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ORIGINAL RESEARCH

Investigating Undergraduates' Online Engagement Behaviors Predictors: The role of Multiple Screen Addictions, Motivation, Academic Success and Autonomous Learning

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Abstract
The aim of this study extends the structural models in the existing literature to understand the role of multiple screen addictions (MSA) in the process while considering the relationships between goal orientation, GPA, and autonomous learning as predictors of online engagement. This study used a relational screening model to explore relations among variables. The participants of the study are 375 university students. Demographic form and different scales were applied. According to the findings of the study, there is a positive relationship between online engagement, intrinsic motivation and autonomous learning. There is a negative relationship between the participants' autonomous learning and multiple-screen addiction. the relationship between extrinsic- intrinsic motivated strategies for learning, grade point average (GPA) and engagement. These research findings can guide the support of online engagement behaviors.

Keywords Multiple screen addictions · Online engagement · Motivation · Academic success · Autonomous learning

1 Introduction

More and more students are using digital resources in higher education and switching to online courses. However, despite the increasing use of digital technology, difficulties in achieving student engagement remain (Henrie et al., 2015). Indeed, online learning brings additional complexity to individuals, and their understanding of motivation and engagement plays key roles in the process (Ferrer et al., 2020). Engagement is affected by many factors, including cognitive, metacognitive, emotional, social, task-related, communication, and foreign language (Amerstorfer & Freiin von Münster-Kistner, 2021). However, it is necessary to pay attention to the negative effects of the problematic use of digital resources and Internet addiction on student engagement.

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Internet addiction (IA) is characterized as an important problem faced by children, adolescents, and adults today. Previous literature revealed that technology-related addictions have antecedents such as background characteristics, parent-level factors, individual habits, and psychological variables (Biswas et al., 2022; Durak, 2019; Durak et al., 2022; Ozturk & Ayaz-Alkaya, 2021; Song & Park, 2019; Taufik et al., 2021). At the same time, IA has many negative consequences such as unhealthy lifestyle, poor sleep quality, depression, loneliness, unhappiness, and decreased life satisfaction (Demir et al., 2020; Lin et al., 2019; Longstreet et al., 2019). As a result, internet addiction is seen as a public health problem with many determinants and negative consequences.

As a result of the diversity in technological devices and the increased access-use time, there is a tendency for addiction to more than one device, application, and service. Hence, individuals use more than one device at the same time and show multi-screen consumption behavior. Screen addiction has sub-types such as IA, digital game addiction, traditional and social media addiction, and smartphones (Şimşir Gökalp et al., 2022). Multi-screen addiction (MSA) is considered as the discomfort and deprivation experienced when not having access to all or a few of these tools. (Saritepeci, 2021). Lin et al. (2020) define screen addiction as a continuum of media behaviors using multiple screen devices, ranging from compulsive media consumption to problematic or pathological behaviors.

Technology addiction is seen as a serious threat to young people and children, and in this direction, the literature mostly focuses on the adolescence period (Şimşir Gökalp et al., 2022; Durak et al., 2024; Durak & Kaygin, 2020; Li et al., 2022). However, it is noteworthy that studies on the effect of MSA on university-level students and its antecedents are limited. Indeed, Lin et al. (2020) reported that adults who multitask using media use these devices for longer. The same study draws attention to the positive relationship between more screen time and having a higher level of MSA (Lin et al., 2020). University students experience the consumption of multiple screens for learning and/or entertainment purposes in the online or face-to-face education process. Considering the time spent in front of the screen and the variety of tasks performed, it becomes necessary to examine university students' problematic screen use behaviors with academic variables. Saritepeci et al. (2022) examined the latent profiles of university students in terms of MSA and suggested that studies should be conducted to better understand the antecedents and results of MSA.

Previous research has found significant relationships between engagement, intrinsic and extrinsic goal orientation, achievement, autonomy, and, GPA (Albrecht et al., 2021; Dincer et al., 2019; Huang & Wang, 2022; Núñez & León, 2019; Rickert & Skinner, 2022). From these points of view, this study proposes a structural model to gain insight into the nomological relationships between engagement, intrinsic and extrinsic goal orientation, GPA, autonomous learning, and, MSA. According to Littlewood (1996), autonomous learners can work independently and use appropriate learning strategies. Autonomy, along with relatedness and competence, is one of the three basic needs individuals need (Ryan & Deci, 2000). Although autonomy is an important issue for the satisfaction of individuals in both face-to-face and online learning processes (Abuhassna et al., 2020), there are limited studies on the relationship of this variable with digital media consumption and problematic use. Goal orientation is related to intrinsic motivation, which includes mastery orientation, and extrinsic motivation, which includes performance orientation (Martin, 2007). Vezne et al. (2022) highlighted the effect of intrinsic and extrinsic goal orientation on various types of online engagement.

Recently, autonomous learning is negatively associated with internet addiction (Huang et al., 2021; Ostovar et al., 2021). In addition, findings are showing that goal orientation partially mediates the relationship between teacher-student relationship and smartphone addiction (Shi et al., 2022). In conclusion, although the early study results draw attention to the relationship between autonomy, intrinsic and extrinsic goal orientation, and internet addiction, it can be argued that there is a gap in the literature on examining the effects of these variables on online engagement together. From these points of view, the model proposed in this study extends the structural models in the existing literature to understand the role of MSA in the process while considering the relationships between goal orientation, GPA, and autonomous learning as predictors of online engagement.

