Artificial Intelligence Addiction, Technostress, and Work-Life Balance Among Academics: An Employee Health Perspective

Raife AŞIK*, Nida EFETÜRK**, Fatoş TOZAK***

Abstract

Aim: This study aims to examine the relationships between artificial intelligence addiction tendencies, technostress levels, and work-life balance among academics within the framework employee health.

Method: This study was designed using a correlational survey model within the framework of quantitative research methods. The population of the study consisted of academics working at universities in Türkiye. Data were collected using a sociodemographic information form, the Artificial Intelligence Addiction Scale, the Technostress Scale, and the Work-Life Balance Scale. Statistical analyses were performed using SPSS for Windows 25.0 software.

Results: The findings indicated that the levels of artificial intelligence addiction (11.12±4.17) and technostress (56.13±12.85) among the participating academics (n=450) were moderate, with techno-overload identified as the most prominent subdimension of technostress. The analyses revealed positive and statistically significant correlations among the variables ($p<0.01$). Regression analysis demonstrated that both artificial intelligence addiction and technostress significantly and positively predicted work-life balance ($R^2=0.315$). From a sociodemographic perspective, younger academics (research assistants) exhibited higher levels of artificial intelligence addiction and work-life balance compared to professors. Additionally, a heavy teaching load of 16 hours or more per week was found to significantly increase the technostress level.

Conclusion: Artificial intelligence addiction and technostress are thought to be viewed not as destabilizing risk factors for academics but rather as a "functional adaptation tool" used to manage academic workload. While this resulting "good stress state" positively supports work-life balance, implementing human-centered digital policies at the corporate level is necessary to prevent long-term cognitive fatigue.

Keywords: Academics, artificial intelligence addiction, technostress, work-life balance.

Özgün Araştırma Makalesi (Original Research Article)
Geliş / Received: 24.03.2026 **Kabul / Accepted:** 09.08.2026
DOI: https://doi.org/10.38079/igusabder.1914738
* Asst. Prof., Dr., Istanbul Okan University, Faculty of Health Sciences, Department of Nursing, Istanbul, Türkiye. E-mail: raife.asik@okan.edu.tr ORCID https://orcid.org/0000-0002-6023-8649
** Asst. Prof., Dr., Kocaeli University of Health and Technology, Department of Nursing, Department of Nursing, Kocaeli, Türkiye. E-mail: nida.efeturk@kocaelisaglik.edu.tr ORCID https://orcid.org/0000-0001-8322-8200
*** Asst. Prof., Dr., Istanbul Okan University, School of Health Services, First Aid and Emergency Care Programme, Istanbul, Türkiye. E-mail: fatos.tozak@okan.edu.tr ORCID https://orcid.org/0000-0002-9509-6062

ETHICAL STATEMENT: This study was conducted following approval No. 199 dated 04/03/2026 from the Ethics Committee of Istanbul Okan University. Informed consent forms were obtained from all participants in accordance with the Declaration of Helsinki.

Akademisyenlerde Yapay Zeka Bağımlılığı, Teknostres ve İş Yaşam Dengesi: Çalışan Sağlığı Perspektifi

Öz

Amaç: Bu çalışmanın amacı akademisyenlerde yapay zekâ kullanımına bağlı bağımlılık eğilimlerinin, teknostres düzeyi ve iş-yaşam dengesi arasındaki ilişkilerini çalışan sağlığı perspektifinden incelemektir.

Yöntem: Araştırma, nicel araştırma yöntemlerinden ilişkisel tarama modelinde tasarlanmıştır. Evrenini Türkiye'deki üniversitelerde görev yapan akademisyenlerin oluşturduğu çalışmada veriler; sosyodemografik bilgi formu, Yapay Zekâ Bağımlılığı Ölçeği, Teknostres Ölçeği ve İş-Yaşam Dengesi Ölçeği kullanılarak toplanmıştır. Veriler, SPSS for Windows 25.0 yazılımı kullanılarak analiz edilmiştir.

Bulgular: Araştırmaya katılan akademisyenlerin (n=450) yapay zekâ bağımlılığı (11,12±4,17) ve teknostres (56,13±12,85) düzeyleri orta seviyede bulunmuş olup, en baskın teknostres alt boyutu "tekno-aşırı yüklenme"dir. Analizler sonucunda, değişkenler arasında pozitif yönlü ve anlamlı ilişkiler saptanmıştır ($p<0,01$). Regresyon analizi sonuçları, yapay zekâ bağımlılığı ve teknostresin iş-yaşam dengesini pozitif yönde anlamlı bir biçimde yordadığını göstermiştir (R^2=,315). Sosyodemografik açıdan, genç akademisyenlerin (araştırma görevlileri) yapay zekâ bağımlılığı ve iş-yaşam dengesi puanları profesörlere göre daha yüksek çıkarken, 16 saat ve üzeri yoğun ders yükünün teknostresi anlamlı düzeyde artırdığı saptanmıştır.

