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Students' Academic Burnout and Perceived Satisfaction During Distance Education

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Abstract

This study aimed to examine the growth trajectories of academic burnout and perceived satisfaction of university students during distance education in Türkiye. It also examined gender and online interaction that might account for students' differences in the level of academic burnout and perceived satisfaction and in the rate of change. Latent growth analysis was used with three measurements of 397 students. The study revealed that students' levels of burnout increased over time during distance education, while their perceived levels of satisfaction decreased. The findings suggested that online interaction may support students' initial levels of satisfaction and burnout; however, it appears insufficient to moderate their longitudinal trajectories of change, buffering against neither the decline in satisfaction nor the increase in burnout over the semester. These patterns were consistent across genders, suggesting that gender-neutral structural interventions may be more broadly effective.

Keywords Academic burnout · Perceived satisfaction · Latent growth analysis · Longitudinal study

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Introduction

With the Covid-19 pandemic, distance education became a necessity worldwide, expanding its scope. This necessity, in turn, led to increased interest in research related to teachers and students in the distance education process (Çebi, 2023; Yu & Cai, 2025). Research on distance education has focused on the quality, advantages, and disadvantages of distance education (Abuhassna & Alnawajha, 2023; Belousova et al., 2022), students' academic (Alim et al., 2023), and psychological outcomes (Wang, 2023), as well as teacher outcomes (Marasi et al., 2022).

Distance education, being a deliberate, long-term strategy, designed for virtual learning, has the advantages of providing temporal and spatial flexibility, reducing education costs, and providing continuous education (Karakoç Öztürk, 2024). On the other hand, studies reveal that it has potential negative effects on student attitudes, behaviors and academic success, such as lack of motivation, (Skliarova et al., 2023), lower rates of persistence, increased course repetition, lower academic outcomes (Bettinger et al., 2017; Hart et al., 2016; Jaggars & Xu, 2016), academic burnout (Chen et al., 2021; Hensley et al., 2022), increased stress and anxiety and lower level of perceived satisfaction (Lukina et al., 2022).

Distance education evolved over time, becoming a necessity and then a habit for educators and students. On the other hand, distance education can sometimes be seen as a temporary response to unforeseen situations, as it is a type of education that can respond quickly to emergencies when the necessary infrastructure is in place (Hodges et al., 2020; Sumer & Yuner, 2021). On January 6, 2023, Turkey experienced one of the most severe disasters in its history. The earthquake, which caused the death of more than 50,000 people, rendered buildings in the region unusable. During this period, university dormitories in different cities were converted into accommodations for earthquake victims, while it was decided that higher education courses would be delivered remotely. In other words, distance education became a solution for schools that would be deeply affected by this disaster. However, while distance education is a solution in such situations, it also brings with it negative consequences that will affect educational outcomes. Studies have revealed that distance education increases students' academic burnout (Barratt & Duran, 2021) and reduces student satisfaction, which is quite noteworthy (Cole et al., 2014; Elshami et al., 2021; Vamosi et al., 2004).

Research reveals that academic burnout is one of the most important factors hindering students' academic achievement (Madigan & Curran, 2021). On the other hand, perceived satisfaction reflecting the students' perception of their own performance which will affect their attitude behavior and attitude, has a critical role of satisfaction in the learning process (Alqurashi, 2018; Butt & Ur Rehman, 2010; Chang & Smith, 2008; Jereb et al., 2018; Kim & Park, 2022). Therefore, this study focused more on academic burnout and perceived satisfaction in distance education process as both variables are influential in both the learning process and outcomes. Despite the accumulated knowledge in research on burnout and satisfaction in distance education (Mosleh et al., 2022; Toubasi et al., 2023), there is a significant gap in the literature regarding research examining the longitudinal relationship between these variables. Therefore, the aim of this study is to examine burnout and satisfac-

tion among Turkish university students longitudinally and to shed light on this gap by investigating the moderating role of online interaction and gender as contextual variables. Based on the accumulated knowledge in previous literature and research findings regarding academic burnout and satisfaction during distance education, we suggest that students' levels of academic burnout will increase and their satisfaction levels will decrease throughout the distance education process. Furthermore, based on the research results emphasizing the importance of interaction during distance education (Chang & Smith, 2008; Landrum et al., 2021; Nambiar, 2020), we believe that online interaction may have significant implications for students' trends of burnout and satisfaction during distance education. This study employs longitudinal design, which allow for the examination of changes in student satisfaction and burnout during distance education over time. It offers a comprehensive understanding of the evolution of satisfaction and burnout over the duration of courses or programs and the dynamic essence of student experiences in distance education. Specifically, this study hypothesizes (H1) that during distance education, students' academic burnout (AB) will increase and perceived student satisfaction (PSS) will decrease. It is also hypothesized (H2) that online interaction will positively impact the level and trend of perceived student satisfaction and academic burnout. In this study, as we anticipated that females and males will be experiencing burnout and satisfaction at different levels and different rate of change in time (H3), we evaluated this hypothesis through a multigroup analysis.

Literature Review

Academic Burnout

Freudenberger (1974) was the first to introduce the important exposition of burnout in academic literature, wherein he characterized it as a persistent state of physical, emotional, and mental exhaustion that results from prolonged and intense exposure to stressors in one's professional and personal domains as a three-component "emotional exhaustion, depersonalization, and reduced personal achievement," commonly observed in individuals working in professions that involve interaction with others. Burnout represents a long and intense experience of occupational stress that manifests as chronic strain and depletion (Vizoso et al., 2019). According to Maslach and Jackson (1981), the most widely used concept of burnout has three factors: emotional fatigue, depersonalization, and decreased individuality. The starting point of burnout is on employees. When considered from the student's point of view, the students' obligations regarding the courses they must fulfill can also be seen as their job (Cazan, 2015). Nevertheless, although burnout is conventionally associated with employee-related contexts, Schaufeli et al. (2002a) introduced a variant of the Maslach burnout inventory specifically adapted to students. Thus, the scale used among students has taken place in the literature as academic burnout (Cazan & Năstasă, 2015).