2 Conceptual Framework

2.1 Theoretical Basis

This research focuses on the prediction of students' online engagement behaviors by multi screen addiction, motivation, academic success and autonomous learning. In this context, the research is theoretically based on social cognitive theory. According to this theory, which provides principles related to educational psychology that are widely applied in education, students' behaviors and environments can affect each other (Schunk & DiBenedetto, 2020). Social cognitive theory conceptualizes the interactional causal structure as triple reciprocal causation, which is a dynamic interaction between personal, behavioral, and environmental influences (Bandura, 1999). Wang and Lin (2006) emphasized this structure by referring to a three-way social cognitive model that should be taken into consideration in the design of online learning systems in their study. In their research, Lin and Bhattacherjee (2009) discussed social support in online learning environments within the framework of the social cognitive model.

2.2 Multiple Screen Addictions

The usage time of screens, which are in all areas of daily life and whose usage is becoming more widespread day by day, increases the usage time of transactions such as banking, e-government, and entertainment purposes such as social media and games (Saritepeci et al., 2022). MSA is the persistence of disorganized media behaviors manifested by maladaptive symptoms (inability to control hunger, withdrawal/escape, loss of productivity, and feeling anxious and lost, etc.) to compulsively use multiple devices such as television, laptop, tablet, and smartphone (Lin et al., 2020). It can also be expressed as excessive, uncontrolled, and obsessive media consumption on screen devices (Saritepeci et al., 2022). Saritepeci (2021) discussed MSA as a behavioral addiction as in smartphone addiction or IA. He stated that one of the important indicators of behavioral addiction is that the person's lack of access to an object or situation causes discomfort or being restricted. There are studies in the literature that deal with MSA from various perspectives. Lin et al. (2020), on the other hand, indicated that multitasking in the media and the use of screen devices were positively related to screening addiction. In addition, they noted that the use of screen devices mediated the positive effects of media multitasking on screen addiction. Şimşir Gökalp et al.

(2022) revealed in their research that multiple-screen addiction has a mediating role in the relationship between self-control and procrastination behavior among adolescents. Li, Lou, and He (2022) explored that parental screen addiction can affect children's screen addiction. Saritepeci et al. (2022) revealed the relationship between university students' player profiles and multi-screen addiction.

2.3 Online Engagement

Participation is a term often used to represent constructs such as quality of effort and involvement in productive learning activities (Kuh, 2009). Student engagement is the degree to which students are actively engaged with the content of a course, by thinking, talking, and interacting with other students in the course and the instructor (Dixson, 2015). According to the context of social constructivism, participation is one of the most important components of an effective learning process. Students spend time and effort learning the course content and skills, have meaningful interactions with other people, and are emotionally involved in the learning process (Yildiz Durak, 2023). Based on the literature, Fredricks et al. (2004) considered participation as three components: behavioral, emotional, and cognitive. On the other hand, Reeve and Tseng (2011) proposed four components to the three-component structure of participation, including active participation, which they defined as the constructive contribution of students to the process.

Student engagement is the primary factor for effective teaching and learning in an electronic learning environment (Wong & Chong, 2018). However, participation in an online learning environment is more dependent on students' disposition than in a face-to-face session because there are fewer external sources of power and motivation (for example, attendance control in face-to-face environments, specific workplaces, and social reinforcements from peers) (Quigley et al., 2022). Redmond, Abavi, Brown, and Henderson (2018) expressed five basic components of online participation in higher education based on the literature in their research: social engagement, cognitive engagement, behavioral engagement, collaborative engagement, and emotional engagement. Paruthi and Kaur (2017) stated that online participation is a different perspective based on conscious attention, compassion, enthusiastic participation, and social connection. Wang and Liu (2019) revealed in their research that individuals' online participation in social media is positively affected by the benefits of social media but negatively affected by its risks. Quigley et al. (2022), on the other hand, concluded in their study with university students that personality traits and stress perceptions affect students' online participation.

2.4 Motivation

Keller (1983) noted that motivation is related to the magnitude and direction of behavior and defined it as the choices people make about which experiences or goals to approach or avoid, and the degree of effort they will specialize in. Motivation is an important variable in learning environments. According to the ARCS model, which explains the factors affecting a person's motivation to learn, Keller has addressed these factors under four headings: attention, relevance, confidence, and satisfaction (Keller, 1987). Many motivating factors, especially willingness, are required for a student to enroll in a learning environment (Law et al., 2019). Deci and Ryan (1981) described people's motivational orientations in three groups intrinsically motivated, extrinsically motivated, or unmotivated. When the individual is intrinsically motivated, the reward for the activity appears to be a part of the activity, and there is no separate reward from the spontaneous feelings and thoughts that accompany the activity. When the individual is extrinsically motivated, behavior tends to be a means to an end rather than a part of the end. People also work for some external reward, such as money, good grades, status, approval, or avoidance of an unpleasant event. When people are not motivated, they tend to be passive and unresponsive. They tend not to act because they believe they cannot have a meaningful impact on their environment (Deci & Ryan, 1981).

