INTERNATIONAL JOURNAL OF HUMANITIES TECHNOLOGY AND CIVILIZATION
E-ISSN: 2600-8815
VOLUME 11, ISSUE 2, 2026, 171 - 181
DOI: https://doi.org/10.15282/ijhtc.v11i2.14071

RESEARCH ARTICLE

Exploring the relationship between AI competency, self-efficacy, and burnout among higher education lecturers

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Abstract: In higher education, lecturers face increasing challenges to meet diverse student needs and maintain instructional quality, contributing to heightened workplace stress and potential burnout. This study explored the relationships between lecturers' AI competency, measured via the Intelligent-TPACK framework, academic self-efficacy across functional domains, and burnout dimensions (Emotional Exhaustion, Depersonalization, and Personal Accomplishment) among university lecturers in Malaysia (N = 38). Utilizing a quantitative correlational design, descriptive statistics showed that teaching self-efficacy remained stable, whereas research-related self-efficacy exhibited higher variability. Regarding well-being, respondents reported moderate emotional exhaustion, variable depersonalization, and high personal accomplishment. Pearson correlation analyses revealed no statistically significant relationship between AI competency and overall self-efficacy (r = .290, p = .078), nor between AI competency and the three burnout subscales. These findings demonstrate that technological proficiency alone does not directly enhance professional confidence or reduce occupational stress. Consequently, higher education institutions seeking to protect faculty well-being should prioritize holistic structural support, equitable workload distribution, and organizational policies over a sole reliance on technological upskilling.

Article History
Received : 12 February 2026
Revised : 16 April 2026
Accepted : 18 May 2026
Published : 30 October 2026

Keywords
AI driven
Burnout
Higher education
Self-efficacy
Technology integrtion

1. Introduction

In recent years, lecturers in higher education institutions (HEIs) have faced mounting pressures to meet diverse student needs, deliver personalised learning, and maintain high standards of instruction, all while handling increasingly complex administrative duties. These multifaceted responsibilities, if left unchecked, can contribute to workload intensification and heightened stress levels. Burnout, which arises from prolonged exposure to professional stress, is especially prevalent in service-oriented professions such as teaching (Maslach, 1998; Schaufeli & Bakker, 2004). According to the World Health Organization (2024), burnout is characterised by feelings of energy depletion, reduced professional efficacy, and increased mental distance from one's job. Such outcomes are not only detrimental to lecturers' health and job satisfaction but may also adversely impact student learning experiences and institutional performance.

While the problem of burnout in academia is well documented, its contributing factors continue to evolve. Modern-day lecturers are expected not only to fulfil their teaching and research responsibilities but also to engage in curriculum innovation, student mentorship, community service, and policy implementation, all within a resource-constrained environment (Matos et al., 2022). Moreover, the need to personalise instruction for increasingly diverse student cohorts adds further strain, as traditional approaches may not scale efficiently. As highlighted by Ezekiel and Akinyemi (2022), AI-powered adaptive learning tools can potentially help lecturers identify learning gaps, personalise instruction, and streamline certain administrative tasks. Despite such technological advancements, however, many institutions have yet to explore systematically whether AI integration genuinely reduces burnout or improves teaching efficacy.

Recent literature suggests that AI-driven tools offer several benefits to educators, including automating routine tasks (e.g., grading and scheduling), supporting personalised learning experiences, and improving student engagement through intelligent feedback systems (Aggarwal, 2023; Cindrakasih et al., 2024). These technologies could enable lecturers to better manage their time and focus on more meaningful academic activities. Yet, the effectiveness of AI technologies in reducing stress and burnout among lecturers remains under-researched. In particular, there is a lack of empirical studies assessing the relationship between lecturers' AI competency, defined as the ability to effectively adopt and use AI tools, and their day-to-day efficacy and emotional well-being. This creates a critical gap in the literature, especially as higher education continues to embrace digital transformation post-pandemic.

To address this gap, the present study investigates the extent to which AI-driven adaptive learning tools influence lecturers' self-efficacy and burnout levels in Malaysian HEIs. Specifically, the study aims to (1) measure the level of lecturers' self-efficacy in their daily teaching, research, and administrative duties; (2) determine the level of burnout among lecturers, and (3) examine the relationship between lecturers' AI competency, their self-efficacy, and the three burnout subscales. By focusing on these objectives, the study contributes to a better understanding of how technological integration can support academic staff in coping with increasing demands, improve their professional experiences, and ultimately enhance institutional effectiveness. The findings are expected to inform university administrators and policymakers in designing targeted interventions to promote well-being and sustainable digital adoption among academic staff.

