2019; Kim et al., 2019; Li & Lajoie, 2022; Zhang & Wu, 2020; Zimmerman, 2000a).

Student engagement in distance education

Student engagement in distance education refers to the degree of active involvement, participation, and commitment demonstrated by students in their learning experiences within distance learning environments (Bond & Bergdahl, 2022). In the relevant literature, student engagement is defined as students' positive behaviors and sense of belonging in the environment, and their degree of engagement with educational activities. It is stated that increasing student engagement will provide a sense of belonging to online learning environments (Stone & O'Shea, 2019) and can have a significant impact on the learning experiences of distance education students in online learning environments (Fatawi et al., 2020).

There are different classifications and models in the literature. Fredricks et al. (2004) conceptualized engagement in three areas: behavioural, emotional, and cognitive. This classification has been widely accepted in studies on engagement. Distance education students' interest and satisfaction (emotional engagement), communication and interaction skills (behavioural engagement), motivation to learn and mental effort (cognitive engagement) in the learning environment are considered important in increasing student engagement in online learning environments. In the engagement model, self-regulation and self-efficacy emerge as important variables that affect student engagement in online learning environments (Doo & Bonk, 2020) and it is known that this relation improves learning outcomes showing a positive relationship with academic achievement (Ergun & Usluel, 2015; Kahu & Nelson, 2018). At this juncture, providing a detailed explanation of the factors influencing student engagement in distance education such as self-regulation and self-efficacy is crucial (Miao & Ma, 2023). A thorough examination of these components is important for a nuanced understanding of the intricate dynamics that contribute to the level of student engagement in the context of distance education. Additionally, addressing smartphone addiction within this context is considered essential. A comprehensive exploration of these variables will enhance our comprehension of the factors shaping student engagement and association with smartphone addiction.

Self-regulation

The concept of self-regulation, which has been defined and modelled from many theoretical perspectives, emerged in the mid-1980s considering the question of how learners can manage their learning processes (Zimmerman, 2013). Self-regulation as described in Bandura's social cognitive learning theory is based on the assumptions that the learner sets learning goals, monitors, and controls the learning process, and changes or regulates it when necessary (Pintrich, 2004). In the literature, this concept was also commonly referred to as self-regulated learning (SRL) by several researchers (Boekaerts & Niemivirta, 2000; Hadwin &

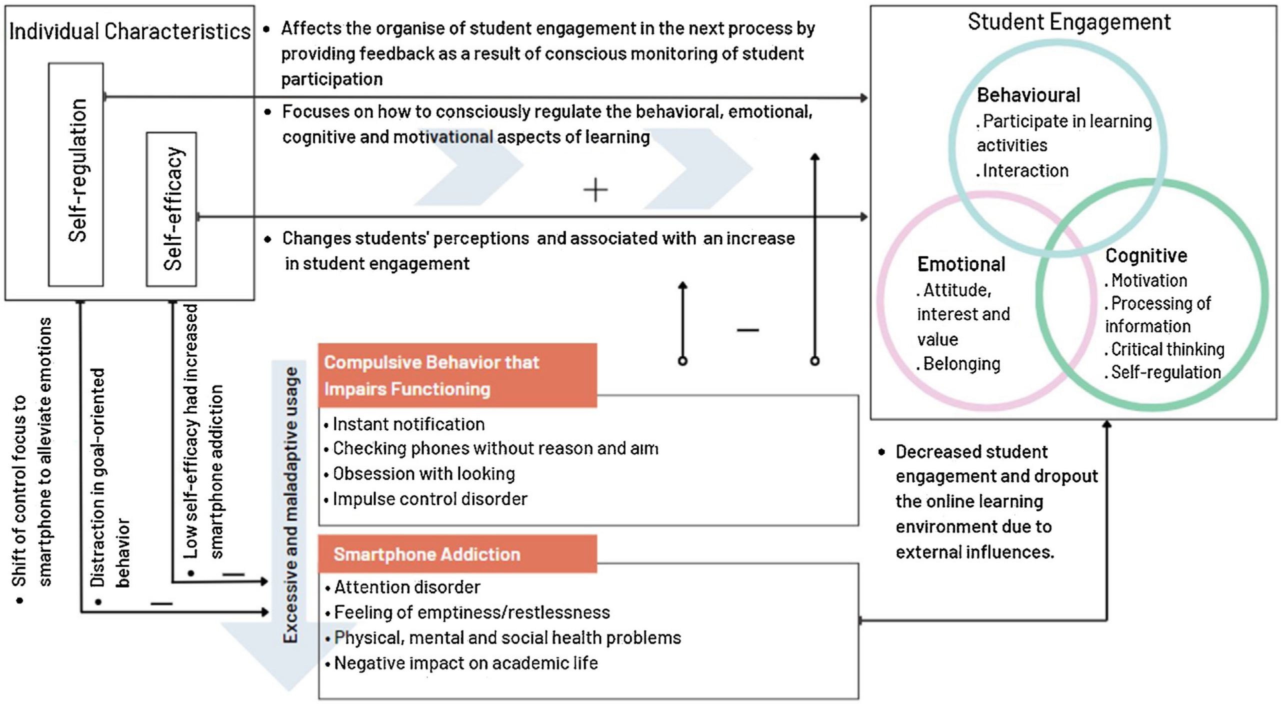

Figure 1. Student engagement, smartphone addiction and related variables.

Oshige, 2011; Pintrich, 2000; Winne & Hadwin, 1998; Zimmerman, 2000a). Although there are different definitions, self-regulation is conceptualized with the dimensions of "*attention, emotion and behaviour regulation*" (Smith-Donald et al., 2007). In particular, the self-regulated learning model proposed by Pintrich (2000) emphasizes how attention and goal orientation are related to self-regulation. Self-regulation, which requires attention and focuses on a specific learning task, is an active initiative that occurs and can be exhausted with behavioural, emotional and cognitive processes (Schmeichel & Baumeister, 2004; Winne, 2011). Within this context, the attention facet of self-regulation holds paramount importance. The attention dimension of self-regulation pertains to an individual's concentration on a given task, orchestrating attention consistently throughout the task by managing and resisting diversions and disregarding stimuli that are irrelevant or potentially disruptive (Kim et al., 2016).

