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Will I lose my job? A longitudinal cross-lagged panel model for technological unemployment anxiety, academic burnout, and quiet quitting

Ali Berke Körün[1] · **M. Yasir Kayar**[2] · **Ünsal Umdu Topsakal**[2] · **Seydi Ahmet Satıcı**[1,3,4]

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Abstract

Rapid advances in artificial intelligence and automation have heightened concerns about future employment, especially among university students. Technological unemployment anxiety has thus emerged as a salient stressor with implications for academic engagement and well-being. This study examined the directional relationships between technological unemployment anxiety, academic burnout, and quiet quitting. Using a two-wave half-longitudinal design, data were collected from 306 students ($M = 21.76$, standard deviation [SD] = 2.50) at 3-month intervals. Cross-lagged analyses showed that technological unemployment anxiety at T1 predicted burnout at T2, and burnout at T1 predicted quiet quitting at T2, supporting Job Demands–Resources (JD–R) and Conservation of Resources (COR) frameworks.

Keywords Technological unemployment anxiety · Academic burnout · Quiet quitting

Résumé

Les progrès rapides de l'intelligence artificielle et de l'automatisation ont intensifié les inquiétudes concernant l'emploi futur, en particulier chez les étudiants universitaires. L'anxiété liée au chômage technologique est ainsi apparue comme un facteur de stress important, ayant des répercussions sur l'engagement académique et le bien-être. Cette étude a examiné les relations directionnelles entre l'anxiété liée

✉ Ali Berke Körün
berke.korun@yildiz.edu.tr

1 Department of Psychological Counseling, Faculty of Education, Yıldız Technical University, 34350 Istanbul, Türkiye

2 Department of Science Education, Faculty of Education, Yıldız Technical University, Istanbul, Türkiye

3 Faculty of Education, Biruni University, Istanbul, Türkiye

4 Near East University, Nicosia, Türkiye

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au chômage technologique, l'épuisement académique et le quiet quitting. À l'aide d'un plan semi-longitudinal à deux vagues, des données ont été recueillies auprès de 306 étudiants (M = 21,76, ÉT = 2,50) à des intervalles de trois mois. Les analyses croisées ont montré que l'anxiété liée au chômage technologique à T1 prédisait l'épuisement à T2, et que l'épuisement à T1 prédisait le quiet quitting à T2, ce qui soutient les cadres théoriques JD–R et COR.

Zusammenfassung
Die rasanten Fortschritte im Bereich der künstlichen Intelligenz und Automatisierung haben die Besorgnis hinsichtlich zukünftiger Beschäftigungsmöglichkeiten verstärkt, insbesondere unter Studierenden. Die Angst vor technologisch bedingter Arbeitslosigkeit hat sich somit als bedeutender Stressfaktor herausgebildet, der Auswirkungen auf das akademische Engagement und das Wohlbefinden hat. In der vorliegenden Studie wurden die gerichteten Zusammenhänge zwischen der Angst vor technologischer Arbeitslosigkeit, akademischem Burnout und dem Phänomen des „Quiet Quitting" untersucht. Mithilfe eines zweiwelligen, halb-längsschnittlichen Designs wurden Daten von 306 Studierenden (M = 21,76, SD = 2,50) im Abstand von drei Monaten erhoben. Kreuzverzögerte Analysen zeigten, dass die Angst vor technologischer Arbeitslosigkeit zum ersten Messzeitpunkt (T1) Burnout zum zweiten Messzeitpunkt (T2) vorhersagte und dass Burnout zu T1 „Quiet Quitting" zu T2 prognostizierte, was die Annahmen des JD–R- und COR-Modells stützt.

Resumen
Los rápidos avances en inteligencia artificial y automatización han incrementado las preocupaciones sobre el empleo futuro, especialmente entre los estudiantes universitarios. La ansiedad por el desempleo tecnológico se ha convertido así en un factor estresante relevante, con implicaciones para el compromiso académico y el bienestar. Este estudio examinó las relaciones direccionales entre la ansiedad por el desempleo tecnológico, el agotamiento académico y el fenómeno conocido como quiet quitting. Utilizando un diseño semilongitudinal de dos mediciones, se recopilaron datos de 306 estudiantes (M = 21,76, DE = 2,50) en intervalos de tres meses. Los análisis cruzados mostraron que la ansiedad por el desempleo tecnológico en T1 predijo el agotamiento académico en T2, y que el agotamiento en T1 predijo el quiet quitting en T2, respaldando los marcos teóricos JD–R y COR.

Introduction

Will today's technology take our jobs away in the future? Every technological advancement can bring this question to mind (Karangutkar, 2023; Kim et al., 2025; Pehlivanoglu, 2024). As we leave the first quarter of the twenty-first century behind, global labor markets and higher education ecosystems are facing a wave of transformation rarely seen in human history (Ginther & Saatcioğlu, 2022). From factory floors to offices, machines are increasingly capable of performing tasks that were once performed only by humans. Well-known global foresight reports indicate that

a substantial share of existing occupations will either be fully automated or undergo radical transformations in how they are performed within the next 5 years (Chung et al., 2025; OECD, 2025; World Economic Forum [WEF], 2025). This situation may cause an increase in technology-related unemployment concerns among people, and this concern may negatively affect their lives. A recent study examining concerns about technology-driven unemployment, particularly in relation to artificial intelligence (AI) systems that extend beyond applied fields, such as engineering, to touch upon the social sciences and even social life itself, shows that AI-driven job loss can trigger shame, social withdrawal, and isolation, thereby increasing psychological vulnerability (Sharma et al., 2025).