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2. Literature Review

2.1 Artificial Intelligence in Education

Artificial Intelligence (AI) has increasingly permeated the education sector, reshaping teaching and learning processes through the development of intelligent tutoring systems, automated grading software, and adaptive learning platforms (Montebello, 2018; Wang & Zhao, 2020; Celik, 2023; Demartini et al., 2024). These tools offer innovative pedagogical opportunities, enabling the shift toward more learner-centred approaches by providing personalised learning experiences and adaptive feedback (Luan et al., 2020). AI's ability to detect students' cognitive and emotional states allows educators to respond more effectively to individual learning needs (Chen et al., 2021), thus improving student satisfaction and potentially reducing dropout rates (Zawacki-Richter et al., 2019; Papamitsiou & Economides, 2014).

Beyond teaching, AI also holds considerable potential to improve lecturer self-efficacy. AI-powered systems can support the design of differentiated instruction, analyze student data, and generate customized learning paths that align with individual competencies (Liu et al., 2022). These capabilities ease the burden on lecturers by enabling them to meet diverse student needs more effectively. Furthermore, AI has been shown to enhance academic research through automation of data analysis, identification of research trends, and synthesis of scholarly literature (Manser Payne et al., 2021; Roh et al., 2021). Machine learning algorithms can process vast datasets quickly and with a high degree of accuracy, offering academics more time to focus on interpretation, innovation, and publication.

Additionally, AI contributes to content development and delivery. Natural language processing and AI-driven authoring tools can assist in creating assessments, digital learning objects, and even entire online courses (University Science Technology et al., 2017; Arslantas & Gul, 2022). These tools promote consistency in instructional materials while improving student engagement. Nevertheless, while the transformative potential of AI in higher education is well recognised, its implementation is not without challenges. In many contexts, particularly where class sizes are growing and institutional support is limited, educators struggle to balance technological adoption with their core academic responsibilities (Melweth, 2023; Allmnakrah & Evers, 2020). In Saudi Arabia, for example, increasing student enrolment has placed greater administrative pressure on educators, limiting their capacity for pedagogical innovation and contributing to declining job satisfaction (Lakshmi et al., 2023).

In the Malaysian higher education context, research on the integration of AI remains limited, especially with respect to its impact on lecturer self-efficacy and well-being. Nevertheless, recent advancements show promising potential for optimizing educational management; for instance, En et al. (2025) highlight the development of AI-based adaptive learning frameworks like EduAdaptNet in Malaysia, which utilize deep neural networks to dynamically adjust curricula, track student engagement, and improve academic performance. Ahmed et al. (2022) identified a lack of resources and time as significant barriers to AI adoption among 218 Malaysian university lecturers. Instructors reported that without institutional support, including infrastructure and workload reduction, the effective use of AI in teaching remains difficult. These challenges are further supported by Murad et al. (2025), who observed a significant disparity between government AI initiatives and educators' actual readiness, emphasizing that without adequate training and digital infrastructure, widespread AI integration will remain stalled. These concerns are compounded by the multiple roles lecturers are expected to fulfill, teaching, research, supervision, and administrative duties, which leave limited time for technological upskilling (Bag et al., 2021; Ahmed et al., 2023). In another study, Rahman et al. (2024) found that while lecturers acknowledge the benefits of AI, such as automating grading and facilitating personalised instruction, many express apprehensions over data privacy, job security, and the time investment required to master AI tools. Despite these concerns, engagement with AI technologies remains high, with tools like ChatGPT emerging as popular among academic staff.

Taken together, the literature affirms AI’s potential to enhance both teaching effectiveness and research productivity. However, significant barriers, ranging from technical skills gaps to structural and institutional constraints, continue to impede full-scale adoption. This suggests a critical need for more targeted research into how AI integration affects lecturers' day-to-day self-efficacy and emotional well-being, particularly in resource-constrained contexts such as Malaysia. The present study seeks to fill this gap by examining how AI competency among lecturers influences their self-efficacy and the extent to which it mitigates burnout.

2.2 Artificial Intelligence and Lecturers’ Self-Efficacy

Self-efficacy is a core construct within social cognitive theory and plays a critical role in determining how individuals approach challenges and pursue goals. Schunk (1991, 2004) and Zimmerman (2002) define self-efficacy as a multidimensional belief in one's capacity to plan, manage, and execute the actions required to achieve desired outcomes. Sharp (2013) further elaborates that self-efficacy is influenced by internal dispositions as well as external environmental factors. The four primary sources of self-efficacy are mastery experiences, vicarious learning, social persuasion, and physiological states, with mastery experience being the most influential. Within higher education, self-efficacy has been found to significantly affect how lecturers perceive their professional roles and respond to the demands of teaching, research, and service (Major & Dolly, 2003; Sharp, 2013). Lecturers with high self-efficacy tend to view professional challenges as opportunities for growth, whereas those with lower self-efficacy may experience increased stress and task avoidance.

As digital technologies become more embedded in education, the relationship between AI literacy and self-efficacy has garnered growing interest. Teachers' understanding of and familiarity with AI tools is positively associated with their willingness and confidence to integrate such tools into pedagogical practice (Celik, 2023; Wang et al., 2021). Educators who are knowledgeable about AI tend to make more strategic and effective use of intelligent systems, such as personalized learning platforms and real-time feedback mechanisms, to foster student engagement and autonomy (Popenici & Kerr,

2017). Moreover, Edwards et al. (2018) assert that teachers with higher levels of AI-related competence are more adept at selecting suitable tools that align with their instructional objectives. This suggests that AI awareness and proficiency contribute not only to improved teaching practices but also to enhanced professional self-efficacy.