Given the enhanced autonomy in managing time, space, and interaction styles within distance education environments, learners' proficiency in regulating their learning becomes paramount (Du et al., 2023). A requisite for success in distance education is the learners' adeptness in independently cultivating and refining their skills (Doo & Bonk, 2020). Consequently, a heightened demand is placed on students to frequently employ their self-regulation skills in distance education (Cakiroglu et al., 2024). It is emphasized that successful students can regulate their cognitive processes, motivational states and behaviours (Zimmerman, 2013), that these students can set high-quality goals, choose the strategies to achieve these goals, monitor their progress, and use the necessary self-regulation skills (Winne & Hadwin, 2008). However, studies have shown that most distance learners have difficulty managing their learning processes (Lehmann et al., 2014), that they tend to continue their distance education activities at a low rate (Littlejohn et al., 2016), and their engagement is highly negatively affected depending on self-regulation skills (Doo & Bonk, 2020).

In distance learning environments where the responsibility for learning is mostly on the learner, it is expected that the individual has self-regulation skills to reach the goal but smartphone addiction, as a distracting factor can negatively affect student behaviour (Fatkuriyah & Sun-Mi, 2021; Mahapatra, 2019). In this context, examining the relationship between self-regulation, student engagement and smartphone addiction in online learning environments will provide useful findings. In summary, hypotheses H1, H2, and H3 are proposed: (H1) There is a significant association between self-regulation skills and behavioural engagement levels of distance education students; (H2) There is a significant association between self-regulation skills and emotional engagement levels of distance education students; (H3) There is a significant association between self-regulation skills and cognitive engagement levels of distance education students.

Self-efficacy

Self-efficacy is defined as a quality that affects the emergence of self-judgment and behaviours to organize and achieve the activities needed to perform a certain performance (Bandura, 1977; Zimmerman, 2000b). According to the concept of self-efficacy, which was first included in Bandura's (1977) social learning theory, the individual is responsible for goal-oriented development and his progress in this process is related to self-beliefs. Self-efficacy beliefs act as a motivational element and influence individual actions, performance, and behaviour.

Self-efficacy has been identified as an important factor in distance education as it can change individuals' perceptions of learning environments (McCoy, 2010). In this context, a framework was presented in the study by Linnenbrink and Pintrich (2003), and the relationship between self-efficacy and student engagement was emphasized in this framework. A multidimensional relationship was established between the behavioural, emotional and cognitive sub-dimensions of student engagement and self-efficacy. It has been stated that self-efficacy can increase student engagement and the result of this will be reflected in learning outcomes. Accordingly, it was stated that the more the student engages in the online learning environment and the more he learns, the better he will perform, and the higher his self-efficacy will be (Linnenbrink & Pintrich, 2003). Studies have shown that there is a negative relationship between self-efficacy and smartphone addiction (Gokcearslan et al., 2016; Lee & Bae, 2018). In summary, hypotheses H4, H5, and H6 are proposed: (H4) There is a significant association between self-efficacy skills and behavioural engagement levels of distance education students; (H5) There is a significant association between self-efficacy skills and emotional engagement levels of distance education students; (H6) There is a significant association between self-efficacy skills and cognitive engagement levels of distance education students.

When considering the connection between self-confidence and student involvement in online educational settings, it becomes evident that the influence of smartphone addiction needs to be considered.

Smartphone addiction

Smartphone addiction is a type of technology addiction (Kim & Byrne, 2011; Lin et al., 2014) and it emerges with repetitive and compulsive behaviour patterns characterized by the presence of behavioural addiction. Accompanying such observations, the term smartphone addiction is the excessive use of smartphones that are difficult to control and the spread of their negative impact on other areas of life (Park & Lee, 2012). Smartphone addiction has been widely reported in recent years with terms such as ¨*smartphone overuse/excessive use*¸ ¨*smartphone abuse*¨and ¨*maladaptive usage*¨(Fu et al., 2021). On the other hand, when we look at the latest definitions of the Diagnostic and Statistical Manual of Mental Disorders (DSM), which is the primary source for diagnosing and understanding addiction, it is seen that addiction is handled without making any terminological distinction. It is claimed that smartphone addiction is similar to other technological addictions, but these devices can be much more dangerous with their unique features such as portability, ease of connection and serving thousands of mobile applications (Lin et al., 2014). Considering recent developments, it has been observed that game addiction, categorized as one of the digital addictions, is now defined within the framework of disorders caused by addictive behaviours in both DSM-5 and the International Classification of Diseases [ICD]-11. Researchers commonly interchange the terms game addiction, internet addiction, and the disorders outlined in these diagnostic criteria in the literature (Fu et al., 2021). However, it is crucial to note that digital addiction encompasses not only video game addiction but also excessive smartphone and social media use. Consequently, the existing diagnostic criteria may fall short of comprehensively capturing the spectrum of digital addictions. It is noteworthy that, despite not being explicitly included in the diagnoses of DSM-5, smartphone addiction is recognized as a pertinent behavioural disorder. According to Andrade et al. (2020), some symptoms concerning withdrawal, tolerance, and disregard refer to the cognitive dimension of problematic use of smartphones. Some researchers propose different conceptualizations of problematic smartphone use (Hamamura et al., 2023). For example, Billieux et al. (2015) suggest that problematic smartphone use is multidimensional, involving pathways like excessive reassurance, impulsivity, and extraversion, leading to various problematic behaviors. Another view sees it as a behavioral addiction, characterized by tolerance, withdrawal, and reckless use, along with functional impairment (Elhai et al., 2019). However, some researchers caution against labelling problematic smartphone use as an addiction, arguing that issues stem from content (e.g., gaming, social networking) rather than the devices themselves (Lowe-Calverley & Pontes, 2020). Considering this, a recent review recommends distinguishing between smartphone and non-smartphone use, as many applications are primarily used on smartphones (Montag et al., 2021). This theoretical study emphasizes that many applications such as social media services have been used mainly or only on smartphone devices and this causes the smartphone to reveal indicators of addiction or disorder like gaming and internet addiction. Together with this, Uzdil and Simsek (2023) suggest that further studies could potentially lead to the inclusion of smartphone addiction as a distinct category in future diagnostic criteria. This underscores the evolving nature of our understanding of digital addictions and the necessity for ongoing research to refine diagnostic classifications.