Beyond these, the fear that "robots will take our jobs" may not be limited to experienced workers; young people about to enter the workforce may also feel this fear. As documented in the 2025 report by Stanford University's Human-Centered Artificial Intelligence Institute, the number of areas where AI models surpass human performance is increasing daily, creating existential pressure on the educated workforce (Stanford Institute for Human-Centered Artificial Intelligence, 2025; Wang et al., 2024). University students who have invested years in their education are watching the rapid advancement of AI and wondering whether they will be able to build stable careers with their degrees or whether they will be replaced by smart machines (Pandurang et al., 2023). As a result, they may feel anxious that automation and AI could take away their opportunities before they even begin their careers. Such anxieties may overshadow students' academic experiences, affecting their motivation, mental health, and outlook on the future. Therefore, understanding the effects of technological unemployment anxiety on university students and how students behave under this anxiety is important in our era, where workplaces are being transformed or eliminated by smart systems.

Technological unemployment anxiety refers to the insecurity or dread that one's future employment prospects are threatened by technological advances such as AI, robots, and algorithms (Civelek & Pehlivanoglu, 2020). In other words, it is the "feeling of insecurity individuals feel about their future" in the face of disruptive technology. This concern goes beyond general job anxieties, stemming from witnessing the increasing capabilities of technology and wondering whether human workers will still be needed. Such concerns have been linked to increased stress levels, reduced self-motivation, and a tendency to weaken an individual's commitment to their job or studies (Civelek & Pehlivanoglu, 2020). In other words, when people feel that their future careers are under threat, this can lead to a range of negative emotions and disengagement. Importantly, concerns about technological unemployment are not a distant theoretical issue but are increasingly being observed among today's university students. University students growing up in the digital age and aware of the rapidly advancing capabilities of AI (Tripathi, 2024) face an uncertain future shaped by technology as they transition from student to professional identity. Recent studies show that many students are concerned that AI will render their chosen professions useless (Kaya & Ates, 2025; Yasar & Karagucuk, 2025). This situation may cause students to doubt that their efforts are being rewarded, leading them to become disengaged from their studies. The question, "If technology/AI takes over my field, will all this hard work go to waste?" can undermine daily motivation. In

this way, technological unemployment anxiety can function as an academic stress factor, consuming students' energy and enthusiasm for learning. A student who constantly worries about the future may struggle to find meaning or urgency in their studies, which can lead to cynicism ("Why bother if a robot will do the job anyway?") and fatigue. These thoughts are important indicators that signal academic burnout.

Burnout is defined by Maslach and Jackson (1981) as a syndrome consisting of three dimensions: emotional exhaustion, depersonalization, and reduced personal accomplishment. However, Schaufeli et al. (2002) characterized burnout in university students as experiencing fatigue from academic demands (exhaustion), exhibiting a cynical and indifferent disposition toward coursework (cynicism), and perceiving oneself as inadequate in academic performance (reduced efficacy, also referred to as reduced academic efficacy). Unlike employee burnout, student burnout represents a progressive erosion of the student–institution bond, where structured academic requirements function as organizational demands (Olson et al., 2025). This condition is not merely an immediate response to workload, but also a chronic syndrome that severely disrupts cognitive functioning and professional identity development before entering the workforce. The source of this burnout is usually thought to be academic demands such as excessive course load (Shamim et al., 2025), exam stress (Fathima et al., 2025), and time pressure (Ahmad et al., 2024). However, recent findings suggest that burnout may stem not only from current academic burdens but also from students' uncertainties and anxieties about the future (Qiang et al., 2024). Similarly, Feng et al. (2025) suggest that increased competition and uncertainty in finding employment after graduation may lead to negative emotions such as fear, excessive stress, and lack of self-confidence in students, thereby undermining psychological well-being. For university students who are simultaneously managing academic demands and trying to shape their future professional identities, the ongoing uncertainty surrounding employability can function as an additional and invisible burden (Jia, 2024). As this burden accumulates, students may begin to experience constant emotional exhaustion, decreased academic participation, and feelings of inadequacy in their studies. In this sense, technological unemployment anxiety may act as a precursor to a specific form of burnout experienced in educational contexts, namely academic burnout (Churampi-Cangalaya et al., 2024; Keshavarzi et al., 2024).

Burnout not only harms students' health and grades, but it can also change their behavior. A notable consequence of academic burnout may be a type of withdrawal often referred to as "quiet quitting." Quiet quitting is a term that has emerged in the workplace and is used to describe employees who do not leave their jobs but mentally disconnect from work, choosing to do only the minimum necessary work (Scheyett, 2023). Individuals experiencing burnout, drained of energy and feeling hopeless about the future, may choose to protect themselves by remaining within the system rather than making the costly decision to completely disconnect from it. Galanis et al. (2023) found that 80% of employees exhibiting quiet quitting tendencies were burned out in their jobs and that quiet quitting behavior emerged as a coping behavior based on burnout. Similarly, it has been observed that individuals experiencing emotional exhaustion are significantly more likely to engage in quiet

quitting behavior (Dilekçi et al., 2025). Although the term "quiet quitting" comes from organizational behavior, the core idea translates to academic settings as well. A burned-out student may not formally drop out of college, but they might psychologically disengage from it. Quiet quitting can manifest as students attending classes only at the minimum required level without dropping out, approaching academic activities half-heartedly, and avoiding doing more than necessary.