Sonuç: Çalışma, yapay zekâ bağımlılığı ve teknostresin akademisyenlerde dengeyi bozan risk faktörlerinden ziyade, iş yükünü yönetmek için kullanılan "fonksiyonel bir adaptasyon" aracı olduğunu göstermiştir. Elde edilen bu "iyi stres" durumu iş-yaşam dengesini pozitif yönde desteklese de uzun vadeli bilişsel yorgunlukları önlemek adına kurumsal düzeyde insan odaklı dijital politikaların hayata geçirilmesi gerekmektedir.

Anahtar Sözcükler: Akademisyen, yapay zeka bağımlılığı, teknostres, iş yaşam dengesi.

Introduction

The rapid advancement of artificial intelligence (AI) technologies, the increasing ease of access to information, and their swift integration into daily life have transformed the human–technology relationship into a new dimension. The loss of control over technology has been conceptualized in the literature as "artificial intelligence addiction"[1]. This construct was operationalised by few psychometric instruments (i.e., AI Addiction Scale–21 [AIAS-21], the Research Artificial Intelligence Addiction Scale particularly designed for scientists and researchers, dependency scales derived from some classical behavioral-addiction conceptualizations like Griffiths' components model)[2-4]. Recently gaining attention in the literature, AI addiction may lead to social isolation and anxiety by diminishing individuals' problem-solving abilities, interpersonal skills, and emotional intelligence[5]. Kooli et al. (2025) suggest that addiction to generative AI may represent a novel behavioral disorder characterized by compulsive use, tolerance, and withdrawal-like discomfort when access to AI tools is restricted[6]. Moreover, intensive use of AI has been associated with concerns such as data privacy risks, digital fatigue, technostress, and job insecurity, all of which pose significant threats to mental health[3]. Consistent with this perspective, Zhang et al. (2024) demonstrated that academic self-efficacy, performance expectations, and academic stress are significant predictors of problematic

AI use among university students. Their findings suggest that AI dependency in educational settings is shaped not merely by exposure to AI technologies but by the combined influence of individual competencies and contextual academic pressures[7].

In recent years, the rapid development of AI alongside digital transformation and its integration into both professional and educational environments have begun to reshape academic processes. While AI enhances academic productivity and accelerates access to information in research activities, it also facilitates the completion of routine administrative tasks—such as paperwork—in a shorter time, thereby allowing academics to allocate more time to their core responsibilities[8]. While this wave of transformation brings with it tremendous opportunities more efficiency, inclusivity, and innovation, it also puts employees, educators, and the organizations (enterprises) in various sectors under considerable stress and psychological pressure[9,10]. The pressure of an expectation of constant connectivity facilitated by omnipresent networks, and the need to cope with the fast pace introduced by digital technologies, is a significant source of stress for academics. This is commonly referred to as technostress, which can be defined as an unwanted effect of the technological demand[9]. Building on the widely accepted framework proposed by Tarafdar et al., technostress is commonly conceptualized through five key “technostress creators”: techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty. Each of these dimensions represents a distinct source of stress associated with the increasing demands of information and communication technologies (ICTs). Previous research has shown that technostress can negatively affect both individual well-being and organizational outcomes[11]. Expanding this perspective, Tarafdar, Cooper, and Stich, introduced the concept of the “technostress trifecta,” distinguishing between techno-distress, which impairs well-being and job performance, and techno-eustress, a positive, challenge-oriented response to technology that can foster engagement, motivation, and improved performance. This distinction provides an important theoretical perspective for understanding the dual nature of technostress, particularly in demanding and adaptive environments such as higher education[12,13].

Continuous exposure to email and message notifications throughout the day may disrupt academics’ work–life balance. Furthermore, the increasing workload driven by technology use may lead to decreased job satisfaction and increased levels of burnout[13].

Additionally, the overload of digital tools and the uncertainty arising from insufficient technological competence may evoke feelings of threat and insecurity. Such conditions negatively affect employees’ work–life balance. Higher levels of technostress are associated with reduced job satisfaction, increased turnover intentions, and decreased productivity[14,15]. Empirical findings from higher education further support this relationship. Truța et al. (2023) reported that academics who remained continuously connected to work through digital technologies experienced higher levels of technostress and lower psychological well-being, with these effects being particularly pronounced among faculty members facing heavier workloads[16]. Likewise, using structural equation modeling, Wang et al. (2023) found that work–home conflict serves as a significant

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antecedent of techno-stressors, which subsequently exert a negative impact on the psychological well-being of academic staff[17].

