Original Article

Attitude Towards Artificial Intelligence as a Mediator of the Relationship Between Job Workload, Academic Performance, and Psychological Well-Being Among Malaysian Academicians

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Abstract

Background: **Academicians in Malaysian public universities are facing increasingly heavy workloads and performance-related pressures, which may adversely affect their psychological well-being. Given the rapid integration of artificial intelligence (AI) in academia, it is essential to understand how attitudes towards AI influence academicians' workload and performance outcomes. This study examined the mediating role of attitude towards AI in affecting the relationship between job workload, academic performance, and psychological well-being among academicians.**

Methods: **A cross-sectional quantitative study was conducted among 465 academicians from Universiti Sains Malaysia, Universiti Teknologi MARA, and Universiti Malaysia Perlis. Four validated instruments were implemented to measure job workload, academic performance, general attitude towards AI, and psychological well-being. Mediation analysis was conducted using structural equation modelling, with job workload and academic performance as independent variables, attitude towards AI as the mediator, and psychological well-being as the dependent variable.**

Results: Attitude towards AI fully mediated the relationships between job workload and academic performance with psychological well-being, as evidenced by their significant indirect effects on job workload (Std β = −0.326, P = 0.004) and academic performance (Std β = 0.394, P < 0.001), while their direct effects on psychological well-being became non-significant (P > 0.05).

Conclusion: **Attitude towards AI acts as a psychological link between job workload, academic performance, and psychological well-being. Embracing a positive and confident attitude towards AI may help protect academicians' psychological well-being amidst the changing atmosphere created by ongoing technological transformation.**

Keywords: *academic performance, artificial intelligence, job workload, mediation study, psychological well-being*

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Introduction

Over the last few decades, the role of academicians in public universities has evolved significantly. While teaching and mentoring remain central, they are now entrusted with a wider range of responsibilities, including delivering lectures, publishing in high-impact journals, securing competitive research grants, engaging in international collaborations, and contributing to institutional administration (1). In Malaysia, the combined influence of global and local educational reforms has made these expectations more demanding in recent years. Public universities, in particular, have been increasingly pressured to improve global rankings, produce impactful research, and ensure graduates are well prepared for a dynamic workforce (2). While these goals are commendable and attainable, academicians, as the primary drivers of these initiatives, face increasingly heavier workloads as they must draw upon their physical, cognitive, and emotional capacities to meet such expectations.

The issue of workload has become increasingly significant among academicians in public universities (3). Their job scopes stretch beyond normal classroom hours, including preparing course materials, supervising students, conducting competitive research, executing research funding applications, attending administrative meetings, and responding to continuous performance audits (4–6). The difficulty of juggling these multiple roles has a negative impact on academic productivity and institutional performance, as well as the physical and psychological health of lecturers (7, 8). Indeed, workload burden has been reported as a major stressor that affects psychological well-being at work (5, 9, 10).

Performance evaluation, particularly in Malaysian universities, places strong emphasis on publications in indexed journals, student satisfaction scores, grant funding, research impact, and global visibility (11). Although such measures can encourage academic excellence, the intense competition among public universities also creates pressure that fuels stress and anxiety, which in turn risks the psychological well-being of academicians (5). Recent studies also reported high stress levels and mental health issues among Malaysian academicians, including anxiety, depression, and reduced job satisfaction (12–15). If left unaddressed, these issues can cause disengagement, diminished productivity, and even turnover intentions (16–18).

Simultaneously, artificial intelligence (AI) has transitioned from a futuristic concept to a practical tool in higher education. Integrating AI into academic settings via adaptive learning platforms, intelligent tutoring systems, and generative AI applications has demonstrated potential to reduce repetitive tasks, enhance productivity, and even provide new insights (19, 20). However, the successful implementation of AI depends largely on the attitudes of academicians towards these technologies. While some educators view AI tools as efficient and empowering, others approach them with scepticism and concern over ethical implications and loss of autonomy (21–23).

Given these considerations, the present study aims to investigate the role of attitude towards AI as a mediating factor in the relationship between job workload, academic performance, and psychological well-being among academicians in Malaysian public universities. This study is significant because it addresses the escalating issue of psychological well-being among Malaysian academicians arising from job demands and performance expectations, which is a concern that affects both individual health and institutional productivity. This study also integrates the variable of attitude towards AI as a mediating factor, thus providing insights into how technology adoption may reshape work-related stress in academic settings.