2.5 Grade Point Average (GPA)

GPA, one of the most studied variables in educational and educational psychology, is not only summaries of what students learn, but also an important determinant of performance and other important life outcomes at other levels of education (Kuncel et al., 2005). School grades are constantly used in awarding awards or determining admission to another school or a master's degree, even as an acceptable estimate for employment (Clark, 1964). GPA, which is one of the most important indicators of university success, potentially affects career prospects in the long run (Feldman & Kubota, 2015). With the widespread use of technology, GPAs are considered a variable in research on technology use. Harman and Toru (2011) examined whether the frequency of mobile phone use is related to academic performance measured by university students' grade point averages. They revealed that the frequency of sending text messages was negatively related to variables such as grade point average and academic level, while the frequency of making mobile phone calls was not. Kurnianingsih et al. (2018) investigated the relationship between the time spent playing internet games by university students and the risk of GPA and internet gaming disorder. While the time/day spent playing online games was associated with the risk of internet gaming disorder, it was not associated with GPA. Tri (2021), on the other hand, investigated the effect of Facebook use on the grade point average of university students and concluded that the use of Facebook statistically affected the average score of the students.

2.6 Autonomous Learning

Autonomy is the ability to take responsibility for one's learning (Holec, 1981). Autonomous learning is student-centered and they actively learn and work in line with the teacher's instructions (Yan, 2012). An autonomous student should be effective in taking responsibility for his learning and should be metacognitively aware of this process while trying to plan, monitor and evaluate his learning (Teng, 2019). Learner autonomy, which forms the basis of lifelong learning, can help to achieve a high level of creativity and independence (Yan, 2012). When the literature is examined, studies on autonomous learning in technology-supported learning environments are seen in recent years. Bai et al. (2022) examined the autonomous learning behaviors of university students in a blended learning environment, and they noted that learning motivation and academic self-efficacy can effectively predict autonomous learning. In addition, they found that learning anxiety and self-efficacy indirectly affect autonomous learning behavior through learning motivation. Polat et al. (2022a) did not examine how university students' readiness for flipped learning, participation, autonomous learning, and computing achievements differed before and after an education in an online flipped classroom, according to gender and feedback groups. The results concluded that the variables of achievement, readiness for flipped learning, and participation increased significantly but did not develop learning autonomy. As a result of his experimental research, Zhang (2022) revealed that the learning system created with artificial intelligence technology improves the autonomous learning ability of individuals. Yildiz Durak (2023) showed that cognitive guidance provided with Chatbot technology did not positively affect visual design self-efficacy, participation, satisfaction, and learner autonomy.

2.7 Relationships between Variables

Active participation is a feature of learner autonomy (Teng, 2019). The motivating style that facilitates students' participation the most is the style that supports autonomy (How & Wang, 2016). Jang et al. (2010) investigated the effect of autonomy support and structure on students' participation. As a result of the research, (a) autonomous support and structure were positively related (b) autonomy support and structure were predictors of behavioral participation of students, and (c) autonomy support was uniquely predictive of students' self-reported participation. In their research with university students, Núñez and León (2019) highlighted that perceived autonomy support supports predicted student engagement.

H1. Autonomous learning is positively associated with online engagement.

Huang et al. (2021) found a negative relationship between autonomous learning and IA. Ostovar et al. (2021) concluded that impaired autonomy/performance is positively associated with IA.

H2. Autonomous learning is negatively associated with multiple-screen addiction.

Motivation plays an important role in promoting successful autonomous learning (Teng, 2019). Bai et al. (2022) stated in their study with university students that learning motivation is positively related to autonomous learning behavior. Kormos and Csizer (2014) also explored that motivational factors show the effect of autonomous learning behavior through self-regulation strategies. Atman Uslu and Yildiz Durak (2022) examined the role of group metacognition and self, collaborative, and socially shared motivational regulation in predicting learner autonomy. Individual regulation of motivation affected learner autonomy, but the effect of self-regulation of intrinsic motivation on the probability of having high or low learner autonomy was not significant.

H3. Autonomous learning is positively associated with intrinsic motivated strategies for learning.

Student engagement and motivation are intrinsically linked (McKenna et al., 2022. Participation is also considered adaptive motivation, as it indicates the quality of motivation and is often listed as a teaching goal (Nie, 2016). Redmond et al. (2018) considered the awareness of motivation as one of the components of emotional involvement. Walker et al. (2006) found in their research that self-efficacy, academic identification, and intrinsic motivation were negatively correlated with motivation and were not associated with extrinsic motivation, and they also indicated that extrinsic motivation predicted superficial cognitive involvement.

H4. Extrinsic motivated strategies for learning are positively associated with online engagement.

Student participation is an important component of success (Kuh, 2006). Kang et al. (2009) examined the variables that affect the learning success of students regarding their participation in electronic learning. Students' participation and participation in discussion showed a higher correlation with learning achievement than other participation variables. In addition, among the variables that affect learning success, students' participation and participation in the discussion were also determined. Zhang et al. (2018) highlighted that participation was positively associated with academic achievement as a result of their research.

H6. Academic achievement is positively associated with online engagement.

Skoric et al. (2009) found that students' video game addiction tendencies were negatively related to school performance. Shi et al. (2022) indicated that achievement goal orientation plays a partial mediating role in the relationship between university students' teacher-student relationships and smartphone addiction. Zhang et al. (2018) concluded that IA is negatively related to academic achievement and that IA predicts academic success. Arian et al.(2018) explored a weak negative significant relationship between IA and academic achievement.

H7. Academic achievement is negatively associated with online multiple-screen addiction.

