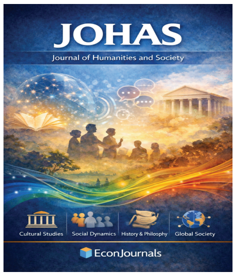


Journal of Humanities and Society

available at http: www.econjournals.com

Journal of Humanities and Society, 2026, 2(1), 42-52.

Digital Overload and Academic Stress: The Mediating Role of Online Disengagement and Cognitive Withdrawal among University Students in Jordan

Sultan Alaswad Alenazi*

Department of Marketing, College of Business, King Saud University, Riyadh, Saudi Arabia.
*Email: sultanalenazi1981@yahoo.com

Received: 05 January 2026 **Accepted:** 12 March 2026 **DOI:** https://doi.org/10.32479/johas.24893

ABSTRACT

The present study aims to explore the phenomenon of digital overload (DO) and its psychological impact on the Jordanian university students, specifically on the levels of academic stress (AS) and disengagement behaviors. It states that the greater a student's exposure to digital platforms in their academic and social life places them under constant informational pressure, too many notifications, and multitasking demands, all of which can lead to cognitive fatigue and rising levels of stress. The study also looks at how two coping strategies (online disengagement [OD] and cognitive withdrawal [CW]) mediate the link between parental involvement and academic achievement. The study also explores how two coping strategies (online disengagement [OD] and cognitive withdrawal [CW]) mediate between parental involvement and academic achievement. The data were gathered by using a structured online questionnaire for 500 samples of undergraduate and postgraduate students from public and private universities in Jordan, whose ages ranged between 18 and 30 years. The scales of perceived DO, OD, CW and AS were established and validated. Confirmatory factor analysis and structural equation modeling were used to test the hypothesized relationships in the data analysis procedures, which were analyzed using SPSS and AMOS. The results indicate that DO has a significant effect on AS for students. Furthermore, OD and CW are important mediators in this relation, suggesting that both behavioral and psychological avoidance are taken up by students in the presence of an excessive digital demand. The study emphasizes the importance of creating a balanced digital learning environment in higher education institutions to reduce cognitive overload and enhance students' digital engagement methods.

Keywords: Digital Overload, Academic Stress, Online Disengagement, Cognitive Withdrawal
JEL Classifications: I21, I23

1. INTRODUCTION

Today's students in higher education are more deeply entrenched in a digital ecosystem that is saturated with both academic and social and entertainment content vying for attention at every turn. The Jordan situation is unusual in the Middle East, where access to the Internet has surpassed 90% and the use of smart phones by young adults is some of the highest in the region, indicating a rapid digital transformation of the education and communication sectors (Al-Enezi, 2025). Following the COVID-19 pandemic, universities have made a wide range of changes to their education sectors, including the introduction of learning management systems (LMS), digital assessment systems and online communication tools. These developments have made access and flexibility easier and more convenient, but at the same time they have increased exposure to daily notifications, academic information, and social media stimuli leading to digital overload and psychological stress (Mohamed Shawky et al., 2026). This study examines four important constructs, DO, AS, OD and CW. DO is an excessive amount of information and notifications that overwhelm the cognitive capacity of a person, resulting in information fatigue and a decline in their ability to pay attention

This Journal is licensed under a Creative Commons Attribution 4.0 International License

effectively (Wang, 2023). AS defined as psychological stress caused by students' expectations of performance, workload and constant engagement with digital academic activities (Ayasrah et al., 2025). The behavioral responses to Ods include reducing the usage of platforms, logging out from systems and avoiding academic applications; and the psychological detachment of reducing mental engagement with digital learning environments (Nuseir et al., 2023; Xu et al., 2026). They are chosen due to the fact that these variables are all interrelated and together account for behavioural and psychological coping patterns with respect to digital stressors, which are only little researched in emerging economies. The choice of Jordan's higher education sector is warranted because of the rapid transformation of the sector towards digitalization and reliance on hybrid learning models.

Choosing Jordan's higher education sector is based on the reasons that the sector is undergoing a rapid transformation towards digitalization and the reliance on hybrid learning models. Education is one of the sectors that plays a crucial role in Jordan's human capital development, featuring more than 300,000 university students enrolled in public and private universities (Bao et al., 2024). There are, however, growing worries about student mental health, digital exhaustion, and a loss of academic interest, especially in the context of technological learning experiences (Upadhayay et al., 2025). This holds true across the world, in markets where digital learning platforms like Moodle, Blackboard and Google Classroom are prevalent in academic delivery. While there is a well-developed body of literature on the adoption of digital learning, engagement with it, and academic outcomes, the connection between digital overload and mechanisms of psychological and behavioral withdrawal is not well understood. Although previous research has found associations between DO and stress (Chauhan et al., 2026), between information overload and cognitive decline (Shatnawi et al., 2024), and between DO and the workplace (Zhou et al., 2025), few studies have simultaneously examined the association between DO and dual mediators, such as behavioral disengagement and CW, in the academic setting (Chung et al., 2025; Shalaby and El-Kasaby, 2024). In addition, the vast majority of studies focus on the Western or East Asian context, with few studies specifically addressing the Higher Education landscape in the Middle East region (Deeb et al., 2025; Tafesse et al., 2024).

Further, the previous studies mostly use cross-sectional designs with no multi-path mediation models, which reduces the explanatory power (Iqbal et al., 2025). Thus, the research objectives of this study were: (1) to examine the impact of DO on AS among university students in Jordan; (2) to analyze the mediating role of OD; (3) to investigate the mediating role of CW; and (4) to develop an integrated structural model explaining psychological and behavioral reactions to DO in academic context. This study is theoretically innovative because it brings stress coping concepts into the digitally saturated academic context, and empirically because it offers a dual-mediation model that incorporates both behavioral and cognitive coping. In practice, it provides guidance for policymakers and university leaders to re-imagine digital learning systems that are both technologically supported and cognitively healthy. It has a strength in its focus on a context that connects DO in the higher education environment in Jordan, which is not often explored but is fast changing with digitalization.

Research motivation arises from the critical need to address the growing problems of student burnout and disengagement in education systems that are digitally dependent, as digital well-being has become a more significant factor in student outcomes. This research situates itself at the nexus of digital transformation, educational psychology, and student well-being, offering a broad and holistic framework that contributes to the understanding of the consequences of overstimulation of digital technologies on the academic landscape in emerging economies.

