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IMPACT OF AI ADOPTION IN HIGHER EDUCATION ON FACULTY JOB INSECURITY: AN EXAMINATION OF AI-INDUCED OCCUPATIONAL STRESS IN DEEMED AND PRIVATE UNIVERSITIES

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Abstract

The rapid integration of Artificial Intelligence (AI) into higher education has transformed instructional processes, administrative efficiency, and research productivity, yet it has simultaneously introduced new psychological and professional challenges for faculty members. This study investigates how AI adoption—measured through AI automation, AI-powered pedagogical tools, and AI-based research and data analytics—shapes faculty job insecurity and occupational stress in deemed and private universities in India. Using a quantitative research design, data were collected from 138 faculty respondents through a structured questionnaire and analyzed using Structural Equation Modeling (SEM). The results indicate that AI adoption significantly predicts job insecurity, as faculty perceive AI-driven tools as potential threats to their professional relevance, control over academic tasks, and long-term job stability. Findings also reveal that job insecurity strongly influences occupational stress, while AI-driven workload increase, role ambiguity, and mental health strain exert additional direct effects on stress levels. Collectively, these outcomes highlight the multidimensional nature of AI-induced pressure on academic staff and the need for supportive institutional strategies. The study underscores the importance of training initiatives, transparent communication, and organizational support systems that can empower faculty to adapt to technological shifts rather than experience them as threats. Although limited by its cross-sectional design and institutional scope, the research offers valuable insights for policymakers and university leaders aiming to implement AI responsibly. Future studies may explore longitudinal impacts, cross-institutional variations, and protective psychological factors related to AI integration in academia.
Keywords: Artificial Intelligence, Job Insecurity, Faculty Stress, Higher Education, Occupational Stress, Structural Equation Modelling.

Introduction

A paradigm shift in the academic functions, teaching and learning methods as well as administrative frameworks in colleges and universities has been hastened by the fast adoption of Artificial Intelligence (AI) technologies in the higher education system. Colleges and universities, especially considered and non-considered higher education institutions have also begun to utilize AI-based systems, like automated evaluation software, predictive modeling or student achievement, content-generation engines, and administrative artificial intelligence platforms. Although these technologies threaten to make work processes more efficient and decision-making more data-driven, the mentioned technologies also transform the professional competencies that are supposed to be possessed by faculty. With AI in the teaching and institutional governance becoming instrumental, faculty members must constantly develop digital skills, modify their teaching practice, and learn to work in AI-aided educational settings. This growing technological environment has opened and presented new possibilities--but has also brought about new weaknesses.

Among the most visible issues that are brought by this technological shift is the sense of job insecurity among the faculty members. As Artificial Intelligence threatens to take over traditionally human-centered work, including that of grading, content design, student support, and administrative organization, faculty feel increasingly threatened by the prospect of losing their role, professional autonomy, and sometimes their academic identity. This perceived danger is exaggerated in intimate and de facto conditions and considered universities, where competition and employment contracts are performance-based and institutional absorption of AI accelerates the worry of job security. The belief that AI would take over some or all of the instructional role adds to the development of the feeling of uncertainty, nervousness, and loss of control over the future of the profession.

These occupational uncertainties fall under the wider scope of AI-induced work stress which is a multi-dimensional issue that impacts the psychological health, job satisfaction, and overall performance of a faculty. Faculty are not only threatened with job loss but with growing workload and worries about AI-based surveillance systems are coupled with the overall burden of learning how to use new technology, and the demand to creatively incorporate technology in the teaching process as AI is implemented. The current research paper will analyse the contribution of the adoption of AI to job insecurity among faculty and place the analysis in the broader context of occupational stress caused by AI innovations. These dynamics are key to designing the institutional policies, support systems, and coping strategies that can guarantee AI revolutionizes higher education and does not jeopardize the welfare and professional stability of academic employees.

Literature Review

Adoption of AI in Higher Education

Through the introduction of Artificial Intelligence (AI) in higher education, the transformation of institutions has been speeded up by enhancing the efficiency of the administrative processes, increasing the variety of teaching and learning experiences, and improving research in scholarly studies. According to Technological Pedagogical Content Knowledge (TPACK) Framework (Mishra and Koehler, 2006), AI technologies are transforming the teaching and learning design and academic duties. In general, AI institution-wide adoption can be divided into three broad groups, namely AI Automation, AI-Powered Pedagogical Tools and AI-Based Research and Data Analytics. All these categories reorganize the faculty roles, expectations, and working conditions, thus creating the base of job insecurity and work stress.