Specifically, the objective of the study is to determine whether attitude towards AI mediates the relationship between: i) job workload and psychological well-being; and ii) academic performance and psychological well-being.

Methods

Study Design

This study employed a quantitative research design using a cross-sectional approach, which is an appropriate method to test the hypothesised relationships between latent variables and capture perceptions at a specific point in time.

Participants and Sampling

The target population consisted of academicians from Malaysian public universities, namely Universiti Sains Malaysia (USM) main campus, Universiti Teknologi MARA (UiTM) Shah Alam, and Universiti Malaysia Perlis (UniMAP). A simple random sampling technique was employed within each of the three participating universities to capture variation across faculties and academic ranks among academicians in Malaysian public universities. The inclusion criteria stipulated that the respondents, regardless of being local or foreign, must be permanent or contract academic staff holding at least a tertiary-level qualification. Academicians in top management positions were excluded, as their job responsibilities and workloads differ from those of teaching lecturers.

The sample size was determined based on a sample size calculation with the following parameters: effect size of 0.02, significance level of 0.05, statistical power of 80%, and three predictor variables (24). After accounting for a 10% dropout rate, the final target sample was anticipated to have 612 participants, with 204 participants equally allocated across the three universities.

Instruments

The study employed a set of validated and adapted self-administered questionnaires to measure job workload, academic performance, attitude towards AI, and psychological well-being. It incorporated four standardised, validated instruments: a job workload scale, an academic performance scale, a General Attitude towards Artificial Intelligence Scale, and a psychological well-being scale, administered within the context of Malaysian public universities. The complete item sets for all four instruments, as administered in this study, can be referred in the Appendix.

The job workload scale was originally developed by Houston et al. (25) and validated using local respondents. The instrument comprises 13 items that capture workload perceptions across teaching, research, and administrative responsibilities (five-point Likert scale). Since some items describe a light workload, these were reverse-scored so that, across all items, higher scores consistently indicate a heavier perceived workload.

The academic performance scale was originally developed by Abubakar et al. (11) and validated using local respondents. The 11-item questionnaire measures university-level academic performance, including academic reputation, graduate employability, research output, internationalisation, faculty quality, and resource availability (five-point Likert scale), with higher scores indicating stronger perceived performance.

The General Attitude towards Artificial Intelligence Scale was locally validated for this study (26). The validated version contains 14 items rated on a five-point Likert scale, which covers both positive items (opportunities, benefits, positive emotions) and negative items (concerns and negative emotions), with higher scores reflecting more favourable attitudes towards AI. Items in the negative dimension (concerns and negative emotions) were reverse-scored before the total score was calculated, so that higher scores consistently indicate more favourable attitudes towards AI.

The psychological well-being scale, originally from Ryff's Psychological Well-being Scale, was locally validated (27). It contains 15 items covering self-acceptance, positive relations with others, personal growth, environmental mastery, and autonomy (seven-point Likert scale), where higher totals reflect stronger well-being. For each scale, band cut-offs classified respondents into low, moderate, and high groups.

Data Collection

Data collection was carried out from April 2025 to June 2025. The study questionnaires were distributed via Google Forms to the participants' institutional mailing addresses, and reminder emails were sent at two-week intervals to encourage participation.

Participation was entirely voluntary, and informed consent was obtained before proceeding to the survey. Ethical approval was obtained from the Human Research Ethics Committee of Universiti Sains Malaysia (approval code USM/JEPeM/KK/24010097). All procedures were conducted in accordance with relevant guidelines and regulations, including the Declaration of Helsinki. Participants were fully informed about their right to withdraw from the study, as well as the anonymity and confidentiality of their responses to protect their privacy.

Statistical Analysis

The hypothesised model was tested with covariance-based structural equation modelling in IBM SPSS Amos (version 24.0; IBM Corp., Armonk, NY, USA), using maximum likelihood estimation. Mediation analysis was conducted using the bootstrapping method with 5,000 resamples to estimate the indirect effects of job workload and academic performance on psychological well-being through attitude towards AI. Statistical significance was established at a 95% confidence interval (CI) or $P < 0.05$. The indirect effect was considered significant if the CI did not include zero.