An important distinction between social networking site use addiction and participation is that, unlike participation, addiction is associated with negative outcomes and the social network becomes uncontrolled and compulsive (Andreassen, 2015). Ganji et al. (2016) concluded that there is a negative significant relationship between IA and academic participation and that IA predicts academic participation negatively. Similarly, Tasş (2017) found that there was a weak negative relationship between IA and school participation and that IA was an important predictor of school engagement. Singh and Srivastava (2021) underlined that IA has a negative effect on students' academic engagement. Shahnaz and Karim (2014) explored that IA was significantly and negatively associated with life satisfaction and participation in life. Zhang et al. (2018) concluded in their study that IA and participation were negatively related and internet addiction predicted academic participation.

H8. Multiple screen addiction is negatively associated with online engagement.

As a result of their research, How and Wang stated that when students learn out of curiosity and are intrinsically motivated, they participate more in learning and are more satisfied with it. Walker, Greene, and Mansel (2006) revealed in their research that self-efficacy, intrinsic motivation, and academic identification are positively related to cognitive engagement and are predictors of cognitive engagement.H9. Intrinsic motivated strategies for learning are positively associated with online engagement.

Demir and Kutlu (2018) finalized that IA predicted academic motivation in a negative and significant way. Similarly, Jannah, Mudjran, and Nirwana (2015) found a significant negative relationship between game addiction and student motivation, and Yaozong (2022) noted a significant negative relationship between smartphone addiction and achievement motivation.

H5. Extrinsic motivated strategies for learning are negatively associated with multiple-screen addiction.

H10. Intrinsic motivated strategies for learning are negatively associated with multiple-screen addiction.

3 Method

3.1 Model of the Study

This study used a relational screening model to explore relations among variables. Relational screening research does not aim to reveal cause and effect among variables, it allows one to make predictions on other variables by determining one variable (Karasar, 2005). We collected data through a survey. Before collecting data, we determined the instruments and tested the instrument's reliability. Moreover, we employed partial least squares structural equation modeling (PLS-SEM) to measure the proposed model (Fig. 1).

H1. Autonomous learning is positively associated with online engagement.

H2. Autonomous learning is negatively associated with multiple-screen addiction.

H3. Autonomous learning is positively associated with intrinsic motivated strategies for learning.

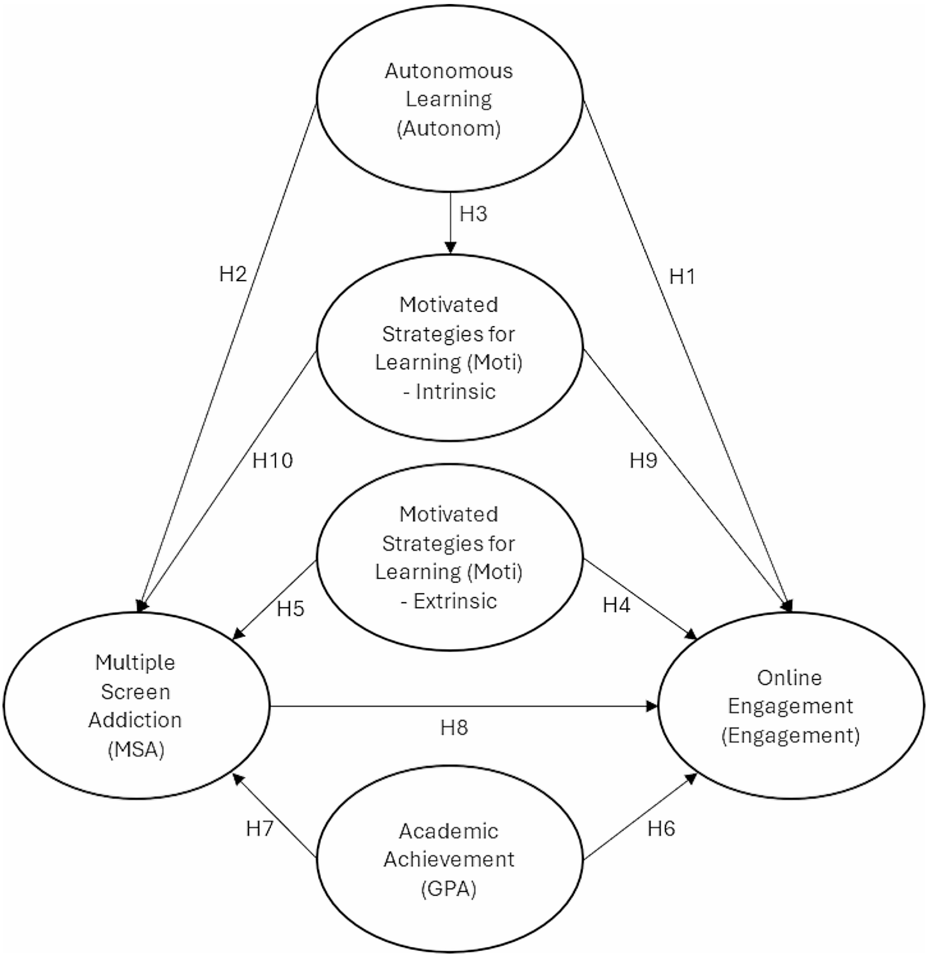

Fig. 1 Proposed Model of the Study

Table 1 Demographic gender, grade, age

		n	%
Gender	Male	107	28.5
	Female	268	71.5
Grade	1	224	59.7
	2	67	17.9
	3	25	6.7
	4	59	15.7
Age	17–22	318	84.8
	23–28	43	11.5
	29–48	14	3.7

Table 2 Technology usage purposes

	N	%
Research	3	0.8
Study	99	26.4
Other	28	7.5
TV series-movies	6	1.6
Playing games	16	4.3
Social media	223	59.5

H4. Extrinsic motivated strategies for learning are positively associated with online engagement.