Accordingly, the relationship between technostress and work–life balance is generally negative. Despite the speed and convenience provided by technology, the blurring of boundaries between professional and personal roles makes it increasingly difficult for individuals to maintain balance[10]. When academics struggle to adapt to technological changes, they may experience stress, pressure, and fear of job loss[10,18]. This pattern is not unique to senior faculty, is not unique: research on technostress among novice teachers suggests that early-career academics, understandably combining the demands of developing professional competence while meeting institutional technological expectations exhibit unique and frequently heightened stress profiles compared to their more experienced colleagues[19], whereas stronger pedagogical–technological competence exists at least in theory to buffer—if not fully eliminate—these effects[20].

Although numerous studies in the literature have examined the effects of technology on employees' stress levels and work–life balance[10,17,18]. Nevertheless, most of the existing evidence has been derived from studies involving university students or teachers in primary and secondary education[7,21]. Comparatively few studies have simultaneously investigated AI addiction, technostress, and work–life balance within the same academic population or explored whether these relationships differ according to academic rank, teaching workload, and other sociodemographic characteristics of academic staff[16-19]. Given the very fast penetration of AI in academic work life, there is an urgent need to comprehensively investigate its impacts on academics' psychological well-being and work–life balance. Accordingly, the main purpose of the current research is to explore AI-related addiction tendencies and levels of technostress, as well as work–life balance among academic professionals in Turkey through an employee health perspective. More specifically, the study seeks to examine (a) the relationships among these three constructs, (b) the extent to which AI addiction and technostress predict work–life balance, and (c) whether these constructs differ according to academics' sociodemographic and occupational characteristics, including academic rank and weekly teaching workload.

We study AI use-related addiction tendencies, technostress, and work-life balance in the academic setting. AI use and technostress may not only be risk factors but also serve a positive role in some contexts as well; however, this depends on the specific scenario. This interpretation is consistent with the techno-eustress perspective, which argues that technology-related demands are not necessarily detrimental. Instead, under appropriate conditions, they may be experienced as manageable challenges that promote effective coping, enhance performance, and foster adaptation rather than acting solely as sources of strain or disruption[12].

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Material and Methods

Study Design and Participants

This was the first cross-sectional study that evaluates the relationship between artificial intelligence (AI) addiction with technostress and work–life balance among academics working in public universities and foundation universities in Turkey. After approval from the institutional ethics committee, data were collected via an online survey (Google Forms) between March and April 2026.

A total of 450 academics aged 18 years and older, employed either full-time or part-time, and who provided informed consent were included in the study. Individuals working outside Turkey, those who had never used AI-supported tools, participants under the age of 18, those who completed the questionnaire incompletely or inaccurately, and those who withdrew from the study were excluded.

Data Collection Instruments

The survey consisted of four sections: The Personal Information Form, the Artificial Intelligence Addiction Scale, the Technostress Creators Scale, and the Work–Life Balance Scale.

Personal Information Form: This form, developed by the researchers, consisted of 13 items. It included questions regarding participants' age, marital status, education level, employment type, and frequency of AI use.

Artificial Intelligence Addiction Scale (AIAS): The Digital Addiction to Artificial Intelligence Scale (DAI), developed by Morales-García et al. (2024) and adapted into Turkish by Savaş (2024), was used to assess AI addiction[21,22]. The scale is unidimensional and consists of 5 items rated on a 5-point Likert scale, yielding a total score ranging from 5 to 25. No reverse-coded items are included. In the present study, Cronbach's alpha coefficient was found to be 0.81.

Technostress Creators Scale (TCS): The Technostress Creators Scale, developed by Tarafdar et al. (2010) and adapted into Turkish by Bulut et al. (2023), was used to measure technostress[23,24]. The scale consists of 22 items rated on a 5-point Likert scale and includes five subdimensions: techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty. Factor loadings ranged between 0.591 and 0.912, and model fit indices (χ^2/df=1.82, CFI=0.902, IFI=0.904, RMSEA=0.071, SRMR=0.03) indicated acceptable fit. The Cronbach's alpha coefficient for the total scale was 0.89 in this study.

Work-Life Balance Scale (WLBS): The Work–Life Balance Scale, developed by Fisher, Bulger, and Smith (2009) and adapted into Turkish by Ekinci and Sabancı (2021), was used to assess participants' work–life balance[25,26]. The scale consists of 17 items rated on a 5-point Likert scale and includes four subdimensions: work interference with life, life interference with work, work enhancement of life, and life enhancement of work. The Cronbach's alpha coefficient for this study was 0.74.

Ethical Statement

This study was approved by the Ethics Committee of Istanbul Okan University (Decision No: 199, dated: March 4, 2026). The developers of the measurement instruments used in the study granted permission. Participants were told that the data collected would be used for scientific purposes only and written informed consent was obtained. They were also told that they could withdraw from the study at any moment.