Smartphone addiction causes negative cognitive, behavioural, and physiological consequences in students (Fu et al., 2021). It is anticipated that this situation may indirectly affect distance education students who are expected to have self-regulation skills. In this context, to understand smartphone addiction in the field of distance education, it is necessary to examine the self-regulation and self-efficacy variables associated with this process (Chen et al., 2017). Hence, based on the aforementioned explanation, it appears that there could be a notable correlation between smartphone addiction, student engagement, self-regulation, and self-efficacy (Choi, 2019; Gokcearslan et al., 2016; Mahapatra, 2019). In summary, hypotheses H7, H8, H9, H10, and H11 are proposed: (H7) There is a significant association between self-regulation skills and smartphone addiction in distance education students; (H8) There is a significant association between self-efficacy skills and smartphone addiction in distance education students; (H9) There is a significant association between smartphone addictions and behavioural engagement levels of distance education students; (H10) There is a significant association between smartphone addictions and emotional engagement levels of distance education students; (H11) There is a significant association between smartphone addictions and cognitive engagement levels of distance education students.

The research was motivated by a thorough analysis of previous studies as reflected in the literature. The primary objective of this study is to construct a path model that explores the interplay between self-regulation, self-efficacy levels, and student engagement within the online learning environments of higher education distance education students. Additionally, the impact of smartphone addiction on this relationship is taken into consideration. In this model, the directions indicated by one-way arrows between the variables constitute the hypotheses of the research (Figure 2).

Gender and age were considered as control variables within the theoretical framework, drawing on insights from existing literature. Previous research emphasizes the diverse behavioural patterns, reaction styles, and personality formations observed in individuals based on gender and age (Wang et al., 2023). A comparative analysis between age groups under 30 and those over 30 suggests that adults beyond the age of 30 tend to demonstrate relatively more mature cognitive processes, heightened responsibilities, and an increased workload (Wen et al., 2023). Considering these considerations, it would be instructive to unveil how the research model diverges concerning age and gender, allowing for refined delineations within distinct demographic characteristics. In addition to the hypothesis, this study tested the research model for the different groups of age and gender.

Method

Design

A cross-sectional descriptive design and path analysis were used to test the relationship between variables using a theoretical structural model as well as the eleven hypotheses. The primary goal was to clarify relationships and enhance understanding of variable intricacies (Cohen et al., 2002). The study involving human participants was reviewed and approved by Atatürk University Educational Sci-

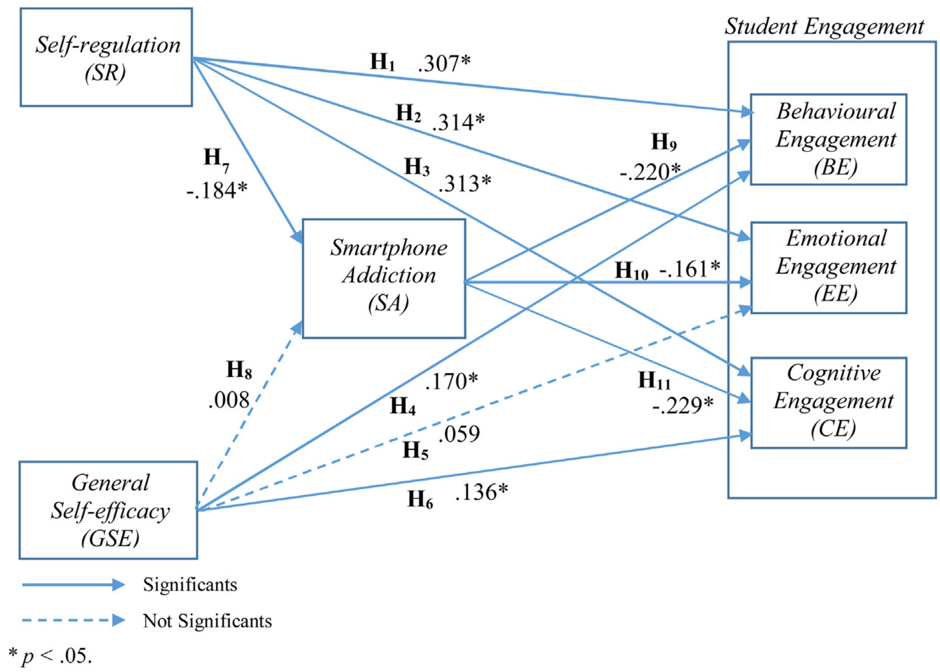

Figure 2. Path analysis and hypothesis test results for the research model (estimated path coefficients).

ences Ethics Committee (EB-14-01). The participants provided their written informed consent to participate in the study.

Participants

The study's population consists of students engaged in distance education at universities offering remote courses in Turkey. The convenience sampling method was employed when selecting the sample from the population. The sample included a total of 1514 students who were enrolled in synchronous distance learning programs. The selection process for the sample involved identifying universities that provided distance education programs. Subsequently, eight public universities offering such major online programs were chosen. The participant selection process for the study comprised several steps aimed at ensuring a comprehensive representation of the distance education landscape. Initially, universities offering distance education were identified, followed by a meticulous selection of institutions delivering programs through online distance education. Subsequently, interviews were conducted with the identified universities to ascertain their accessibility and willingness to collaborate. The final selection encompassed universities that demonstrated both accessibility and a cooperative stance. From the pool of students enrolled in online distance education programs, those actively participating in live sessions were purposively chosen to form the study's sample group. These steps collectively represent a systematic approach to participant selection, ensuring a diverse sample of students with various experiences and perspectives in the realm of remote education.

The universities attended by the participants implement flexible and contemporary learning models, providing education to students through online courses. Participants share an online campus environment within the distance education programmes at their universities. These programs offer a diverse array of courses across various subjects, enabling students to advance and complete their studies at their own pace. The course content is delivered through a variety of learning materials, online resources, and interactive media tools. Virtual classrooms and interactive online courses contribute to a flexible learning experience for the students. While midterm exams and assessments are typically carried out online, the final exam is conducted in a face-to-face format.