H5. Extrinsic motivated strategies for learning are negatively associated with multiple-screen addiction.

H6. Academic achievement is positively associated with online engagement.

H7. Academic achievement is negatively associated with online multiple-screen addiction.

H8. Multiple screen addiction is negatively associated with online engagement.

H9. Intrinsic motivated strategies for learning are positively associated with online engagement.

H10. Intrinsic motivated strategies for learning are negatively associated with multiple-screen addiction.

3.2 Participants

The participants of the study are university students. The participants are 375 people from 18 universities, 11 faculties, and 27 different departments. Looking at Tables 1 and 71.5% ($n=268$) of the participants were female and 28.5% ($n=107$) were male and 59.7% ($n=224$) were first-year students and almost all (84.8%, $n=318$) were between the ages of 17–22.

Table 2 shows that more than half of the participants (59.5%, $n=223$) use technology as a social media tool. While 26.4% ($n=99$) use technology for study purposes, this rate drops below 1% for research purposes (0.8%, $n=3$).

As seen in Table 3, almost all of the participants (99%, $n=373$) have a phone. Similarly, almost all of them (80%, $n=299$) have a computer. About 1 in 5 (80%, $n=66$) have a tablet, while approximately 1 in 10 have a smartwatch or wristband (9%, $n=33$).

Table 4 shows that almost half of the participants (47.7%, $n=179$) had a weekly lesson preparation time of five hours or less. When looking at the technology usage periods, the

Table 3 Technological tools owned

	F	%
Phone	373	99
Computer	299	80
Tablet	66	18
Smartwatch or bracelet	33	9

Table 4 Course preparation and technology usage times

	Time (h)	*n*	%
Average weekly allotted time (in hours) to prepare for lessons	0–5	179	47.7
	6–10	92	24.5
	11–15	44	11.7
	16–20	36	9.6
	21–24	24	6.4
Daily use of digital technology for educational purposes (in hours)	0–5	309	82.4
	6–10	58	15.5
	11–15	5	1.3
	16–20	1	0.3
	21–24	2	0.5
Daily non-educational use of digital technology (in hours)	0–5	299	79.7
	6–10	65	17.3
	11–15	4	1.1
	16–20	4	1.1
	21–24	3	0.8

educational usage and non-educational usage periods are similar to each other. For example, while the rate of those who use technology for educational purposes between 0 and 5 h a day is 82.4% ($n=309$), the rate of non-educational use is 79.7% ($n=299$).

3.3 Instruments

Demographic form It is a form consisting of 7 questions developed by the researchers to obtain the demographic information of the students. Questions are about age, class, and technology usage status.

Academic Achievement GPA is the common measure used to assess students' performance. Academic achievement data is represented by the Grade Point Average (GPA) of students. Students have been asked about their current GPAs, and their GPAs have been utilized as a measure of achievement within the scope of the study.

Online Engagement Scale (OSE): OSE was developed by Dixson (2015) and adapted into Turkish by Polat et al. (2022b). OSE was employed to reveal students' engagement in online learning environments. The 5-point Likert scale consists of 4 sub-dimensions, skills, emotion, engagement, and performance, and a total of 19 items. The Cronbach alpha coefficient of the scale was calculated as 0.90. According to Cortina (1993), it is acceptable. Some examples of the scale items are as follows: I listened to the lesson attentively. I read the course materials carefully.

Multiple Screen Addiction Scale (MSA): This scale was developed by Sarıtepeci (2021) and is a 5-point Likert scale, used to determine the multi-screen addiction levels of university students. It contains 16 items in total, 8 items in the Compulsive Behavior dimension, 3 items in the Loss of Control dimension, and 4 items in the Excessive Screen Time dimension. In this study, 10 items were used. The Excessive Screen Time dimension (items 1,2 and 3), The Compulsive Behavior dimension (items: 6,8, 9,15) the Loss of Control dimension (12,14,16). The Cronbach alpha coefficient of the scale was calculated as 0.80. According to Cortina (1993), it is acceptable. Some examples of the scale items are as follows: I feel the need to be constantly interacting with some type of screen. I can't control the amount of time I spend in front of any screen.

Motivated Strategies for Learning Questionnaire (MSLQ) The motivation scale was used to decide the motivation of university students. A 7-point Likert scale consists of 31 items in total. The motivation scale was developed by Pintrich et al. (1991) and adapted into Turkish by Büyüköztürk et al. (2004, p. 232). The scale has a modular structure and can be used separately as the scores to be obtained from the subscales according to the purpose of use. The main component of value is intrinsic goal setting, extrinsic goal setting, and task value; the main component of expectation is the perception of self-efficacy regarding learning and performance and belief in control about learning; the affective main component consists of test anxiety factors. extrinsic goal orientation including items 7, 11, 13, and 30, and intrinsic goal orientation including items 1, 16, 22, and 24. were used in this study to determine learners' motivation sources. The Cronbach alpha coefficient of the scale was calculated as 0.74. According to Cortina (1993), it is acceptable. Some examples of the scale items are as follows; (Extrinsic) The most satisfying thing for me is getting a good grade in class. (Intrinsic) The most satisfying thing for me in this course is being able to understand the content as much as possible.