Statistical Analysis

Data were analyzed using SPSS for Windows 25.0. Descriptive statistics (frequency, percentage, minimum–maximum values, mean, and standard deviation) were calculated. Normality was assessed by skewness and kurtosis coefficients. Parametric tests were applied when the data met normality assumptions. Independent samples t-tests and one-way analysis of variance (ANOVA) were used to compare differences between groups. Post hoc tests were performed with Tukey or Games–Howell depending on homogeneity of variances.

Pearson correlation analysis was used to analyze the relationships between variables, whereas multiple linear regression analysis was utilized to assess predictive relationships. A statistically significant value was established at $p<0.05$.

Results

The study included 450 academic staff members as participants. The average age of the participants was 42.42±10.37 years. Most were married (68.9%) and had a doctoral degree (83.3%). In terms of degree academic ranks, 23.8% were Assistant Professors, 23.1% were Professors and 21.6% were Research Assistants for professional experience, 27.3% had ≥21 years and 24.4% had 6–10 years.

Most participants (72.2%) were employed at state universities, and most of them also worked full-time (97.6%). The most reported weekly teaching load was 11–15 hours (28.4%), and the total weekly working time was 40–49 hours (48.7%). On the artificial intelligence (AI) usage side, 40.2% of participants have been using AI tools for 1–2 years, and 38.9% of them reported spending less than 2 hours per week on these tools. The primary purposes of AI use included translation (71.1%), academic writing and editing (64.0%), and literature review and preparation of course materials (56.0%). The most frequently used tools were ChatGPT (84.0%), Gemini (56.0%), and NotebookLM (30.4%). Those who used other tools accounted for 3.6%, while 5.6% reported using them for different purposes (Table 1).

Table 1. Results on the descriptive characteristics of individuals (n=450)

Sociodemographic Characteristics	**Min-Max**	**Mean**	**Standard Deviation**
Year	18-76	42.42	10.37
		Number (n)	**Percentage (%)**
Marital Status	Married	310	68.9
	Single	140	31.1
Education Level	Master's Degree	71	15.8
	Doctoral degree	375	83.3
	Others	4	0.9
Academic Title	Research assistant	97	21.6
	Lecturer	60	13.3
	Assistant Professor	107	23.8
	Associate Professor	82	18.2
	Professor	104	23.1
Professional Experience (Year)	0–5 years	86	19.1
	6–10 years	110	24.4
	11–15 years	85	18.9
	16–20 years	46	10.2
	21 years and over	123	27.3
Institution Type	State	325	72.2
	Private	125	2.8
Weekly Course Hours	0–5 hours	72	16.0
	6–10 hours	82	18.2
	11–15 hours	128	28.4
	16–20 hours	90	20.0
	21 hours and over	78	17.3
Weekly work hours	<40 hours	137	30.4
	40–49 hours	219	48.7
	50–59 hours	52	11.6
	≥60 hours	42	9.3
Time to start AI tools	<6 months	63	14.0
	6 – 12 months	133	29.6
	1–2 years	181	40.2
	>2 years	73	16.2
Frequency of using AI tools	<2 hours per week	175	38.9
	3–6 hours per week	153	34.0
	7–9 hours per week	58	12.9
	>10 hours per week	64	14.2

Purpose of using AI tools	Translation	320	71.1
	Writing articles	288	64.0
	Literature review	252	56.0
	Preparing course documents	252	56.0
	Data analysis	118	26.2
	E-mail communication	107	23.8
	Coding	64	14.2
	Others	16	3.6
Commonly used AI tools	ChatGPT	378	84.0
	Gemini	252	56.0
	NotebookLM	137	30.4
	Copilot	73	16.2
	Others	25	5.6

The mean total score of the participants on the Artificial Intelligence Addiction Scale (AIAS) was determined to be 11.12±4.17, and the mean total score on the Technostress Creators Scale (TCS) was 56.13±12.85. Among the sub-dimensions of the TCS, the highest mean score was for Techno-overload (14.11±4.15), followed by Techno-complexity (12.82±3.82) and Techno- uncertainty (10.32±3.47); the lowest mean score belonged to the Techno-insecurity sub- dimension (8.67±3.23). The mean total score on the Work-Life Balance Scale (WLBS) was 49.48±8.14, with the highest score among the sub-dimensions being Positive Effect of Work on Life (16.04±5.27), followed by Positive Effect of Life on Work (13.91±4.91), Negative Effect of Life on Work (10.34±2.59), and Negative Effect of Work on Life (9.19±2.81) (Table 2).