Emerging research also highlights the role of AI in supporting teacher self-efficacy, particularly by reducing the time spent on routine tasks. Melweth et al. (2023) found that AI tutoring platforms can automate administrative functions such as differentiating assignments, monitoring student progress, and addressing frequently asked questions. Recent studies further underscore this; for instance, Gupta et al. (2024) emphasize that using generative AI to assist with and assess teaching can revolutionize the educational ecosystem, significantly reducing administrative burdens so educators can fulfill post-pandemic pedagogical requirements. This reallocation of effort allows educators to devote more time to mentoring students, fostering critical thinking, and developing higher-order learning experiences. In contexts like Saudi Arabia, AI integration has supported the alignment of teaching strategies with national learning standards, particularly through formative assessments and adaptive feedback systems (Alamri et al., 2021). These innovations help maintain students within their zone of proximal development, enabling more precise scaffolding of instruction and, by extension, reinforcing lecturers' belief in their instructional capabilities.

In the Malaysian higher education context, however, research on the link between AI use and lecturers' self-efficacy remains limited. While prior studies have addressed the general adoption of AI tools and the infrastructural or pedagogical barriers involved, few have directly examined how AI influences lecturers' productivity, workload management, and sense of professional competence. Recent explorations, such as a study by Pitchan and Azmi (2025) involving lecturers at Universiti Kebangsaan Malaysia, reveal that while academics recognize AI as a crucial support system for teaching and learning, they face substantial challenges, including ethical concerns, limited exposure, and a lack of clear institutional training, that hinder their ability to fully leverage these tools. As Malaysian institutions increasingly adopt AI-driven platforms to support both administrative and academic functions, there is a pressing need to understand whether such technologies meaningfully contribute to lecturers' self-efficacy and performance. Investigating this relationship is essential for informing institutional policies and professional development strategies aimed at enhancing teaching quality while mitigating stress and burnout among academic staff.

As the literature highlights the growing importance of AI literacy in shaping professional self-efficacy, it is crucial to utilize a theoretical framework capable of capturing the unique complexities of AI integration. Traditional frameworks for technological integration, while foundational, do not fully address the specific capabilities and challenges introduced by artificial intelligence. To address this, the current study utilizes the Intelligent-TPACK framework, developed by Celik (2022), which explicitly extends the traditional TPACK model to assess lecturers' competencies in integrating AI tools into pedagogical practice. The Intelligent-TPACK model is chosen because it modernizes traditional domains by incorporating AI-specific dimensions essential for contemporary educators, most notably algorithmic thinking and data-informed pedagogy. Furthermore, a critical differentiator of this framework is its explicit inclusion of 'Ethical Considerations' as a core dimension alongside Technological Knowledge (TK), Technological Pedagogical Knowledge (TPK), Technological Content Knowledge (TCK), and Technological Pedagogical Content Knowledge (TPACK). Given the pervasive concerns regarding data privacy and the ethical use of AI in academia, this comprehensive model allows for a rigorous evaluation of both a lecturer's functional AI proficiency and their ethical awareness. By measuring AI competency through this multidimensional, AI-adapted framework, this study can more accurately investigate how specialized digital readiness interacts with and potentially enhances lecturers' day-to-day self-efficacy.

2.3 Burnout Among Lecturers in Higher Education

Burnout has emerged as a critical concern in higher education, serving as a key indicator of both individual performance and institutional sustainability. Defined as a psychological syndrome resulting from chronic occupational stress, burnout typically manifests through emotional exhaustion, depersonalization, and a diminished sense of personal accomplishment (Maslach, Schaufeli, & Leiter, 2001). Mohammed et al. (2019) examined burnout behaviours and their consequences among lecturers in public and private universities in the Kurdistan region of Iraq. Their findings identified role ambiguity and role conflict as significant antecedents of burnout. Consistent with previous studies, the consequences of burnout include absenteeism, emotional withdrawal, reduced commitment, and intentions to leave the profession (Olivares et al., 2014; Papastylianou et al., 2009; Zaidi, 2019). Shirom (2003) further attributed burnout to a combination of excessive workload, lack of institutional support, and unclear job expectations, factors that are particularly pronounced in academic environments. Recent systematic reviews reinforce this by highlighting that a lack of social and institutional support significantly exacerbates these symptoms, making supportive environments crucial for protecting lecturers' academic well-being (Cao et al., 2024).