2. THEORETICAL BACKGROUND

The current study was based mainly on a theoretical framework that includes two theories: Cognitive load theory (CLT) and Stress-Strain-Outcome (SSO) theory, which together offer a solid lens for understanding the relationship between DO and AS and behavioral and cognitive withdrawal among university students in Jordan. The justification for the integration of these theories is that CLT helps to elucidate the source of cognitive overload, while SSO helps to understand the psychological and behavioural effects that can be observed as a result of the prolonged exposure to such overload, so as to provide a complete causal chain to the proposed model. CLT suggests that human cognitive processing is limited, and if they are overwhelmed by information, then they cannot process, store, and retrieve information. Multiple stimuli like notifications, online lectures, discussion forums, social media interruptions and so on, appear in digital learning environments all the time and in total surpass students' working memory (Jannat et al., 2026). This is an exact match of the construct of DO which is the excessive cognitive load placed on digital environments. Research in the past has shown that high information level and continuous digital distractions affect concentration, cause mental fatigue, and decrease academic efficiency (Jannat et al., 2026; Shalaby and El-Kasaby, 2024).

In CLT contexts, researchers have long adopted this to describe learning inefficiencies in online learning settings, especially those which rely on multitasking (Zhou et al., 2025). Hence, CLT offers a robust theoretical base to the understanding of the origin of the critical stressor of DO in the Jordanian higher education context. Therefore, CLT offers a solid theoretical base to understand why DO is a critical stressor in the Jordanian higher education context. But behavioral responses like psychological detachment and avoidance are not fully captured by CLT. Thus, the SSO model (Koeske and Koeske, 1993) has been added to help explain how stressors are mediated to outcomes via internal strain mechanisms. This model proposes that environmental stressors (DO) create stress (AS) and this stress in turn results in behavioral and psychological consequences of disengagement and withdrawal. This framework has been successfully applied and validated in research on workplace burnout, social media fatigue, and AS (Julmi et al., 2022). In the educational context, SSO has been applied to describe students' burnout, decreased engagement, and avoidance in online learning settings (Wang, 2023). Both theories are relevant, as CLT helps to identify why cognitive overload happens and SSO helps to understand how cognitive overload becomes a stress response and avoidance behaviors.

The dual-theoretical lens enhances the conceptual validity of the suggested mediation pathway for OD and CW. These connections have been supported by previous research. For example, the over-exposure to digital content has been found to cause cognitive fatigue and lower platform engagement (Khan et al., 2024; Xu et al., 2026). Likewise, AS has been found to have a mediation role between digital pressure and burnout among students (Al-Enezi, 2025). Other behavioral mechanisms of avoidance have also been identified as coping strategies to digital stress, including app discontinuance and the silencing of notifications (Nuseir et al., 2023). Additionally, CW is consistent with psychological disengagement theory, as people tend to withdraw their mental effort from a stressful situation to spare their cognitive capacity (Iqbal et al., 2025). Higher education research also shows that long-term exposure to digital devices leads to lower motivation, concentration, and engagement with learning activities (Wang, 2023). Overall, the CLT and the SSO framework give a complete account for the development of DO into AS and further into behavioral and CW among university students. The theoretical integration of this not only deepens the conceptual basis of the study but also connects between cognitive psychology and stress-based behavioral models, all in a unified digital educational context.

2.1. Digital Overload and Academic Stress

New digital settings in higher education are defined by constant information overload, meaning that students have to be able to receive all information from the academic environment, such as lecture content and platform updates, at the same time. This sustained exposure leads to cognitive overload, when the amount and complexity of information surpass the capacity of working memory (Li et al., 2026). This overloading leads to challenges with attention allocation, lower comprehension efficiency, and higher mental fatigue, especially in DO (Zhou et al., 2025). Evidence shows that overuse of digital devices is linked to poorer cognitive control and academic performance (Khalili et al., 2025). Meanwhile, learners suffer from emotional fatigue and increased psychological stress as they are exposed to notifications and academic work continuously (Tafesse et al., 2024). In terms of broader stress, the SSO framework outlined how external environmental stressors become internal psychological strains, which are experienced as anxiety, fatigue and a lower capacity to cope (Ayasrah et al., 2025). In the educational environment, digital demands are chronic stressors that increase students' perceived workload and reduce their capacity to engage in learning activities over a prolonged period (Shalaby and El-Kasaby, 2024). Research also indicates that high levels of digital intensity in environments have adverse effects on attention span and emotional fatigue, further confirming the link between information saturation and academic strain (Julmi et al., 2022). Furthermore, the cognitive psychology literature states that when people are not able to handle informational demands effectively, stress reaction increases when people feel a lack of control over learning tasks (Mohamed Shawky et al., 2026).

- H_1: DO has a positive effect on AS among university students.

2.2. Digital Overload and Online Disengagement Behaviour

Digital technologies' integration in higher education has profoundly changed the way that students engage with academic content, and this has resulted in a high frequency of notifications, platform updates, and online academic demands for students. However, when faced with too much exposure, students can easily reach a point of cognitive overload, meaning the prolonged use of digital systems is beyond what they can focus on at 1 time (Al-Enezi, 2025). This slowly diminishes the desire to stay active in any digital learning environment, and fosters behavioral withdrawal from online platforms. According to CLT, learners' interaction behavior tends to decrease as a self-regulation strategy to reduce cognitive load when facing high-density informational environment repeatedly (Li et al., 2026). Empirical research also demonstrates a strong link between over multitasking and a decrease in platform engagement and avoidance tendencies, with users trying to restore cognitive balance (Wang, 2023; Khalili et al., 2025). Behavioral stress view entails that environmental stressors trigger psychological stress, which in turn gives rise to adaptive or avoiding coping strategies (Nuseir et al., 2023). In digital learning environments, such stress can manifest in withdrawal responses when users try to avoid stimuli that seem to be causing them stress (Bao et al., 2024). Previous studies also found that persistent digital pressure makes users less engageable with the platforms by decreasing the frequency of logins, deactivating notifications, and decreasing the interaction with academic applications (Mohamed Shawky et al., 2026). In educational environments, this behavioral withdrawal is becoming more prevalent among students who struggle to cope with the constant online academic demands, resulting in diminished participation and engagement (Khan et al., 2024). Moreover, research has shown that avoidance behaviours are coping strategies that help restore cognitive balance in the context of overstimulated environments (Zhou et al., 2025).

- H_2: DO has a positive effect on OD behaviour.