AI Automation

Academic automation through AI employs machine learning, natural language processing, and prediction programs to facilitate grading, scheduling, and administrative coordination. Sentiment analysis and Natural language models are used to evaluate assignments by automated grading systems that avoid the need to spend as much time on manual evaluation (Zawacki-Richter et al., 2019). Timetabling systems that run with AI will be able to optimize their classroom assignments based on faculty workload and student preferences (Luckin et al., 2016). Learning patterns of students are also mapped by predictive systems and suggested personalized course of action, which enhance the efficiency of education (Holmes et al., 2021). These technologies have improved the effectiveness of operations but at the same time they are substituting ordinary academic activities that have been carried out by the faculty members, this has been a challenge to redundancy and lack of professional autonomy.

AI-Powered Pedagogical Tools

AI pedagogic technologies facilitate individualized learning, feedback in real time and student engagement. The adaptive learning systems accommodate instructional materials based on the strengths and weaknesses of learners (Nguyen et al., 2020). Virtual assistants powered by AI, including chatbots, provide instant replies to questions of the students, which helps decrease the load on the instruction (Wollny et al., 2021). Intelligent tutoring systems also provide additional learning experiences through the provision of automated feedback and gamification of learning (Chen et al., 2021). Although these instructional technologies enhance the effectiveness of teaching, they also demand redesigning of curriculum, incorporating AI-based analytics, and ongoing revision of digital literacy of the faculty, adding additional cognitive load and stress.

AI-Based Research and Data Analytics

AI has revolutionized the field of academic research with its enhanced data-processing, plagiarism and performance measurements. Plagiarism detecting tools based on deep learning, like Turnitin, reinforce academic integrity because they are efficient in identifying similarities patterns (Foltynek et al., 2020). Research analytics based on AI allow the faculty to interact with complex data sets, and engage in high-level predictive modeling (Jordan, 2019). Moreover, AI-based assessment systems determine the quality of publications, the pattern of peer-reviews, and teaching performances, encouraging the use of evidence to make decisions in higher education institutions (Zhai et al., 2021). However, the growing reliance on AI due to academic evaluation may produce a greater surveillance and performance pressure which may break faculty morale and psychological health.

Job Insecurity in the Context of AI Adoption

Job insecurity is one of the main antecedents of stress at workplace since it is a perceived threat of a job loss or something precious in the job of an employee. The Conservation of Resources (COR) Theory (1989) of Hobfoll states that employees do their best to preserve the necessary resources, such as job security, and view the automation of AI as a potential threat to resources. With AI-based grading, scheduling, and tutoring systems, fears of redundancy, skills obsolescence, or less valuable human expertise might be triggered in the context of higher education. De Witte (1999) discovered that perceived job insecurity lowers job satisfaction, job motivation, and organizational commitment, which leads to the poor performance of the employees.

In addition, Psychological Contract Theory (Rousseau, 1995) argues that the adoption of AI by institutions without clear communication and training or with no promise of job resecurity may lead to a sense of psychological obligation violation on stability and professional esteem by the faculty. These types of violations not only increase job insecurity but also promote mistrust and reduce well-being. These insecurities can be further increased in private and deemed universities, where employment contracts might be temporary and performance-based, and in which AI adoption is a major cause of occupational vulnerability.

Faculty Stress Associated with AI Adoption

Workload Increase

Even though AI is aimed to decrease the workload of the administration, its implementation often leads to a rise in the workload of the faculty. Faculty has to acquire new platforms, redesign instructional resources, handle AI-generated analytics as well as troubleshoot technical problems (Coombe et al., 2020). High job demands including technological adaptation in combination with low autonomy or institutional support result in high-strain job conditions according to Karasek Job Demand Control Model (1979). Consequently, faculty are under more psychological pressure, have more time commitments and role expectations.

Role Ambiguity

The adoption of AI will obscure the traditional role of faculty, bringing in ambiguity concerning the job tasks, power, and anticipations. With AI tools replacing tutoring, grading, and content delivery, faculty will find it hard to comprehend their new roles (Zhou and Gao, 2021). According to Role Theory (Kahn et al., 1964), poor role expectation is the cause of cognitive strain, emotional exhaustion, and low job satisfaction. Devoid of order or administrative lucidity, faculty can become insecure, underestimated, or professionally dislocated within AI-enabling settings.