Taking all of this into account, the Job Demands–Resources (JD–R) model and Conservation of Resources (COR) theory provide a comprehensive theoretical framework for explaining the relationships between technological unemployment anxiety, burnout, and quiet quitting. The JD–R model explains employees' (and students') well-being levels based on the balance of demands and resources in the work environment. As Bakker and Demerouti (2007) have stated, high job demands place a certain burden on the individual by requiring constant physical and mental effort; if compensatory resources are insufficient, this situation leads to burnout in the long term. Therefore, high levels of technological unemployment anxiety, similar to the constant demands of work life, can drain a student's energy and motivation, setting the stage for burnout. The COR theory, however, interprets stress through the individual's motivation to protect valued resources. Hobfoll (2011) stated that people act with the motivation to hold on to, protect, and increase the resources they have, and that stress largely stems from these resources being threatened or lost. According to this theory, when individuals face the threat of losing their resources (e.g., time, energy, skills, and social support), they experience stress and develop behaviors aimed at acquiring more resources or defending their existing resources to protect themselves. From this perspective, concerns about technological unemployment can trigger a strong stress response by creating the perception that the student's future job security, financial stability, or professional skills may be slipping away. When these theoretical frameworks are considered together, it can be argued that concerns about technological unemployment may both create a high demand burden for students, potentially leading to burnout, and also lead them to engage in passive withdrawal behavior (quiet quitting) due to a perception of resource loss. Although empirical research focusing specifically on university students remains limited, evidence from organizational contexts suggests that fears of being "replaced" by AI are associated with increased emotional burnout among employees (Kong et al., 2021; Yam et al., 2023). In turn, burnout has been discussed as a potential antecedent of withdrawal-oriented work attitudes (Safariyani & Fadillah, 2025).

The present study

Taken together, these theoretical perspectives and emerging empirical findings highlight a coherent explanatory framework, yet they also reveal a notable gap in the higher education context, where the dynamic relationships among technological unemployment anxiety, academic burnout, and quiet quitting remain largely unexamined. Although each of these concepts has been examined separately, the need to bring them together to better understand student well-being in an era of rapid technological change is clear. To date, few studies have examined how students'

concerns about artificial intelligence and automation may influence academic outcomes such as burnout and disengagement. The current research fills this gap by examining a chain reaction that begins with career-related anxiety and could potentially result in a quiet withdrawal from academic life. Drawing on JD–R and COR theories, we conceptualize technological unemployment anxiety as a new form of academic demand (and anticipated resource depletion) that could erode students' mental resources and thus increase the risk of burnout. In turn, burnout is expected to act as a harbinger of quiet quitting attitudes, as exhausted students reduce their efforts defensively to cope. In conclusion, the purpose of this study is to examine whether technological unemployment anxiety among university students contributes to academic burnout and, consequently, to tendencies toward quiet quitting. Drawing upon the literature and theories discussed, this study proposes the following hypotheses:

H1 *Baseline technological unemployment anxiety positively and longitudinally predicts subsequent academic burnout over time.*

H2 *Academic burnout at earlier stages positively and longitudinally predicts subsequent academic quiet quitting tendencies over time.*

By testing these hypotheses, this study sought to clarify the impact of career anxiety related to technological developments on students' well-being and academic behavior and to provide insight into how the narrative that "technology is taking our jobs" is quietly shaping students' educational journeys today. The proposed

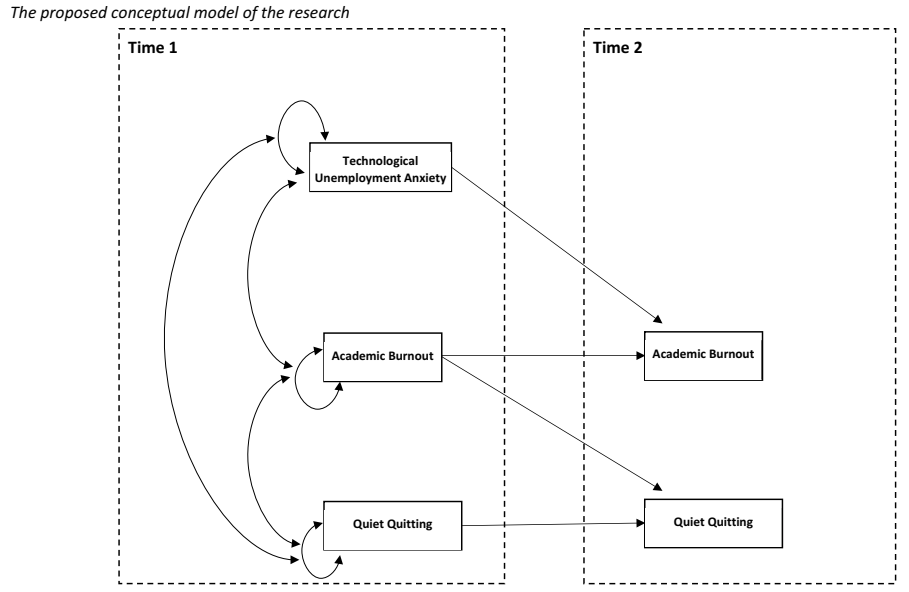


Fig. 1 The proposed conceptual model of the research

longitudinal associations and the overarching conceptual framework of the study are visually represented in Fig. 1.