2.3. Online Disengagement Behaviour and Academic Stress

In the digitally intensified higher education environment, the students' engagement with the learning process has become more variable, as a result of the constant informational pressure and cognitive overload. People's attempts to avoid too many digital inputs often result in withdrawal strategies, which may involve restricting access to academic platforms and decreasing involvement in online learning activities. These behaviors arise as adaptive coping strategies to re-establish cognitive balance when perceived demands are greater than available attentional capacity (Li et al., 2026). According to research in cognitive psychology, students who are constantly exposed to complex and fragmented digital information suffer from reduced sustained attention and fatigue, leading to weaker academic engagement (Chauhan et al., 2026). Once someone becomes cognitively exhausted, they may be more inclined to avoid difficult tasks, because they want to avoid more mental effort (Tafesse et al., 2024). This mechanism is supported by empirical research conducted in digital learning contexts, which shows that students in high informational pressure conditions tend to show a decrease in their interaction with the platform and academic participation (Shatnawi et al., 2024). Environmental demands are a source of internal strain that directly impact avoidance and disengagement from the environment, as seen from a SSO perspective (Zhou et al., 2025). In educational environments, frequent exposure to notifications related to academic assignments and the need to multitask can cause emotional exhaustion and motivate them to be less active with learning systems (Khan et al., 2024). Research also indicates that those exposed to continuous digital stress tend to disengage from digital spaces as a mechanism to avoid DO and restore mental balance (Deeb et al., 2025). Besides, decreased engagement has been associated with a drop in academic performance and learning satisfaction in technology-mediated learning systems (Shalaby and El-Kasaby, 2024).

- H_3: OD behaviour has a positive effect on AS among university students.

2.4. Digital Overload and Cognitive Withdrawal

Students in higher education today are constantly bombarded with academic information via email, lectures, and notifications on platforms like Google Classroom, which requires a constant attention to this information by their cognitive systems. Once these demands are present for an extended period that exceeds a reasonable level, an individual's psychological withdrawal becomes a coping mechanism to preserve cognitive resources. According to CLT the working memory is limited and when it is overloaded, mental efficiency decreases and the individual becomes less involved in complex cognitive processes (Iqbal et al., 2025). When an overload lasts for a long time, the learner may switch from being engaged to a psychological distance in order to minimize mental effort (Upadhayay et al., 2025). In the digital learning environment, empirical evidence reveals that learners' exposure to information streams at high frequency causes a decrease in attentional control and an increase in mental fatigue, which leads to cognitive withdrawal tendencies (Iqbal et al., 2025). Withdrawal does not only take a behavioral form, but it also manifests psychologically as a decrease in emotional investment in learning activities and the lack of cognitive involvement (Chung et al., 2025). Persistent environmental demands create internal strain that result in adaptive coping responses like disengagement and psychological distancing (Tafesse et al., 2024) from SSO perspective. In educational settings, this strain is exacerbated by test-related stress and the constant availability of electronic devices, resulting in emotional fatigue and diminished cognitive focus (Chung et al., 2025). Additional research research suggests that continued digital exposure reduces cognitive persistence, which increases a person's tendency to mentally disengage from challenging tasks to avoid escalation of overload (Nuseir et al., 2023). The withdrawal behavior is linked to lower learning absorption, diminished academic motivation, and decreased retention of information in technology-mediated educational environments (Xu et al., 2026). Moreover, psychological studies indicated that cognitive withdrawal is an adaptive mechanism that restores balance when the environmental challenge is greater than coping (Jannat et al., 2026).

- H_4: DO has a positive effect on CW.

2.5. Cognitive Withdrawal and Academic Stress

Academic stress is not only determined by the external load but also by the internal psychological reactions to the continuous exposure to the digital load of university students in the current context of digital learning. Excessive informational pressure can lead to cognitive fatigue, emotional exhaustion and decreased coping ability, all of which increase stress perceptions. Theories of stress state that when the environmental demands are greater than the individual's adaptive resources, the individual experiences strain, which in turn has a negative impact on psychological well-being (Iqbal et al., 2025; Tafesse et al., 2024). However, it is exacerbated in digitally mediated academic settings where constant connectivity and unceasing academic notifications reduce recovery time and cause mental fatigue. Additionally, the literature from cognitive psychology states that when learners are not able to process the incoming information efficiently, they get tired, and fatigue eventually be converted into stress-related outcomes (Zhou et al., 2025). Studies suggest that the extended use of digital learning environments may lead to feelings of emotional burnout, difficulty focusing, and increased anxiety in students (Khan et al., 2024). This cognitive load hinders the students' capacity to manage their emotions properly, making them more susceptible to stress reactions (Wang, 2023). In the wider field of education, researchers stress how digital fatigue and diminished attentional control negatively affect students' psychological resilience within online learning environments (Nuseir et al., 2023). This loss of resilience then leads to increased vulnerability to stress if there is insufficient time for the brain to recover from the stress of academic demands (Julmi et al., 2022). Moreover, studies indicate that people under chronic mental fatigue are more likely to perceive academic tasks as difficult to handle, which further increases the stress felt (Upadhayay et al., 2025).

- H_5: CW has a positive effect on AS among university students.

2.6. Mediating Roles of Online Disengagement and Cognitive Withdrawal

Digital exposure to information and the impact on student well-being can be best analyzed with an integrated lens of cognitive theories and stress-based theories in higher education contexts that are highly information and information-driven. Students' cognitive systems are constantly stimulated, giving rise to overload conditions that affect attention, memory processing, and emotional control (Deeb et al., 2025). Such overloading can lead students to use coping strategies (behavioral and psychological) to adapt to the situation, such as online system disengagement and mental detachment from academic tasks (Xu et al., 2026). Environmental demands cause internal strain, leading to observable outcomes like disengagement behaviours and emotional exhaustion (Khalili et al., 2025). Research has empirically demonstrated that extended and continuous use of digital learning platforms without sufficient recovery time results in increased fatigue, diminished motivation, and decreased cognitive resilience (Xu et al., 2026). The result is a vicious cycle in which students gradually withdraw from digital environments as a coping mechanism to alleviate mental load (Li et al., 2026). Additionally, psychological withdrawal/behavioural avoidance acts as complementary strategies for people to seek control over the information overload in the environment (Upadhayay et al., 2025). These mechanisms all contribute to lowering active academic involvement and making them more susceptible to stress if academic demands are unchanged (Iqbal et al., 2025). In addition, research indicates that cognitive and behavioral withdrawal can exacerbate each other's impact, further compromising psychological functioning in individuals experiencing DO (Zhou et al., 2025). Thus, the combination of these two mediating pathways offers a comprehensive explanation for how sustained digital pressure becomes academic stress, and a more holistic understanding of students' response system in technology-rich educational environments. Research model of the study is presented in Figure 1.

- H_6: OD and CW jointly mediate the relationship between DO and AS among university students.