Autonomous Learning Scale (AL): This scale was developed by Macaskill and Taylor (2010) and adapted into Turkish by Alkan and Arslan (2019). AL scale aims to identify the autonomous learning of students. The 5-point Likert scale has two subscales (Independence of Learning and Study Habits.) and 12 items. In this study, only the Independence of Learning subscale was employed. The Cronbach alpha coefficient of the scale was measured as 0.80, which Cortina (1993) Accordingly, this value is acceptable. Some examples of the scale items are as follows: I am open to doing the same things in different ways. I enjoy being given challenging assignments.

3.4 Data Collection and Analysis

The students were informed about the purpose of the study voluntarily, and all the scales were administered via the online form. After providing participants with instructions regarding the purpose of the study, an online scale was administered. The online scale was shared with students via email and social media. PLS-SEM (Hair et al., 2012) is the appropriate method for complex models and small sample sizes that do not show normal distribution. This method and Smart PLS 3.0 software were used in this study. In the proposed model in this study, there are several constructs and indicators. PLS-SEM is the appropriate method considering the current study's purpose, sample size, and complexity of the model. Data analysis was made in two steps. Firstly, the measurement model analyzed the indicators in the model and secondly the structural model was tested.

i) Factor loadings, Cronbach's alpha for internal consistency, construct reliability coefficients, and average variance (AVE) values of the constructs were used to evaluate the reflective validity of the measured model.

The cutoff point for factor loadings used is 0.60 (Afthanorhan, 2013). Cronbach's alpha and composite reliability values were examined for reliability. Cronbach's alpha value (Cortina, 1993) and composite reliability value (Joreskog 1971) of 0.70 and above can be considered acceptable. Another important point is examining multicollinearity to evaluate the measurement model. Multicollinearity is relevant to assessing how indicator correlations affect the standard errors of weight estimates (Benitez et al., 2020). Multicollinearity is examined using VIF values. According to Fox (2019), VIF values below 10 are satisfactory. The cutoff point for AVE used is 0.50. The fact that the AVE value is greater than 0.50 indicates that more than half of the variance is explained by the latent variable (Benitez et al., 2020).

ii)The structural model: Proposed model is tested via path coefficients and t values.

4 Results

Table 5 shows factor loadings, average variance extracted (AVE), composite reliability (CR), and Cronbach's alpha (CA) values. Almost all factor loadings values are higher than 0.60 which is good (Afthanorhan, 2013). The lower ones (MSA11, OSE22, OSE23, OSE41, and OSE42) were not removed in order not to reduce the content validity. AVE, which measures the amount of variance a latent variable captures from its indicators relative to the amount of variance due to measurement error, is used to assess convergent validity (Fornell & Larcker, 1981). CR, known as construct reliability, measures the reliability of a latent variable (construct) represented by several measured variables. It evaluates whether the set of items that make up the factor in factor analysis reflects the construct coherently (Raykov, 1997). CA is one of the most common measures of internal consistency. It evaluates how closely related a set of elements is. Mainly, it is the average of possible item-total correlations multiplied by the number of items in the scale. It assumes each item has an equal contribution to the construct (Cronbach, 1951). AVE values above 0.50; CR and CA values above 0.70 indicate that internal consistency and reliability are a good fit (Hair et al., 2017).

Heterotrait-Monotrait Ratio (HTMT) is a criterion used to evaluate discriminant validity in research models that include latent variables. The HTMT ratio is calculated by dividing the average of item correlations between constructs (heterotrait) by the average of item correlations within the same construct (monotrait). A lower HTMT value indicates higher discriminant validity, indicating that the constructs differ from each other. Table 6 displays the results of the HTMT Ratio. Values that are different from 1 and below 0.90 indicate satisfactory discriminant validity (Henseler et al., 2015).

In order to determine the existence of multicollinearity in regression analysis, the Variance Inflation Factor (VIF) is used. VIF measures how much the variance of an estimated regression coefficient increases due to multicollinearity (Belsley et al., 1980). Table 7 presents the VIF values. Values below 10 indicate that there is no multicollinearity problem (Fox, 2019).

Table 5 Factor loadings, AVE, CR, and CA values

Constructs	Item	Loading	AVE	CR	CA
GPA	GPA	1.00	1.00	1.00	1.00
Autonom	AL1	0.73	0.51	0.86	0.80
	AL2	0.67			
	AL3	0.60			
	AL4	0.72			
	AL6	0.80			
	AL7	0.74			
MSA	MSA11	0.54	0.50	0.84	0.77
	MSA13	0.65			
	MSA22	0.63			
	MSA24	0.73			
	MSA31	0.74			
	MSA32	0.76			
Intrinsic Moti	MSLQ11	0.64	0.53	0.82	0.71
	MSLQ12	0.80			
	MSLQ13	0.70			
	MSLQ14	0.77			
Extrinsic Moti	MSLQ21	0.83	0.55	0.83	0.72
	MSLQ22	0.83			
	MSLQ23	0.68			
	MSLQ24	0.61			
Engagement	OSE11	0.75	0.50	0.92	0.90
	OSE12	0.75			
	OSE13	0.73			
	OSE14	0.76			
	OSE15	0.70			
	OSE16	0.64			
	OSE17	0.75			
	OSE21	0.80			
	OSE22	0.57			
	OSE23	0.57			
	OSE25	0.65			
	OSE41	0.58			
	OSE42	0.59			

Table 6 HTMT results

	Autonom	Extrinsic Moti	Engagement	GPA	MSA	Intrinsic Moti
Autonom						
Extrinsic Moti	0.64					
Engagement	0.61	0.58				
GPA	0.15	0.09	0.20			
MSA	0.26	0.12	0.19	0.09		
Intrinsic Moti	0.47	0.68	0.47	0.12	0.13	