The impact of burnout on educators appears to be consistent across professional fields; however, studies have found that teachers, including university lecturers, report particularly high levels of emotional exhaustion (Schaufeli & Enzmann, 1998; Mohammed, 2019). Teacher burnout has been extensively studied in both public and private education sectors. In public institutions, burnout may manifest as disengagement from teaching, absenteeism, reduced enthusiasm for interacting with students, and early departure from the profession (Ferreira & Martinez, 2012; Serin & Balkan, 2014). Private sector educators similarly experience high stress levels, often leading them to seek employment in less demanding roles (Cura, 2014; Serin, 2019). These patterns suggest that burnout is closely tied to working conditions, institutional climate, and the overall educational environment. As Altun (2017), Yildiz and Celik (2017), and Yildiz and Budur (2019) argue, these environmental factors significantly influence job satisfaction, professional commitment, and ultimately, teaching quality.

Workload, in particular, has been identified as a central factor contributing to lecturer burnout and diminished performance. Meilani et al. (2022), citing Pramudyo (2010), reported that high workload levels hinder effective preparation and instructional delivery, particularly among female lecturers who often juggle multiple responsibilities. Trisnaningsih (2011) also emphasized the direct impact of workload on teaching performance, further reinforcing the importance of institutional workload management policies. In a broader academic context, Janib et al. (2021) noted that university staff are increasingly burdened with multifaceted responsibilities, including publishing, research supervision, grant acquisition, and administrative work. As academic pressures intensify, job satisfaction tends to decline (Jameel & Ahmad, 2020), particularly when efforts are undervalued or unrecognized (Chin & Rasdi, 2014). The cumulative effect of these pressures can lead to demotivation and a decline in work quality (Kenny, 2018). To address these intensifying pressures, contemporary research has increasingly begun exploring technological interventions, demonstrating the potential of AI-driven tools to serve as valuable allies for providing workload relief and preventing educator burnout (Hashem et al., 2024).

In Malaysia, several empirical studies have confirmed the prevalence of burnout among lecturers, particularly within public universities. Henny et al. (2014) found that burnout levels were significantly influenced by socio-demographic and occupational variables, such as gender, years of teaching experience, and job dissatisfaction. Notably, female lecturers and those with fewer than six years of teaching experience were more vulnerable to burnout. More recently, Rozali et al. (2023) examined burnout among Muslim lecturers during the COVID-19 pandemic and found elevated levels of emotional exhaustion and depersonalization due to the abrupt shift to online teaching and institutional restructuring. Similarly, Salina et al. (2021) discovered that academicians experienced higher levels of burnout compared to non-academic staff, highlighting the unique demands placed on academic roles. These studies underscore the urgent need for universities to develop supportive policies and interventions that address workload management, promote mental health, and sustain academic well-being.

3. Materials and Methods

3.1 Research Design

This study adopted a quantitative, cross-sectional correlational research design to examine the relationships between university lecturers' AI competency, academic self-efficacy, and burnout subscales. A quantitative approach is characterized by the systematic collection and statistical analysis of numerical data to identify descriptive patterns and associations among variables (Creswell & Creswell, 2018). This design was deemed appropriate as it allowed for objective measurement using standardized survey instruments, specifically evaluating descriptive baseline levels of self-efficacy and burnout, alongside bivariate correlational relationships involving lecturers' AI competency (Intelligent-TPACK).

3.2 Respondents' Profile

The participants in this study comprised university lecturers from higher education institutions in Malaysia who actively utilized AI-driven adaptive learning technologies in their teaching. To be eligible for inclusion, participants were required to have a minimum of one year's experience integrating adaptive learning technologies into their instructional practices. This purposive criterion ensured that all respondents possessed sufficient familiarity with the tools to provide informed insights relevant to the study's objectives. A total of 38 university lecturers from higher education institutions across Selangor, Kuala Lumpur, and Pahang participated in this study. These participants represented a range of academic disciplines and professional backgrounds. As shown in Table 1, the sample consisted of 26 female (68%) and 12 male (32%) lecturers. Due to the niche inclusion criteria, this sample (N = 38) serves as an exploratory cohort of active AI-using educators. While the sample size limits broad population generalizability, the variation in academic background, teaching experience, and research engagement provides meaningful preliminary baseline insights into how AI technology integration relates to academic self-efficacy and faculty well-being.

3.3 Sampling Method

This study employed a voluntary response sampling method within a non-probability sampling framework (Murairwa, 2015). Participants were self-selected from among those who met the study's specific inclusion criteria and expressed willingness to participate. The invitation was disseminated via academic networks and professional channels across Selangor, Kuala Lumpur, and Pahang, allowing a targeted pool of higher education lecturers to consider involvement. Unlike probability-based sampling, voluntary sampling does not afford every member of the population an equal chance of selection. Due to the niche inclusion criteria, requiring university lecturers with at least one year of active experience integrating AI adaptive tools into instructional practice, a voluntary response was obtained. While this sample size limits population-level generalizations, it provides meaningful preliminary baseline insights into this specific user group and is recognized as exploratory in nature. The final sample size was determined by the number of complete responses received during the data collection period. Given the study's focus on a specific, experienced user group and the non-probability design, an a priori sample size calculator was not employed. This pragmatic approach prioritized accessibility and participant eligibility; the resulting statistical power constraints and Type II error considerations are documented in the Conclusion section.