Methods

Participants and procedure

This longitudinal study utilized a two-wave panel design to examine the temporal links between technology-related job insecurity, academic burnout, and quiet quitting. Data were collected in two measurement periods at 3-month intervals. Participants were selected from higher education institutions using convenience sampling, and participation was entirely voluntary. All questionnaires were administered online using a secure survey platform, and the order of instruments was kept consistent across both measurements to minimize potential measurement bias. Prior to participation, individuals were informed about the purpose of the study, that participation was voluntary, and that they had the right to withdraw at any stage without consequences. At the first measurement period (time 1 [T1]), data were collected from 603 participants at the end of September 2025. By the end of December 2025, during the second measurement period (time 2 [T2]), 443 participants completed the follow-up survey. This specific 3-month interval was operationally designed to mirror the structural lifecycle of a single academic semester within the Turkish higher education system, capturing students' psychological trajectory from the baseline orientation and course-selection week in September to the final examination period in late December. To enable longitudinal analysis, responses were matched across two measurement waves. This matching was conducted using a self-generated identification code created by participants based on the first three letters of their mother's first name, the first three letters of their father's first name, and the last three digits of their student identification number. This procedure allowed for accurate linkage of responses across time while preserving participant anonymity and avoiding the collection of directly identifiable personal information. As a result of this matching process, a final sample of 306 participants who provided complete and corresponding data at both time points was obtained. The attrition rate (approximately 49% from T1 to T2) was primarily attributable to typographical inconsistencies in self-generated identification codes during the time 2 matching process, as well as students' limited availability during the late-December final examination period. To examine the possibility of attrition bias, participants who dropped out were compared with the final matched sample on all baseline time 1 variables (anxiety, burnout, and quiet quitting) and demographic characteristics (age and gender) using independent samples *t*-tests and chi-squared analyses. The findings revealed no statistically significant differences between the groups ($p > 0.05$), suggesting that the missing data were completely at random (MCAR) and unlikely to have introduced systematic bias into the model estimations. To ensure accurate estimation of within-person variation and cross-lagged effects, only these matched cases were retained for the longitudinal analyses. The mean age of the matched sample was

21.76 years (standard deviation [SD] = 2.50). Among these participants, there were 257 women (84%) and 49 men (16%). This gender distribution reflects the typical student demographic profile of the faculties (e.g., Education and Social Sciences) from which the convenience sample was predominantly drawn in Türkiye. To capture a sample with mature professional identity projections and acute awareness of upcoming market entry realities, the study intentionally recruited upper-level undergraduate students (third- and fourth-year students) who face immediate proximity to graduation. Although cumulative grade point averages (GPA) were collected at baseline, student grades were not formally treated as control covariates in the final structural models because their early semester correlations with late-semester quiet quitting tendencies were statistically nonsignificant, thereby prioritizing optimal model parsimony. Furthermore, while the utilization of a convenience sampling method introduces an inherent selection bias that limits the absolute generalizability of the findings, this approach allowed for a realistic tracking of cohesive student cohorts within their natural institutional cycle. To mitigate potential gender bias arising from this imbalance, gender was treated as a covariate and statistically controlled within the structural equation modeling analyses. Participants reported an average daily technology use of 5.57 h (SD = 2.26). Additional information regarding the demographics of the participants is presented in Table 1.

Table 1 Demographic information of participants

Variable	Frequency	Percentage
Gender		
Female	257	84.0
Male	49	16.0
Marital status		
Single	242	79.1
In a relationship	64	20.9
Grade		
Third year of university	101	33.0
Fourth year of university	205	67.0
Post-graduation orientation		
Academic research	45	14.7
Applied profession (e.g., engineering, teaching)	175	57.2
Art production or design	8	2.6
Private sector/business world	39	12.7
Public service	39	12.7

Ethics

The study received ethical approval from the Yıldız Technical University Institute of Social Sciences Ethics Committee (approval number E-20260208115), and all research procedures were conducted in accordance with the principles of the Declaration of Helsinki.

Measures

Technological unemployment anxiety

The Technological Unemployment Anxiety Scale was developed by Civelek and Pehlivanoglu (2020) to measure individuals' anxiety related to technology-induced unemployment. Although the scale was originally designed for employees, it was also deemed appropriate for use with university students, as its items primarily reflect concerns about future job loss and skill obsolescence resulting from technological advancements. From this perspective, the scale captures forward-looking unemployment anxiety, which is highly relevant for students who are preparing to enter the labor market. The scale has 12 items (e.g., "I believe that technological advances could completely eliminate the field in which I am trained") on a 5-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). It comprises three subdimensions: lack of technical skill, incremental technological improvements, and technological disruption. In the original scale development study, Cronbach's alpha coefficients for the three subdimensions were reported as 0.83, 0.89, and 0.86, respectively. In the present study, Cronbach's alpha for the total scale was 0.89 at time 1 and 0.91 at time 2. Confirmatory factor analysis supported the original three-factor structure of the scale, yielding an acceptable model fit to the current sample: $\chi^2/df = 3.29$, Goodness-of-Fit Index (GFI) = 0.94, Normed Fit Index (NFI) = 0.93, Incremental Fit Index (IFI) = 0.95, Tucker–Lewis Index (TLI) = 0.93, Comparative Fit Index (CFI) = 0.95, Standardized Root Mean Square Residual (SRMR) = 0.06, and Root Mean Square Error of Approximation (RMSEA) = 0.08. All standardized factor loadings were statistically significant ($p < 0.001$). Internal consistency coefficients indicated high reliability for the total scale, with Cronbach's alpha values of 0.89 at time 1 and 0.91 at time 2.

Maslach Burnout Inventory–Student Survey (MBI–SS)

Schaufeli et al. (2002) developed the Maslach Burnout Inventory–Student Survey to assess students' burnout levels, and the scale was adapted into Turkish by Balkis et al. (2011). The scale consists of 15 items (e.g., "I feel tired when I get up in the morning and I have to face another day at the university") rated on a 7-point Likert-type scale and includes three subdimensions: emotional exhaustion, cynicism, and academic efficacy. In the adaptation study, Cronbach's alpha for the total scale was reported as 0.83. In the present study, Cronbach's alpha for the total scale was calculated as 0.90 at both time 1 and time 2.