Academic burnout is a psychological phenomenon arising from persistent exposure to stressors in the academic setting. This state can leave students feeling incapable of meeting their academic obligations, disinterested in their studies, and uncertain

about their ability to attain their academic objectives (Aguayo et al., 2019). Researchers have shown high burnout among university students (Law, 2007; Marôco et al., 2020; Ye et al., 2021). The consequences of academic burnout on students are severe and can go as far as dropping out of school (Mostert & Pienaar, 2020). Charkhabi et al. (2013) identified three critical rationales for the significance of academic burnout among students. Firstly, it has a detrimental impact on student's academic achievement. Secondly, it impairs the dynamics between students and academic personnel. Lastly, it diminishes students' inclination toward pursuing their education.

Previous studies have identified several antecedents that may affect students' academic burnout levels. These are physical activity and mental resistance (Cheung & Li, 2019), academic stress (Safarzaie et al., 2017), self-efficiency and academic engagement (Ugwu et al., 2013) and perfectionism (Yu et al., 2016). Furthermore, previous literature has shown that high academic burnout and high anxiety in university students trigger depression (Menacho-Rivera et al., 2025). The research of Hwang and Kim (2022) revealed that academic burnout negatively affects student output. Previous studies have also established that learners afflicted with heightened levels of academic burnout exhibit substandard academic performance and demonstrate a propensity for absenteeism (Singh et al., 2021). Since academic burnout is a syndrome negatively associated with psychological health, educational interventions should be designed to reduce burnout and increase psychological well-being in university students (Vizoso et al., 2019).

To date, numerous research have revealed that students experience burnout (Chen et al., 2021; Hensley et al., 2022) and high prevalence of burnout adversely affect them. Burnout has been associated with health issues and can lead to psychological and behavioral problems, including depression, absenteeism, school dropout, and academic underperformance (Maslach, 1978; Salmela-Aro et al., 2009). Distance education, providing limited opportunities for interaction with instructors and peers, and placing the onus of learning on students, generally led to academic burnout (Hensley et al., 2022). Rudman and Gustavsson (2012) revealed that academic burnout gets worse as the semester continues. Similarly, Chen et al. (2021) observed increased burnout and decreased engagement during distance education. There is a clear consensus that burnout, having a negative impact on both life and academic satisfaction, leads to decreased academic performance.

Perceived Student Satisfaction

In the services offered related to higher education, students are the direct recipients of the service and their satisfaction can easily be achieved with superior service standards. (Jereb et al., 2018). According to students, receiving quality education leads to improved learning opportunities, and their satisfaction or dissatisfaction with faculty members greatly influences their academic success or failure (Butt & Ur Rehman, 2010).

The most important factor that determines student satisfaction in universities is meeting student expectations and providing a service quality that exceeds expectations (Elliott & Shin, 2002). The social and physical factors of a higher education institution's services can greatly influence the degree to which it attracts students to

that university and the overall satisfaction of students. This is also the case in distance education programs. It is stated in the literature that the effectiveness and efficiency of the coordination of course management and student support services in schools by providing distance education affects student satisfaction. (DeBourgh, 2003). Therefore, one of the factors related to success and student satisfaction in the implementation of distance education is related to how education is conducted (Kerzic et al., 2021). Research exploring the factors contributing to student satisfaction in online courses typically highlights elements such as interactivity, computer self-efficacy, course content, self-regulation, course design, teacher feedback, quality of materials and activities, technical support, and perceived utility (Kerzic et al., 2021; Landrum et al., 2021).

Student satisfaction is constantly shaped by students' experiences on campus (Elliott & Shin, 2002). However, in distance education, students cannot experience being a student on campus because they do not receive education directly on campus. distance learning can be negatively impacted by the requirement for physical resources, including technical hardware, learning management systems, communication platforms, various software applications, and proficiency in operating systems, which encompass the ability to utilize them effectively, thus leading to a decrease in student satisfaction (Kerzic et al., 2021; Ko & Rossen, 2017). Additionally, student satisfaction can be influenced by various factors, such as the promptness of feedback received from students regarding teaching practices, educators' efforts in structuring courses and delivering distance instruction, the adaptation of pedagogical approaches to the online learning environment, and the facilitation of student engagement and feedback mechanisms (Wang et al., 2022). Nambiar (2020) observed a decline in the level of interaction between instructors and students during distance education. Within the realm of distance instruction, students often encounter challenges such as inadequate guidance in navigating course materials, excessive workload, and widespread concerns about the lack of practical training opportunities or the diminishing quality thereof, which are not adequately addressed within the framework of online learning. (Jaggars & Xu, 2016). Therefore, interactions with staff, faculty, and classmates are important components of satisfaction in distance education, as in face-to-face education. (Landrum et al., 2021). Student satisfaction is also considered important in distance education, as research accepts that student satisfaction can affect results such as academic success, retention and student motivation (Wong & Chapman, 2023).

Methodology

Sample and Procedure

We conducted this study in the distance education period due to the devastating Earthquake in Türkiye. We took three measurements in a 6-month period (second term of education). The study sample consisted of 397 senior students from various departments and faculties. Mean age of the study sample was 20.10.

As depicted in Fig. 1, female students outnumber male students. Upon examination of the distributions across faculties, it is observed that the faculty of humanities and social sciences has the highest representation of students in the sample. However, the faculty of science has the lowest proportion of students. The proportions of faculties in the sample are, respectively, faculty of humanities and social sciences, faculty of sport sciences, faculty of health sciences, and faculty of science.

Measures

Perceived Student Satisfaction Scale

The scale is developed by Aristovnik et al. (2020) based on European Students' Union survey (2020). It composed of five items regarding the satisfaction with university services and support during online learning. It is a 5-point Likert scale ranging from 1 (Very Dissatisfied) to 5 (Very Satisfied). A sample item starts as "regarding the support from your teachers/professors". The scale demonstrates good reliability, with a McDonald's Omega (ω) of.852. Furthermore, convergent validity was strong, as evidenced by an Average Variance Extracted (AVE) value of.708.