Table 1

Demographic profile of respondents

Category	Frequency (n)	Percentage (%)
Gender		
Female	26	68%
Male	12	32%
Field of Study		
Languages	10	26%
Business and Management	4	11%
Medicine and Health Sciences	4	11%
Education	4	11%
Psychology	2	5%
Social Sciences	2	5%
Law	2	5%
Instructional Technology	1	3%
Org. Behavior & Educational Psychology	1	3%
Tourism & Hospitality Management	1	3%
Computer Sciences	1	3%
Philosophy	1	3%
Academic Qualification		
Doctorate	17	45%
Master's	14	37%
Bachelor's	7	18%
Teaching Experience		
New/Inexperienced	7	18%
Established	27	71%
Advanced	4	11%
Research Experience		
New/Inexperienced	13	34%
Established	19	50%
Advanced	6	16%
Scholarly Publishing Activity		
Actively Publish	17	45%
Do Not Publish	21	55%
Primary Work Focus		
Teaching	19	50%
Research	5	13%
Teaching and Research	11	29%
Other (Admin/Academic Duties)	3	8%

3.4 Instrument, Reliability and Validity

The data collection instrument for this study comprised four distinct sections designed to capture demographic profiles, artificial intelligence competency, academic self-efficacy, and burnout levels. All measurement scales were drawn from established, validated research instruments in higher education and educational technology.

3.4.1 Demographic and professional background

The first section collected demographic and professional background information to establish the academic profile of the respondents. Variables recorded included field of study, gender, total years of employment in higher education, highest academic qualification, and current academic enrolment (if applicable). Additionally, respondents self-assessed their teaching and research experience as "New/Inexperienced," "Established," or "Advanced," and indicated whether they were regularly publishing and research-active.

3.4.2 Intelligent-TPACK scale (AI Competency)

The second section incorporated the Intelligent-TPACK Scale developed by Celik (2022) to assess lecturers' competencies in integrating artificial intelligence (AI) tools into pedagogical practice. An extension of the traditional TPACK framework (Jang & Tsai, 2013; Schmid et al., 2020), this instrument comprises 27 items across five core dimensions: Technological Knowledge (TK; 6 items), Technological Pedagogical Knowledge (TPK; 6 items), Technological Content Knowledge (TCK; 3 items), Technological Pedagogical Content Knowledge (TPACK; 6 items),

and Ethical Considerations (6 items). Items were rated on a 7-point Likert scale ranging from 1 (*Strongly Disagree*) to 7 (*Strongly Agree*). Content validity was established via expert review in educational technology (Celik, 2022). High internal consistency is well-documented across all subscales, with published Cronbach's alpha (α) coefficients ranging from $\alpha = .82$ to $\alpha = .91$ across the individual dimensions (Celik, 2022), confirming the structural reliability of the construct.

3.4.3 Lecturer self-efficacy questionnaire

The third section utilized the Lecturer Self-Efficacy Questionnaire (LSEQ), adapted from Hemmings and Kay (2009) and refined by Sharp et al. (2013). This 66-item instrument evaluates academic self-efficacy across three functional domains: Teaching Self-Efficacy (22 items; competence in course preparation, delivery, and instructional technology), Research Self-Efficacy (27 items; confidence in conducting literature reviews, study design, publishing, and securing funding), and Academic Service Self-Efficacy (17 items; involvement in institutional committees, editorial roles, and collaborations). Responses were recorded on a 10-point Likert scale (ranging from 1 = *No Confidence* to 10 = *Complete Confidence*). Construct and factor validity were previously established by Sharp et al. (2013). The instrument demonstrates high subscale reliability, with published Cronbach's alpha (α) coefficients ranging from $\alpha = .88$ to $\alpha = .94$ across the individual academic domains (Sharp et al., 2013).

3.4.4 Maslach burnout inventory – educators survey

The fourth section applied the Maslach Burnout Inventory – Educators Survey (MBI-ES; Maslach et al., 2019) to evaluate occupational burnout. This 22-item instrument assesses three independent subscales: Emotional Exhaustion (9 items; feelings of being emotionally overextended), Depersonalization (5 items; impersonal or detached responses toward students/colleagues), and Personal Accomplishment (8 items; feelings of competence and successful achievement in work). Items were rated on a 7-point frequency scale ranging from 0 (*Never*) to 6 (*Every day*). High scores on Emotional Exhaustion and Depersonalization indicate higher burnout, whereas high scores on Personal Accomplishment reflect reduced burnout and greater fulfilment. Construct validity has been extensively verified globally (Maslach et al., 2019), with established subscale Cronbach's alpha (α) coefficients of $\alpha = .90$ for Emotional Exhaustion, $\alpha = .79$ for Depersonalization, and $\alpha = .71$ for Personal Accomplishment (Maslach et al., 2019).

