

Job Demands, Interpersonal Job Resources, and Job Satisfaction among Chinese University Faculty: The Moderating Role of Artificial Intelligence Use

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ABSTRACT

University faculty in China are under increasing pressure in relation to their teaching, research, administrative duties and performance evaluations, while artificial intelligence (AI) is becoming increasingly embedded in academic work. Drawing on the Job Demands–Resources (JD-R) framework, this study examines the relationship between job demands, interpersonal job resources, and job satisfaction, and investigates whether the use of AI moderates these relationships. Data were collected from 225 faculty members working at Chinese universities via an online survey. Partial least squares structural equation modelling (PLS-SEM) was conducted using SmartPLS 4.1.0.8. The results showed that job demands were negatively associated with job satisfaction, whereas interpersonal job resources were positively associated with it. AI use was found to significantly moderate both relationships. Specifically, higher AI use weakened the negative association between job demands and job satisfaction, while strengthening the positive association between interpersonal job resources and job satisfaction. The model explained 49.5% of the variance in job satisfaction. These results imply that AI use not only acts as an independent technological factor, but also influences how faculty respond to existing working conditions. This study extends the JD-R framework to AI-enabled academic work, highlighting the importance of integrating AI adoption with workload management and interpersonal support in universities.

Keywords: Artificial Intelligence Use, Job Demands, Interpersonal Job Resources, Job Satisfaction, University Faculty

INTRODUCTION

Faculty members at Chinese universities are under considerable and mounting pressure due to their teaching responsibilities, research requirements, administrative duties and performance evaluations. Research performance in particular has become an important component of faculty evaluation, and university teachers are expected to balance teaching and research responsibilities within increasingly competitive academic environments. Previous studies have shown that teaching demands, conflict between teaching and research, and research pressure are associated with emotional exhaustion, burnout, and lower job satisfaction among Chinese university faculty (Han et al., 2020; Cao et al., 2024; Z. Zhang et al., 2026). Conversely, job resources, particularly support from colleagues, supervisors, and institutions, can facilitate coping with demanding working conditions and foster more positive work experiences (Han et al., 2020; Mudrak et al., 2018). Therefore, it is important to understand how university faculty respond to high job demands and available job resources in Chinese higher education.

The growing use of artificial intelligence (AI) brings a new dimension to this issue. AI-enabled tools can assist faculty with tasks such as information retrieval, content generation, data analysis, teaching preparation, research activities and administrative work. This could potentially reduce the time and effort required for certain academic tasks. However, improved efficiency does not necessarily mean lower work pressure. As AI

becomes more widely incorporated into academic work, productivity benchmarks may rise, creating expectations for faster task completion, greater research output and the management of more responsibilities simultaneously. Recent evidence suggests that generative AI may transform rather than simply reduce academic workloads, as efficiency gains can be accompanied by new responsibilities relating to output verification, ethical judgement and academic integrity (Su et al., 2026). There are also concerns that AI-enabled productivity acceleration may challenge traditional output-based academic evaluation systems (Baciu et al., 2026). Therefore, AI may have a dual role in academic work, i.e., it can facilitate task completion while also contributing to the intensification of performance expectations.

Despite these developments, research into faculty working conditions and research into the use of AI in higher education have largely remained separate fields of study. The Job Demands–Resources (JD-R) framework has shown that job demands can reduce job satisfaction, while job resources can increase it (Han et al., 2020; Mudrak et al., 2018). Meanwhile, emerging studies have examined AI adoption, technostress and faculty well-being (Cambra-Fierro et al., 2025; Wang & Yao, 2025), but most have focused on the direct consequences of technological use. Fewer studies have examined whether AI use changes the strength of the relationships between existing job demands, job resources, and job satisfaction. This distinction is important because, while AI may help faculty manage demanding tasks, widespread AI use may also alter performance expectations and the utilisation of existing resources. To address this gap, the present study examines the relationships between job demands, interpersonal job resources, and job satisfaction among Chinese university faculty, investigating whether AI use moderates these relationships. In doing so, the study extends the JD-R framework to AI-enabled academic work, providing a more contextualised understanding of the role of AI in faculty job satisfaction.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Job Demands, Interpersonal Job Resources, and Job Satisfaction

Job demands refer to aspects of work that require sustained physical or psychological effort and therefore consume employees' energy and other personal resources (Bakker & Demerouti, 2024). In university settings, such demands may arise from heavy workloads, time pressure, competing teaching and research responsibilities, and difficult interpersonal interactions. These conditions are particularly relevant to Chinese university faculty, who often need to balance teaching, research performance, administrative responsibilities, and promotion requirements. Recent evidence shows that time-related job demands increase perceived time pressure and are associated with poorer well-being among university faculty in China (Chen et al., 2022). Similarly, both challenge and hindrance stressors have been found to negatively predict job satisfaction among Chinese university teachers (Xu et al., 2023). More broadly, recent research indicates that greater job demands, particularly long working hours and teaching workload, can undermine the well-being of Chinese faculty (Zhao et al., 2024).