The Quiet Quitting Scale (student survey)

The Quiet Quitting Scale was developed by Savaş and Turan (2023) to measure university students' levels of quiet quitting within an academic context. Although the concept of quiet quitting has predominantly been examined in employee populations, this scale conceptualizes quiet quitting as a student-specific behavioral pattern characterized by reduced academic commitment, decreased motivation, prioritization of social life, and self-protective academic engagement. The scale consists of 16 items (e.g., "I find it meaningless to engage in profession-related activities beyond what is taught in classes") rated on a 5-point Likert-type scale ranging from 1 ("strongly disagree") to 5 ("strongly agree") and comprises four subdimensions: decreased commitment, amotivation, socialization, and self-protection. In the original scale development study, Cronbach's alpha for the total scale was reported as 0.94. In the present study, Cronbach's alpha for the total scale was calculated as 0.80 at both time 1 and time 2. To examine the construct validity of the scale in the present sample, a confirmatory factor analysis (CFA) was conducted using the baseline data. The findings supported the original four-factor structure and indicated an acceptable model fit: $\chi^2/df = 4.321$, GFI = 0.968, NFI = 0.950, TLI = 0.935, CFI = 0.960, SRMR = 0.050, and RMSEA = 0.078. Furthermore, all standardized factor loadings were statistically significant ($p < 0.001$), supporting the psychometric adequacy of the instrument within the student sample.

Data analysis

Data analyses were conducted in several stages. First, descriptive statistics were calculated for all study variables at time 1 and time 2 using IBM Statistics (version 27). The internal consistency of the measurement instruments was assessed using Cronbach's alpha coefficients. Subsequently, bivariate correlations among the variables were examined to identify their concurrent associations across measurement periods. To assess the potential threat of common method bias arising from the self-report nature of the data, Harman's single-factor test was performed using exploratory factor analysis. Finally, to examine temporal and reciprocal relationships among the variables within a half-longitudinal design, a cross-lagged panel model was employed using AMOS Graphics 2024. Model fit was evaluated using multiple goodness-of-fit indices, including the chi-squared to degrees of freedom ratio (χ^2/df), the Comparative Fit Index (CFI), the Tucker–Lewis Index (TLI), the Root Mean Square Error of Approximation (RMSEA), and the Standardized Root Mean Square Residual (SRMR). This approach allowed for the simultaneous estimation of autoregressive paths and cross-lagged effects across the two measurement waves, thereby providing insight into the directional associations between the constructs over time. To evaluate the statistical validity and precision of these direct path estimations, bootstrapping with 5000 resamples was utilized to generate 95% bias-corrected confidence intervals.

Results

Preliminary analyses

Prior to the main analyses, preliminary analyses were conducted to examine descriptive statistics, internal consistency reliability coefficients, and bivariate correlations among the study variables. Means, standard deviations, and reliability estimates for all variables at both measurement periods are presented in Table 2.

As presented in Table 2, the variables measured at the same time point exhibited positive and statistically significant correlations. Furthermore, the positive and significant correlations observed between time 1 and time 2 indicate the temporal stability of the study variables. Additionally, to evaluate the potential threat of common method variance before proceeding to the structural model testing, Harman's single-factor test was performed via exploratory factor analysis. The unrotated factor solution indicated that the single largest factor accounted for 24.14% of the total variance at time 1 and 24.89% at time 2. Because these values are well below the critical 50% threshold, it demonstrates that common method bias does not pose a substantial threat to the validity of the datasets (Podsakoff et al., 2003).

Cross-lagged panel analysis

To examine the long-term relationships between the study variables, a cross-lagged panel model was tested using structural equation modeling. Prior to the main cross-lagged panel analyses, longitudinal measurement invariance testing was conducted for the Quiet Quitting Scale to examine the stability of the construct across the two measurement waves. First, the configural invariance model was tested and subsequently compared with the metric invariance model, in which factor loadings were constrained to equality over time. The findings supported metric invariance, as the changes in fit indices remained below the recommended cutoff criteria (ΔCFI = 0.002, ΔRMSEA = 0.004) (Cheung & Rensvold, 2002). These results indicate that the latent structure of quiet quitting was interpreted consistently across time points, thereby supporting the validity of the subsequent cross-lagged panel estimations. The model included autoregressive paths for academic burnout and quiet quitting, as well as cross-lagged paths reflecting the assumed directional effects between the concepts. Consistent with the half-longitudinal design of the study, technological unemployment anxiety was included at time 1 as the primary baseline predictor of time 2 outcomes; its time 2 variance was excluded from the structural path model to optimize model parsimony and maintain a direct focus on the sequential hypotheses. Age and gender were included as control variables, and direct paths to the time 2 outcome variables were specified. The model was estimated using maximum likelihood estimation in AMOS Graphics 24. Overall model fit indices indicated that the proposed model demonstrated an acceptable fit to the data (χ^2/df = 2.428; GFI = 0.983; AGFI = 0.939; NFI = 0.968; RFI = 0.915; IFI = 0.981; TLI = 0.948; CFI = 0.980; SRMR = 0.037; RMSEA = 0.068) (Fig. 2).