Results

Sociodemographic Characteristics

A total of 465 valid responses were obtained from academicians across public universities, representing a response rate of 76.0%. The demographic characteristics of the respondents are presented in Table 1.

More than half of the respondents were female (59.4%), while 40.6% were male. The mean age was 41.30 years (SD = 6.77), with 81.7% being married. Most participants identified as Malay (88.4%), with smaller proportions of Chinese (6.4%), Indian (2.2%), Indigenous Sabah/Sarawak (0.8%), and international respondents (2.2%). In terms of academic position, the largest group was senior lecturers (60.2%), followed by lecturers (21.1%), associate professors (15.9%), and professors (2.8%). Most respondents held a PhD (81.9%), while 18.1% possessed a Master's degree.

Participants were almost equally distributed across universities: UiTM (31.6%), UniMAP (34.2%), and USM (34.2%). In terms of faculty type, the majority were from engineering (36.6%), followed by science and technology (26.5%), social sciences and humanities (15.5%), architecture, planning and design (11.2%), and business and management (10.3%).

Descriptive Findings

Table 2 presents the descriptive statistics for the four study variables. Overall, academicians reported a moderate level of job workload (M = 35.38, SD = 6.99), a high level of academic performance (M = 44.51, SD = 5.94), a moderately positive attitude towards AI (M = 52.57, SD = 7.02), and a high level of psychological well-being (M = 78.57, SD = 10.86).

Table 1. Sociodemographic characteristics of participants (N = 465).

Variable	Frequency (%)	Mean (SD)
Gender		
Male	189 (40.6)	
Female	276 (59.4)	
Age (years)		41.30 (6.77)
< 40	212 (45.6)	
40 to 60	248 (53.4)	
> 60	5 (1.0)	
Ethnicity		
Malay	411 (88.4)	
Chinese	30 (6.4)	
Indian	10 (2.2)	
Indigenous Sabah/Sarawak	4 (0.8)	
International	10 (2.2)	
Academic position		
Lecturer	98 (21.1)	
Senior lecturer	280 (60.2)	

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Table 1. (*continued*)

Variable	Frequency (%)	Mean (SD)
Associate professor	74 (15.9)	
Professor	13 (2.8)	
University		
UiTM	147 (31.6)	
UniMAP	159 (34.2)	
USM	159 (34.2)	
Faculty type		
Engineering	170 (36.6)	
Science and technology	123 (26.5)	
Business and management	48 (10.3)	
Social sciences and humanities	72 (15.5)	
Architecture, planning and design	52 (11.2)	
Education level		
Master's degree	84 (18.1)	
PhD	381 (81.9)	
Marital status		
Single	77 (16.6)	
Married	380 (81.7)	
Divorced/widowed	8 (1.7)	

SD = standard deviation.

Table 2. Descriptive profile of the study variables.

Variable	Level	*n* (%)	Mean (SD)	Minimum	Maximum
Job workload	Low	115 (24.73)	35.38 (6.99)	16	55
	Moderate	323 (69.46)			
	High	27 (5.81)			
Academic performance	Low	12 (2.58)	44.51 (5.94)	17	55
	Moderate	55 (11.83)			
	High	398 (85.59)			
Attitude towards AI	Low	2 (0.43)	52.57 (7.02)	31	70
	Moderate	219 (47.10)			
	High	244 (52.47)			
Psychological well-being	Low	5 (1.08)	78.57 (10.86)	26	103
	Moderate	171 (36.77)			
	High	289 (62.15)			

SD = standard deviation; Job workload, academic performance, and the attitude towards artificial intelligence scale were measured using a five-point Likert scale. The psychological well-being scale was measured using a seven-point Likert scale.

The data also met the assumption of univariate normality. Based on Kline's recommended thresholds for large samples (|skewness| < 3.0 and |kurtosis| < 10.0), all variables were within the acceptable range. Job workload and attitude towards AI showed near-normal distributions, while academic performance (skewness = −1.898, kurtosis = 6.011) and psychological well-being (skewness = −0.589, kurtosis = 1.675) were slightly negatively skewed but remained within acceptable limits. Therefore, the assumption of univariate normality was satisfied.