Mental Health Impacts

The mental health effects of the changes posed by the introduction of AI are considerable: the fear of being replaced, a sense of constant upskilling, more surveillance, and accelerated technological change. According to the Transactional Model of Stress and Coping (Lazarus and Folkman, 1984), stress is created when individual coping resources are less than the perceived demands. Such factors as the fast spread of AI, insufficient training, and lack of institutional assistance can make faculty feel threatened by AI, which can result in anxiety, burnout, and chronic stress. These psychological health burdeners are very strong specifically in the competitive academic context where AI-generated metrics are used to determine performance assessment, promotion, and job security.

Hypotheses Development

H1: AI Automation, AI-Powered Pedagogical Tools, and AI-Based Research & Data Analytics significantly influence the Adoption of AI in Higher Education.

The implementation of AI in the university starts with the incorporation of the main technological subsystems which are automation technologies, pedagogical applications and AI-driven research analytics. AI automation simplifies routine administrative procedures, such as grading and scheduling, and makes the use of AI more efficient and presents institutions with the preparedness to use AI (Luckin et al., 2016; Holmes et al., 2021). Adaptive learning systems and virtual assistants are AI-based pedagogical tools that improve the quality of instruction and create personalized learning conditions (Nguyen et al., 2020; Wollny et al., 2021). The AI-based research and data analytics enhance academic integrity and research productivity through the detection of plagiarism and the model of large data (Foltynek et al., 2020; Jordan, 2019). These technological enablers are the primary determinants of AI adoption in higher education taken together, meaning that the more AI subsystems are used, the higher the chances of institutional AI adoption.

H2: Workload Increase, Role Ambiguity, and Mental Health Impact significantly influence the Faculty Stress Stress among faculty manifests in various ways as AI enters the systems of universities. It burdens faculty with the need to learn new technologies and update course design and deal with AI-generated analytics (Coombe et al., 2020). Role ambiguity is caused by the overlapping of the traditional teaching roles with the algorithmic decision-making where the expectations and responsibilities are not clear (Zhou and Gao, 2021). The effects of mental health occur when the high rate of technological change, fear of job loss and increased performance control causes psychological strain on psychological resilience (Lazarus and Folkman, 1984). Altogether, these subdimensions reflect the emotional, cognitive, and operational forms of stress caused by AI, which means that the problem of faculty stress is a multidimensional concept that is determined by the requirements of AI integration.

H3: Adoption of AI in Higher Education has a significant positive influence on Job Insecurity among faculty members. The adoption of AI dramatically transforms the functions of academics through uncertainty automated systems, which used to be done by faculty, which include grading, tutoring, assessment, and scheduling. Hobfoll (1989), states that the employees get stressed when their valuable resources like job security are at risk as it is shown in the Conservation of Resources (COR) Theory. With more of the teaching and administration burden being offloaded to AI-hung programs, the faculty might feel less and less relevant to what is happening, which will cause a greater fear of being removed or becoming irrelevant. Also, Psychological Contract Theory (Rousseau, 1995) defines that, with the adoption of AI, institutions that do not provide sufficient guarantees, training, or transparency lead to the disappointment of implicit expectations of job security, which generates intense feelings of insecurity. Therefore, the widespread application of AI technologies will probably increase the feeling of job insecurity among university staff.

H4: Job Insecurity significantly influences Faculty Stress among faculty members. Job insecurity is cited as one of the significant stressors at work that adversely impacts on the workforce wellbeing, motivation, as well as performance (De Witte, 1999). Fear of being substituted by AIs or becoming professionally irrelevant also adds the pressure of psychological strain, anxiety, and emotional burnout in the context of higher education. Transactional Model of Stress and Coping (Lazarus and Folkman, 1984) states that stress occurs when the personal and institutional demands surpass the individual and institutional coping resources. The lack of anticipations concerning the future of work, role ambiguity, and career continuity lead to high occupational stress. Thus, job insecurity is one of the major mechanisms by which AI adoption is also a contributor to faculty stress.

Methodology

The proposed study used quantitative research design to determine the effects of adoption of Artificial Intelligence (AI) in higher education on faculty job insecurity and work-related stress among teaching professionals in Karnataka deemed and private universities. The purposive sampling method was employed to address full-time faculty members that have personal experience with AI-based academic systems including automated grading tools, LMS analytics, AI-driven research platforms, and virtual pedagogical assistants. G*Power 3.1 (Faul et al., 2009) was used to calculate the minimum required sample size with the following parameters: $f2 = 0.15$, $\alpha = 0.05$, power $= 0.80$ which gave a recommended sample size of 129 respondents to use in the structural model. One hundred and fifty questionnaires were given out of which 138 valid questionnaires were received and kept being analyzed.