The data on gender, age, marital status, and employment status obtained from the demographic information form were collected to determine whether the developed model differs according to these variables. Data on variables related to graduation level and distance education information were collected to present the demographic characteristics of the participant group. A cut-off value of 30 years of age was taken by determining the middle value over the data related to the age variable. The distribution was presented according to this value. While forming the groups, two groups were formed 30 years old and below and 31 years old and above, paying attention to the balance of the number of students in both groups. Of the participants, 55.6% ($n = 842$) were women and 44.4% ($n = 672$) were men. The age distribution of the participants ranged between 18 and 65, with a mean age of 33.11 years ($SD = 10$-09, $min = 22$, $max = 45$). The 64.6% ($n = 987$) of the participants had at least a bachelor's degree, 57.5% ($n = 871$) were regularly employed in any job and 54% ($n = 817$) of the participants were married. It was determined that more than half of the participants (58.7%) had completed only one-course semester in distance education.

Instruments

Student's Engagement Scale

¨*Student Engagement Scale in Online Learning Environments*ẅas used in the study, which was developed by Sun and Rueda (2012) and the validity and reliability study of its Turkish form was carried out by Ergun and Usluel (2015). As an operational definition, engagement refers to the level of dedication students demonstrate in their efforts to excel and accomplish desired objectives (Sun & Rueda, 2012). scale aims to describe students' perceptions of student engagement, which is emphasized to have a significant impact on learning outcomes in online learning environments. The scale consists of three sub-factors ¨*emotional*ẅith six items such as "*I like taking the online class*", ¨*cognitive*ẅith eight items such as "*I check my schoolwork for mistakes*" and ¨*behavioural*ẅith five items such as "*I follow the rules of the online class*" and 19 items in total. The scale is a 5-point Likert type, and the scale items are "Strongly disagree = 1", "Disagree = 2", "Neither agree nor disagree = 3", "Agree = 4" and "Strongly agree = 5" has been rated. The results of the confirmatory factor analysis yielded the following values (χ^2/df = 3.04, RMSEA = .072, SRMR = .059, CFI = .96, NNFI = .96). These results indicate that the model fits at a satisfactory level. For the reliability assessment of the scale, the internal consistency coefficient was calculated as 0.88. On a factor basis in the study, the alpha values (α) were determined as follows: α = .82 for *behavioural engagement*, α = .88 for *emotional engagement*, and α = .86 for *cognitive engagement*. Omega coefficients were found to be like alpha coefficients. High scores mean that the student's level of engagement in the online learning environment is high; low scores mean that the level of engagement is low.

Self-regulation (Attention Control Dimension) Scale

In the study, the ¨*Attention Control Dimension of Self-Regulation Scale*, whose original form was developed in German by Schwarzer et al. (1999) and adapted to the Turkish version by Cevik et al. (2017) was used. The scale measures attention control in goal pursuit. In the study, it was preferred because it is a tool that evaluates the individual characteristics of the participant that facilitates the participant to focus his/her attention while performing his/her task in the online learning process and to control his/her movements by avoiding the distraction (smartphone use) around him/her. The scale consists of one factor and seven items such as "*if an activity requires a problem-oriented attitude, I can control my feelings*". The scale is in 4-point Likert type and the scale items are scored as "Totally False = 1", "Slightly True = 2", "Moderately True = 3" and "Completely True = 4". The results of the confirmatory factor analysis yielded the following values (χ^2/df = 2.85, RMSEA = .069, SRMR = .034, CFI = .99, NNFI = .98). These results indicate that the model fits at an excellent level. The Cronbach's alpha reliability coefficient of the scale was calculated as .84 and the Omega coefficient was .85. The high scores of the participants mean that their level of attention control of self-regulation is high, while low scores mean that their level is low.

General Self-efficacy Scale

The ¨*General Self-Efficacy Scale*¨was used in the study, the original form of which was developed by Schwarzer and Jerusalem (1995) and the validity and reliability study of the Turkish version was performed by Aypay (2010). The scale aims to determine the perceptions of the person's ability to cope with stressful and challenging life events in general. In the research, the general self-efficacy scale was preferred since it was aimed to determine the characteristics related to psychological well-being in more than one field. There is a single factor and ten items such as "*I can concentrate on one activity for a long time, if necessary*" and "*When I worry about something, I cannot concentrate on an activity*". The scale is in 5-point Likert type and the scale items are scored as "Totally Incorrect = 1", "Slightly True = 2", "Moderately True = 3" and "Completely True = 4". The results of the confirmatory factor analysis in the study yielded the following values (χ^2/df = 2.26, RMSEA = .059, SRMR = .039, CFI = .97, NNFI = .98). The Cronbach's alpha reliability coefficient of the scale was calculated as .89. The test-retest reliability coefficient of the scale was found to be .81 and the Omega coefficient was .80. The 10 items were summed and averaged to obtain the variable of self-efficacy after reversing scores of the reverse questions, with higher scores indicating a higher sense of *self-efficacy*. The high scores mean higher general self-efficacy levels.

Smartphone Addiction Scale-Short Version (SAS-SV)

In the study, the SAS-SV was used, the original form of which was developed by Kwon et al. (2013) and the validity and reliability study of the Turkish form was performed by Noyan et al. (2015). The SAS-SV that has been translated into multiple languages stands as one of the most used scales for assessing smartphone addiction (Servidio et al., 2023). Consisting of 10 items, it evaluates the risk of six problematic smartphone use symptoms (Lopez-Fernandez, 2017): Loss of control (Items 1 and 8), disruption (Items 2 and 10), disregard (Items 3 and 7), withdrawal (Items 4 and 5), preoccupation (Item 6), and tolerance (Item 9). These are rooted in symptoms of substance dependence and pathological gambling disorders outlined in the DSM-III and DSM-IV. This scale was developed based on an addiction framework that emphasizes symptoms such as withdrawal, excessive use, and tolerance (Kwon et al., 2013). According to the study by Kwon et al. (2013), a short form of the scale can be used to identify individuals who may be at a higher risk of developing smartphone addiction and smartphones lead to addiction symptoms like desire, withdrawal, tolerance, disruption in daily activities, and a preference for online relationships, and these indications were validated through diagnosis. The scale with a single-factor structure is a 6-point Likert type, consisting of 10 items such as "*Having a hard time concentrating in class, while doing assignments, or while working due to smartphone use*". Scale items were scored as "Strongly Disagree = 1", "Disagree = 2", "Partly Disagree = 3", "Partly Agree = 4", "Agree = 5", "Strongly Agree = 6". The results of the confirmatory factor analysis in the study yielded the following values (χ^2/df = 2.39, RMSEA = .068, SRMR = .059, CFI = .95, NNFI = .94). These values indicate that the scale has good construct validity. The Cronbach's alpha and Omega reliability coefficient of the scale was calculated as .91. The higher the score obtained from the test, the higher the risk for *smartphone addiction*.