Measurement Model

Composite reliability (CR) and average variance extracted (AVE) were computed for each latent construct using the standardised factor loadings derived from the confirmatory factor analysis (Table 3). Every construct evaluated in this study recorded a CR ranging from 0.705 to 0.911, which has successfully surpassed the universally accepted reliability threshold of CR ≥ 0.70 (28), demonstrating robust internal consistency across all measures.

Table 3. Standardised factor loadings, composite reliability, and average variance extracted for the latent constructs.

Latent construct	Item indicator	Standardised loading (*β*)	CR	AVE
Job workload				
Workload management	JW1	0.74	0.705	0.448
	JW2	0.71		
	JW3	0.54		
Teaching and research	JW4	0.82	0.727	0.360
	JW5	0.64		
	JW6	0.56		
	JW8	0.45		
	JW9	0.45		
Work environment	JW10	0.58	0.786	0.428
	JW11	0.51		
	JW12	0.71		
	JW13	0.75		
	JW14	0.69		
Academic performance				
	AP1	0.71	0.910	0.481
	AP2	0.66		
	AP3	0.69		
	AP4	0.70		
	AP5	0.73		
	AP6	0.71		
	AP7	0.71		
	AP9	0.72		
	AP10	0.69		
	AP11	0.66		
	AP12	0.64		

(*continued on next page*)

Table 3. (*continued*)

Latent construct	Item indicator	Standardised loading (β)	CR	AVE
Attitude towards AI				
Positive	AI1	0.65	0.911	0.565
	AI2	0.80		
	AI3	0.82		
	AI4	0.87		
	AI5	0.77		
	AI6	0.63		
	AI7	0.71		
	AI8	0.73		
Negative	AI15	0.62	0.877	0.547
	AI16	0.70		
	AI17	0.84		
	AI18	0.84		
	AI19	0.75		
	AI20	0.66		
Psychological well-being				
Self-acceptance	PWB1	0.82	0.818	0.600
	PWB2	0.79		
	PWB5	0.71		
Positive relations with others	PWB6	0.54	0.705	0.448
	PWB13	0.70		
	PWB16	0.75		
Personal growth	PWB11	0.82	0.845	0.646
	PWB12	0.79		
	PWB14	0.80		
Environmental mastery	PWB4	0.88	0.807	0.593
	PWB8	0.85		
	PWB9	0.53		
Autonomy	PWB15	0.94	0.885	0.721
	PWB17	0.79		
	PWB18	0.81		

CR = composite reliability; AVE = average variance extracted

In terms of convergent validity, the subscales for attitude towards AI (positive: AVE = 0.565; negative: AVE = 0.547) and the majority of the psychological well-being dimensions (self-acceptance: AVE = 0.600; personal growth: AVE = 0.646; environmental mastery: AVE = 0.593; autonomy: AVE = 0.721) achieved the ideal benchmark of AVE ≥ 0.50 (28).

Conversely, the AVE values of the five constructs fell below the 0.50 threshold: workload management (AVE = 0.448), teaching and research (AVE = 0.360), work environment (AVE = 0.428), academic performance (AVE = 0.481), and positive relations with others (AVE = 0.448). To preserve content validity and optimise overall structural model fit parameters, all items within these constructs were deliberately retained. Following the statistical guidelines established by Fornell and Larcker (28), a low AVE remains psychometrically adequate if the construct's CR is higher than 0.60. Given that the CR values for all five affected constructs comfortably exceeded this benchmark (ranging from 0.705 to 0.910), the convergent validity and reliability of the model are considered statistically sufficient for subsequent analysis.

Structural Model (Direct Effect)

Structural equation modelling was employed to examine the direct relationships of job workload and academic performance with psychological well-being, using separate models for each predictor. The model indicated that job workload had a significant negative effect on psychological well-being (β = −0.229, P < 0.001), suggesting that academicians with a heavier workload were associated with lower psychological well-being. For the academic performance model, the analysis showed a significant positive effect on psychological well-being (β = 0.314, P = 0.002), indicating that academicians who perceived higher academic performance experienced better psychological well-being.