Table 2. Participants' results on AI addiction, technostress and work-life balance

Scales and Subdimensions	**Number of Items**	**Min-Max**	**Mean±SD**
AI Addiction Scale	5	5.00-23.00	11.12±4.17
Technostress Creators Scale	22	25.00-93.00	56.13±12.85
Techno-Overload	5	5.00-25.00	14.11±4.15
Terchno-Invasion	4	4.00-20.00	10.22±4.06
Techno-Complexity	5	5.00-23.00	12.82±3.82
Techno-Insecurity	4	4.00-20.00	8.67±3.23
Techno-Uncertainity	4	4.00-20.00	10.32±3.47
Work Life Balance Scale	17	19.00-74.00	49.48±8.14
Negative Effect of Work on Life	5	5.00-25.00	16.04±5.27
Negative Effect of Life on Work	6	6.00-30.00	13.91±4.91
Positive Effect of Life on Work	3	3.00-15.00	10.34±2.59
Positive Effect of Work on Life	3	3.00-15.00	9.19±2.81

According to Pearson correlation analysis results, a moderately positive and significant relationship was found between the Artificial Intelligence Addiction Scale (AIAS) and the Technostress Creators Scale (TCS) ($r=0.421$, $p<0.01$). Similarly, a moderately positive and significant relationship was found between the AIAS and the Work-Life Balance Scale (WLBS) ($r=0.347$, $p<0.01$). The relationship between the TCS and the WLBS was also moderately positive and significant ($r=0.547$, $p<0.01$) (Table 3).

Table 3. Relationship between AI Addiction Scale, Technostress Creators Scale and Work-Life Balance Scale

AI Addiction Scale			Technostress Creators Scale	Work-Life Balance Scale
AIAS	**r**	1	. 421*	.347*
p			.000	.000
TCS	**r**	. 421*	1	.547*
	p	.000		.000
WLBS	**r**	.347*	.547*	1
	p	.000	.000	

* p<0.01 significant

According to the independent samples t-test results, there was no significant difference ($p>0.05$) in the mean scores of the Artificial Intelligence Addiction Scale (AIAS), Technostress Creators Scale (TCS), and Work-Life Balance Scale (WLBS) among participants based on their marital status, type of institution, and employment type. One-way analysis of variance results showed a significant difference in AIAS scores based on education level ($F=4.759$, $p=0.009$); academics with master's degrees (12.48±4.12) had higher AI addiction scores than those with doctoral degrees (10.88±4.10). Significant differences were found in both AIAS ($F=9.028$, $p<0.001$) and WLBS ($F=6.145$, $p<0.001$) scores based on academic title. Research assistants had the highest AIAS scores (12.42±4.04), while professors had lower AIAS (9.63±3.98) and WLBS (46.48±8.30) scores compared to other titles. In terms of academic seniority, academics with 0–5 years of experience had significantly higher AIAS and WLBS scores than those with 21 years or more of experience ($p<0.05$). Weekly teaching load only affected TCS scores ($F=5.543$, $p<0.001$), and academics with 16–20 and 21 hours or more of teaching load had higher technostress levels than those with 0–5 hours of teaching load. In addition, the frequency of using artificial intelligence tools affected AIAS scores; As weekly usage increased, the level of AI addiction level, and academics who used AI for 10 hours or more per week (14.25±4.08) scored significantly higher than those who used it for 2 hours or less per week (9.82±3.91) (Table 4).

Table 4. Comparison of AIAS, TCS and WLBS Scores according to participants' sociodemographic characteristics.

Sociodemographic characteristics	**AIAS Mean±SD**	**TCS Mean±SD**	**WLBS Mean±SD**
Marital Status			
Single	11.34±4.24	56.55±12.79	49.35±7.84
Married	11.02±4.15	55.95±12.90	49.53±8.28
Test & p	t=0.761, p=.447	t=0.462, p=.645	t=-0.220, p=.826
Institution Type			
Government	11.16±4.14	56.10±12.88	49.12±8.33
Private	11.02±4.27	56.23±12.83	50.40±7.55
Test & p	t=0.302, p=.763	t=-0.101, p=.920	t=-1.496, p=.135
Mode of operation			
Full time	11.10±4.18	56.15±12.90	49.43±8.15
Partial Time	11.91±3.80	55.36±11.20	51.45±7.43
Test & p	t=0.634, p=.526	t=0.201, p=.841	t=-0.816, p=.415
Education Level			
Master Degree	12.48±4.12	57.87±12.76	50.96±7.95
Doctoral Degree	10.88±4.10	55.87±12.87	49.25±8.20
Test & p	F=4.759, p=.009*	F=1.185, p=.307	F=2.010,
			p=.135
Academic Title			
Research assistant (a)	12.42±4.04	54.79±12.91	50.02±8.05
Lecturer (b)	11.83±4.05	58.80±12.74	49.77±7.95
Assistant Professor (c)	11.85±4.03	57.66±12.80	51.82±7.80
Associate Professor (d)	10.00±4.02	55.57±12.85	49.35±8.10
Professor(e)	9.63±3.98	54.71±12.88	46.48±8.30
Test & p	F=9.028, p<.001*	F=1.654, p=.160	F=6.145,
	a, c > d, e		p<.001*
			a, c > e
Professional Experience			
0–5 years(a)	12.48±4.02	54.92±12.90	49.50±8.05
6–10 years(b)	12.02±4.03	57.51±12.84	50.80±7.98
11–15 years(c)	11.46±4.05	57.87±12.76	51.53±7.90
16–20 years(d)	9.96±4.00	54.91±12.83	48.96±8.10
≥21(e)	9.57±3.97	55.01±12.89	47.05±8.25
Test & p	F=9.485, p<.001*	F=1.236, p=.295	F=5.036,
	a, b, c > d, e		p=.001*
			b, c > e
Weekly work hours			
0–5 hours	12.24±4.05	51.11±12.71	50.13±8.10
6–10 hours	10.46±4.08	53.60±12.82	48.91±8.04
11–15 hours	10.98±4.12	57.52±12.86	48.77±8.00
16–20 hours	11.48±4.09	58.78±12.89	50.20±8.02
≥ 21 hours	10.59±4.10	58.10±12.87	49.78±8.06