Table 2 Descriptive statistics, reliability, and correlation findings

Variable	Correlations						Descriptive statistics and reliabilities				
	1	2	3	4	5	6	Mean	SD	Skewness	Kurtosis	α
1. Technological unemployment anxiety T1	–						26.06	8.51	0.466	−0.086	0.89
2. Technological unemployment anxiety T2	0.580**	–					25.42	8.72	0.284	−0.616	0.91
3. Academic burnout T1	0.400**	0.288**	–				53.17	16.18	0.018	−0.330	0.90
4. Academic burnout T2	0.342**	0.400**	0.648**	–			53.66	16.33	−0.269	−0.491	0.90
5. Quiet quitting T1	0.353**	0.237**	0.577**	0.420**	–		42.77	9.73	0.267	0.055	0.80
6. Quiet quitting T2	0.236**	0.287**	0.503**	0.635**	0.571**	–	42.90	10.02	0.164	−0.125	0.80

**$p < 0.01$; means represent average cumulative total scores rather than item-level averages. Minimum and maximum possible total scores vary depending on the number of items in each scale/subscale and their respective Likert formats

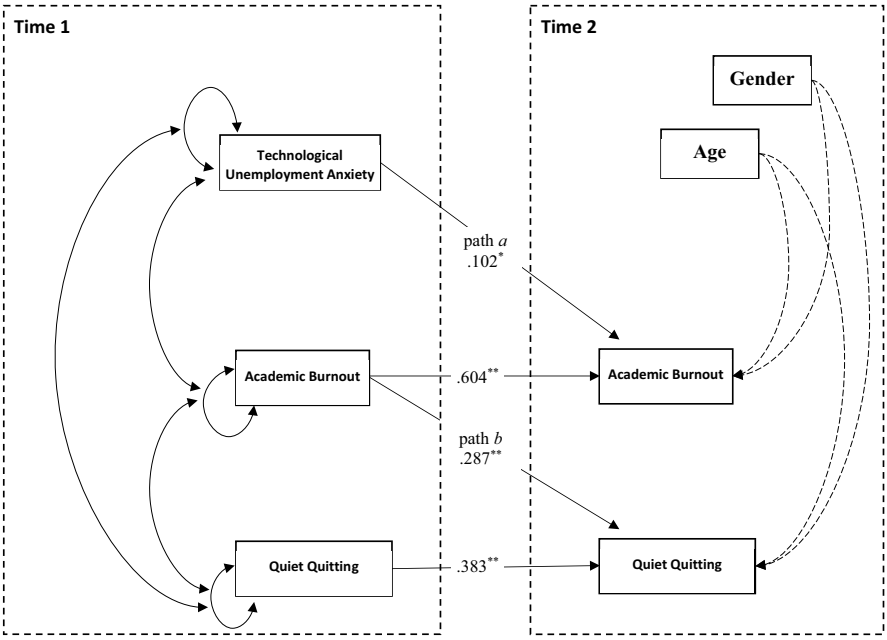


Fig. 2 Cross-lagged panel model for a half-longitudinal design for testing the associations between technological unemployment anxiety and quiet quitting via academic burnout. $^{*}p < 0.05$, $^{**}p < 0.01$

The results showed that all autoregressive paths were statistically significant, indicating the temporal stability of academic burnout and quiet quitting over a 3-month interval. Academic burnout at time 1 significantly predicted academic burnout at time 2 ($\beta = 0.604$, confidence interval [CI] [0.495, 0.694], $p < 0.01$), and quiet quitting at time 1 significantly predicted quiet quitting at time 2 ($\beta = 0.384$, CI [0.245, 0.504], $p < 0.01$). As for cross-lagged effects, technological unemployment anxiety at time 1 significantly predicted academic burnout at time 2 ($\beta = 0.102$, CI [0.063, 0.201], $p < 0.05$), indicating that high levels of job insecurity concerns are associated with increased academic burnout over time. Academic burnout at time 1 also significantly predicted quiet quitting at time 2 ($\beta = 0.287$, CI [0.176, 0.402], $p < 0.01$), indicating that burnout contributes to subsequent disengagement tendencies.

Discussion

In this study, the relationships between technological unemployment anxiety, academic burnout, and quiet quitting among university students were examined using a longitudinal design. Temporal and structural connections between variables were tested using correlation analysis and cross-lagged panel model (CLPM) analysis. Correlation results revealed positive and significant relationships between technological unemployment anxiety, academic burnout, and quiet quitting in both T1 and

T2 measurements. The CLPM findings showed that technological unemployment anxiety at T1 significantly predicted academic burnout at T2, while academic burnout at T1 significantly predicted quiet quitting at T2. These findings suggest that the relationships among the variables point to a longitudinal structural pattern within the higher education context, rather than being merely temporary or concurrent associations. However, it is important to note that the cross-lagged effect of technological unemployment anxiety on subsequent academic burnout, while statistically significant, is relatively small. This modest effect size suggests that while future-oriented technological anxiety acts as an active cognitive stressor, it operates as a distal antecedent rather than a dominant, proximal academic demand such as active course loads or immediate exam stress. The findings obtained are discussed below within the framework of the Job Demands–Resources (JD–R) model and Conservation of Resources (COR) theories and literature.

Correlation analyses indicate that there are meaningful relationships between the variables at both time points. This stable relationship over time is consistent with studies showing that technological uncertainties and the emotional and behavioral responses they elicit in students operate as a simultaneous process (Bradley & Howard, 2023; Flynn et al., 2020). In the context of a semi-longitudinal design, this situation can be explained by the JD–R model as the variables in question being permanent psychological tendencies reflected in the students' educational process rather than momentary reactions. According to the model, the uncertainties individuals are exposed to, i.e., demands, increase the risk of burnout by straining their psychological resources, while resource depletion weakens motivational processes and triggers withdrawal behaviors (Bakker et al., 2023). Similarly, from the perspective of COR theory, students' perceptions of resource loss in relation to their future careers lead to a chain of psychological consequences that are fundamental determinants of stress (Halbesleben et al., 2014).