The data were collected using a structured questionnaire with 24 items measured on a five-point Likert scale. All constructs of the conceptual model AI Adoption in Higher Education (AI Automation, AI-Powered Pedagogy, AI-Based Research and Analytics), the Workforce Insecurity, and Faculty Stress (Workload Increase, Role ambiguity, Mental Health Impact) were operationalized based on four validated items that were modified by existing scales and based on theoretical background related to COR Theory, Role Theory, and the Job Demand Control Model. The instrument was pilot tested to make it understandable and edited to guarantee content validity.

The analysis of the data was performed using SPSS 26 and SmartPLS 4, and the analysis was performed in several steps (descriptive statistics, reliability testing (Cronbach alpha and Composite Reliability), validity testing (AVE, Fornell-Larcker, HTMT), multicollinearity (VIF), and Partial Least Squares Structural Equation Modeling (PLS-SEM) to test the hypothesized relationships. The direct and mediating effects were tested by bootstrapping (5,000 resamples). Such a strict methodology meant that there would be strong measurement and structural model tests of the causes of occupational stress due to AI among faculty at universities.

Data Analysis and Interpretation

The reliability and convergent validity test proved that all the constructs were employed to assess the AI adoption, job insecurity and faculty stress framework had good psychometric qualities. The alpha and composite reliability (CR) values of each construct were found to be high and were over the acceptable alpha value of 0.70 (Nunnally and Bernstein, 1994) which meant that the indicators had excellent internal consistency. The standardized factor loadings were within the range of 0.908 and 0.943, and the above is above the loading criterion of 0.70 recommended by Hair et al. (2017), which showed effective item reliability. Also, the value of the Average Variance Extracted (AVE) of all constructs such as AI Automation (AVE = 0.869), AI-Powered Pedagogical Tools (AVE = 0.882), AI-Based Research and Data Analytics (AVE = 0.866), Adoption of AI in Higher Education (AVE = 0.878), Job Insecurity (AVE = 0.830), Workload Increase (AVE = 0.838), Role Ambiguity All these findings complement the notion that each construct possesses high levels of convergent validity and represents the desired latent dimension of the broader model explaining the effects of AI on occupational stress in faculty.

Table 1: Reliability and Convergent Validity

Construct/Indicators	Indicator Loadings	Cronbach's alpha	Composite reliability	Average Variance Extracted (AVE)
AI Automation		**0.925**	**0.925**	**0.869**
AA1	**0.936**			
AA2	**0.93**			
AA3	**0.931**			
AI Powered Pedagogical		**0.933**	**0.934**	**0.882**
AP1	**0.941**			
AP2	**0.938**			
AP3	**0.939**			
AI Based Research and Data Analytics		**0.922**	**0.924**	**0.866**
AR1	**0.939**			

AR2	**0.921**			
AR3	**0.93**			
Adoption of AI in Higher Education		**0.93**	**0.931**	**0.878**
AAI1	**0.943**			
AAI2	**0.936**			
AAI3	**0.933**			
Job Insecurity		**0.897**	**0.898**	**0.83**
JI1	**0.908**			
JI2	**0.916**			
JI3	**0.909**			
Workload Increase		**0.904**	**0.908**	**0.838**
WI1	**0.908**			
WI2	**0.913**			
WI3	**0.926**			
Role Ambiguity		**0.923**	**0.927**	**0.866**
RA1	**0.94**			
RA2	**0.926**			
RA3	**0.925**			
Mental Health Impact		**0.914**	**0.915**	**0.853**
MH1	**0.922**			
MH2	**0.926**			
MH3	**0.923**			
Faculty Stress		**0.921**	**0.921**	**0.864**
FS1	**0.925**			
FS2	**0.935**			
FS3	**0.929**			

The Fornell Larcker criterion was used to discuss the discriminant validity of the measurement model, that is, that the square root of the Average Variance Extracted (AVE) of each construct (indicated on the diagonal) exceed its relationships with all the other constructs (Fornell and Larcker, 1981). The findings evidently meet this criterion: every construct, such as AI Automation (√AVE = 0.932), AI-Powered Pedagogical Tools (√AVE = 0.939), AI-Based Research and Data Analytics (√AVE = 0.930), Adoption of AI in Higher Education (√AVE = 0.937), Job Insecurity (√AVE = 0.911), Faculty Stress (√AVE = 0.929), Work It implies that the variables of AI adoption, job insecurity, and faculty stress are not overlapping and empirically distinct, so that the latent constructs of the model are being measured with no redundancy and reflect theoretically valid constructs of division between dimensions (Hair et al., 2017).