3. METHODOLOGY

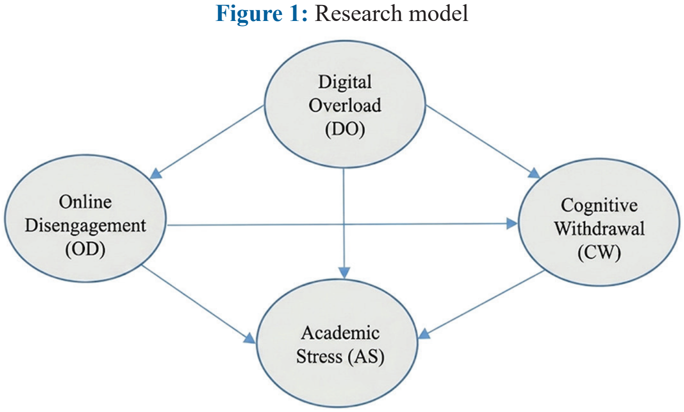
3.1. Research Design

The design of this study is quantitative research with the test of causal relationships. The direct and indirect relationships among the variables in the model were tested using SEM. The research model investigates the impact of DO on AS with the involvement of the mediators of OD and CW behaviours. The sample involved in the research included university students aged 18-30, and who are actively using digital learning platforms in Jordan. Convenience sampling method was used to collect the data online. Data in the research was obtained using a survey technique which is conducted through the internet. The questionnaire was designed in Google Forms and shared with the respondents via social media and other learning environments. The application reached 500 participants and all the questionnaires were accepted as valid and used in the analysis process.

3.2. Data Collection

A structured questionnaire form was used as a data collection tool. A questionnaire is divided into two parts. The first part is the questions used to identify the demographic characteristics of the participants (age, gender, education level and the time spent on internet every day). In the second part, there are scale expressions to measure the variables analyzed in the research. The items in this section were adapted from previously developed and validated scales. All scales in this study were translated into Arabic and were adapted from other studies which were validated and reliable. DO was assessed using a self-administered questionnaire that was based on previous literature about digital information overload (Jannat et al., 2026). The modified scale consisted of 15 statements covering the experiences of continuous notifications, pressure on the academic platforms, and demands for multitasking.

Figure 1: Research model



Some of the sample items include: "I feel overwhelmed by the amount of digital academic information I receive daily" and "It feels like I never have enough time to consume digital academic information." A four-item scale developed by Al-Enezi (2025) and Shatnawi et al. (2024) was used to measure the DO. Three items were used as the scale for measuring the OD, adapted from Xu et al. (2026). The three-item scale developed by Julmi et al. (2022) was used to assess CW. A 4-item scale was used for the AS variable as appropriate statements were included according to the stress measurement framework developed by (Nuseir et al., 2023). The scales were measured on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree).

The adaptations to Arabic were done using back translation and expert opinion. The scale items used in this study were adopted from the previous studies which were developed and validated in the literature. The sources and types of the scales used are described above. In the translation process of the scales to Arabic, attention was paid to ensure the linguistic translation as well as maintaining the conceptual and cultural equivalence. The translation - translation method was used. The scale items were translated into Arabic using the services of educational experts, followed by back-translation into English by an expert linguist and finally by comparing the items with the original. Following the linguistic adjustment of selected items, some items were simplified based on comments and the final survey form was developed. A number of data quality checks were performed before analysis to ensure that the data were reliable and robust. The online survey system was set up so that no questionnaires were entered if they were incomplete, only completed questionnaires were entered. Straight-lining was explored in response patterns and no cases were excluded because of variance checks. Descriptive statistics and standardized z-scores were used to detect any extreme values that may have influenced the results, and no such outliers were found. Furthermore, the study included attention-check questions in the questionnaire to assure the respondent's attention, and only those that passed the attention checks were chosen. According to these procedures 500 responses were found to be valid and suitable for final analyses and hence adding reliability and credibility to the findings. Common Methods Bias was a methodological risk in this study as the data were being taken from a single source with a cross-sectional design. To manage this risk, steps were carefully designed into the research process according to the recommendations of Podsakoff et al. (2003). To reduce the social desirability and evaluation concerns of the participants, it was ensured that their answers would be strictly confidential and completely anonymous, and a voluntary consent form was handed to the participants. Secondly, the survey instructions were explicit: That the questions had no "right or wrong answers" and that the participant should reflect on their "true thoughts," and not on a strategic answer for the questions. Finally, the items on the scales were kept short, clear and easy to understand to avoid creating an artificial correlation, caused by ambiguity in the scale items. This study was conducted with the ethical approval of the appropriate Institutional Human Research Ethics Committee (Approval No: 143/2025). All potential participants were given an informed consent form and students who signed were studied.

3.3. Data Analysis

SPSS and AMOS software were used to analyze the data. Firstly, descriptive statistics for the data set were computed and tests of the data set for a normal distribution were performed. To test the internal consistency of the scales used in this study, reliability analyses were carried out and Cronbach's Alpha coefficients were calculated. Construct validity of the scales was tested by using confirmatory factor analysis (CFA). SEM was chosen over other methods since the relationships suggested in the research model were to be tested. Goodness of fit of the model was assessed by fit indices: CFI (comparative fit index), TLI (Tucker-Lewis index), RMSEA (root mean square error of approximation) and χ^2/df (Chi-square/degree of freedom), and the suitability of the model was determined by whether these indices were within acceptable limits. Furthermore, mediation effects were analyzed within the framework of SEM in AMOS. This method allowed us to estimate both direct and indirect effects, and to consider the measurement error problem, achieving a complete evaluation of the proposed model. The indirect paths' significance was evaluated with Sobel tests and the results showed that the mediation of OD and CW were confirmed. Therefore, SEM was judged to be suitable and scientifically sound to test mediation in this study.

4. FINDINGS

4.1. Descriptive Statistics

The following demographic characteristics of those who completed the study are presented: The participants' gender, academic level, field of study, and time spent digitally engaging with learning was captured and provided as descriptive data. This information is used to help understand the structure of the sample and to assess whether the findings are those of the sample or not. The general demographic information of the participants is summarized and presented in Table 1 below as follows: Gender, Academic Level, Subject, and Daily Use of Digital learning. The sample is mainly constituted by male students (52.6%) and undergraduate students (63.8%) who are engaged in structured academic learning. The field of study distribution indicates that most of the participants come from social sciences (39.4%), business related field of studies (28.7%) and information technology programmes (21.5%). They have significantly more hours of daily digital learning engagement time, with 88.9% reporting over 4 h/day of digital learning engagement. This indicates that the samples are exposed to continuous academic digital environments very high, which is directly related to the study focus on DO and their psychological implications.