Within the framework of these theoretical approaches, the positive relationship between technological unemployment anxiety and academic burnout and quiet quitting indicates that the perception of career uncertainty created by digital transformation is related to students' psychological functioning. Technological unemployment anxiety can be considered an intense cognitive demand for students in terms of the JD–R model (Jagodics & Szabó, 2023). The fear of future unemployment, the disappearance of current job areas, or the obsolescence of professional skills created by artificial intelligence and automation can cause anxiety for students. Research also shows that career stress increases among students in fields experiencing employment problems (Han et al., 2021). From a COR perspective, this leads to similar stress responses among university students. This situation may create anxiety among students that fundamental resources such as future status, economic independence, and professional competence may be lost before they even enter the workforce. In response to this threat, they may remain constantly on guard.

The relationship between academic burnout and quiet quitting indicates that burnout is associated with students' tendency to psychologically withdraw from the educational process. This relationship reveals a result that aligns with the health impairment process in the JD–R model. According to the model, increasing future anxiety and demands deplete individuals' emotional energy, weakening the psychological

bond they have established with their profession (Martínez-Díaz et al., 2023). In educational processes, students may experience academic stress and lose motivation when faced with similar demands (Yang et al., 2025). Research indicates that academic stress also brings mental health issues, seriously undermining academic motivation (Halliburton et al., 2025). Students who experience a loss of motivation may reduce their willingness to work hard in their studies and focus only on meeting the minimum requirements for graduation. According to COR theory, this situation is a resource-conservation strategy developed by individuals showing signs of burnout to avoid entering a spiral of loss (Bardoel & Drago, 2021). University students, however, may withdraw their academic interest to conserve their remaining emotional and cognitive energy as they feel academically burned out.

Cross-lagged panel model (CLPM) analyses, which help clarify the temporal precedence between variables, reveal the existence of meaningful longitudinal relationships. According to the model's first finding, technological unemployment anxiety T1 significantly predicts academic burnout T2. From the Job Demands–Resources (JD–R) model perspective, this finding can be explained by the emergence of demands requiring constant effort in situations such as job insecurity among university students. Demands requiring constant effort create various individual, social, and organizational problems (Mazzetti et al., 2023). Increasing perceptions of job insecurity, along with digitalization, automation, and artificial intelligence, can create uncertain demands that require constant cognitive and emotional effort for university students. Such uncertainties can erode students' psychological resources and increase academic burnout, particularly by weakening their sense of control over their professional future (Díaz-Fúnez et al., 2025; Lara-Moreno et al., 2025). When evaluated within the framework of the Conservation of Resources (COR) theory, technological unemployment anxiety reflects a perceived threat to the loss of fundamental resources such as future employment, competence, and status (Jawahar et al., 2022). With the proliferation of artificial intelligence tools, this threat may become permanent. This could create a process that increases academic burnout by consuming students' emotional energy over time.

Furthermore, according to the model, academic burnout in T1 positively predicts quietly quitting in T2. Within the JD–R model, academic burnout is associated with a decrease in students' cognitive capacity for their academic roles and a weakening of their psychological commitment (Cho et al., 2023). Students who feel academically burned out, along with employment problems, also experience problems with their intrinsic motivation (Bellini et al., 2022). When these results are considered together, university students, who are constantly exposed to different demands in both their educational and professional lives, may feel academically exhausted. Therefore, over time, a decrease in their efforts toward their studies and academic responsibilities may be observed. They may withdraw from their educational lives to face fewer demands. From the perspective of COR theory, academic burnout indicates that an individual's current resources are significantly depleted, while quiet quitting emerges as a protective adaptive response aimed at avoiding further loss of these resources (Egozi Farkash et al., 2022; Gao, 2023). Academic burnout can cause both emotional and cognitive strain, as it is a risk factor for numerous characteristics such as students' well-being and emotional regulation skills (Iuga & David,

2024). Students who are emotionally and cognitively exhausted owing to academic difficulties may switch to energy-saving mode to continue their education. In this context, when evaluated from the students' perspective, quiet quitting may be a defense mechanism developed against long-term psychological strain rather than passive disengagement. Furthermore, while established pedagogical concepts such as academic disengagement or passive absenteeism capture general detachment, we intentionally utilize the term quiet quitting. Unlike passive absenteeism, which implies a physical or structural non-attendance, quiet quitting captures a specific, self-protective strategy where the student remains physically present and formally responsive within the educational system but consciously caps their cognitive effort at the absolute minimum required to pass. This successfully translates the contemporary occupational phenomenon into the higher education ecosystem, capturing a deliberate shift in motivational boundaries.

Limitations and future directions

Although this study presents strong findings revealing the temporal relationships between technological unemployment anxiety, academic burnout, and quiet quitting, the results should be evaluated within certain limitations. First, although the cross-lagged panel model (CLPM) used in the study allows for examining the temporal order between variables, it does not fully disentangle interindividual stationary differences. Therefore, while the relationships obtained indicate time-dependent changes, they do not allow for strict causal inferences. In future studies, models such as the random intercept (RI)-CLPM, which can distinguish random intersections, (Huseynzade 2026) and experimental studies may be better options for causality. Additionally, given the relatively small effect size ($\beta = 0.10$) of the cross-lagged path from technological unemployment anxiety to academic burnout, the longitudinal association should be interpreted cautiously. Although statistically significant, the finding appears to reflect a modest developmental process that likely operates in conjunction with other unmeasured academic, contextual, or personal factors. Second, the sample of the study is limited to university students continuing their education in Türkiye. Academic culture, employment security laws, educational opportunities, and technological infrastructure capabilities may vary from country to country. Therefore, it is recommended to work with students who continue their education in different cultural contexts, in addition to the findings obtained. Furthermore, the sample exhibits a significant gender imbalance, with 84% female participants. Although this distribution reflects the typical student demographic profile of the specific faculties sampled and gender was statistically controlled as a covariate in all standard error of the mean (SEM) analyses to mitigate potential bias, this imbalance remains a limitation for the generalizability of the findings across genders. Similarly, the study experienced a relatively high attrition rate of approximately 49% from time 1 to time 2. While our preliminary drop-out analyses confirmed that this loss occurred completely at random (MCAR) and did not introduce systematic attrition bias into the model estimates, future research should employ stronger retention strategies to maintain a more balanced and complete sample across measurement