Table 2: Discriminant Validity (Fornell–Larcker criterion)

	1	2	3	4	5	6	7	8	9
AI Automation	**0.932**								
AI Based Research and Data Analytics	**-0.081**	**0.93**							
AI Powered Pedagogical	**0.092**	**0.075**	**0.939**						
Adoption of AI in Higher Education	**0.493**	**0.487**	**0.555**	**0.937**					
Faculty Stress	**0.251**	**0.253**	**0.267**	**0.459**	**0.929**				
Job Insecurity	**0.472**	**0.394**	**0.452**	**0.812**	**0.498**	**0.911**			
Mental Health Impact	**-0.038**	**0.052**	**-0.067**	**-0.018**	**0.388**	**0.029**	**0.924**		
Role Ambiguity	**0.052**	**-0.006**	**0.039**	**0.032**	**0.408**	**0.021**	**0.006**	**0.931**	
Workload Increase	**-0.037**	**0.043**	**0.04**	**0.035**	**0.416**	**0.011**	**-0.025**	**0.024**	**0.916**

4.1 Structural model assessment and hypotheses testing

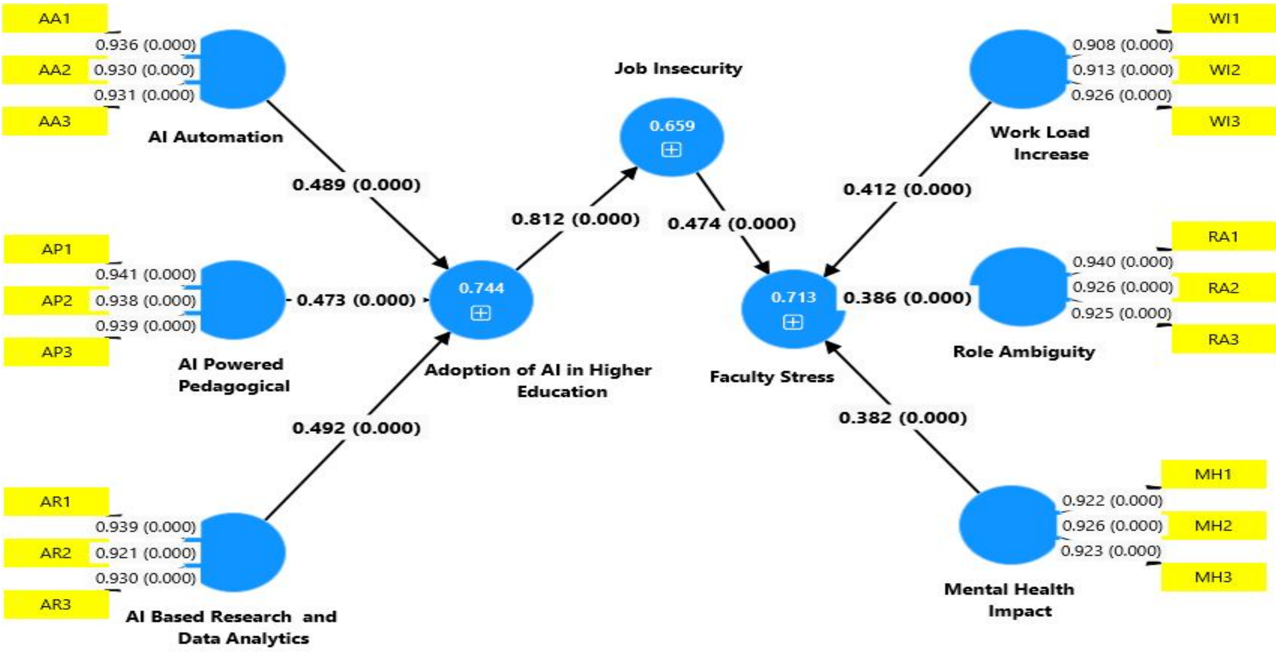

Figure 1: Structural Estimate

Table 3: Hypothesis testing result

Hypothesis	Paths	Beta	Standard deviation (STDEV)	T statistics	P values
H1	AI Automation -> Adoption of AI in Higher Education	0.489	0.028	17.462	0.000
	AI Based Research and Data Analytics -> Adoption of AI in Higher Education	0.492	0.027	18.261	0.000
	AI Powered Pedagogical -> Adoption of AI in Higher Education	0.473	0.030	15.632	0.000
H2	Mental Health Impact -> Faculty Stress	0.382	0.030	12.773	0.000
	Role Ambiguity -> Faculty Stress	0.386	0.028	13.730	0.000
	Workload Increase -> Faculty Stress	0.412	0.027	15.447	0.000
H3	Adoption of AI in Higher Education -> Job Insecurity	0.812	0.015	53.388	0.000
H4	Job Insecurity -> Faculty Stress	0.474	0.030	15.882	0.000

The results presented in the structural model indicate that all the hypothesized relationships were not less significant with p <.001. In H1, AI Automation (β =0.489, t =17.46) and AI-Powered Pedagogical Tools (β = 0.473, t =15.63) and AI-Based Research and Data Analytics (β =0.492, t =18.26) represented strong positive effects on Adoption of AI in Higher Education, which confirms that a combination of AI elements is effective in driving institutional AI uptake. In the case of H2, Workload Increase (β = 0.412, t = 15.45), Role Ambiguity (β = 0.386, t = 13.73), and Mental Health Impact (β = 0.382, t = 12.77) were all significantly relevant to higher Faculty Stress, and it is demonstrated that AI-induced job demands are a strong predictor of stress. H3 was also confirmed and indicated that Adoption of AI made a significant positive impact on Job Insecurity (β = 0.812, t = 53.39), which demonstrates that there are greater fears concerning role displacement among the faculty. Lastly, H4 was confirmed, and Job Insecurity was a significant predictor of Faculty Stress (β = 0.474, t = 15.88) and proved that insecurity is a significant psychological stressor in AI-integrated academic setting. Collectively, these findings validate the theoretical framework and support the cascading nature of the effect of AI adoption on faculty well-being.

Conclusion