Procedure

This cross-sectional study was conducted in the spring semester of 2019 to analyse the data collected from students enrolled in any distance education programme at ten different universities in Turkey, who received distance learning via online live lectures. Data were collected through an online questionnaire distributed via e-mail to the students participating in the study. Participants were sent a link explaining the purpose of the study and were asked to participate voluntarily. Written informed consent was obtained from all participants before the completion of the questionnaire. Participation in the study was not compulsory. The academic staff of the distance education units of the universities shared the information note prepared by the researcher, including the purpose of the study and the data collection process, with the sample group online via the student's e-mail account. Students were informed that they did not have to participate, that all responses were anonymous, and that they were free to refuse to answer any question. No identifying information (name, e-mail address, etc.) was collected about the participants. The time needed to fill out the questionnaire was approximately twenty minutes.

Data analysis

Path analysis modelling was used to test the hypothesised model in the study. According to the literature, model good fit indicators depend on the number of samples, and the limit value for the number of samples is 250 (Hair et al., 2014). Since the sample size was 1514 in the current study, good fit indicators, and the suggested model for large sample groups were used. In the study, as model fit indicators, Chi-Square Good Fit (χ^2) ($p <$ .05), χ^2/df (0 $\leq \chi^2/df <$ 3), Root Mean Square Errors of Approximation (RMSEA) (0 ≤ RMSEA ≤ .05), Comparative Fit Index (CFI) (.97 ≤ CFI < 1.00), Standardized Root Mean Square Residual (SRMR) (0 ≤ SRMR ≤ .05), Adjusted Goodness of Fit Index (AGFI; .95 ≤ NFI ≤ 1.00), Normized Fit Index (NNFI; .95 ≤ NFI ≤ 1.00) and Non-Normalized Fit Index

/ Tucker-Lewis Index (NNFI / TLI; .97 ≤ CFI < 1.00) criteria were considered (Brown, 2015; Jöreskog et al., 2016; Kline, 2011).

To perform the path analysis; loss and outlier control, sample size, univariate and multivariate normality, and multicollinearity assumptions should be provided (Hair et al., 2014; Kline, 2011; Tabachnick & Fidell, 2012). Since the data is collected through the online form with defined options, there are no incorrect or missing values on the data set. After the missing value analysis, the raw scores in the data set were converted into z-scores and tested for the existence of unidirectional and multidirectional extreme values. It is stated that the z scores of the variables in the data set should be between −3 and +3 (Kline, 2011). Mahalanobis distances of the variables were calculated for multidirectional. After the examinations, 24 observations that were determined to produce unidirectional and multidirectional extreme values were removed from the data set. The sample of the study consists of 1514 students and the relevant sample size meets the assumption. It was observed that the skewness values of the variables in the research model varied between 1.080 and −.282, the kurtosis values ranged between .887 and −.590, and the univariate normality assumption was met. The multivariate kurtosis coefficient for the research model was calculated as 1.215. In addition, the multivariate kurtosis coefficient value (1.215) was below the critical value suggested by Raykov and Marcoulides (2008). The critical value for this study was calculated as 2208 within $p\,(p+2)$.

The data set of the study provides the assumption of multivariate normality for the whole sample group. Distributions obtained from scatter diagram matrices exhibit distributions close to ellipse showing that multivariate normality and linearity are provided. The correlation coefficients between the variables should be less than .90 to avoid the multicollinearity problem (Tabachnick & Fidell, 2012). The correlations between the research variables were found to vary between -.391 and .627 values. This indicates that there is no multicollinearity problem between both independent variables and research variables. Therefore, it was determined that the data set in this study met the path analysis assumptions.

The data obtained within the scope of the research were analyzed using the path analysis technique. LISREL 8.71 program was used for data analysis. In the path analysis, the Maximum Likelihood Method was used as the estimation method. Path analysis, in which more than one dependent variable is employed, is used to examine causal relationships in a theoretically constructed measurement model (Schumacker & Lomax, 2010). One of the most important advantages of path analysis is that it allows observing both direct and indirect relationships in the structural model.

Results

Before presenting the findings related to the model, it would be useful to provide descriptive statistics. Concerning the study variables, the mean score for *self-regulation* (attention control dimension) was 3.01 (*SD* = 0.66), the mean score for *general self-efficacy* was 3.23 (*SD* = 0.59), the mean score for *smartphone addiction* was 3.70 (*SD* = 1.47), *behavioural engagement* had a mean score of 3.12 (*SD* = 0.53), the *affective engagement* had a mean score of 3.20 (*SD* = 0.78), and *cognitive engagement* had a mean score of 3.58 (*SD* = 0.83). Based on these findings, it is evident that, on average, participants show a moderate level of *smartphone addiction*.

Considering the results of the studies in the literature and the relevant theoretical frameworks, the compatibility of the proposed research model was tested with the path analysis statistics. In the related analysis, the Maximum Likelihood Method was used as the estimation method. The structural research model fits well in the confirmatory analysis with the likelihood method: $\chi^2/df = 3.46$, IFI = .98, CFI = .98, GFI = .90, RMSEA = .04. The fact that the RMSEA value (.042) is in the perfect fit index value range indicates that the structural validity of the overall research model is close to perfect. The fact that the other fit indices are also in the perfect fit index value range supports the finding that the research model has a good fit.