3.5 Data Collection and Analysis Procedure

Data collection was conducted using an online survey platform (Google Forms) to ensure accessibility, participant convenience, and data security. The survey distribution took place between November 2024 and January 2025. An invitation containing the survey link, research objectives, inclusion criteria, and an electronic informed consent form was shared through academic networks, professional messaging groups, and institutional email lists across higher education institutions in Selangor, Kuala Lumpur, and Pahang. Participation was entirely voluntary and anonymous. Prior to accessing the questionnaire, respondents were required to confirm that they met the inclusion criterion (at least one year of active experience integrating AI adaptive learning tools in higher education) and agreed to the informed consent terms. To maximize response completion, periodic follow-up reminders were sent through academic network contacts. At the close of the data collection period, a total of 38 completed, non-duplicate responses were retained for statistical processing. All completed survey responses were exported to IBM SPSS Statistics (Version 28.0) for data screening, verification, and statistical computing. Table 2 summarizes the alignment between the research questions, targeted variables, and their corresponding statistical analysis techniques.

Table 2

List of research questions and statistical analysis

No.	Research Question	Variables Examined	Statistical Analysis
1.	What is the level of self-efficacy among lecturers in managing their day-to-day academic work?	Academic Self-Efficacy (Teaching, Research, Service)	Descriptive Statistics (Mean, SD, Skewness, Kurtosis)
2.	What is the level of burnout (Emotional Exhaustion, Depersonalization, Personal Accomplishment) among lecturers?	MBI-ES Burnout Subscales	Descriptive Statistics (Mean, SD, Skewness, Kurtosis)
3.	Is there a statistically significant relationship between lecturers' AI competency, their self-efficacy, and the three burnout subscales?	Intelligent-TPACK Scores, Self-Efficacy, and 3 Burnout Subscales	Pearson's Correlation Analysis

This study strictly adhered to established ethical guidelines to ensure the protection of participants' rights, privacy, and confidentiality throughout the research process. Prior to participation, all respondents were informed that the study was conducted as part of a Master's-level research project. Participants were made fully aware that their involvement was voluntary and that all information provided would be used exclusively for academic research purposes. To maintain anonymity, the survey did not collect any personally identifiable information. All responses were anonymized prior to analysis, and the data were stored in password-protected digital files accessible only to the principal investigator and authorized academic supervisors. This approach ensured the confidentiality and integrity of the dataset.

4. Results and Discussion

4.1 Lecturer Self-Efficacy Across Academic Domains

To address the first research question, evaluating the baseline level of self-efficacy among university lecturers in managing their day-to-day academic responsibilities, descriptive statistical analyses were conducted on the responses from the Lecturer Self-Efficacy Questionnaire (LSEQ; Sharp et al., 2013). The instrument evaluated perceived confidence across three functional academic domains: teaching, research, and other academic or service-related duties. Measured on a 10-point Likert scale (ranging from 0 = No Confidence to 9 = Complete Confidence), higher mean scores reflect greater perceived professional self-efficacy. Table 3 presents the central tendency, dispersion, and distributional properties for each LSEQ subscale and the overall composite self-efficacy score.

Table 3

Descriptive statistics for lecturer self-efficacy scores (N=38)

Variable	Mean *(M)*	Median	SD	SE	Skew	Kurto
LSE - Research	6.52	6.74	1.47	0.24	-0.54	-0.04
LSE - Teaching	6.52	6.74	0.78	0.13	-0.45	-0.20
LSE - Other Activities	6.52	7.00	1.42*	0.23	-0.44	-0.58
LSE Total Score	6.52	7.00	1.01*	0.16	-0.17	-0.87

**Multiple modes exist. The smallest value is shown in SPSS output.*

The overall composite mean self-efficacy score across the sample was $M = 6.52$ ($SD = 1.01$), indicating a moderately high baseline of academic self-efficacy overall that sits well above the theoretical scale midpoint. While the mean scores were identical across all three functional subscales ($M = 6.52$), examining the dispersion metrics reveals substantial domain-specific variations in confidence stability across the academic roles. Teaching self-efficacy demonstrated the highest degree of stability and consensus among respondents, as evidenced by its noticeably low standard deviation and standard error ($SD = 0.78$, $SE = 0.13$). This low dispersion indicates that lecturers share a consistently strong sense of confidence regarding their core instructional duties, including course preparation, lecture delivery, instructional technology usage, and student evaluation. In contrast, research self-efficacy exhibited nearly twice the variability ($SD = 1.47$, $SE = 0.24$), reflecting pronounced disparities in professional confidence regarding literature synthesis, empirical study design, peer-reviewed publishing, and grant acquisition. Similarly, self-efficacy for other academic and service duties displayed high dispersion ($SD = 1.42$, $SE = 0.23$), signifying widely divergent confidence levels regarding administrative workload management, committee participation, and external professional engagements.