4.2. Reliability and Validity Analysis

The Cronbach's alpha values of all scales are >0.80. According to the CFA results, the variables fit the model at an acceptable level (CFI = 0.948, TLI = 0.942, RMSEA = 0.049, χ^2/df = 2.41). All constructs have good internal consistency and fit the model well as shown in Table 2. The fact that the Cronbach's Alpha values of all scales used in the study are above 0.80 indicates that the measurement tools have a high level of internal consistency. This means that the scales are reliable. The results of the CFA indicate that the model fits the data well; especially CFI value (0.948) and TLI value (0.942) are >0.90, showing good fit, RMSEA value (0.049) is <0.05, showing excellent fit, and χ^2/df ratio is 2.41, indicating acceptable fit. The results of this study supports that the variables used in the research model are structurally valid and reliable. The analysis of students' perceptions of the variables' averages reveals that DO (4.02) and AS (4.08) are at a medium-high level, whereas OD (3.72) and CW (3.65) behaviours are at a moderate level. The fact that the standard deviations are in the range of 0.74-0.86 indicates that there is reasonable variation among the participants and the responses are not highly concentrated. Based on the presented result from SEM as shown in Table 3, it can be concluded that all the proposed hypotheses are accepted and both OD and CW are significant mediating factors in the model. The model results show that DO has a significant and positive effect on AS (β = 0.42, P < 0.001). Likewise, DO positively affects OD (β = 0.47, P < 0.001) and CW behaviours (β = 0.39, P < 0.001). OD and CW both have a positive effect on AS (β = 0.31 and β = 0.28, respectively, P < 0.001). The Sobel test results indicate that OD and CW are important mediating variables in the relationship between DO and AS. The results indicate that students who face excessive demands in digital learning may

Table 1: Demographic profile of respondents (n=500)

Variable	Category	Frequency	Percentage
Gender	Male	263	52.6
	Female	237	47.4
Academic level	Undergraduate	319	63.8
	Postgraduate	181	36.2
Field of study	Social sciences	197	39.4
	Business studies	143	28.7
	Information technology	108	21.5
	Other fields	52	10.4
Daily digital learning use	1-3 h	55	11.1
	3-5 h	102	20.4
	5-7 h	171	34.2
	More than 7 h	172	34.3

Table 2: Reliability and validity analysis results

Variable	Cronbach's alpha	Mean	Standard deviation
DO	0.90	4.02	0.78
OD	0.87	3.72	0.86
CW	0.89	3.65	0.81
AS	0.92	4.08	0.74

Table 3: Structural equation model hypothesis test results

Path	Standard β	P-value	Result
DO→AS	0.42	<0.001	Supported
DO→OD	0.47	<0.001	Supported
OD→AS	0.31	<0.001	Supported
DO→CW	0.39	<0.001	Supported
CW→AS	0.28	<0.001	Supported
DO→OD→AS	–	Sobel P<0.01	Mediation confirmed
DO→CW→AS	–	Sobel P<0.01	Mediation confirmed

experience direct AS, but become accustomed to coping with these demands in behavioural and psychological ways that can subsequently increase AS mediated through them.

4.3. Confirmatory Factor Analysis

In this research, construct validity of the measurement tools was tested using CFA. CFA is an analysis method employed to assess if the variables connecting to the theoretically defined structures are statistically substantiated based on the expected factor structure (Kline, 2012). The results of this analysis indicate the reliability of the measurement model when tested in terms of the loading of the items on the factors within the scales. It is assumed that the four main variables have theoretically distinguishable constructs. In the case of CFA, it was determined whether these constructs were meaningfully represented in the measurement model. It was then necessary to analyse the validity of the measures (convergent validity, discriminant validity and representativeness) of each construct of the model and to test the reliability of the measurement dimension of the model before moving on to the next structural analyses. The confirmatory factor analysis results, as shown in Table 4, show that the factor loadings, convergent validity and reliability of all constructs in the measuring model are satisfactory. When the CFA results are analysed, it is seen that the item loadings of each variable vary between 0.73 and 0.85. They are much higher than the factor loading limit of 0.50 recommended in the literature, thus supporting the construct validity of the instrument (Hair et al., 2014). The loading coefficients of all loading items are known to be statistically significant ($t > 11$, $P < 0.001$) and all items sufficiently predict the factors on which they are loading. The AVEs (average variance extracted) of each sub-dimension fall between 0.58 and 0.65. The AVE values indicate the explanatory power of the constructs, and values >0.50 mean that the latent constructs are well captured by the items. In all variables, the internal consistency of the measurements is high with CR values above 0.85, thus reliability of the measurements is guaranteed. The Cronbach's alpha coefficient that exceeds 0.70 are regarded as a strong indicator of the consistency of scales (Fornell and Larcker, 1981). The results of the study suggest that the measurement models of all four constructs employed is valid and reliable.

Table 4: Confirmatory factor analysis results

Variable	Item code	Factor load	t-value	AVE	CR
Digital overload	DO1	0.79	12.61	0.62	0.88
	DO2	0.83	13.28		
	DO3	0.76	12.04		
	DO4	0.81	13.15		
Online disengagement	OD1	0.75	11.88	0.60	0.86
	OD2	0.82	13.36		
	OD3	0.77	12.22		
Cognitive withdrawal	CW1	0.78	12.40	0.61	0.87
	CW2	0.84	14.02		
	CW3	0.76	12.18		
Academic stress	AS1	0.85	14.88	0.65	0.90
	AS2	0.80	13.41		
	AS3	0.82	13.95		
	AS4	0.78	12.73		

All factor loadings are significant at P<0.001 level. AVE: Average variance explained, CR: Composite reliability

4.4. Correlation Analysis

Pearson correlation coefficients were computed among the key variables of the research to pre-evaluate the direction and significance of the proposed relationships among the variables in the structural model. Correlation analysis is not only used to see if the variables in the model have statistically significant relationships but also before going to SEM analysis to collect preliminary information whether the theoretical model is empirically supported or not. The mean and standard deviation (SD) values of the variables also help to understand the overall trend and distribution of the sample level in the study. Table 5 shows the correlation matrix, which offers initial information on the direction and strength of the relationships between the key variables of the study. The Table 5 shows that there were significant and positive relationships among all the variables in the study. DO was determined to be highly positively correlated with AS ($r = 0.63$, $P < 0.01$). This finding demonstrates that digital exposure is an independent factor of stress, as it is a burden to the mind of students and to their cognitive/psychological processes. Moderately significant relationships were also found for DO with both OD ($r = 0.54$) and CW ($r = 0.49$) behaviours. This discovery echoes the fact that students are more likely to adopt protective strategies in response to high demands of digital learning. High similarity in the correlation of the two behaviours ($r = 0.57$) indicates that this correlation may stem from a similar psychological basis, coping and self-regulation under cognitive strain. Furthermore, the behavioural and psychological responses to stress formation in a digital learning environment are highly related, as evidenced from the significant associations that AS has with OD ($r = 0.51$) and with CW ($r = 0.47$). Before SEM, these relationships give preliminary information about the possibility of their statistical significance and indicate that the theoretical model is supported by these relationships.