In the present study, job demands capture work pace, effort, energy expenditure, time pressure, and team conflict. These indicators reflect not only the intensity of academic work but also the extent to which work consumes faculty members' time and psychological resources. Although some demanding work conditions may occasionally be experienced as motivating, the combination examined here includes persistent time pressure and interpersonal conflict, both of which are more likely to deplete resources and generate unfavorable evaluations of one's work. Faculty experiencing higher levels of these demands are therefore expected to report lower job satisfaction. Accordingly, we propose:

H1. Job Demands are Negatively Associated with Job Satisfaction.

Job resources refer to aspects of work that facilitate goal achievement, reduce the costs associated with demanding work, and support motivation and professional functioning (Bakker & Demerouti, 2024). In academic work, interpersonal resources are especially important because faculty frequently rely on colleagues and supervisors for information, feedback, coordination, emotional support, and assistance in addressing

teaching and research-related problems. Such support can reduce the need to cope with work difficulties alone and can create a more supportive evaluation of the work environment.

Recent studies provide support for this relationship in higher education. Adequate social support has been identified as an important job resource supporting university teachers' well-being, particularly in demanding academic environments (Virtanen et al., 2026). Among university teachers in Western China, perceived organizational support was positively associated with job satisfaction, partly through stronger work engagement (Chen, 2025). More recent evidence among Chinese university teachers also shows that supportive departmental leadership is positively associated with affective job satisfaction (Li et al., 2026). Because the job resources examined in the present study primarily reflect supportive relationships with coworkers and supervisors, stronger interpersonal resources are expected to help faculty deal with work problems more effectively and develop more favorable evaluations of their jobs. Thus:

H2. Interpersonal job resources are positively associated with job satisfaction.

The Moderating Role of Artificial Intelligence Use

The increasing integration of AI into academic work may change how university faculty experience existing job demands and resources. From a JD-R perspective, AI use can provide additional resources by improving efficiency, supporting task completion, and increasing autonomy, while simultaneously creating new demands associated with learning, verification, insecurity, and technological adaptation (Chuang et al., 2025; Y. Zhang et al., 2026). A recent systematic review of AI adoption in the workplace similarly shows that its consequences for employee well-being vary across work contexts and depend on how AI changes autonomy, stress, and job characteristics (Soulami et al., 2024). AI use may therefore alter the way existing job conditions are translated into employees' evaluations of their work rather than exerting only an independent effect on job satisfaction.

For university faculty facing high job demands, AI may reduce the personal resources required to complete demanding tasks. AI tools can assist with information retrieval, content preparation, data processing, drafting, and other routine or cognitively intensive activities, potentially allowing faculty to complete tasks more efficiently. Evidence from higher education indicates that AI adoption can be associated with lower stress and more positive faculty well-being (Cambra-Fierro et al., 2025; Liu et al., 2025). However, greater AI use does not necessarily eliminate work pressure. Research on academic workload suggests that generative AI may reduce effort in some routine tasks while simultaneously introducing additional responsibilities for output verification, ethical judgment, and academic integrity (Su et al., 2026). Moreover, as AI increases the speed with which academic tasks can be completed, performance expectations may also rise, potentially intensifying rather than reducing perceived demands. Thus, AI use may either help faculty cope with demanding work or contribute to new forms of work intensification. Because these competing mechanisms make the direction of the interaction theoretically uncertain, we propose:

H3. AI use moderates the association between job demands and job satisfaction.

AI use may also change how faculty benefit from interpersonal job resources. Support from colleagues and supervisors can provide information, feedback, problem-solving assistance, and guidance, while AI tools may help faculty translate such support into concrete work outputs more efficiently. For example, advice from a colleague or supervisor may be combined with AI-assisted searching, drafting, analysis, or revision, potentially increasing the usefulness of interpersonal resources. In this sense, AI use may complement rather than replace existing job resources. At the same time, greater reliance on AI may reduce the need for some forms of interpersonal interaction. Research has shown that frequent interaction with AI at work can increase feelings of social disconnection and loneliness when AI begins to substitute for interaction with human coworkers (Tang et al., 2023). Therefore, AI may either strengthen the benefits of interpersonal job resources by complementing human support or weaken them by partially substituting for interpersonal exchange. Given these competing possibilities, we propose:

H4. AI use moderates the association between interpersonal job resources and job satisfaction.