Online Interaction Scale

The scale is developed by Aristovnik et al. (2020) based on European Students' Union survey (2020). It composed of three items assessing the frequency of communication with different university stakeholders during the period of remote learning. Respondents rated their interaction frequency on a 6-point scale: 1 (Never), 2 (Once or twice a month), 3 (Once a week), 4 (A few times a week), 5 (Every day), and 6

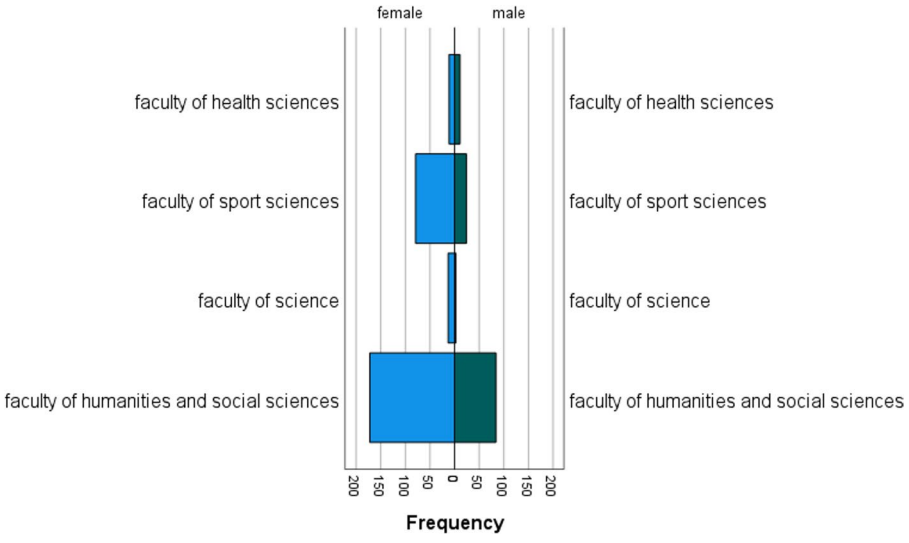


Fig. 1 Distribution of students to faculties

(Several times a day). A sample item is: "How often do you communicate online with fellow?" The scale demonstrated acceptable reliability, with a McDonald's Omega (ω) of 0.723. Convergent validity was supported by an AVE value of 0.551.

Academic Burnout Scale

The construct of Academic Burnout was measured using the Maslach Burnout Inventory–Student Survey (MBI-SS), originally developed by Schaufeli et al. (2002b). For this study, the validated Turkish adaptation by Çapri et al. (2011) was employed. The scale comprises 13 items distributed across three factors. Respondents rated the frequency of their feelings on a 7-point Likert-type scale ranging from 0 (Never) to 6 (Always). A sample item from the Emotional Exhaustion subscale is: "I feel emotionally drained by my classes." The scale demonstrated acceptable to good reliability for the subscales in the adaptation study, with reported Cronbach's alpha internal consistency coefficients of 0.76, 0.82, and 0.61, respectively.

Plan of Analysis

Firstly, absolute and relative stability of PSS and AB were analyzed. Then, LGM analysis was conducted. In LGM analysis we followed three stages which were recommended by Farrell (1994). At the first stage, within the scope of the first hypothesis (H1), we tested the LGM model, given in Fig. 2, for the overall sample. The LGM model parameters (intercept mean, slope mean, intercept variance etc.) were

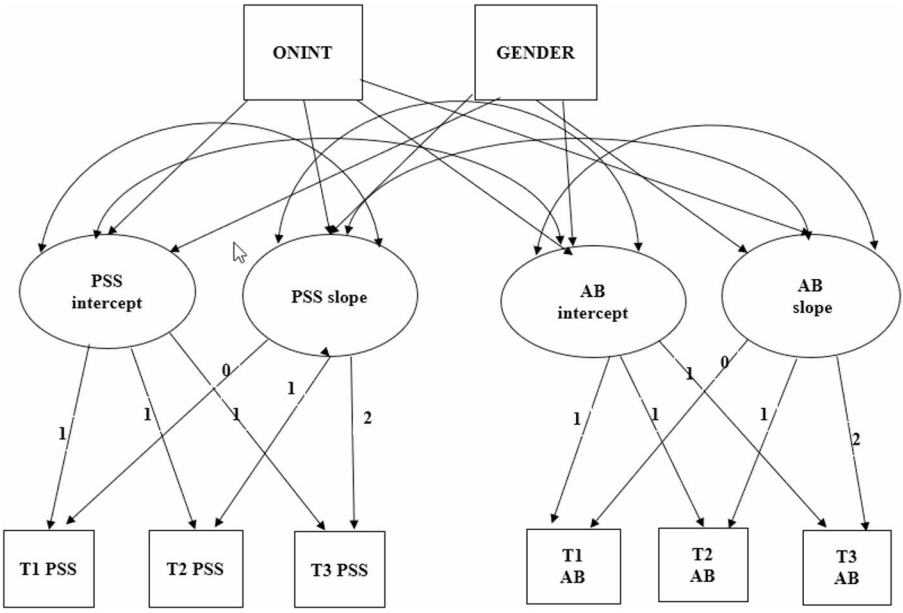


Fig. 2 Conceptual model. Note: *T* time, *PSS* perceived student satisfaction, *ONINT* online interaction, *AB* academic burnout, The double-headed arrows indicate the estimated covariances between the growth parameters

estimated based on structural equation modeling. The LGM model fit is evaluated with the following model fit indices: the chi-square statistics, Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI), Standardized-Root Mean Square (SRMR).

At the second stage of the analysis, within the scope of the second hypothesis (H2), predictors of growth were added to the base LGM model. The possible predictors were online interaction (ONINT) and gender. We examined whether these two predictors accounted for individual differences in the initial level of PSS and AB, as well as differences in the rate of change.

At the third and the last stage of analysis, within the scope of the third hypothesis (H3), we conducted multigroup analysis (male vs. female) within the LGM model with predictors. The aim of the multigroup analysis was to detect magnitude of the gender interaction on the structural model.