Table 1
Path coefficients, t-values and hypothesis test results

Hypotheses	Path	Path Coefficient (β)	t-Values	Results
H_1	SR → BE	.307	6.44	Supported
H_2	SR → E	.314	7.57	Supported
H_3	SR → CE	.313	7.58	Supported
H_4	GSE → BE	.170	3.76	Supported
H_5	GSE → EE	.059	1.49	Not Supported
H_6	GSE → CE	.136	3.47	Supported
H_7	SR → SA	−.184	−4.25	Supported
H_8	GSE → SA	.008	0.18	Not Supported
H_9	SA → BE	−.220	−7.22	Supported
H_{10}	SA → EE	−.161	−6.17	Supported
H_{11}	SA → CE	−.229	−8.59	Supported

Note. SR = Self-regulation; GSE = General Self-efficacy; SA = Smartphone Addiction; BE = Behavioural Engagement; EE = Emotional Engagement; CE = Cognitive Engagement.

The theoretically constructed research model was tested because of the data obtained, and the significance levels of possible relationships were determined. To test the hypotheses regarding the research model, it was determined whether the effect paths showing the correlation between the variables in the model were significant or not. The path diagram of the structural model obtained after the analysis and the estimated path coefficients (β) of possible relationships are presented in Figure 2. To test the hypotheses regarding the research model, it was determined whether the effect paths showing the correlation between the variables in the model were significant or not. In this context, the conceptual representation of the path analysis in Figure 2 is shown by looking at whether the hypotheses are meaningful or not.

When the significance of the effects on the conceptual representation of the research model is examined; It is seen that hypotheses H5 and H8 were rejected, while other hypotheses were accepted. Table 1 shows the correlations in the research model, t values, findings related to the hypothesis results, and the standardized path coefficients (β) related to the correlations obtained because of the path analysis. It was decided to accept and reject the hypotheses established considering the path coefficients and t values defined in the research model.

Table 1shows that, the effect of *self-regulation* (control dimension) on *smartphone addiction* (β = −.184, $p < .05$), the effect on *behavioural engagement* (β = .307, $p < .05$), the effect on *emotional engagement* (β = .314, $p < .05$) and its effect on *cognitive engagement* (β = .313, $p < .05$) were found to be significant. Based on the relevant findings, the H1, H2, H3, and H7 hypotheses were accepted. The effect of *general self-efficacy* on *smartphone addiction* (β = .008, $p < .05$) and the effect on *emotional engagement* (β = .059, $p < .05$) were insignificant, and the effect on *behavioural engagement* (β = .170, $p < .05$) and its effect on *cognitive engagement* (β = −.136, $p < .05$) were found to be significant. Based on the relevant findings, the H5 and H8 hypotheses were rejected, while the H4 and H6 hypotheses were accepted. The effect of *smartphone addiction* on *behavioural engagement* (β = −.220, $p < .05$), the effect on *emotional engagement* (β = −.161, $p < .05$), and the effect on *cognitive engagement* (β = −.229, $p < .05$) was found to be significant. Therefore, hypotheses H9, H10 and H11 were accepted.

It is important to calculate the direct, indirect, and total effects between the related variables together with the findings regarding whether the correlations in the research model are statistically significant. Thus, it is possible to explain the relations between the variables in a cause-effect correlation and to interpret the indirect

Table 2
Standardized direct, indirect and total effect

	Path		Standardized Effect		
	Direct	Indirect	Total		
SR	→	SA	−.184*	----	−.184*
GSE		(R^2 = .03)	.008	----	.008
SR	→	BE	.307*	.041*	.348*
GSE		(R^2 = .28)	.170*	−.002	.168*
SA			−.220*	----	−.220
SR	→	EE	.314*	.030*	.344*
GSE		(R^2 = .17)	.059	−.001	.058
SA			−.161*	----	−.161*
SR	→	CE	.313*	.042*	.355*
GSE		(R^2 = .26)	.136*	−.002	.134*
SA			−.229*	----	−.229*

(CI's 95%, * $p < .05$) SR = Self-regulation; GSE = General Self-efficacy; SA = Smartphone Addiction; BE = Behavioural Engagement; EE = Emotional Engagement; CE = Cognitive Engagement.

effects. Table 2 shows the standardized direct, indirect, and total effects of the research model.

While interpreting the direct, indirect, and total effect values in the research model shown in Table 2, the effect size rules suggested by Cohen (1988) were considered ($d = 0.1 \leq$ low; 0.3; $0.3 \leq$ medium; 0.5; $0.5 \leq$ high). Table 3 shows that only three per cent (R = .17, R^2 = .03) of the *smartphone addiction* variable can be explained by *self-regulation* (control dimension) and *general self-efficacy*. It was concluded that the direct effect of *self-regulation* (control dimension) on *smartphone addiction* was statistically significant, while the direct effect of the *general self-efficacy* variable on *smartphone addiction* was not statistically significant. The *self-regulation* (control dimension) directly affects *smartphone addiction* at a low level with an effect size of $d = -0.184$. Furthermore, the mediation effect of *smartphone addiction* is shown in Table 3. The results found that the indirect effect of *smartphone addiction* is significant. The results found that indirect effects of *self-regulation* (control dimension) through *smartphone addiction* have a statistically significant, low-level, indirect effect with an effect size of $d = 0.041$ on *behavioural engagement*, $d = 0.030$ on *emotional engagement*, and $d = 0.042$ on *cognitive engagement*. Thus, *smartphone addiction* mediates the association of *self-regulation* (control dimension) with *behavioural*, *emotional*, and *cognitive engagement*.

Comparison of model differences between age and gender groups

Table 3 presents the standardized direct, indirect, and total effects of the research model concerning age and gender groups.

Participants were divided into two sub-groups according to their ages: (1) 30 years and under and (2) 31 years and older, balanced according to frequency and percentage distribution. The path model was tested for both age groups. The fit indices for the group aged 30 and under (χ^2/df = 2.177, RMSEA = .042, CFI = .98, SRMR = .039, AGFI = .87, NFI = .97, NNFI = .98) and for the group aged 31 and older (χ^2/df = 2.371, RMSEA = .044, CFI = .98, SRMR = .041, AGFI = .87, NFI = .96, NNFI = .98) were all within the good fit index ranges recommended in the literature. This indicates that the structural model shows a good fit for both age groups. For participants aged 30 and under, the direct effect of *self-regulation* (attention control dimension) on *smartphone addiction* was statistically significant, while the effect of *general self-efficacy* on *smartphone addiction* was not. For participants aged 31 and older, *self-regulation* (attention control dimension) had a greater effect on student engagement in online learning environments, and *smartphone addiction* did not have a significant effect, highlighting an important age-based difference.