Table 7 Inner VIF values

	Autonom	Extrinsic Moti	Engagement	GPA	MSA	Intrinsic Moti
Autonom			1.48		1.36	1.00
Extrinsic Moti			1.61		1.59	
Engagement						
GPA			1.03		1.02	
MSA			1.09			
Intrinsic Moti			1.44		1.43	

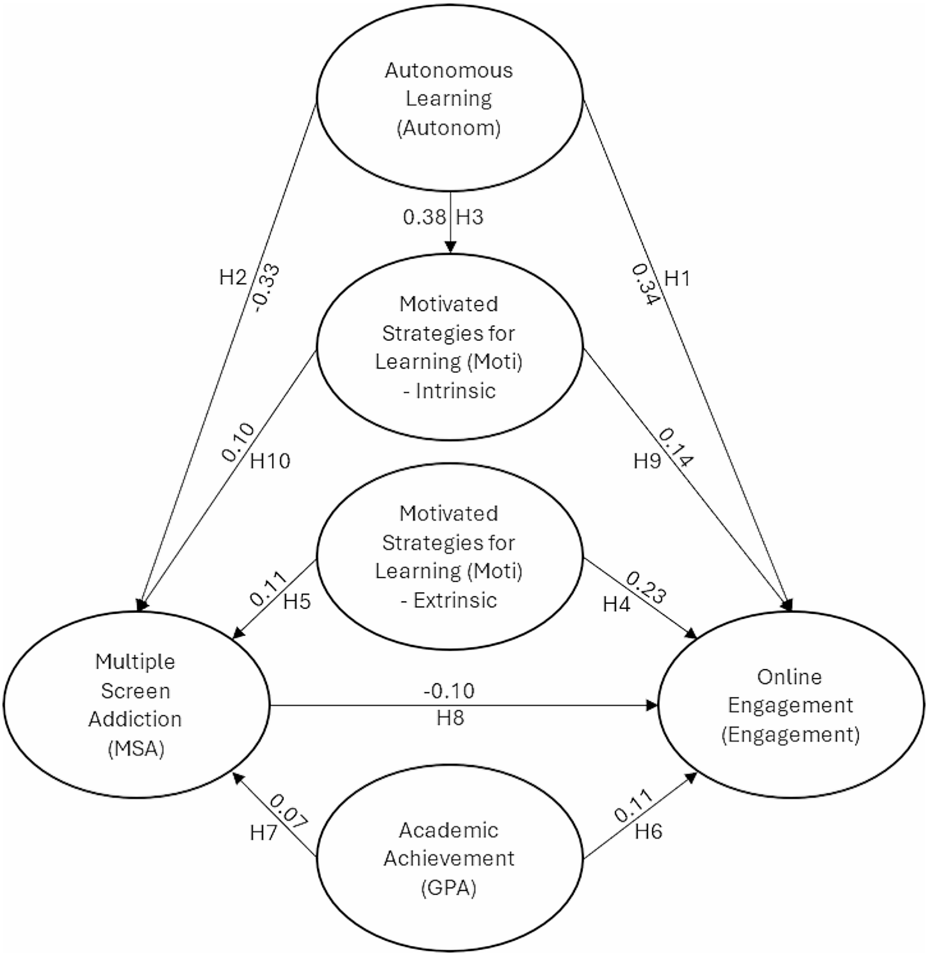

Fig. 2 Structural Model

The structural model was given in Fig. 2; Table 8. These show the results of the hypothesis test. According to the results, seven of the hypotheses were supported and three of them were not (H5, H7, and H10). Accordingly, (H1) there is a significant structure between autonomy and engagement (β=0.34; $p<.001$). Autonomous learners are more engaged,

Table 8 Structural model results

Hypothesis	Path	Path coefficient	t-value	*p*	Supported
H1	Autonom -> Engagement	0.34	5.67	0.00	Yes
H2	Autonom -> MSA	-0.33	5.73	0.00	Yes
H3	Autonom -> Intrinsic Moti	0.38	7.84	0.00	Yes
H4	Extrinsic Moti -> Engagement	0.23	3.61	0.00	Yes
H5	Extrinsic Moti -> MSA	0.11	1.70	0.09	No
H6	GPA -> Engagement	0.11	2.47	0.01	Yes
H7	GPA -> MSA	0.07	1.37	0.17	No
H8	MSA -> Engagement	-0.10	2.26	0.02	Yes
H9	Intrinsic Moti -> Engagement	0.14	2.36	0.02	Yes
H10	Intrinsic Moti -> MSA	0.10	1.61	0.11	No

and there is a significant negative structure between (H2) autonomic and MSA (β=-0.33; $p<.001$). Autonomous learners have lower MSA status, and there is a significant positive structure between (H3) autonomic and intrinsic motivation ($\beta=0.38$; $p<.001$). Autonomous learners have high intrinsic motivations, and there is a significant positive structure between (H4) extrinsic motivation and engagement ($\beta=0.23$; $p<.001$). Extrinsically motivated learners are more engaged, and (H5) extrinsic motivation is not associated with multiple-screen addiction ($\beta=0.11$; $p>.001$). In other words, we cannot conclude that extrinsically motivated learners have lower MSA status. (H6) GPA is associated with engagement ($\beta=0.11$; $p<.05$). More engaged students have higher GPAs, and (H7) GPA is not associated with multiple screen addiction ($\beta=0.07$; $p>.001$). In other words, we cannot conclude that those with low MSA scores have a high GPA. There is a significant negative structure between (H8) MSA and engagement (β=-0.10; $p<.05$). Those who have lower MSA status are more engaged, and there is a significant positive structure between (H9) intrinsic motivation and engagement ($\beta=0.14$; $p<.05$). In other words, intrinsically motivated learners are more engaged. (H10) Intrinsic motivation is not associated with multiple-screen addiction ($\beta=0.10$; $p>.001$). In other words, we cannot conclude that those with low MSA scores are intrinsically motivated.