Correlations

As presented in Table 1, correlations between PSS and AB were significant. For males, correlations between three time points for PSS were lower than females. Also, AB scores had lower correlations for males than females. Correlations for females range from 0.41 to 0.77 and 0.34 to 0.77 for males. When we examined the means, we detected that the males had started the term with higher means and continued higher in PSS scores than females. Variability of PSS scores a bit higher in females. AB means higher for females than males. Females started the term with higher academic burnout (AB) and increased by the end of the term. Also for females, variability of AB score is higher than males.

We also examined correlations between moderator variable, online interaction (ONINT), with PSS and AB scores for three time points. We examined correlations by gender. Table 2 represents correlations between ONINT with PSS and AB scores.

According to Table 2, ONINT scores had weak yet significant correlations between PSS and AB score at three time points both for males and females. Both for females and males, online interaction had positive correlation with PSS however, negative correlation with AB. It can be said that a higher PSS was accompanied by higher online interaction. Conversely, a higher AB was derived with lower online interaction.

Basic Model

At the first stage of analysis, we tested basic LGM, given in Fig. 2, for the overall sample. The basic linear model showed adequate fit (Bentler, 1990; Browne & Cudeck, 1993):$2(6)=20.891$, $p=0.002$; RMSEA$=0.079$; CFI$=0.983$; TLI$=0.957$; SRMR$=0.031$. Estimated model parameters were represented in Table 3.

The significance of the slope means for PSS in the linear growth model indicates that there was a significant growth across three measurements. The estimated means for PSS across the three measurements were 19.201, 18.737, and 18.273 respectively. A significant covariance between intercept and slope for PSS was found. The initial level of PSS is related to the rate of change over time. A negative covariance between slope and intercept, along with positive slope variance, suggests that students who started with higher

Table 1 Means, standard deviation and intercorrelations for PSS and AB for three time points

	Female						Male					
	PSS			AB			PSS			AB		
	T1	T2	T3	T1	T2	T3	T1	T2	T3	T1	T2	T3
T1	1.00			1.00			1.00			1.00		
T2	0.67	1.00		0.70	1.00		0.56	1.00		0.61	1.00	
T3	0.54	0.70	1.00	0.41	0.77	1.00	0.40	0.63	1.00	0.34	0.77	1.00
M	18.97	18.03	18.23	31.69	34.48	35.94	20.10	18.91	18.76	30.29	31.93	33.51
SD	3.54	4.15	4.28	9.21	9.34	10.75	3.69	3.73	3.94	9.20	8.43	9.94

All correlations are significant at $p < 0.001$

Table 2 Correlations between Online Interaction, PSS and AB for three time points

	Female						Male					
	PSS			AB			PSS			AB		
	T1	T2	T3	T1	T2	T3	T1	T2	T3	T1	T2	T3
ONINT	0.34**	0.29**	0.31**	−0.34**	−0.38**	−0.37**	0.35**	0.37**	0.31**	−0.23*	−0.29**	−0.25**

**p < 0.001; *p < 0.05

Table 3 Parameter estimates for basic LGM of PSS and AB

Measures	Effect	t value	*p*
PSS			
Intercept mean	19.315	106.135	0.000
Slope mean	−0.460	−4.654	0.000
Intercept variance	10.501	8.291	0.000
Slope variance	2.415	4.186	0.000
AB			
Intercept mean	31.373	67.670	0.000
Slope mean	1.933	6.981	0.000
Intercept variance	76.370	11.086	0.000
Slope variance	25.923	10.328	0.000
Covariances			
$PSS_{intercept}$ - PSS_{slope}	−1.345	−2.036	0.042
$AB_{intercept}$ - AB_{slope}	−18.030	−5.579	0.000
$PSS_{intercept}$ – $AB_{intercept}$	−14.603	−7.830	0.000
$PSS_{intercept}$ - AB_{slope}	1.004	0.950	0.342
PSS_{slope} - AB_{slope}	−2.032	−3.430	0.001
$AB_{intercept}$ –PSS_{slope}	1.334	1.167	0.243
R^2			
PSS1	0.789	-	0.000
PSS2	0.653	-	0.000
PSS3	0.830	-	0.000
AB1	0.890	-	0.000
AB2	0.802	-	0.000
AB3	0.966	-	0.000

PSS (intercept mean) experienced slower change (smaller slopes) in time. The negative slope mean indicates decrease in PSS during the term. Hence, the hypothesis regarding the decrease of PSS in the latent-growth model was confirmed. For AB, significant slope means in the linear growth model indicated significant growth across three measurements. The estimated means for AB in the three measurements were 31.373, 33.306, and 35.239, respectively. A significant covariance between intercept and slope for AB was found. The initial level of AB was related to the rate of change over time. Also, the positive slope mean indicates increase in AB during the term. Hence, the hypothesis regarding the increase of AB in the latent-growth model was confirmed. A negative covariance between slope and intercept, along with positive slope variance, suggests that students who started with higher AB (intercept mean) experienced slower change (smaller slopes) in time. The substantial variability, for both PSS and AB, suggests that there were notable differences among individuals in terms of their initial levels (significant intercept variance) and the patterns of change over time (significant slope variance).

There were substantial covariances between PSS and AB intercepts and between PSS and AB slopes. The path from PSS intercept to AB intercept was significant *(*$t = -7.830$, $p < 0.05$), indicating that initial levels of PSS were related to initial level of AB. Also, the path from PSS slopes to AB slopes was significant *(*$t = -3.430$, $p < 0.05$), indicating that growth rate in PSS was related to growth rate of AB.

The R-square statistics reveal how much of the variance in the observed variables can be explained by the factors of the growth curve. A small R-square suggests that

the observed changes are mostly unrelated to time (Stoolmiller, 1994). In our base model, all R-square values obtained are substantial, with the least explained variance being 0.641 observed at time3 in PSS.

Predicting Change in Growth Model

After we obtained adequate fit for the basic model, we moved to the second stage of the analysis. In line with H2, predictors of growth were added to the base LGM model. The possible predictors were online interaction (ONINT) and gender. We examined whether these two predictors accounted for individual differences in the initial level of PSS and AB, as well as differences in the rate of change. We conducted LGM analyses for the overall sample. The basic linear model showed adequate fit (Bentler, 1990; Browne & Cudeck, 1993) :2(10)=28.277, p=0.002; RMSEA=0.068; CFI=0.986; TLI=0.963; SRMR=0.031. Estimated model parameters were represented in Table 4.