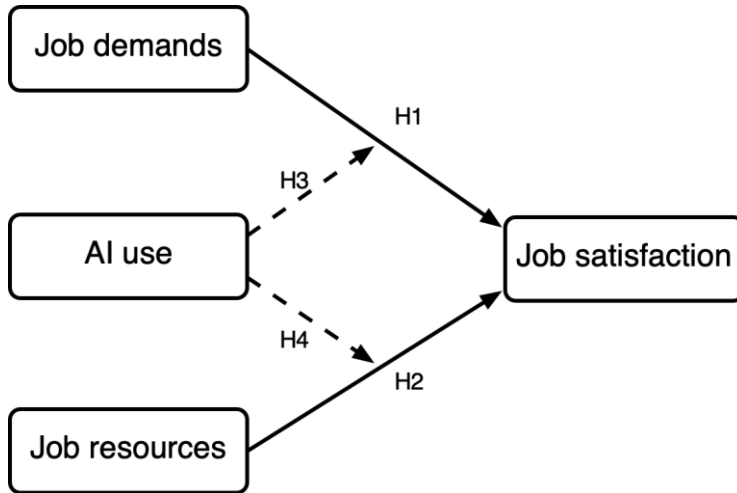


Figure 1. Conceptual framework

METHODOLOGY

Participants and Procedure

Data were collected from May 15 to June 15, 2026, through an online questionnaire administered via Wenjuanxing, a widely used online survey platform in China. The target population consisted of faculty members currently employed at Chinese universities. The questionnaire was distributed through academic and professional networks, including WeChat groups, WeChat Moments, QQ groups, and respondent referrals. Because participants were recruited through these channels rather than probability-based sampling, a nonprobability sampling approach was employed. The final sample represented faculty members from different academic disciplines and academic ranks, as well as both public and private universities. Respondents were not required to be frequent users of AI, because sufficient variation in AI use was necessary to examine its proposed moderating role.

After data screening, 225 valid responses were retained for analysis. Responses that did not meet the data-quality criteria, such as extremely short completion times or substantial missing information, were excluded. An a priori power analysis was conducted using G*Power to assess sample-size adequacy. With an effect size of $f^2=0.15$, $\alpha=0.05$, statistical power = 0.95, and five predictors in the most complex endogenous equation, the minimum required sample size was 138. The final sample of 225 therefore exceeded this requirement. As shown in Table 1, 54.7% of the respondents were male and 45.3% were female. Most respondents worked at public universities (85.8%), and the sample included faculty members from a range of academic ranks, disciplines, and levels of academic experience.

Before beginning the questionnaire, participants were informed of the purpose of the study and that participation was voluntary. They were also informed that their responses would remain confidential, would be used solely for academic research, and that they could discontinue participation at any time. Proceeding with the questionnaire indicated informed consent. The dataset used for analysis contained questionnaire responses and demographic information but no direct personal identifiers.

Table 1. Demographic Characteristics of Respondents

Variable	Category	n	%
Gender	Male	123	54.7%
	Female	102	45.3%
Age	Below 30	44	19.6%

	30–39	58	25.8%
	40–49	98	43.6%
	50–59	23	10.2%
	60 and above	2	0.9%
Highest academic qualification	Bachelor's degree or below	21	9.3%
	Master's degree	108	48.0%
	Doctoral degree	96	42.7%
Academic rank	Lecturer or below	125	55.6%
	Associate Professor	64	28.4%
	Professor	33	14.7%
	Other	3	1.3%
Years of academic experience	Less than 5 years	63	28.0%
	5–10 years	65	28.9%
	11–15 years	44	19.6%
	16–20 years	28	12.4%
	More than 20 years	25	11.1%
Academic discipline	Humanities & Social Sciences	43	19.1%
	Business & Management	39	17.3%
	Science	32	14.2%
	Engineering & Technology	42	18.7%
	Medicine & Health Sciences	25	11.1%
	Agriculture	20	8.9%
	Arts & Other	24	10.7%
University type	Public university	193	85.8%
	Private university	32	14.2%
Administrative responsibility	Yes	31	13.8%
	No	194	86.2%

Measures

The questionnaire comprised 20 items measuring job demands, interpersonal job resources, job satisfaction, and AI use. All items were rated on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The questionnaire was translated from English into Chinese and then back-translated into English. Before formal data collection, the translated wording was reviewed for clarity and relevance to the university work context. The complete measurement items and their sources are presented in Table 2. All four constructs were specified as reflective in the measurement model.