The results of this research point to a paradigm but difficult change in the field of higher education when artificial intelligence starts gaining in academic and administrative processes in institutions. The findings affirm that AI Automation, AI-Powered Pedagogical Tools, and AI-Based Research and Data Analytics are very helpful in adopting AI in universities. Nevertheless, faculty well-being is not the issue without repercussions because of this institutional adoption. The review showed that AI-based transformations pose a considerable risk to the faculty, indicating that lecturers view AI as a possible risk to workplace security and role irrelevance. Furthermore, the Workload Increase, Role Ambiguity, and Mental Health Impact dimensions became the important predictors of the Faculty Stress, and it was proven that AI implementation initiates new employment requirements, uncertainties, and psychological strains. Notably, the Job Insecurity per se was also observed to accelerate the stress among faculty members, which is evidence of an indirect effect of the adoption of AI on occupational strain, namely, increased insecurity.Altogether, the research paper demonstrates a two-sided truth: although the use of AI has significant academic and practical advantages, it at the same time alters both the position of faculty and fosters fear of the job. These lessons highlight why higher education institutions need to implement human-friendly approaches to AI and focus on explicit communication, skill building, job specification, and psychological support systems to make sure that technological progress does not harm the welfare of the faculty. Through these favourable organizational cultures and open AI application guidelines, colleges can maximize the potential of AI without jeopardizing the professional safety and psychological well-being of their faculty and their overall employment prospects.

Future Implications and Limitations of the Study

This paper presents significant results of AI implementation in higher education on faculty job insecurity and occupational stress; nevertheless, there are limitations that present the opportunities to research it in the future. First, the research is based on cross-sectional evidence, which does not allow to determine long-term psychological impacts or a change in faculty perceptions with the development of AI tools, with longitudinal research in the future having the potential to monitor changes over time. Second, the study only involved faculty in a few selected deemed and private universities, which might not be quite representative of generalizing the results to public institutions or other educational settings where AI levels of adoption vary. Third, the measurement constructs relied on self-reported answers, which can be affected by social desirability or perceptual bias; a combination of qualitative interviews or behavioural data might be used to enhance the insights. These limitations notwithstanding, the results have significant implications on higher learning policy and practice in areas of ethical implementation of AI in institutions, specific training, role ambiguity, and enhancement of psychological and organizational support systems. Moderating variables that might be investigated in future studies include digital literacy, institutional culture, or leadership support to find out the protective factors that reduce the adverse impact of the AI-related job insecurity and faculty stress.

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