Test & p	F=2.334, p=.055	F=5.543, p<.001*	F=0.654,
		c, d, e > a	p=.624
Frequency of using AI tools			
≤2 hours per week	9.82±3.91	54.87±12.71	48.12±8.01
3–6 hours per week	12.86±4.02	56.42±12.83	49.95±8.02
7–9 hours per week	13.99±4.11	57.01±12.76	50.11±8.07
≥10 hours per week	14.25±4.08	57.22±12.90	50.28±8.12
Test & p	F=18.42, p<.001**	F=1.11, p=.345	F=0.89
		b, c, d > a	p=.448

*Tukey HSD applied **Games-Howell test applied

The regression model established in terms of factors affecting artificial intelligence addiction was found to be significant (F (2, 447)=54.624, p<0.001) and explained 19.6% of the variance in AIAS scores (R^2=0.196). The analysis showed that the Technostress Creators Scale (TCS) and the Work-Life Balance Scale (WLBS) were positive and significant predictors of AIAS; TCS (β=0.330, t=6.511, p<0.001) was the strongest predictor, followed by WLBS (β=0.166, t=3.288, p=0.001). The regression model based on technology use (TCS) was also found to be significant (F (2, 447)=125.447, p<0.001) and explained 36% of the variance in TCS scores (R^2=0.360). In this model, WLBS was determined as the strongest predictor of TCS (β=0.455, t=11.287, p<0.001), and AIAS came in second place (β=0.263, t=6.511, p<0.001). Similarly, the regression model examining the effects of WLBS and TCS on work-life balance scale (WLBS) was also found to be significant (F(2, 447)=102.932, p<0.001) and explained 31.5% of the variance in WLBS scores (R^2 = 0.315). In this model, TCS was the strongest predictor (β=0.487, t=11.287, p<0.001), followed by WLBS (β = 0.142, t = 3.288, p = 0.001) (Table 5).

Table 5. Multiple linear regression analysis of the Artificial Intelligence Addiction Scale (AIAS), the Techno-Stress Creators Scale (TCS), and the Work-Life Balance Scale (WLBS)

							%95 Confidence Interval	
AIAS	Independent Variable	*B*	*SD*	*β*	*t*	*p**	Lower Limit	Upper Limit
	(Constant)	0.885	1.113	–	0.796	0.427	-1.303	3.073
	TS	0.107	0.016	0.330	6.511	0.001	0.076	0.138
	WLB	0.085	0.026	0.166	3.288	0.000	0.034	0.136
	R=0.443 R^2=0.196 Adjusted R^2=0.193 F=54.624 p<0.001 Durbin-Watson=1.538							
							%95 Confidence Interval	
TCS	Independent Variable	*B*	*SD*	*β*	*t*	*p**	Lower Limit	Upper Limit

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	(Constant)	11.538	3.012	–	3.831	0.000	5.62	17.45
	WLB	0.720	0.064	0.455	11.287	0.000	0.595	0.845
	AIA	0.809	0.124	0.263	6.511	0.000	0.566	1.052
	$R=0.600$ $R^2=0.360$ Adjusted $R^2=0.357$ $F=125.447$ $p<0.001$ Durbin-Watson=2.081							
							%95 Confidence Interval	
WLBS	Independent Variable	*B*	*SD*	*β*	*t*	*p**	Lower Limit	Upper Limit
	(Constant)	29.097	1.456	–	19.985	0.000	26.24	31.95
	AIA	0.277	0.084	0.142	3.288	0.001	0.112	0.442
	TS	0.308	0.027	0.487	11.287	0.000	0.255	0.361

$R=0.562$ $R^2=0.315$ Adjusted $R^2=0.312$ $F=102.932$ $p<0.001$ Durbin-Watson=2.011

Discussion

In this study, it was found that there were positive correlations between AI addiction, technostress, and work-life balance. Furthermore, it was determined that AI addiction and technostress significantly predict work-life balance.