Table 4 Linear growth model of PSS and AB with moderator variables

Measures	Estimate	t value	p
Intercepts			
PSS	13.407	17.168	0.000
AB	43.317	21.283	0.000
Slopes			
PSS	−0.179	−0.390	0.696
AB	3.820	3.040	0.002
Covariances			
$PSS_{intercept}$ - PSS_{slope}	−1.353	−2.473	0.013
$AB_{intercept}$ - AB_{slope}	−19.382	−6.331	0.000
$PSS_{intercept}$ – $AB_{intercept}$	−10.627	−6.805	0.000
$PSS_{intercept}$ - AB_{slope}	1.509	1.658	0.097
PSS_{slope} - AB_{slope}	−2.035	−3.749	0.000
$AB_{intercept}$ –PSS_{slope}	1.333	1.544	0.123
Regression weights			
$PSS_{intercept}$ ON online	0.528	7.286	0.000
$PSS_{intercept}$ ON gender	1.221	3.349	0.001
PSS_{slope} ON online	0.014	0.323	0.747
PSS_{slope} ON gender	−0.298	−1.396	0.163
$AB_{intercept}$ ON online	−1.214	−6.432	0.000
$AB_{intercept}$ ON gender	−1.760	−1.851	0.064
AB_{slope} ON online	−0.151	−1.300	0.194
AB_{slope} ON gender	−0.507	−0.863	0.388
R^2			
PSS1	0.794	-	0.000
PSS2	0.637	-	0.000
PSS3	0.847	-	0.000
AB1	0.896	-	0.000
AB2	0.802	-	0.000
AB3	0.959	-	0.000

Overall Patterns: Intercepts and Slopes

After adding the moderators into the base LGM, we saw that intercept of PSS was still significant however slope of PSS was insignificant. The estimated means for PSS across the three measurements were 19.216, 18.756, and 18.297 respectively. Due to insignificant slope, it cannot be interpreted as significant linear change over time. Therefore, while there may be a relationship between the initial level of PSS and the rate of change, that change is not statistically significant.

For AB, significant slope in the linear growth model indicated significant growth across three measurements. The estimated means for AB in the three measurements are 31.331, 33.281, and 35.231, respectively. A significant covariance between intercept and slope for AB was found. The initial level of AB is related to the rate of change over time. A negative covariance between slope and intercept, along with positive slope variance, suggests that students who started with higher AB (intercept mean) experienced slower increases (smaller slopes). The substantial variability suggests that there were notable differences among individuals in terms of their initial levels (significant intercept variance) and the patterns of change over time (significant slope variance).

Relationships Between PSS and AB

There were substantial covariances between PSS and AB intercepts and between PSS and AB slopes. The path from PSS intercept to AB intercept was significant *(t* = −6.805, $p < 0.01$), indicating that higher initial levels of PSS were related to lower initial level of AB. Students who start with higher levels of PSS tend to start with lower levels of AB. Also, the path from PSS slopes to AB slopes was significant *(t* = −3.749, $p < 0.01$), indicating that growth rate in PSS was related to growth rate of AB. Negative covariance between PSS and AB slopes suggests that the rate of change of these two variables over time is negatively related. In other words, students who experience faster change in PSS tend to experience slower change in AB.

Role of Online Interaction: Initial Levels vs. Slopes

While online interaction significantly predicted the intercepts (initial levels) of both PSS and AB, it did not significantly predict the slopes (rates of change) for either variable.

Online interaction significantly predicted initial PSS levels ($\beta = 0.528$, $t = 7.286$, $p < 0.001$) and initial AB levels ($\beta = -1.214$, $t = -6.432$, $p < 0.001$), indicating that students reporting higher online interaction began the semester with greater satisfaction and lower burnout. However, online interaction did not significantly predict the rate of change in PSS ($\beta = 0.014$, $p = 0.747$) or AB ($\beta = -0.151$, $p = 0.194$). This suggests that although online interaction was associated with students' baseline well-being at the semester's start, it did not buffer against the longitudinal decline in satisfaction or increase in burnout as the semester progressed.

Being a male rather than being a female is a significant factor on PSS levels too. However, the rate of change in PSS did not depend on online interaction and gender.

The higher initial level of AB was related to lower online interaction and did not depend on gender. Like PSS, the rate of change in AB did not depend on online interaction and gender. Hence, the hypothesis regarding the effect of online interaction on PSS and AB in the latent-growth model was partially confirmed. All R-square values obtained are substantial, with the least explained variance being 0.637 observed at time3 in PSS.

Clarification: PSS Slope Inconsistency Between Models

An apparent inconsistency between models requires clarification. In the basic model (Table 3), the overall PSS slope was statistically significant ($\beta = -0.460$, $p < 0.001$), indicating average decline in satisfaction across the sample. However, when gender and online interaction were entered as predictors in the overall model (Table 4), the slope became non-significant ($\beta = -0.179$, $p = 0.696$). This does not indicate absence of satisfaction decline, but rather reflects how predictor variables account for variance in the trajectory. When the multigroup model (Table 5) examined males and females separately, both groups demonstrated significant satisfaction decline (females: $\beta = -0.378$, $p = 0.001$; males: $\beta = -0.646$, $p = 0.001$).