Mediation Analysis

Two structural models were fitted in IBM SPSS Amos with 5,000 bootstrap resamples, and an indirect path was counted as significant only when its 95% bias-corrected interval excluded zero.

Job Workload, Attitude towards AI and Psychological Well-Being

The model fit was acceptable (χ^2/df = 3.259, CFI = 0.919, TLI = 0.903, RMSEA = 0.071). Job workload exerted a significant total effect on well-being (β = −0.230, P = 0.019). However, when introducing the mediator, the direct workload path was no longer significant (β = 0.097, P = 0.579), whereas the indirect path remained significant (β = −0.326, P = 0.004; 95% BC CI: −1.787, −0.080). This demonstrates full mediation, such that a heavier workload would dampen the enthusiasm for AI, which in turn reduces psychological well-being (Figure 1).

Academic Performance, Attitude towards AI, and Psychological Well-Being

This model also demonstrated a good fit to the data (χ^2/df = 2.941, CFI = 0.938, TLI = 0.930, RMSEA = 0.065). Academic performance had a significant positive total effect on psychological well-being (β = 0.314, P = 0.002). Once the mediator was included, the direct effect of academic performance on psychological well-being became non-significant (β = −0.080, P = 0.628), while the indirect effect remained significant (β = 0.394, P < 0.001; 95% BC CI: 0.133, 2.122). These findings suggest full mediation, which implies that higher academic performance was associated with a more positive attitude towards AI, which in turn improved psychological well-being (Figure 2).

Table 4 summarises the total, direct, and indirect effects of job workload and academic performance on psychological well-being through the mediator.

Discussion

This study examined academicians' psychological well-being by investigating the roles of job workload and academic performance, with the attitude towards AI as the mediating mechanism. Across both models, attitude towards AI fully mediated the relationships between job workload and psychological well-being, as well as between academic performance and psychological well-being. These findings align with the objectives and propose that attitude towards AI is an important psychological mechanism through which job workload and academic performance influence psychological well-being.