Discussion of Findings on AI Addiction, Technostress and Work-Life Balance

In the literature, it was emphasized that digitally literate professionals position AI not as a threat or an addictive element, but as a 'supportive tool' that enhances their performance[27]. A recent study by Alhur et al. (2025) on educators in higher education also indicated that academics tended to verify and critically filter the content produced by AI tools, rather than passively consuming them[28].

In this study, it was revealed that academics generally experienced a moderate level of technostress. However, when the sources of stress were examined, the "Techno-overload" sub-dimension was the most dominant factor, while the "Techno-insecurity" sub-dimension was at the lowest level. As indicated in the study by Kumar et al. (2024), it was shown that technology was increasingly blurring the lines between work and private life[29].

Like other studies, this research showed that academic autonomy, knowledge, and professional status have a high impact on work-life balance, positively influencing employees' work-life balance[10]. Moreover, the fact that the 'Negative Impact of Life on Work' is higher than the interference of work with life was also consistent with research showing that family and personal responsibilities can affect the job performance of academics more in recent years[30]. This situation suggested that the role conflict developing from life to work was becoming increasingly visible among academics.

Discussion of the Relationship Between Artificial Intelligence Addiction, Technostress, and Work-Life Balance

In the literature it was stated that artificial intelligence systems were initially used to reduce workload, but as use and addiction increase, they can trigger stress factors by creating a sense of loss of professional autonomy and control in individuals[28].

The significant relationship found between artificial intelligence addiction and work-life balance in this study was compatible with studies showing that digital transformation and artificial intelligence tools disrupt the balance between professional and social roles by leading individuals towards a 'culture of being online at all times'[10]. This situation suggested that as academics integrate artificial intelligence into work processes and the level of addiction to these tools increases, the intrusive effect of technology on personal time and psychological recovery may also increase.

The most striking finding of the study, which differs from the general trend in the literature, was the positive relationship found between technostress and work-life balance. Although much of the existing literature suggested that technostress disrupts the work-life balance by consuming personal time[17,18], the results of this study indicated that academics have a high capacity for balance even under technological pressure. The last point may explain the finding that academics also experience less burnout despite increasingly having adverse demands to technology over time. While some earlier studies carried out in the context of COVID-19 much like our own found a negative impact of technostress on academics through increasing workload, complexity, uncertainty and technology-related burden[31,32], these studies also imply that technostress is not a constant state but may abate as individuals become more experienced with digital technologies. Accordingly, Boyer-Davis and Berry (2022) presented that faculty embraced less technostress over time, especially with improved computer anxiety, suggesting prolonged exposure to technology may elicit adaptation[31]. In addition, it seems that organizational factors are crucial protective factors. The positive effect of supportive organizational environments and institutional technical support is confirmed by earlier studies indicating that these conditions reduce technostress[33,] and lead to efficient work practices among university teachers. So, it is possible that academic in the present study was able to balance their work–life in spite of facing technostress as along with technological demands there were also adaptation and organizational support which were not limited to an occupational stressor. The increased use of artificial intelligence by academics who manage to maintain work-life balance can be interpreted as them using these technologies as a "productivity tool" that facilitates their lives and creates personal time for themselves[2]. In a cross-sectional study conducted with 651 academics in China, academics stated that they use artificial intelligence not only because it is "logical," but also they want to improve themselves, feel independent, or are open to innovation[34]. This situation showed that the use of artificial intelligence can be considered not only a risk factor for academics but also a functional tool that helps balance workload.

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Discussion of AI Addiction, Technostress, and Work-Life Balance Levels According to Sociodemographic Characteristics

In the present study, AI addiction scores were significantly higher among academics holding a master's degree and research assistants than among PhD holders and professors. This finding suggests that AI tools may be adopted more extensively as a strategic adaptation resource during the early stages of an academic career. One possible explanation is that early-career academics experience greater pressure to achieve academic productivity and meet institutional performance expectations, leading them to rely more heavily on AI tools. Consistent with this interpretation, previous research has reported that academics facing institutional performance expectations and publication pressure increasingly use AI tools to cope with expanding workloads and often perceive these technologies as a "lifeline"[28]. In contrast, it is noteworthy that professors and senior academics have low AI addiction scores but significantly weaker work-life balance scores compared to other groups. Indeed, the literature indicates that artificial intelligence tools provide academics with significant time savings by automating intensive administrative and academic tasks[28]. However, Cazan et al. (2024) emphasized that older and more experienced academic staff may have lower levels of digital literacy, making adaptation to new technologies more difficult and stressful for them[35]. Therefore, the findings strongly supported the thesis of Klimova and Pikhart (2025) that the increase in the level of "addiction" to artificial intelligence observed in young academics may actually be a strategic coping factor that alleviates the stress created by academic workload and protects professional well-being[5]. When the relationship between weekly teaching load and technostress was examined, it was observed that technostress increased significantly as the teaching load increased. Akbar et al. (2025) stated that the expectation of constant accessibility brought about by digital transformation leads to cognitive overload and technological burnout in educators with heavy teaching loads[10]. This finding aligns with the view that technological stress stems not only from the tool itself but also from the tool being placed as an additional 'work demand' on an already existing workload[29].