Table 5 Multi group linear growth model of PSS and AB with moderator variables

Measures	Female			Male		
Intercepts	Estimate	*t* value	*p*	Estimate	*t* value	*p*
PSS	18.888	92.473	0.000	19.946	64.442	0.000
AB	31.378	60.358	0.000	30.197	38.526	0.000
Slopes						
PSS	−0.378	−3.232	0.001	−0.646	−3.359	0.001
AB	2.146	6.640	0.000	1.655	3.382	0.001
Covariances						
$PSS_{intercept}$ - PSS_{slope}	−1.137	−1.738	0.082	−1.768	−1.740	0.082
$AB_{intercept}$ - AB_{slope}	−20.537	−5.486	0.000	−17.192	−3.260	0.001
$PSS_{intercept}$ – $AB_{intercept}$	−9.975	−5.402	0.000	−11.648	−4.065	0.000
$PSS_{intercept}$ - AB_{slope}	0.802	0.749	0.454	2.881	1.716	0.086
PSS_{slope} - AB_{slope}	−1.776	−2.847	0.004	−2.560	−2.433	0.015
$AB_{intercept}$ –PSS_{slope}	0.525	0.524	0.600	3.006	1.806	0.071
Regression weights						
$PSS_{intercept}$ ON online	0.511	5.892	0.000	0.573	4.367	0.000
PSS_{slope} ON online	0.027	0.549	0.582	−0.019	−0.236	0.813
$AB_{intercept}$ ON online	−1.350	−5.989	0.000	−0.914	−2.710	0.007
AB_{slope} ON online	−0.181	−1.303	0.192	−0.082	−0.387	0.699
R^2						
PSS1	0.829		0.000	0.702		0.000
PSS2	0.645		0.000	0.605		0.000
PSS3	0.851		0.000	0.815		0.000
AB1	0.961		0.000	0.759		0.000
AB2	0.805		0.000	0.784		0.000
AB3	0.945		0.000	1.000		0.000

This pattern indicates that gender and online interaction account for individual variation in satisfaction trajectories in the overall model. The longitudinal decline in satisfaction is robust and present in both gender groups, but individual variation in this decline can be partially explained by gender and online interaction levels. The significant slopes in the gender-specific analyses confirm the validity of H1 regarding declining satisfaction over time.

Multi Group Analysis of Latent Growth Model with Moderator Variables

After we obtained adequate fit for the LGM with moderators, we moved to the third and the last stage of the analysis. In line with H3, we analyzed LGM with moderator variable (online interaction) for groups of gender. Hence, gender was found as a significant predictor of PSS and AB level, we wanted to make a comparison through multi group analysis. We examined whether the online interaction could explain the individual differences in the initial levels of PSS and AB, as well as the differences in the rate of change for both male and female groups. Estimated model parameters were represented in Table 5.

Female Students: Satisfaction and Burnout Trajectories

When the LGM parameters were examined for females, it was seen that the slope of PSS was significant. The estimated means for PSS across the three measurements were 18.888, 18.509 and 18.131 respectively. An insignificant covariance between intercept and slope for PSS was found. The initial level of PSS is unrelated to the rate of change over time. This suggests that the rate of change in PSS over time is not related to the initial level of PSS. While the significant slope indicates that overall change over time is significant, the insignificant covariance between intercept and slope highlights the independence of initial level of PSS and rates of change within the sample. Namely, females who start with higher initial levels of PSS were not necessarily experienced a different rate of change compared to those who started with lower PSS. For AB, it was seen that the slope was positive and significant. It means that AB scores got higher over time. The estimated means for AB across the three measurements were 31.738, 33.884 and 36.031 respectively. A significant covariance between intercept and slope for AB was found. The initial level of AB is related to the rate of change over time. Negative covariance between slope and intercept with positive slope means that females who started with higher AB go up slower (smaller slopes).

PSS-AB Relationships for Females

There were substantial covariances between PSS and AB intercepts and between PSS and AB slopes. The path from PSS intercept to AB intercept was significant *(*$t = -5.402$, $p < 0.05$), indicating that initial levels of PSS were related to initial level of AB. In other words, females who start with higher levels of PSS tend to start with lower levels of AB. Also, the path from PSS slope to AB slope was significant *(*$t = -2.847$, $p < 0.05$), indicating that growth rate in PSS was related to growth rate of AB.

Negative covariance between PSS and AB slopes suggests that the rate of change of these two variables over time is negatively related. Namely, females who experience faster change in PSS tend to experience slower change in AB.

Online Interaction Effects for Females

The higher initial level of PSS was related to higher online interaction ($t=5.892$, $p<0.05$). However, the rate of change in PSS did not depend on online interaction ($t=0.549$, $p>0.05$). It can be concluded that online interaction is not a significant factor influencing a female's PSS level. The higher initial level of AB was related to lower online interaction ($t=-5.989$, $p<0.05$. Like PSS, the rate of change in AB did not depend on online interaction and was not a significant factor influencing a female's AB. All R-square values obtained are substantial, with the least explained variance being 0.645 observed at time2 (PSS2) in PSS.

Male Students: Satisfaction and Burnout Trajectories

When the LGM parameters were examined for males, it was seen that the slope of PSS was significant. The estimated means for PSS across the three measurements were 19.946, 19.301 and 18.655 respectively. An insignificant covariance between intercept and slope for PSS was found. Like in females, the initial level of PSS is unrelated to the rate of change over time. This suggests the rate of change in PSS over time is not related to the initial level of PSS. While the significant slope indicates that overall change over time is significant, the insignificant covariance between intercept and slope highlights the independence of initial level of PSS and rates of change within the sample. In other words, males who start with higher initial levels of PSS were not necessarily experienced a different rate of change compared to those who started with lower PSS. For AB, it was seen that the slope was positive and significant. It means that AB scores got higher over time. The estimated means for AB across the three measurements were 30.197, 31.853 and 33.508 respectively. A significant covariance between intercept and slope for AB was found. The initial level of AB is related to the rate of change over time. Negative covariance between slope and intercept with positive slope means that males who started with higher AB go up lower (smaller slopes).

PSS-AB Relationships for Males

There were substantial covariances between PSS and AB intercepts and between PSS and AB slopes. The path from PSS intercept to AB intercept was significant *(*$t=-4.065$, $p<0.05$), indicating that initial levels of PSS were related to initial level of AB. Like in females, males who start with higher levels of PSS tend to start with lower levels of AB. Also, the path from PSS slope to AB slope was significant *(*$t=-2.433$, $p<0.05$), indicating that growth rate in PSS was related to growth rate of AB. Negative covariance between PSS and AB slopes suggests that the rate of change of

these two variables over time is negatively related. Like in females, males who experience faster improvements in PSS tend to experience slower improvement in AB.