All four constructs were specified as reflective constructs. Job demands were measured using five items adapted from Metzger (2024), whose item selection was informed by Karasek’s Job Content Questionnaire. The items captured work pace, work intensity, effort, time adequacy, and team conflict. The item concerning sufficient time to complete tasks was reverse-coded. Interpersonal job resources were measured using five items adapted from Metzger (2024), capturing supportive relationships with colleagues and supervisors, access to help, and understanding from colleagues. Job satisfaction was measured using five items capturing overall job satisfaction, positive feelings about the employing organisation, workplace relationships, job security, and perceived concern from management. AI use was measured using five items adapted from the ICT-use

measure reported by Abdulkareem et al. (2024), replacing references to ICTs with AI. AI use was conceptualised as respondents' overall involvement with AI in their work. The reflective specification assumes that this underlying involvement is manifested in task-related use, interaction, perceived importance, and confidence in using AI. Accordingly, the measure represents broad work-related AI use rather than behavioural frequency alone.

Table 2 Measurements

Construct	Items	Sources
AI use	AI use1: I use AI to process and analyze data and information relevant to my job responsibilities AI use2: I make use of AI to automate and streamline repetitive tasks in my job AI use3: I find AI use to be essential for successfully carrying out my job responsibilities AI use4: I am comfortable and confident in my ability to effectively use AI in my work AI use5: I frequently interact with AI to access information necessary for my work	Abdulkareem et al. (2024)
Job Demand	JD1: My job requires me to work very fast JD2: My job requires me to work very hard JD3: I need a lot of effort in my job JD4 (R): I have enough time to do my tasks JD5:I have conflicts in the team	Metzger (2024)
Interpersonal Job Resources	JR1: I get on well with my co-workers JR2: I can ask my co-workers for help if necessary JR3: My co-workers understand if I have a bad day JR4: I get on well with my supervisors JR5: I can ask my supervisors for help if necessary	Metzger (2024)
Job satisfaction	JS1: I feel close to people at work JS2: I feel good about working at the company JS3: I feel secure about my job JS4: I believe management is concerned about me JS5: I am satisfied with my job overall	Abdulkareem et al. (2024); Macdonald & MacIntyre (1997)

Note. (R) denotes a reverse-coded item (JD4).

Data Analysis

Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to test the proposed model in SmartPLS 4.1.0.8. This method was appropriate because the study aimed to explain the variance in job satisfaction and to examine the moderating role of AI use in the relationships between job demands, interpersonal job resources and job satisfaction.

The analysis proceeded in two stages. First, the reflective measurement model was evaluated based on indicator loadings, Cronbach's alpha, composite reliability (ρ_A and ρ_C), average variance extracted (AVE) and the heterotrait–monotrait ratio of correlations (HTMT; Henseler et al., 2015). Full collinearity variance inflation factors (VIFs) were also examined as an additional diagnostic tool to detect potential common method bias (Kock, 2015). As statistical diagnostics alone cannot confirm the absence of common method variance in cross-sectional self-report data, the results were interpreted with caution (Podsakoff et al., 2003). Secondly, the structural model was evaluated using path coefficients, structural VIFs, coefficients of determination (R^2) and effect sizes (f^2). Statistical significance was assessed using 10,000 non-parametric bootstrap resamples and bias-corrected confidence intervals.

To examine the moderating role of AI use, interaction terms were included in the structural model between job

demands and AI use, and between interpersonal job resources and AI use. Significant interaction effects were further interpreted using simple slope plots at one standard deviation below and above the mean AI use score. Due to the cross-sectional and single-source design, all estimated relationships were interpreted as statistical associations rather than causal effects.

RESULTS

Measurement Model Assessment

As shown in Table 3, the measurement model demonstrated satisfactory reliability and convergent validity. Indicator loadings ranged from 0.735 to 0.882, with all items exceeding the recommended threshold of 0.70. Cronbach's alpha values ranged from 0.833 to 0.919 and composite reliability values ranged from 0.835 to 0.944 for rho_A and from 0.882 to 0.938 for rho_C. AVE values ranged from 0.599 to 0.753, exceeding the recommended threshold of 0.50 and supporting convergent validity. Full collinearity VIF values ranged from 1.140 to 1.728, indicating that there were no substantial collinearity concerns. Overall, the results support the satisfactory reliability of the indicators, the internal consistency of the model, and its convergent validity.