Finally, the study found that while addiction scores increased with the frequency of AI tool use, this did not significantly affect technostress or work-life balance. This suggested that even if the duration of AI use increases, academics believe this process does not create a "technological invasion," but rather demonstrates controlled use. The literature emphasized that when individuals have high levels of 'technological self-efficacy' and digital resilience, they can successfully manage this process without experiencing stress, even if the duration and intensity of technology use increase[23]. Although the high level of education and analytical skills of academics may have turned the duration of artificial intelligence use into an addiction, thanks to their self-efficacy, they may have transformed this situation from a destructive stress into a stimulating force, defined in the literature as positive stress[36,37].

Discussion of Findings Regarding the Prediction of AI Addiction in Terms of Technostress and Work-Life Balance

When the factors predicting AI addiction were examined in the study, it was seen that both technostress and work-life balance significantly and positively affected this addiction. In the literature, the potential of artificial intelligence to reduce workload and automate processes for academics was emphasized as the main driving force behind the trend towards these tools[38]. In this context, Alhur et al. (2025) stated that educators under high performance expectations and publication pressure become dependent on artificial intelligence with the motivation to cope with increasing workload and speed up work processes[28].

The results obtained in the context of the predictors of technostress revealed that both work-life balance and AI addiction increase the level of technostress. The literature suggested that the effort to balance work and private life using technological tools paradoxically triggers feelings of "technological invasion" and "overload." High dependence on AI tools forces academics into continually digital interaction and increases mental fatigue, which is a primary component of technostress[18]. Bottaro et al. (2024) demonstrated that excessive technology use deprived the work environment of spatial and temporal boundaries; this case blurred the line between professional demands and private life, significantly disrupting work- life balance[18]. Studies by Agarwal and Goel (2024) indicated that the positive effects of AI on workload management and efficient time management allowed employees to create personal time for themselves[39]. In conclusion, AI addiction and technostress function not as burnout factors for academics but rather as strategic components used to harmonize work and private life roles in the digital age.

Conclusion

This study suggested that the relationship between academics in Turkey, which is at the center of digital transformation, have with artificial intelligence (AI) tools was not only a destructive source of "addiction" or "stress" from the perspective of employee health, as it was commonly believed, but can also function as a strategic mechanism that harmonizes professional and personal life. The most fundamental finding obtained because of the research was that academics use AI tools not as an uncontrolled and pathological tendency, but as a "productivity lever" that alleviates the workload under the pressure of academic productivity. The conclusion reached because of the analyses, that "technostress and artificial intelligence addiction positively affect work-life balance," draws a unique "academic adaptation" picture, deviating from the traditional approaches in the literature that technostress always disrupts the balance.

When sociodemographic findings were examined, it was seen that young academics and research assistants, thanks to their digital aptitude, manage their workloads by turning more towards AI, thus creating time for their private lives (maintaining work-life balance). To conclude, heavy use (addiction) of academics to AI is essentially a "functional adaptation" device designed to cope with the increasing pace and manage the boundaries between work-life and private life in the digital age. But this functional use also conceals long-term hidden dangers to mental health, such as cognitive fatigue, loss of professional autonomy, and the pressure of being “always available.

Recommendations

University administrations should consider the AI integration process not merely through a technical infrastructure lens, but as an exercise in developing "human-centered" policies that promote employee well-being. The foundation of a secure digital working environment should be developed to help academics see AI as an ally rather than an adversary. Institutional-level initiatives are necessary: continuous training in digital literacy and technical support mechanisms to minimize technostress levels and strengthen technological adaptation of older and more senior academics should be applied. To counteract the “always being on” phenomenon caused by digitalization, academics should regulate their digital accessibility (email, messages from students, etc.) beyond working hours, and institutional limits should be set to allow for a clear distinction between work life and private life. Academics should refrain from giving up their own pedagogical autonomy and critical thinking skills by submitting to the comforts of AI tools by employing a “critical evaluator” stance when using these tools, confirming content rather than passively consuming them. Technology breaks should be scheduled throughout the day when you fully disconnect from your screens and digital notifications to avoid cognitive overload and mental fatigue.

Limitations and Future Research

This study is a cross-sectional survey and does not reflect changes over time. Future research could also incorporate longitudinal studies to monitor the long-term impacts of AI usage on academics (e.g., potential risks for burnout or loss of autonomy that may emerge over time).

Acknowledgements: No financial support was received for this study.

Conflict of Interest: The authors declare that they have no conflicts of interest.

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