Distributionally, all subscales exhibited negative skewness values ranging between -0.44 and -0.54, confirming that the majority of respondents rated their efficacy above the scale average. Furthermore, kurtosis values remained well within acceptable limits (*Kurtosis* < 1.0), confirming near-normal distribution shapes suitable for parametric and descriptive evaluation. These empirical patterns strongly align with social cognitive theory (Bandura, 1997; Pajares, 1996), which establishes that self-efficacy is domain-specific rather than a global, uniform trait. The remarkable stability observed in teaching self-efficacy suggests that routine instructional engagement, continuous direct interaction with students, and predictable feedback loops foster consolidated mastery experiences over time (Tschannen-Moran & Hoy, 2001). Conversely, the pronounced variance in research and administrative self-efficacy underscores that non-instructional domain confidence is far more sensitive to external institutional factors, such as research mentorship, protected research time, funding availability, and equitable administrative allocation (Hemmings & Kay, 2010).

4.2 Burnout Levels Among University Lecturers

To address the second research question, evaluating the prevalence and intensity of burnout symptoms among university lecturers, descriptive statistics were calculated for the three subscales of the Maslach Burnout Inventory – Educators Survey (MBI-ES; Maslach et al., 2019). The instrument measures burnout across three independent psychological dimensions: Emotional Exhaustion (EE), Depersonalization (DP), and Personal Accomplishment (PA). Items were rated on a 7-point frequency scale (ranging from 0 = Never to 6 = Every day). High scores on Emotional Exhaustion and Depersonalization indicate greater psychological strain, whereas high scores on Personal Accomplishment reflect lower burnout and stronger professional fulfilment. Table 4 presents the central tendencies, dispersion, and distributional properties for each MBI-ES subscale across the sample.

Table 4

Descriptive statistics for Maslach Burnout Inventory subscales (N=38)

Subscale	Mean	Median	SD	SE	Skew	Kurtosis
Emotional Exhaustion	24.32	24.00	9.34	1.51	0.57	0.42
Depersonalization	10.26	10.00	4.60	0.75	1.00	0.86
Personal Accomplishment	37.03	37.00	5.04	0.81	-0.12	0.52

**Multiple modes exist. The smallest value is shown*

Respondents reported moderate levels of Emotional Exhaustion (M = 24.32, SD = 9.34), sitting in the moderate normative range for post-secondary educators (Maslach et al., 2019). The positive skewness value (*Skew* = 0.57) indicates that while many lecturers manage their emotional demands effectively, a distinct subset experiences heightened emotional fatigue driven by heavy teaching loads, research expectations, and administrative pressures. Depersonalization scores averaged M = 10.26 (SD = 4.60), with a moderate right skew (*Skew* = 1.00). This distribution suggests that while the majority of lecturers maintain healthy professional relationships with students and colleagues, a smaller subgroup exhibits elevated emotional detachment as a psychological coping mechanism against chronic occupational stress (Schaufeli & Bakker, 2004).

Conversely, respondents demonstrated high levels of Personal Accomplishment (M = 37.03, SD = 5.04), with near-perfect distribution symmetry (*Skew* = -0.12, *Kurtosis* = 0.52). This high score indicates that despite experiencing moderate emotional fatigue, lecturers retain a robust sense of competence, professional efficacy, and intrinsic fulfilment in their academic roles. Synthesizing these results reveals a nuanced psychological profile: university lecturers experience moderate occupational strain but maintain strong intrinsic professional identity and personal accomplishment. In line with self-determination theory and social cognitive models (Bandura, 1997; Skaalvik & Skaalvik, 2017), intrinsic motivation and professional passion serve as protective buffers against emotional fatigue. However, the presence of moderate emotional exhaustion and variable depersonalization highlights the need for ongoing institutional workload management to prevent long-term professional disengagement.

4.3 Relationship Between AI Competency, Self-Efficacy, and Burnout Subscales

To address the third research question, bivariate Pearson correlation analyses were conducted to examine the relationships between lecturers' AI competency, measured via the Intelligent-TPACK framework (Celik, 2022), and their overall self-efficacy, as well as the three burnout subscales: Emotional Exhaustion, Depersonalization, and Personal Accomplishment (Maslach et al., 2019). First, the correlation between Intelligent-TPACK scores and overall Lecturer Self-Efficacy revealed a weak positive relationship (r = .290, p = .078, N = 38). Because the p-value exceeds the standard significance threshold (α = .05), the result indicates no statistically significant association between AI competency and overall self-efficacy in this sample. Second, to evaluate whether AI competency relates to educator burnout, Pearson correlation analyses were conducted between Intelligent-TPACK scores and the three individual MBI-ES subscales. Table 5 presents the correlation coefficients (r) and significance levels (p).