4.5. Difference Analysis According to Gender

Independent sample t-test was used to check for difference in the levels of AS, OD and CW among the gender of the participants. This analysis is relevant not only in terms of assessing the impact of gender on student psychological and behavioural reactions in digital learning environments, but also for analyzing the impact of gender on the learning environment. Data presented in Table 6 show that there was a difference between the genders in DO, AS, and CW as shown by the mean value and the independent samples t-test results. According to the results of independent sample t-test, the mean perception level of female participants regarding DO ($\bar{X} = 4.05$, $SD = 0.77$) was higher than that of male participants ($X = 3.92$, $SD = 0.80$), but this difference was not statistically significant ($t = 1.58$, $P = 0.114$). This finding would imply that

Table 5: Correlation matrix and descriptive statistics table

Variable	1	2	3	4	Mean	SD
DO	—				4.02	0.78
OD	0.54**	—			3.72	0.86
CW	0.49**	0.57**	—		3.65	0.81
AS	0.63**	0.51**	0.47**	—	4.08	0.74

**:All correlations are significant at p < .01 level. SD: Standard deviation

Table 6: Mean values and t-test results according to gender variable

Variable	Gender	Mean	SD	t	P-value
DO	Female	4.05	0.77	1.58	0.114
	Male	3.92	0.80		
AS	Female	4.10	0.73	2.31	0.021
	Male	3.88	0.76		
OD	Female	3.76	0.84	1.88	0.061
	Male	3.61	0.87		
CW	Female	3.69	0.80	2.37	0.018
	Male	3.47	0.83		

the female students feel the pressure of digital learning a little more strongly than male students, but not significantly. But the close relationship of the p-value to the 10% criterion suggests that this trend could be more pronounced with a larger population. According to the independent sample t-test, there is a significant difference between the AS level for female participants and the level for male participants (P = 0.021), and the level of cognitive withdrawal for female participants and the level of cognitive withdrawal for male participants (P = 0.018). The gender difference with regard to OD behaviour was near statistical significance (P = 0.061). The results of the study indicate that the psychological and behavioral reactions of female students are stronger in terms of digital learning pressure.

4.6. Difference Analysis According to Age Groups

One way analysis of variance (ANOVA) was used to compare the age groups of the participants on the presence of a significant difference in AS, OD and CW level. This analysis is significant, because it provides an indication of how age factor affects student behavioural and psychologic reactions. The ANOVA showed that there was a significant difference between age group in OD, but no difference in DO, AS and CW (Table 7). ANOVA results indicated that there was a significant difference in age group only in OD behaviour (P = 0.029). In the *post-hoc* analysis, it was found that the average Ods of the individuals within the age group 26-30 were >18-22 age group. No statistically significant difference was found between the age groups in their DO, AS and CW level. The results indicate that, in particular, older students at universities are more aware of the reduction in the interaction with digital learning platforms than younger students.

4.7. Test of Mediation Effects

Within the scope of the SEM, the mediating role of OD and CW behaviours in the effect of DO on AS was analysed. Mediation analyses can be used to simultaneously test both direct and indirect effects via mediators. All direct, indirect and total effects in the model were computed and the relationship dynamics between the variables were detailed in this context. The standardized coefficients and the total effect of each path are reported below in a table. Based on the presented findings in Table 8, the mediation analysis results indicate the direct, indirect and total effects of DO on AS via OD and CW. According to the SEM findings, DO has a positive and significant direct effect on AS with a value of β = 0.42. This indirect channel of influence is also highly reinforced via OD and CW behaviours, however. The total effect of DO on AS was the sum of the direct effect (B = 0.23) plus the indirect effect (B = 0.23). This indicates that the mediating variables also have

Table 7: ANOVA results according to age groups

Variable	F	P-value	Significant difference
DO	1.34	0.261	No
AS	2.91	0.055	No
OD	3.56	0.029	Yes*
CW	1.72	0.162	No

*P<0.05 level is considered significant

Table 8: Direct, indirect and total impact values

Path	Direct impact	Indirect impact	Total impact
DO→AS	0.42	0.23	0.65
DO→OD	0.47	—	—
OD→AS	0.31	—	—
DO→CW	0.39	—	—
CW→AS	0.28	—	—

Indirect effect=DO→OD→AS+DO→CW→AS. All paths are significant at P<.001

a remarkable structural role in the model and have a remarkable contribution in the explanation of the perception of academic stress. Similarly, a significant mediation effect was observed between DO and AS with the intermediary of OD behaviour (β indirect = 0.47 × 0.31 = 0.15), while also a mediation effect was observed between DO and AS with the intermediary of CW behaviour (β indirect = 0.39 × 0.28 = 0.11). Such mediation relationships are also statistically significant (P < 0.01) according to the results of the Sobel test. The findings indicate that at the cognitive level as well as at the behavioural level students adopt different defence mechanisms against the high degree of demands they are faced with in digital learning environment and that these mechanisms are directly connected to students' sense of AS.

5. DISCUSSION

This study investigated the impact of DO on AS of university students in Jordan, while focusing on the mediating effects of OD and CW. The results lend strong support for the proposed model and are consistent with the CLT and the SSO framework, and give a thorough account of how permanent digital exposure manifests in psychological strain and AS. The first key finding is that DO is related in a significant positive manner to AS. This finding aligns with CLT theory, which proposes that overloading the information input overload the working memory, causing cognitive fatigue and compromising processing speed (Al-Enezi, 2025; Li et al., 2026). The findings echoed those of Tafesse et al. (2024), who reported that multitasking in digital environments negatively impacts attentional control, as well as the findings of Zhou et al. (2025), who associated high exposure to screens with higher stress and lower well-being. The empirical research in higher education also corroborates this correlation, with a consistent finding of anxiety and emotional exhaustion being linked to ongoing academic engagement online (Jannat et al., 2026). While others studies state that digital tools can be a calming force when used within a well-designed learning system, context and design are found to have a moderating effect (Shalaby and El-Kasaby, 2024). The second finding is that DO does indeed have a positive effect on the OD behaviour. This finding is consistent with earlier studies that found that overstimulation of digital platforms leads to a decrease in platform use and avoidance of notifications as coping mechanisms (Ayasrah et al., 2025; Mohamed Shawky et al., 2026).

The high cognitive demands of students using digital learning can cause them to withdraw from educational platforms in order to restore their cognitive balance, as noted by Xu et al. (2026). This behaviour is in line with the theory of selective avoidance, which involves limiting exposure to avoid mental fatigue (Khalili et al., 2025). But contrasting results of Chung et al. (2025) suggest that some users may feel more engaged despite feeling overloaded or burdened because of academic stress, reflecting variation in coping strategies. The third finding indicates that the influence of OD is positive to AS. This relationship is theoretically supported by the SSO Model, which suggests that avoidance behaviours might initially be coping strategies but can have a negative impact on academic readiness, thereby intensifying stress (Nuseir et al., 2023; Zhou et al., 2025). Iqbal et al. (2025) also reported similar evidence, indicating that a disengaged response in high demand situations results in resource depletion and strain. Similarly, Upadhayay et al. (2025) found that low participation in digital learning system affects the academic confidence and stress level of students. But there is some evidence that short-term withdrawal can provide a temporary stress reduction, suggesting a two-way effect for varying durations and intensities (Khan et al., 2024). The fourth finding is that DO make a significant contribution to CW. This finding is closely supported by Tafesse et al. (2024), who indicate that prolonged cognitive overload is associated with mental detachment and less information processing. Likewise, Khan et al. (2024) suggests that if cognitive systems are overloaded, learners psychologically withdraw to keep their mental resources intact.