Online Interaction Effects for Males

The higher initial level of PSS was related to higher online interaction ($t=4.367$, $p<0.05$). However, the rate of change in PSS did not depend on online interaction ($t=-0.236$, $p>0.05$). It can be concluded that online interaction is not a significant factor influencing a male's PSS level. The higher initial level of AB was related to lower online interaction ($t=-2.710$, $p<0.05$. Like PSS, the rate of change in AB did not depend on online interaction and was not a significant factor influencing a male's AB. All R-square values obtained are substantial, with the least explained variance being 0.605 observed at time2 (PSS2) in PSS.

Gender Differences: Comparative Analysis

The multigroup analysis revealed partially distinct initial patterns between males and females. Interestingly, males began with higher initial satisfaction levels but experienced steeper satisfaction decline over the semester (−0.646 vs. −0.378), suggesting that despite starting in a more favourable position, they experienced greater disengagement over time. To formally evaluate whether these differences were statistically significant, we conducted chi-square difference tests for multigroup invariance (Table 6).

The non-significant chi-square difference test ($\Delta\chi^2(4)=0.088$, $p=0.999$) indicates that the regression parameters do not differ significantly between male and female students. Both genders show comparable patterns in how online interaction influence initial satisfaction and burnout levels, as well as their change over time. Importantly, online interaction was not a significant predictor of change over time (slopes) for either gender. Importantly, online interaction was not a significant predictor of change over time (slopes) for either gender.

Hypothesis 3 was partially supported. Male and female participants differed significantly in their initial levels of satisfaction and burnout, with females reporting higher initial burnout (31.378) than males (30.197) and lower initial satisfaction (18.888) than males (19.946). However, the effects of online interaction on longitudinal trajectories were comparable across genders. The structural features of distance learning—increased self-regulation demands, reduced in-person community, and reliance on mediated interaction—affected both genders similarly. This suggests that gender-neutral interventions focused on maintaining meaningful interaction and support throughout the semester may be more effective than gender-specific approaches.

Table 6 Chi-square difference test results

Model	χ^2	df	p
Constrained (Equal across gender)	32.619	16	0.008
Unconstrained (Free across gender)	32.531	20	0.038
$\Delta\chi^2$ Difference Test	0.088	4	0.999

Discussion

Research has shown that academic burnout tends to increase in distance education contexts (Chen et al., 2021; Hensley et al., 2022), while students' satisfaction with the learning process may decrease (Lukina et al., 2022). Previous studies have associated these outcomes with various challenges in online learning environments, including reduced social interaction and feelings of isolation (McInnerney & Roberts, 2004), limited engagement opportunities (Herrington et al., 2003), and increased demands placed on students (Roddy et al., 2017). However, to the best of our knowledge, no study has examined the longitudinal relationship between burnout and satisfaction during the distance education process. To address this gap, the present study investigates changes in students' academic burnout and perceived satisfaction over time. Based on prior research, it is hypothesized that students' burnout levels will increase, whereas their satisfaction levels will decrease during the distance education process. In this context, the primary aim of this study is to longitudinally examine students' academic burnout and perceived satisfaction using latent growth analysis.

Within the scope of the first research hypothesis, it was found that students' levels of burnout increased over time during the distance education process, while their perceived levels of satisfaction decreased. The observed increase in burnout is consistent with the findings of Huang et al. (2024). The academic challenges and stress experienced by students during distance learning may contribute to higher levels of burnout. On the other hand, students' perceived satisfaction was found to decline over time. Previous research indicates that reduced interaction with peers and instructors, along with increased learning responsibilities placed on students, is associated with lower levels of academic satisfaction (Elliott & Shin, 2002; Kerzic et al., 2021; Landrum et al., 2021). These findings suggest that as the distance learning process continues, students' satisfaction may gradually decrease.

An important finding emerged regarding the differential effects of online interaction on initial satisfaction/burnout levels versus longitudinal trajectories. Online interaction was strongly associated with students' baseline well-being, those with higher online engagement started the semester with greater satisfaction and lower burnout. This suggests that online interaction serves an important role in students' initial adjustment to distance learning, consistent with prior research demonstrating that learner-instructor and learner-content interactions are significant predictors of student satisfaction (Alqurashi, 2018; Muzammil et al., 2020), and that perceived social presence in online environments is positively associated with both satisfaction and perceived learning (Richardson & Swan, 2003; Sharif Nia et al., 2023). However, online interaction did not significantly moderate the rate of change in either satisfaction or burnout. Despite engaging in more online interaction, students still experienced declining satisfaction and increasing burnout as the semester progressed. This nuanced finding suggests that the structural features of distance education itself, reduced in-person classroom community, increased self-regulation demands, and inherent isolation, may be primary drivers of longitudinal burnout and satisfaction trajectories. Indeed, research has shown that isolation and elevated stress in online learning environments are directly associated with academic burnout even when social support mechanisms are present (Liu et al., 2022), and that the transition to

distance education significantly reduces students' emotional engagement, largely due to the concurrent decline in human interaction, compared to traditional face-to-face learning environments (Lemay et al., 2021; Salta et al., 2021).Furthermore, the heightened self-regulation demands inherent to distance education have been identified as a persistent structural challenge that significantly affects both satisfaction and well-being over time (Edisherashvili et al., 2022; Turan et al., 2022), with longitudinal evidence confirming that increases in perceived workload are positively associated with increases in burnout across the semester (Pham Thi et al., 2024). In other words, while online interaction helps with initial adjustment, it appears insufficient to prevent the fundamental challenges posed by distance learning's inherent structure.