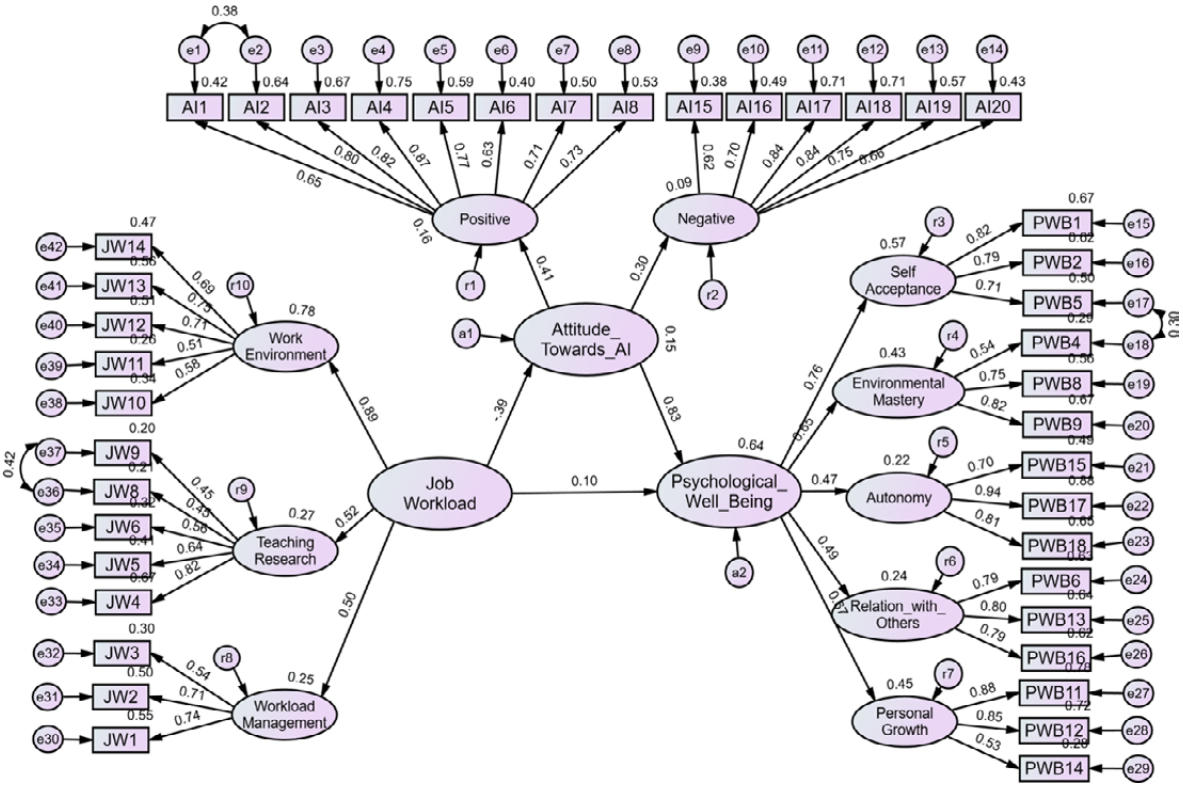


Figure 1. Mediation model of attitude towards AI between job workload and psychological well-being.

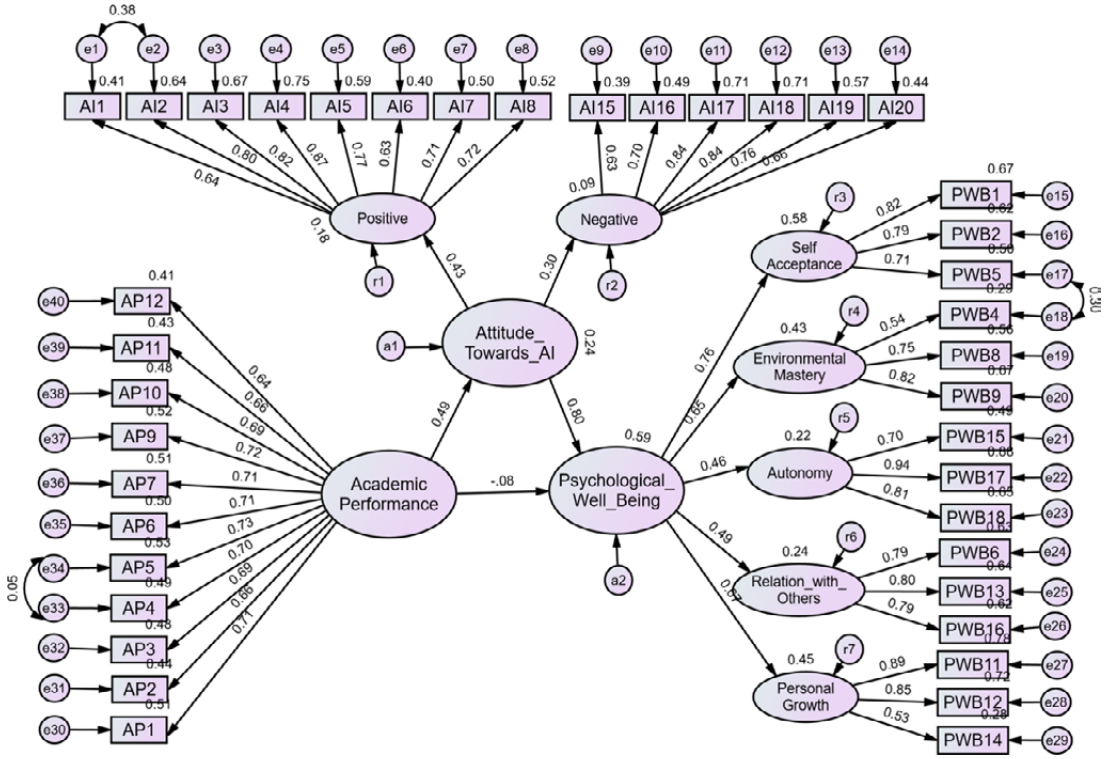


Figure 2. Mediation model of attitude towards AI between academic performance and psychological well-being.

Table 4. Total, direct, and indirect effects of job workload and academic performance on psychological well-being.