5 Discussion

In this study, 10 hypotheses that examine the variables that explain the online engagement behaviors of 375 undergraduate students studying at various universities in Turkey were tested. According to the findings of the study, there is a positive relationship between online engagement and autonomous learning (H1). In support of this finding, various studies have emphasized the existence of a strong relationship between engagement and autonomous learning (e.g. MacDougall, 2008). According to Deci and Ryan (1987), autonomy is the actions that a person is responsible for and chooses. In the study conducted by Atman Uslu and Yildiz Durak (2022), autonomy is defined as the capacity to control one's tendency based on one's wishes, ability, and freedom to control, and it is emphasized that it is related to self-regulation. Indeed, in the self-regulated learning process, there is engagement at the center of the process (MacDougall, 2008; Vezne et al., 2022). Torres and Beier (2018), on the other hand, emphasize the existence of opportunities in online learning platforms that will support autonomous learning, such as progress at one's own pace, preferences in course options, and flexibility from time to time.

There is a negative relationship between the participants' autonomous learning and multiple-screen addiction (H2). Şimşir Gökalp et al. (2022) explored that learner control has a direct effect on technology addictions. In this context, the student's pathological use and the behavior of controlling the intensity of use may be associated with autonomy.

The H3 hypothesis tests the relationship between intrinsic motivated strategies for learning and autonomous learning. Intrinsic motivation is about the inherent desire to learn, while extrinsic motivation is about trying to achieve good results in the context of external incentives. According to Dickinson (1995), there are various concepts such as decision-making and critical reflection at the intersection of learner autonomy and motivation. Ushioda (2011) and Spratt et al. (2002) emphasize that motivation has a significant impact on autonomy as a prerequisite.

The H4 hypothesis tests the relationship between extrinsic motivated strategies for learning and engagement. According to self-determination theory, motivation is divided into intrinsic and extrinsic motivation (Ryan & Deci, 2000). Soufi et al. (2014) characterize motivation as a factor influencing people's control of their behavior and emphasize that extrinsic motivation is associated with lower autonomy. Therefore, a lack of motivation can prevent engagement.

Hypotheses H5, H7, and H10 test the relationship between extrinsic motivation, GPA, intrinsic motivation, and MSA, respectively. In this study, the types of motivation differ from the current research results as there is no relationship between GPA and MSA. Studies have shown that behavioral addictions such as smartphone addiction (Samaha & Hawi, 2016), internet addiction (Iyitoğlu & Çeliköz, 2017), and technology addiction (Yildiz-Durak, 2018a, 2020) negatively affect academic performance. The problematic use of digital technologies both reduces the attention of the students to the lesson in the classroom and causes a decrease in the academic study time the students (Arefin et al., 2018). According to Yildiz Durak et al. (2022), similar results were reached and they emphasized that the relationship between the use of digital technologies and academic achievement resembles a humpback-shaped curve, and it can be advantageous to use it at an optimum level. In this context, the relationships between extrinsic motivation, GPA, intrinsic motivation, and MSA can be examined in depth by performing longitudinal studies on the amount of addictive use.

Hypotheses H6, H8, and H9 test the relationship between GPA, MSA, and intrinsic motivation and engagement, respectively. It causes many situations such as lack of engagement, poor academic performance, dissatisfaction, and low motivation in classroom environments (Yildiz Durak, 2018b). Therefore, engagement is positively related to GPA and intrinsic motivation as it matches the activities of students in online learning environments such as interaction with resources, communication, and participation in course activities. On the other hand, it is expected that MSA and engagement are negatively related. Problematic technology use during or outside the classroom can affect students' attention, concentration, and learning processes and have a negative impact on their academic success and engagement (Gerosa et al., 2020; Przybylski & Weinstein, 2017; Yildiz Durak et al., 2022).

This study has some limitations. First of all, it should be kept in mind that socially desirable data may have come since addictive behaviors were collected with self-report data collection tools. In this study, autonomy is considered a variable in the model as an antecedent variable. In future studies, the relationship of research variables at the level of autonomy can be investigated. It is important to support the findings of this study by conducting experimental studies that will examine the effect of online engagement and motivation on multiple-screen addiction. Also, the effect of motivation and GPA in predicting MSA has not been confirmed. An in-depth examination of the reasons for this situation may be the subject of future research. Academic achievement and autonomous learning are seen to be related in the literature. The mediating effect of motivation types in this relationship can be examined in the future.

Data Availability Our data are not yet available online in any institutional database. However, we will send the whole data package by request. The request should be sent to Assoc. Professor Hatice YILDIZ DURAK: hatyil05@gmail.com.

Declarations

Ethical approval The research was conducted in a school in Turkey and approved by the school administration. Participation was voluntary and anonymous. Informed consent was obtained from all participants.

Conflicts of interest We have not received any funding or other support to present the views expressed in this paper. The authors declare no conflicts of interest with respect to the authorship or the publication of this paper.

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