In two empirical studies Bao et al. (2024) and Upadhayay et al. (2025) also show that constant digital exposure causes emotional exhaustion and cognitive fatigue. Some studies have proposed, however, that the withdrawal effects can be mitigated by the instructional structure, which is referred to as adaptive learning design (Mohamed Shawky et al., 2026; Wang, 2023). In the fifth finding, cognitive withdrawal is shown to significantly enhance academic stress. This is consistent with Hobfoll's resource depletion approach, indicating that withdrawal decreases cognitive resources needed for academic coping (Julmi et al., 2022). The same was found by Ayasrah et al. (2025) who reported that psychological detachment from tasks creates stress because of decreased control perception. Shalaby and El-Kasaby (2024) also found that cognitive disengagement has a negative impact on academic performance and emotional stress. Other studies, however, propose that the withdrawal may be emotional recovery, thus proposing a non-linear relationship between withdrawal and stress (Jannat et al., 2026). Overall, the mediation results indicate that both OD and CW play a significant role in the mediation process between DO and AS. This discovery builds on previous work, as it combines the behavioural and cognitive routes as a single model. Previous studies, such as Wang (2023), pointed out partial mediation over strain responses, and this study extends the literature to include the dual mediation mechanisms. Khalili et al. (2025) further validate the view that there is a multi-pathway approach to coping that produces coping outcomes in digital environments. But few studies have focused on both mediators simultaneously and this is especially novel in higher education settings. Overall, the results indicate that DO is a direct stressor and also a behavioural and CW indirect stressor on AS. This integrated evidence confirms well with previous studies and extends them with a dual path mediation approach for digitally intensive learning environments.

5.1. Theoretical Contributions

Theoretically, the present study is important by incorporating the CLT and the SSO framework to describe the two mediation processes by which DO leads to AS. CLT offers the cognitive support and provides an explanation of why too much digital information overloads working memory, distracts attention, and causes mental fatigue. This study takes a practical approach to CLT and applies it to the continuous digital learning environments as it reveals that overload is not just a learning inefficiency problem, it's a psychological stressor for higher education environments. The SSO framework provides additional support to the model by clarifying the processes by which environmental stressors produce strain responses that can lead to behavioural and psychological outcomes. In this study, the theories are combined to provide an overall explanatory mechanism of the relationship between cognitive overload and the stress outcomes in the context of OD and CW. Theoretically, this study brings together previously distinct analyses of behavioural and cognitive responses to form a dual pathway of mediation, thereby enriching the theoretical understanding. Furthermore, this study builds upon previous research, in that digital overload has been shown here as not only a direct cause of stress but also an indirect cause via adaptive coping strategies. This helps fill literature in digital learning stress by connecting the cognitive psychology and organizational stress theories in one academic context. The results also advance theories of resource depletion processes (Hobfoll, 1989) and digital fatigue mechanisms Al-Enezi (2025) providing an enriched theoretical account of how students can be stressed when they use digital tools.

5.2. Practical Implications

This research offers a number of important practical implications for university administrators and educational policy makers. The results indicate that there is a strong connection between the excessive use of digital platforms without structuring and the stress level of students. The universities should therefore reform digital learning systems to eliminate the unnecessary notifications and the fragmenting contents delivery and multitasking requirements. A well-planned learning schedule and minimizing digital disruption can help to reduce cognitive overload. Moreover, educators need to be prepared to create content that is commensurate with cognitive capacity limits, making digital content brief, interactive, and well sequenced. LMS should have options where students can adjust the level of notification and minimize disengagement behaviors. Support services for mental health issues should also be included in the school setting, as they can contribute to stress related to DO. Student engagement patterns also should be monitored at institutions to look for signs of CW and disengagement early. Digital detox programs and adaptive learning support are examples of early intervention strategies that can help minimize risks of burnout. Overall, the study underscores the importance of wellrounded digital transformation strategies in higher education focusing on cognitive well-being as well as academic achievement.

5.3. Social and Policy Implications

The results of this study have important social implications, underlining the psychological burden of digital dependency in youth. In societies such as Jordan, where digital learning is becoming increasingly prevalent, students' excessive exposure to digital media can lead to increased stress levels, which in turn can have a negative impact on their mental health in the long run. Incorporating policy measures in educational structures to limit the amount of digital learning and ensure its sustainability for student well-being. National education policies must support schools to adopt digital well-being guidelines that reduce cognitive overload and help promote healthy screen time management. Educational programs can also raise awareness among students and their families about the hazards of prolonged engagement with digital content and promote healthy habits for using technology. Additionally, embedding digital well-being indicators in national education quality evaluations could enable systematic tracking of students' psychological well-being. A societal perspective may include decreased productivity, heightened anxiety and diminished academic resilience as a result of unmanaged DO. Thus, policy-level interventions are needed to keep digital transformation in education human-centred and not just a technology intervention.

5.4. Implications for Teaching and Academics

This study highlights the need for cognitively balanced teaching strategies in digital environments for educators. Teachers need to provide a reasonable amount of homework, notification, and multiple digital tasks. Instead, they need to use a segmented approach to learning, with breaks for cognitive recovery. Hybrid learning models that combine online and offline learning that minimize cognitive stress should also be encouraged in academic institutions. Digital pedagogy and cognitive load management are key areas for training in faculty development programmes. In addition, teachers should keep a close watch on the ways students interact in class to know when to suspect that they are not engaged or making progress. Apart from this, this study also indicates the need to alter the academic assessment process, which is currently reliant on ongoing digital interaction, thus lowering the level of stress that develops among students.

6. CONCLUSION

The findings of this study indicate that DO has a significant impact, both direct and indirect, on AS among the University Pupils. The results validate the hypothesis that continuous accessing of digital learning environments leads to cognitive strain that elicits behavioral and psychological coping reactions. Although adaptatively beneficial, these mechanisms over time exacerbate AS levels. This study combines CLT and SSO framework, giving a comprehensive explanation of how digital learning environments impact student well-being. The dual mediation model emphasizes that the direct effects of DO on AS are not the only ones, but that intermediate behavioral and cognitive processes also contribute to AS. Overall, the study underscores the importance of the development and implementation of balanced digital learning environments that emphasize cognitive sustainability, psychological wellbeing and effective learning design in contemporary higher education settings.