When the online interaction variable is assigned as a moderator, the growth observed in academic burnout curves is statistically significant, indicating that online interaction is not a significant variable influencing the *rate of increase* in academic burnout. This finding indicates that the primary underlying cause of burnout is the very nature of the distance learning process itself. Burnout has been observed to be associated with unmet social and academic needs of students, experienced stress, and ineffective educational materials (Kim et al., 2018; Maslach & Leiter, 1997). The absence of traditional classroom settings can lead to weakened social bonds among students, triggering feelings of loneliness and social isolation. Research by Ye et al. (2021) and Karimi et al. (2014) underscores the importance of social support in buffering against burnout. Another characteristic of face-to-face education is providing students with a social learning environment. Distance education, however, requires greater self-regulation and discipline, leading to academic pressure and increased burnout (Gao, 2023). The fact that online interaction fails to moderate this trajectory implies that merely increasing opportunities for online interaction may be insufficient to prevent burnout over time. While online interaction was associated with students' initial satisfaction and burnout levels, it did not buffer against their longitudinal decline. Instead, this finding suggests that merely increasing the frequency of online interaction may be insufficient; instead, interventions should focus on enhancing the quality and meaningfulness of interactions. Indeed, a systematic literature review by Abuhassna and Alnawajha (2023) shows that interaction alone is insufficient. The research reveals that while interaction increases student satisfaction, it remains limited in the face of the structural demands of distance education. In particular, the negative correlation between structure and dialogue (Horzum, 2017) demonstrates the difficulty of increasing dialogue in highly structured distance learning environments. This situation forces students to demonstrate greater autonomy, and this forced autonomy can lead to cognitive and emotional burnout, regardless of the level of interaction. Interventions must address the structural features of distance learning that create ongoing demands for self-regulation and isolation throughout the semester.

Finally, in the research, the role of the gender variable was examined through multigroup analysis. It was observed that females exhibited higher levels of burnout at the outset compared to males, and they also experienced a more rapid increase in burnout throughout the process. Female students may be more likely to internalize stressors and experience emotional exhaustion (Fiorilli et al., 2022). Moreover, the coefficient of online interaction regulating the change in burnout levels was higher

for females compared to males, suggesting that females are more influenced by the lack of communication in online education (Theodoratou et al., 2023).

The findings of the current study indicate that, despite continued interaction, student burnout increased and satisfaction decreased. While Moore (1973) conceptualized interaction as a key element in reducing transactional distance in distance education, the present results suggest that the mere presence of interaction may not be sufficient to prevent negative learner outcomes such as burnout and declining satisfaction. This suggests that structural self-regulation demands may have a greater impact than dialogue levels alone. Furthermore, it can be said that distance education practices with appropriate and structured features increase retention, as also noted by Yu et al. (2020). Moreover, these practices increase satisfaction, as also noted by Gavrilis et al. (2020), and therefore we recommend the implementation of dual interventions as structured protocols that balance three types of interaction through synchronous sessions and peer groups, as shown in our study, and explicit self-regulated learning training, which Andrade (2014) showed reduces operational distance while improving performance. Among the implementation barriers, increased faculty workload and technology-related limitations affecting students emerge as major challenges (Abuhassna & Alnawajha, 2023; Achuthan et al., 2021). These challenges can be overcome with support mechanisms such as phased pilot applications with low-cost tools and teaching assistant support.

Furthermore, it demonstrated that females experience a more rapid increase in burnout with the decrease in online interaction, highlighting the need for gender-sensitive structural interventions in distance education. Our finding that female students experience faster burnout tendencies requires an explanation that extends beyond the observed low online engagement. Multiple intersecting mechanisms based on structural inequalities, cultural norms, and psychological processes likely contribute to the increased vulnerability of women in distance education contexts, particularly within Türkiye's socio-cultural environment. Structurally, we believe that women facing what they call a multiple burden, the simultaneous demands of education, housework, and often employment may be triggering this vulnerability (Augustus, 2021; Richardson et al., 1999).

Limitations

Data collection occurred in Türkiye following both the COVID-19 pandemic and the February 6, 2023 earthquakes that displaced millions and caused over 50,000 fatalities. These overlapping crises may introduced widespread trauma, economic disruption, and ongoing stress that we did not systematically measure. Our results may not generalize to students in stable conditions or regions without recent collective trauma. Future research should control for disaster exposure and economic strain, comparing affected versus unaffected populations to disentangle pedagogical effects from crisis-induced stressors. Despite these limitations, our findings offer insights for institutions in crisis contexts, suggesting that interaction enhancement alone may be insufficient without comprehensive support addressing basic needs and mental health.

Implications for Practice

The findings of this study underscore the importance of proactive strategies in distance education. To prevent the decrease in satisfaction and address and prevent the increase in burnout, educational institutions and policymakers are encouraged to prioritize the implementation of interaction and supportive structures. Fostering interactive learning experiences, providing timely feedback, and optimizing course navigation enhance students' satisfaction levels longitudinally while preventing them from experiencing academic burnout.

Furthermore, our findings suggest that simply increasing the frequency of online interactions may be insufficient; instead, interventions should focus on improving the quality and meaningfulness of those interactions. Future mixed-methods research could explore whether interaction quality (e.g., peer support, collaborative learning, and instructor responsiveness) differentially affects burnout trajectories compared to interaction frequency alone.

Future Directions

Despite the valuable insights offered by this longitudinal study, several limitations should be addressed in future research. First, the representativeness of the sample may impact the generalizability of the findings and the interpretation of burnout and satisfaction trajectories. Additionally, given the multifaceted nature of these variables, future endeavors could benefit from incorporating qualitative methodologies to capture the subjective experiences and contextual nuances that influence student well-being in distance education.

Furthermore, while this study identified online interaction as a key moderator, future research should develop more comprehensive, multi-level frameworks by integrating additional contextual variables. These models should incorporate: (a) student-level factors such as digital literacy, motivation, and self-regulation; (b) instructor-level factors including pedagogical support and workload; (c) institutional-level factors like platform quality and technical support; (d) social factors such as peer and family support; and (e) socioeconomic and cultural factors including internet connectivity and gender roles. By examining these variables as potential moderators or mediators, researchers can better explain why distance learning affects students differently and identify the most effective intervention points. Also, future research should incorporate additional contextual variables such as digital literacy levels, socioeconomic status, institutional platform quality, and internet connectivity to develop more comprehensive models of distance learning experiences. These factors may serve as moderators or mediators of the relationships identified in this study.

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Authors' Contribution All authors contributed equally to this work.

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Data Availability The data used in this study can be shared by the authors upon reasonable request.

Declarations

Ethical Conduct Ethical approvals required for this study were obtained, and all ethical principles were strictly adhered to throughout the research process.

Conflict of Interest The authors declare no conflict of interest.

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