waves. Third, the research is based on a semi-longitudinal design that includes only two time points. Two-wave models offer limited time resolution for examining directional relationships between variables and do not allow for testing more complex developmental patterns. Multicohort longitudinal designs with more measurement points and longer time lags would be more conducive to revealing the nonlinear or cyclical forms of the dynamic relationships between technological unemployment anxiety, academic burnout, and quiet quitting. Finally, although technological unemployment anxiety, which was the focus of this study, was identified as an important predictor of burnout, it is not the only factor affecting academic burnout. Owing to the scope of the study, other structural factors such as heavy administrative workload, management support, or salary satisfaction were not included in the model. The most critical recommendation for future research is to examine protective factors that could mitigate these sequential cross-lagged relationships over time. Furthermore, supporting quantitative data with in-depth interviews with academics could provide a more detailed understanding of the motivations underlying the quiet quitting process.

Implications

The findings of this study indicate that technological unemployment anxiety is not merely an abstract concern about the future for university students but rather a broader psychosocial process associated with academic burnout and quiet quitting tendencies over time. In this respect, the results indicate that digitalization and automation discourse can have indirect but powerful effects on students' academic motivation, learning investment, and psychological attachment to the university. Theoretically, the findings support the applicability of the Job Demands–Resources (JD–R) and Conservation of Resources (COR) theories to student samples. Technological unemployment anxiety functions as a type of academic demand for students and, at the same time, as a threat of future resource loss; this situation leads to the depletion of emotional resources over time.

The fact that academic burnout leads to quiet quitting shows that burnout is not merely a result but a central process that shapes the individual's motivational withdrawal from academic life. This situation shows that even if students do not drop out of school, they mentally disconnect from academic and social processes, adopting a "minimum effort" strategy where they reduce their participation in classes to a minimum and focus solely on obtaining a diploma. Instead of labeling students with low participation or motivation as "uninterested" or "lazy," higher education administrators and faculty members may be better off assessing this situation as a symptom of burnout. To systematically disrupt this resource loss spiral and mitigate these institutional demands, universities must transition from passive information sharing to structured, proactive interventions. First, rather than traditional career counseling, university career centers should design and implement "AI-resilience workshops." These programs must specifically focus on human–AI collaboration, teaching students how to utilize digital automation tools as complementary assets in their future fields, thereby directly converting macro-level technological anxiety into

an active psychological resource and a sense of professional competence. Second, because early semester career anxiety significantly predicts late-semester burnout, student welfare and counseling centers should establish "early warning and screening systems." Conducting brief, universal screenings for future-oriented career stress during orientation weeks can help identify at-risk students before their emotional resources are depleted. Additionally, institutional training should be provided to academic advisors to recognize the early behavioral markers of academic burnout, such as a sudden shift from proactive engagement to mere compliance, allowing for timely mentoring interventions. Strengthening career counseling services, providing realistic and transparent information about the digital transformation process, and developing skill-based programs that support students' perceptions of professional competence could be important protective factors in this context.

As a result, these sequential developmental paths, beginning with technological unemployment anxiety, leading to burnout, and relating to quiet quitting, threaten the quality of higher education. If the goal is for students to be involved in the educational process not only physically in the classroom but also cognitively and emotionally, universities must provide an ecosystem that supports students' future security. Students are concerned that their future professions will become obsolete in the face of rapidly advancing artificial intelligence and automation technologies, and this uncertainty is consuming them academically. In this context, university career centers and relevant academic units should pursue strategies that transform technology from a threat into an area of competence. Integrating courses focused on artificial intelligence literacy, digital technology applications, and contemporary employment skills into university curricula can strengthen students' sense of control over the future and prevent burnout.

Conclusions

This study examined the relationships between technological unemployment anxiety, academic burnout, and quiet quitting among university students in a cross-lagged panel design. Cross-lagged panel model analysis revealed that technological unemployment anxiety among university students predicted academic burnout over time, while academic burnout predicted quiet quitting. The findings indicate that digitalization and employment uncertainty do not merely create immediate anxieties but also erode students' psychological resources, fostering tendencies to withdraw from academic life. Consistent with Job Demands–Resources and Conservation of Resources theories, technology-induced unemployment anxiety functions as a persistent demand for students and, at the same time, as a threat of future resource loss. In this process, academic burnout emerges as a key indicator of weakened psychological resources and functions as a significant longitudinal predictor of quiet quitting. These findings suggest that quiet quitting is not a sudden or superficial attitude, but rather a behavioral outcome of long-term psychological strain. The study contributes to the literature by addressing quiet quitting not only as a phenomenon specific to working life but also as an adaptation pattern that can emerge in the context

of higher education. In a period of accelerating digitalization, supporting students' perceptions of uncertainty about the future and their psychological resources may play a critical role in reducing academic burnout and the associated tendency to withdraw. In this respect, the findings point to the importance of student support systems and career-oriented interventions in universities.

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Data availability Data will be available on request.

Declarations

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