The study was constrained by certain factors, and some future research directions are presented. Although the findings of this study are valuable, the study has some limitations. The study employs a cross-sectional design that does not allow you to determine the direction of causation between variables. Longitudinal studies are suggested to study digital overload and stress overtime. Data measured via self-report methods could have response bias. Objective behavioural data including actual usage of platforms should be included in future research. The study is conducted with university students in Jordan; therefore, the results may not be generalizable to other cultural or educational settings. The model needs to be replicated in other countries and educational systems. Further, future studies may consider aspects to be moderated including digital literacy, personality traits, and institutional support. Finally, experimental designs may give more convincing causal evidence of the effects of DO on AS.

REFERENCES

Al-Enezi, F.K. (2025), The mediating role of academic resilience between digital overload and school burnout among high school students in Kuwait. Educational Process: International Journal, 17(4), e2025341.

Ayasrah, M.N., Khasawneh, M.A.S., Almulla, M.O., Aboutaleb, A.H. (2025), Design and validation of the AI-integrated metacognitive learning resilience scale (AIIMLR Scale) for secondary school students in Jordan: Insights from the network analysis perspective. Journal of Computer Assisted Learning, 41(5), e70127.

Bao, D., Mydin, F., Surat, S., Lyu, Y., Pan, D., Cheng, Y. (2024), Challenge-Hindrance stressors and academic engagement among medical postgraduates in China: A moderated mediation model. Psychology Research and Behavior Management, 17, 1115-1128.

Chauhan, R., Jishtu, H., Kumar, N., Basheer, S. (2026), Unplugged escapes: Validating digital free tourism motivations scale and unraveling the impact of social space technostress on destination preferences. Journal of Hospitality and Tourism Insights, 9(3), 1144-1161.

Chung, D., Zhang, Y., Wang, J., Meng, Y. (2025), Unpacking young adults' fact-checking intent on oral health misinformation: Parallel mediating roles of need for cognition and perceived seriousness-a cross-sectional study. Healthcare, 13(11), 1354.

Deeb, S., Alfrookh, M.H., Zurayqi, A.K., Dweik, Y.F., Dabash, M.R., Deeb, N., Amro, A.M. (2025), Navigating the digital shift: A cross-sectional study on social media usage, academic performance, and family dynamics among university students in Palestine during COVID-19 quarantine. Frontiers in Education, 10, 1532416.

Fornell, C., Larcker, D.F. (1981), Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39-50.

Hair, J.F. Jr., Sarstedt, M., Hopkins, L., Kuppelwieser, V.G. (2014), Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. European Business Review, 26(2), 106-121.

Hobfoll, S.E. (1989), Conservation of resources. A new attempt at conceptualizing stress. American Psychologist, 44(3), 513-524.

Iqbal, F., Noreen, F., Iqbal, S., Farooq, U., Batool, Q., Shahbaz, S. (2025), The impact of role overload on healthcare workers' psychological distress and well-being: The mediating role of task distraction and moderating roles of resilience and emotional intelligence. PLOS

Mental Health, 2(12), e0000461.

Jannat, T., Reza, M.N.H., Arefin, M.S., Uddin, M.A., Chuen Khee, E.P., Pervez, N. (2026), Procrastination trap: The hidden link between stress, anxiety, amotivation and academic dishonesty. Journal of Academic Ethics, 24(1), 45.

Julmi, C., Pereira, J.M., Bramlage, J.K., Jackenkroll, B. (2022), Explaining the relationship between ethical leadership and burnout facets in the academic context: The mediating role of illegitimate tasks. International Journal of Organization Theory and Behavior, 25(1-2), 39-55.

Khalili, F., Jabali, O., Saeedi, M., Jabali, S. (2025), Screens of suffering: How Gaza war news impacts students' minds and motivation. BMC Public Health, 25(1), 4148.

Khan, R., Warriach, N.F., Arshad, A. (2024), Influence of information overload and information irrelevance on information avoidance behavior: The mediating role of social network fatigue. Gomal University Journal of Research, 40(3), 370-384.

Kline, R.B. (2012), Assumptions in structural equation modeling. In: Handbook of Structural Equation Modeling. New York: Guilford Press. p111-125.

Koeske, G.F., Koeske, R.D. (1993), A preliminary test of a stress-strain-outcome model for reconceptualizing the burnout phenomenon. Journal of Social Service Research, 17(3-4), 107-135.

Li, J., Wang, J., Tian, Y., Cui, D., Xu, X., Zhang, Q., Ni, X., Yu, C. (2026), Parental harsh parenting and non-suicidal self-injury among Chinese adolescents: The role of emotional uncontrollability, deviant peer affiliation, school disengagement, and self-control. Frontiers in Psychiatry, 16, 1732342.

Mohamed Shawky, L.E., Abou Shaheen, R., Abdel Fattah Ahmed Zewie, M. (2026), Impact of smart phone addiction and cyberloafing behaviors on nursing students' academic procrastination. Egyptian Journal of Health Care, 17(1), 628-645.

Nuseir, M.T., El Refae, G.A., Alshurideh, M., Urabi, S., Al Kurdi, B. (2023), Media fatigue during COVID-19 work technology conflict as mediator role. In: The Effect of Information Technology on Business and Marketing Intelligence Systems. Cham: Springer. p131.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.Y., Podsakoff, N.P. (2003), Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), 879-903.

Shalaby, Y.M.A., El-Kasaby, W.H. (2024), Modeling the causal relations between mind wandering, digital readiness and academic engagement in E-learning among University students. Kurdish Studies, 12(2), 529-539.

Shatnawi, H.S., Alananzeh, O.A., Darabseh, F., Masa'Deh, R.E. (2024), Workplace sexual harassment and withdrawal behaviors among female workers in Jordanian hotels, the mediating role of emotional exhaustion. Geo Journal of Tourism and Geosites, 52(1), 65-76.

Tafesse, W., Aguilar, M.P., Sayed, S., Tariq, U. (2024), Digital overload, coping mechanisms, and student engagement: An empirical investigation based on the SOR framework. Sage Open, 14(1), 21582440241236087.

Upadhayay, R., Verma, K., Sharma, D.N. (2025), Cyber Psychological Impact of Online Learning on University Students. In: 2025 12th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO). IEEE. p1-6.

Wang, F. (2023), School burnout and mind wandering among adolescents: The mediating roles of internet addiction and the moderating role of resilience. The Journal of Genetic Psychology, 184(5), 356-371.

Xu, J., Ismail, A., Ramayah, T., Liew, C. W. S., & Zheng, C. (2026). Scrolling to apathy? The relationship between short video addiction and the "lying flat" tendency among Chinese university students. Frontiers in Psychology, 17, 1685559.

Zhou, J., Jin, L., Hu, Y. (2025), From distraction to addiction? Understanding academic cyberslacking as a behavioral dependency among medical students. Frontiers in Psychology, 16, 1592370.