Participants were also divided into two sub-groups based on gender, and the path model was tested for these groups. The fit indices for female participants (χ^2/df = 2.448, RMSEA = .043, CFI = .98, SRMR = .037, AGFI = .88, NFI = .97, NNFI = .98) and for male participants (χ^2/df = 2.455, RMSEA = .047, CFI = .98, SRMR = .043, AGFI = .86, NFI = .97, NNFI = .98) were within the recommended ranges, indicating a good fit for both gender groups. For female participants, the direct effect of *self-regulation* (attention control dimension) on *smartphone addiction* was statistically significant, whereas *general self-efficacy* was not. In contrast, for male participants, neither *self-regulation* nor *general self-efficacy* had a significant direct effect on *smartphone addiction*. Notably, *self-regulation* had a moderately significant effect on student engagement in online learning environments for male participants, differing from the female group.

Discussion

Considering that students are in constant contact with their smartphones in their daily lives and that they attend distance education courses with their smartphones, the necessity of investigating the variables related to student engagement with the mediator effect of smartphones in distance education programs becomes evident. In the current study, which examined the level of engagement in online learning environments of distance education students in Türkiye in terms of their smartphone addictions, self-efficacy and self-regulation skills, the direct and indirect effects of the relation of the defined variables were tested through the theoretical model.

Association between self-regulation and self-efficacy with smartphone addiction

A direct, negative, and significant correlation was found between self-regulation (control dimension) and smartphone addiction in distance education students. This result is in line with those of previous studies (Lee et al., 2015; Mascia et al., 2020). In the study conducted with university students, it was identified that students exhibiting high smartphone addiction tend to possess lower self-regulation skills. Furthermore, it was observed that students experience frequent interruptions from smartphone applications while engaging in their work (Mascia et al., 2020). In addition, it has been stated that smartphones distract attention from the learning process (Lee et al., 2015), and the negative correlation between self-regulation and smartphone addiction causes low academic performance (Mahapatra, 2019). This relation will help in discovering other relations in educational psychology (Ching & Tak, 2017). According to the results of the study, which is like the results of the research in the literature, smartphone addiction increases as the self-regulation (control dimension) skills of distance education students decrease.

There was no significant correlation between general self-efficacy and smartphone addiction of distance education students. Gokcearslan et al. (2016) also did not find a highly significant relationship between general self-efficacy and smartphone addiction through the cyberloafing tool effect, while Choi (2019) stated that students with low self-efficacy showed high smartphone addiction. According to these results, the relationship between general self-efficacy and smartphone addiction is controversial.

Association between self-regulation and self-efficacy with student engagement

According to the results, self-regulation (control dimension) has a moderately positive and significant effect on student engagement. In the results of the study by Coelho et al. (2019), self-regulation was

Table 3
Statistical difference test results in the path of the structural model between age and gender groups

Path	Age 30 and under			Age 31 and older			Female			Male		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
SR→SA	−.160*	----	−.160*	−.283*	----	−.283*	−.263*	----	−.263*	−.055	----	−.055
GSE→SA	.024	----	.024	.104	----	.104	.058	----	.058	−.043	----	−.043
SR→BE	.220*	.001	.221*	.197*	.003	.200*	.182*	−.002	.180*	.140*	.009	.149*
GSE→ BE	.304*	−.001	.303*	.301*	−.009	.292*	.226*	.067*	.293	.400*	.012	.412*
SA→ BE	.009	----	.009	.031	----	.031	−.254*	----	−.254	-.213*	----	−.213*
SR→EE	.109	−.004	.105	−.004	.010	−.006	.082	−.001	.081	.021	.008	.029
GSE→EE	.257*	.025*	.282*	.400*	.027*	.427*	.229*	.049*	.278*	.405*	.010	.415*
SA→EE	−.157*	-----	−.157*	−.095	-----	−.095	−.178*	-----	−.178*	−.174*	-----	−.174*
SR→CE	.187*	−.002	.185*	.098	−.007	.091	.143*	−.001	.142*	.126*	.012	.138*
GSE→CE	.252*	.015	.267*	.321*	.019	.340*	.234*	.062*	.296*	.383*	.016	.399*
SA→CE	−.092*	----	−.092*	−.066	----	−.066	−.236*	----	−.236*	−.286*	----	−.286*

(CI's 95%, * $p < .05$) SR = Self-regulation; GSE = General Self-efficacy; SA = Smartphone Addiction; BehE = Behavioural Engagement; EmoE = Emotional Engagement; CogE = Cognitive Engagement.

determined as the variable that correlates with student engagement at the highest level and it was seen as an important criterion for determining the duration of participation in an online activity in goal-oriented behaviour in the distance education environment (Cho & Shen, 2013). When the relationship emerged in terms of the sub-dimensions of student engagement, a direct positive and significant relationship was found between self-regulation (control dimension) and behavioural, emotional, and cognitive engagement. As a result, it becomes clear that self-regulation skills should be taken into consideration when designing online learning environments in distance education (Zhang & Wu, 2020).

There is a low level of positive correlation between general self-efficacy and student engagement. Considering the correlation in terms of sub-dimensions, as the general self-efficacy levels of distance education students increase, their behavioural engagement in online learning environments also increases, albeit at a low level. The belief that one has the necessary skills to perform a task is associated with behavioural engagement (Pintrich, 2004). There was no significant correlation between general self-efficacy and the emotional engagement of distance education students. This result is similar to the study of Manwaring et al. (2017). This may be because the distance education students participating in the study are mostly students who have completed the first semester. Longer periods spent in online learning environments may cause distance education students to increase their experience, be motivated by more feedback from the instructor, and develop emotional engagement in the learning environment by interacting with other distance education students in the learning community. This may reveal the need to focus on student support (technical support, the process of the distance education program, etc.) for those new to an online program. A low-level positive and significant correlation was found between the general self-efficacy and cognitive engagement of distance education students. Accordingly, as the general self-efficacy levels of distance education students increase, their cognitive engagement in distance learning environments also increases, albeit at a low level. A similar relationship was found in the study conducted by Manwaring et al. (2017).