Predictor	Total β	Direct β	Indirect β	*P*-value (total)	*P*-value (direct)	*P*-value (indirect)	Result
Job workload	−0.230	0.097	−0.326	0.019	0.579	0.004	Full mediation
Academic performance	0.314	−0.080	0.394	0.002	0.628	< 0.001	Full mediation

β = standardised coefficient; mediator = attitude towards AI; 95% bias-corrected bootstrap CIs excluded zero for both indirect effects (job workload: −1.787, −0.080; academic performance: 0.133, 2.122).

The negative association between job workload and psychological well-being is consistent with previous studies, which showed that a heavy workload significantly contributes to reduced well-being and burnout among university academicians. A systematic review which involved more than 43,000 academicians also identified excessive workload, limited institutional support, and workplace conflict as the main risk factors for poor well-being (29). The present findings suggest that this relationship is partly explained by academicians' attitudes towards AI. Heavy workloads have been associated with higher levels of technostress (30), which in turn makes academics more likely to view technology negatively. Previous studies among teachers have shown that workload, role demands, and technical demands can increase digital stress, while organisational support helps reduce these negative effects (31). When academicians experience high workloads, they may perceive AI as an additional burden rather than a useful resource, which may contribute to lower psychological well-being.

Furthermore, the positive association between academic performance and psychological well-being is consistent with prior research, which suggested that better-performing employees generally report higher levels of well-being (32, 33). The present study extends this finding by showing that attitude towards AI mediates this relationship. Academicians with higher academic performance were more likely to have positive attitudes towards AI, which in turn was associated with better psychological well-being. This finding aligns with previous studies that indicated that individuals with greater technological confidence tend to perceive AI as a useful tool rather than a threat, resulting in lower technostress and better work outcomes (34, 35). These results suggest that positive attitudes towards AI may help academicians use AI to support productivity and manage work demands more effectively, thereby enhancing the psychological benefits associated with higher academic performance (36–39).

Overall, these findings suggest that attitude towards AI is more than simply a factor influencing technology adoption. It is an important psychological mechanism through which job workload and academic performance affect psychological well-being. This has practical implications for Malaysian higher education as AI becomes increasingly integrated into teaching, research, and administrative tasks. However, several limitations should be considered. As noted in the measurement model subsection, five constructs (workload management, teaching and research, work environment, academic performance, and positive relations with others) have shown that the AVE values fell below the conventional 0.50 threshold, indicating some shared item-level error. Despite their acceptable CR, these constructs should be interpreted with this limited convergent validity in mind. Job workload and academic performance were also tested in separate structural models, so the reported path coefficients do not account for the covariance between these two predictors. In addition, the sample was limited to three public universities, and this might undermine the generalisability of the findings to other higher education settings. Future research could test the positive and negative attitude dimensions as separate, parallel mediators to clarify whether they operate through the same or different pathways. Future research should also include measures of AI experience and AI literacy, and recruit participants from a wider range of higher education institutions to improve the validity and generalisability of the findings.

Conclusion

This study demonstrated that academicians' psychological well-being is shaped not only by job workload and academic performance, but critically by attitudes towards artificial intelligence. The findings suggest that workload conditions and academic performance can influence well-being primarily through how academicians perceive and engage with AI, highlighting attitude towards AI as a key psychological mechanism in digitalised academic environments. Despite being limited to public universities and not accounting for prior AI experience, the findings have provided useful insights into how technology attitudes shape mental health outcomes in higher education. Future studies are recommended to expand the scope of investigation across different academic disciplines, institutional types, and industry sectors, which could improve the generalisability of the findings or provide a more comprehensive understanding of this topic in higher education and broader professional contexts.

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Ethics of Study

All procedures involving research study participants were approved by the Human Research Ethics Committee of Universiti Sains Malaysia (approval code: USM/JEPeM/KK/24010097). All methods were performed in accordance with relevant guidelines and regulations, including the Declaration of Helsinki. Informed consent was obtained from all individual participants included in the study.

Conflict of Interest

None.

Funds

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Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Authors' Contributions

Conception and design: NSR, RI, NAG, SS, NSA, NAH
Analysis and interpretation of the data: NAA
Drafting of the article: NAA
Final approval of the article: NSR
Statistical expertise: NSR
Obtaining of funding: NSR, RI, NAG, SS, NSA, NAH
Administrative, technical, or logistic support: NSR, RI, NAG, SS, NSA, NAH
Collection and assembly of data: NAA

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