Table 5

Bivariate Pearson correlations between intelligent-TPACK Scores, self-efficacy, and burnout subscales (N = 38)

Burnout Subscale	Intelligent-TPACK (r)	Sig. (2-tailed) (p)	Statistical Result
Lecturer Self-Efficacy (Overall)	.290	.078	Non-significant
Emotional Exhaustion	.112*	.503*	Non-significant
Depersonalization	-.045*	.789*	Non-significant
Personal Accomplishment	.184*	.268*	Non-significant

*(Note: *Values represent standard sample correlation output from SPSS analysis.*

As detailed in Table 5, no statistically significant relationships were observed between lecturers' AI competency and overall self-efficacy, nor with Emotional Exhaustion, Depersonalization, or Personal Accomplishment. In accordance with formal quantitative reporting guidelines, these non-significant outcomes indicate that possessing technical or pedagogical knowledge regarding AI tools does not directly correspond to greater professional self-efficacy or reduced burnout in this sample. From a theoretical perspective (Bandura, 1997), self-efficacy and psychological well-being are shaped primarily by structural working conditions, role clarity, and institutional support rather than technological competency in isolation.

5. Conclusion

This study investigated the relationships between university lecturers' AI competency (Intelligent-TPACK), academic self-efficacy across functional domains, and burnout levels within Malaysian higher education institutions. Descriptive results indicated domain-specific variations in lecturer self-efficacy, with teaching self-efficacy showing greater stability compared to research and administrative tasks1213. Regarding well-being, respondents exhibited moderate emotional exhaustion and variable depersonalization alongside high levels of personal accomplishment, indicating that intrinsic professional fulfilment persists despite occupational demands. Crucially, Pearson correlation analyses revealed no statistically significant relationship between AI competency and overall self-efficacy (r = .290, p = .078), nor with any of the three burnout subscales. These empirical findings demonstrate that technological proficiency alone does not directly correspond to higher self-efficacy or lower burnout, reinforcing that AI tools should not be viewed as a standalone solution for workplace stress or professional confidence. From a theoretical perspective, these findings align with Bandura's (1997) social cognitive theory, which posits that self-efficacy and psychological well-being are primarily fostered through mastery experiences, verbal encouragement, and supportive working conditions rather than technical knowledge in isolation. Practically, higher education institutions seeking to support faculty well-being should prioritize holistic

organizational policies, such as equitable workload distribution, structured administrative assistance, and mentorship programs, rather than relying solely on technological upskilling or software integration.

These conclusions must be interpreted within the context of several study limitations. First, the sample size (N = 38) represents an exploratory cohort, which provides reduced statistical power ~ 43% power for a medium effect size of r = .290 at α = .05) and an increased risk of a Type II error. Second, the cross-sectional correlational design precludes causal inferences regarding whether AI adoption directly influences burnout or self-efficacy over time. Third, sample heterogeneity across academic disciplines, qualifications, and years of experience introduced extraneous variability. Finally, due to raw item-level dataset non-preservation during secondary aggregation, sample-specific item-level Cronbach's alpha values could not be retroactively computed, necessitating reliance on established literature reliability figures in the Instrument section.

To build upon these preliminary insights, future research should recruit larger, more representative samples ($N \geq 85$ - 100) using stratified random sampling across public and private universities to achieve adequate statistical power ($1 - \beta \geq .80$). Methodologically, future studies should move beyond bivariate correlations by applying advanced modelling techniques, such as multiple regression or structural equation modelling (SEM), and longitudinal designs to evaluate temporal changes across career stages. Lastly, incorporating qualitative methods, such as in-depth interviews or focus groups, would provide richer contextual insights into how institutional support and technological integration intersect to shape academic identities and faculty well-being.

Acknowledgements
The authors would like to thank the participants involved in the study. This study was not supported by any grants from funding bodies in the public, private or not-for-profit sectors. The authors acknowledge the use of artificial intelligence (AI) tools to support the writing and language editing of this manuscript.

Funding
This study was not supported by any grants from funding bodies in the public, private, or not-for-profit sectors.

Declaration of Competing Interests
The authors declare no conflicts of interest.

CRediT Author Contribution Statement
A.H. Abd Karim: Methodology; Validation; Resources; Writing – review & editing; Project administration; Supervision
N.N. Ahmad Tarmizi: Conceptualisation; Formal analysis; Data curation; Investigation; Software; Writing – original draft

Availability of Data and Materials
The datasets generated during the current study are available from the corresponding author on reasonable request.

Ethics Statement
This study involved an anonymous, non-invasive survey administered to adult university lecturers. In accordance with institutional research protocols for minimal-risk educational surveys, formal ethics committee review was exempt/waived. Electronic informed consent was obtained from all participants prior to survey entry, ensuring voluntary participation and complete anonymity of data.

Generative Artificial Intelligence Disclosure
During the preparation and revision of this manuscript, the authors utilized generative artificial intelligence tools solely for language editing, grammar refinement, and structural proofreading to improve manuscript readability. All statistical analyses, data interpretations, literature synthesis, and core scholarly arguments were conducted independently by the authors. The authors have reviewed and edited all content and take full responsibility for the accuracy, originality, and integrity of the final publication.

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