Association between smartphone addiction and student engagement

A low-level, negative significant correlation was found between smartphone addiction and the dimensions of student engagement of distance education students (behavioural, emotional, and cognitive). Accordingly, as distance education students' smartphone addiction increases, student engagement in online learning environments decreases. In support of this situation, Soni et al. (2017) found that individuals spend a significant part of their time using their smartphones, and because of this, their addiction tendencies increase. According to this study, it was concluded that the participants were not only smartphone addicts but also caused significant behavioural problems due to smartphone addiction. According to the results of the current study, it was found that the smartphone addiction behaviours of distance education students negatively affect student engagement in online learning environments. Significant negative moderating effects of smartphone addiction are highlighted (Li et al., 2023; Mascia et al., 2020). According to these studies, it was found that the participants were not only smartphone addicts but also caused significant behavioural problems due to smartphone addiction.

The fact that smartphones are always in our hands the problems in controlling their use (Osorio-Molina et al., 2021) and the constant development of new applications (Wu et al., 2021) make smartphone addiction different from other addictions and make the role of smartphones in different environments open to discussion. Looking at its reflections in the context of education, it is seen that smartphone addiction can affect the interest in the learning environment and reduce the attention level of addicted users. In the literature, it has been stated that the risk of addiction negatively affects academic performance (Abbasi et al., 2021). As a result of the current study, it was revealed that the smartphone addiction behaviours of distance education students negatively affected the relationship between self-regulation (control dimension) and student engagement in distance learning environments. When considering at the perspective of the sub-dimensions of student engagement, it was seen that this mediating effect had a greater effect on behavioural engagement, which includes the degree of active participation in learning activities, and cognitive engagement, which includes mental effort, compared to emotional engagement, which includes emotional responses. In this context, it is important to carry out studies to reduce the negative effects of addictive behaviours by using the potential effects of smartphones in distance learning environments.

Structural model differences in terms of gender and age

In the gender-comparison model, while female participants showed similar relationships to the base model, there was a deviation from the structural model in male participants, suggesting that self-regulation did not have a significant effect on smartphone addiction. When scrutinizing the results by gender, an increase in smartphone addiction correlated with a more significant decline in student engagement among female students compared to their male counterparts. It can be inferred that females face a higher risk of smartphone addiction and demonstrate lower student engagement than males. Existing literature also suggests that females are more prone to developing smartphone addiction (Jin Jeong et al., 2020).

The analyses further unveiled that the self-regulation skills of participants aged 31 and older (attention control dimension) exert a more positive influence on student engagement dimensions in distance learning environments compared to participants aged 30 and under. As individuals age, their mental maturity escalates, leading to an enhanced sense of learning responsibility (Méndez et al., 2024). When examining model disparities based on age variables, deviations were noted from participants aged 30 and below, with no significant relationship between smartphone addiction and behavioural engagement, while this difference intensified in male participants. In light of these findings, participants aged 31 and above face a higher risk of smartphone addiction than their younger counterparts. However, given the marginal difference, it can be asserted that they share a similar level of addiction risk. Despite the comparable risk of smartphone addiction between adolescents and adults, studies highlight a higher motivation for coping with addiction in young individuals (Wen et al., 2023). One study in the literature suggests that smartphone addiction increases with age (Mancinelli et al., 2021), while another proposes a higher risk of smartphone addiction among individuals aged 21-23 (Baskan et al., 2023). Considering these conflicting outcomes in the literature, the relationship between age and smartphone addiction remains debatable.

Limitations and future directions

The study findings have been based on data obtained from distance education students studying at eight universities offering fully online programs. In future studies, this study can be repeated by collecting data from a larger sample group that is more representative of the research population. The study data were collected with self-report scales. Future research can be done with experimental designs to reveal causal correlations. Furthermore, future research should build upon the findings of this study not only to further investigate the identified correlations but also to explore preventative measures and their application in the field of distance education, specifically targeting smartphone addiction. While the SAS-SV effectively measures smartphone addiction, the lack of clinical application should be considered a limitation. Future research could extend the current study by incorporating objective measurements to identify indicators of addiction, thereby enhancing the clinical relevance and accuracy of the findings.

Implications and conclusions

The findings of the study have significant implications for improving student engagement in online learning environments. Firstly, it was observed that self-regulation plays a crucial role in enhancing student engagement. Therefore, when designing online learning environments, it is recommended to incorporate interactive learning dashboards and online feedback systems that cater to the self-regulation skills of distance education students, while also making these environments accessible via mobile devices. To mitigate the negative impact of smartphone addiction, educational institutions should leverage smartphone applications with educational features in online learning environments. Utilizing mobile applications to send instant notifications reminding and informing students about learning tasks can help counter distractions. Additionally, goal-oriented tasks that promote focused attention can be integrated into online learning environments, taking advantage of the strengths and connectivity provided by smartphones. It is imperative to create specific areas within online learning environments that cater to smartphone usage and conduct further studies, particularly within the framework of self-regulation theory, to enhance student engagement. Furthermore, these implications emphasize the importance of fostering self-regulation skills among students through interventions such as goal setting, time management, and metacognitive strategies. Moreover, recognizing the mediating role of smartphone addiction highlights the need for interventions that address smartphone usage habits and promote healthy digital behaviours. Educational institutions should raise awareness among students about the potential negative consequences of excessive smartphone use on their engagement in online learning and consider implementing guidelines or educational programs to encourage responsible smartphone usage and digital well-being. Lastly, the weak correlation between general self-efficacy and student engagement suggests the existence of additional factors influencing student engagement in online learning. Future research should explore these factors in more depth, including the influence of social support, learning environment design, and instructional strategies.

In conclusion, these implications underscore the importance of considering self-regulation skills and addressing smartphone addiction when designing effective interventions aimed at enhancing student engagement in distance learning environments.

Data availability on request from the authors

The data that support the results of the study are available from the corresponding author upon reasonable request.

CRediT authorship contribution statement

Memnüne Kokoç: conceptualization; data curation; formal analysis; investigation; methodology; writing - original draft; revision. Yüksel *Göktaş*: supervision.

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Conflict of Interest

The authors declare that they have no potential conflict of interest.

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