Table 3. Assessment of the measurement model

Constructs	Items	Factor loadings	Cronbach's alpha	Composite reliability (rho_A)	Composite reliability (rho_C)	Average variance extracted (AVE)	Full collinearity VIF
AI Use	AI use1	0.808	0.887	0.890	0.917	0.688	1.502
	AI use2	0.828					
	AI use3	0.827					
	AI use4	0.843					
	AI use5	0.840					
Job Demands	JD1	0.858	0.919	0.944	0.938	0.753	1.140
	JD2	0.860					
	JD3	0.860					
	JD4	0.882					
	JD5	0.878					
Interpersonal Job Resources	JR1	0.836	0.892	0.895	0.920	0.698	1.429
	JR2	0.805					
	JR3	0.846					
	JR4	0.856					
	JR5	0.834					
Job Satisfaction	JS1	0.735	0.833	0.835	0.882	0.599	1.728
	JS2	0.800					
	JS3	0.756					

	JS4	0.785					
	JS5	0.793					

Table 4 shows the HTMT results. All HTMT values were below the conservative threshold of 0.85. The highest value, 0.620, was found between AI use and job satisfaction. This indicates that the four constructs are empirically distinct, thus supporting adequate discriminant validity.

Table 4. Discriminant validity test using the HTMT criterion

Constructs	1	2	3	4
1. AI Use				
2. Job Demands	0.118			
3. Interpersonal Job Resources	0.451	0.208		
4. Job Satisfaction	0.620	0.169	0.535	

Note. HTMT values below 0.85 indicate adequate discriminant validity.

Structural Model Assessment

Table 5 presents the results of the structural model assessment. Job demands were negatively associated with job satisfaction ($\beta=-0.270$, $t=5.996$, $p<0.001$), thus supporting H1. Conversely, interpersonal job resources were positively associated with job satisfaction ($\beta=0.338$, $t=4.759$, $p<0.001$), thus supporting H2. The variance inflation factor (VIF) values for the structural paths ranged from 1.079 to 1.264, indicating that there were no substantial concerns regarding collinearity.

The model explained 49.5% of the variance in job satisfaction ($R^2=0.495$). The effect sizes of interpersonal job resources and job demands on job satisfaction were $f^2=0.178$ and $f^2=0.134$, respectively. These results suggest that job demands and interpersonal job resources both contribute meaningfully to explaining differences in faculty job satisfaction.

Moderating Role of AI Use

The moderating effects of AI use were estimated using the built-in moderation procedure in SmartPLS 4, which implements the two-stage approach. The structural model included the direct effects of job demands, interpersonal job resources, and AI use on job satisfaction, together with the AI use $\times$ job demands and AI use $\times$ interpersonal job resources interaction terms. Significance was assessed using 10,000 bootstrap subsamples and bias-corrected confidence intervals. Significant interactions were interpreted using simple slope plots at one standard deviation below and above the mean AI-use score.

The direct path from AI use to job satisfaction was positive and statistically significant ($\beta=0.463$, $p<0.001$). The interaction between job demands and AI use was also positive and statistically significant ($\beta=0.207$, $p<0.001$), supporting H3. Given the negative association between job demands and job satisfaction, the positive interaction coefficient indicates that this negative association became weaker at higher levels of AI use. The interaction effect size was $f^2=0.080$.

The interaction plots further illustrate these patterns. Figure 2 shows that the negative association between job demands and job satisfaction weakens as AI use increases. The estimated slopes at low (-1 SD), mean, and high ($+1$ SD) levels of AI use were -0.477 , -0.270 , and -0.063 , respectively. Figure 3 shows that the positive association between interpersonal job resources and job satisfaction strengthens as AI use increases, with corresponding slopes of 0.185 , 0.338 , and 0.491 . These patterns suggest that higher AI use attenuates the negative association between job demands and job satisfaction while amplifying the positive association between interpersonal job resources and job satisfaction.

Table 5. Assessment of the structural model

Relationship	β	SE	t	p	BCI		VIF	f ²	R ²
					LB	UB			
H1: Job Demands -> Job Satisfaction	-0.270	0.045	5.996	< .001	-0.327	-0.185	1.079	0.134	0.495
H2: Interpersonal Job Resources -> Job Satisfaction	0.338	0.071	4.759	< .001	0.218	0.452	1.264	0.178	
H3: AI Use x Job Demands -> Job Satisfaction	0.207	0.043	4.791	< .001	0.123	0.264	1.081	0.080	
H4: AI Use x Interpersonal Job Resources -> Job Satisfaction	0.153	0.062	2.458	.007	0.056	0.262	1.103	0.037	

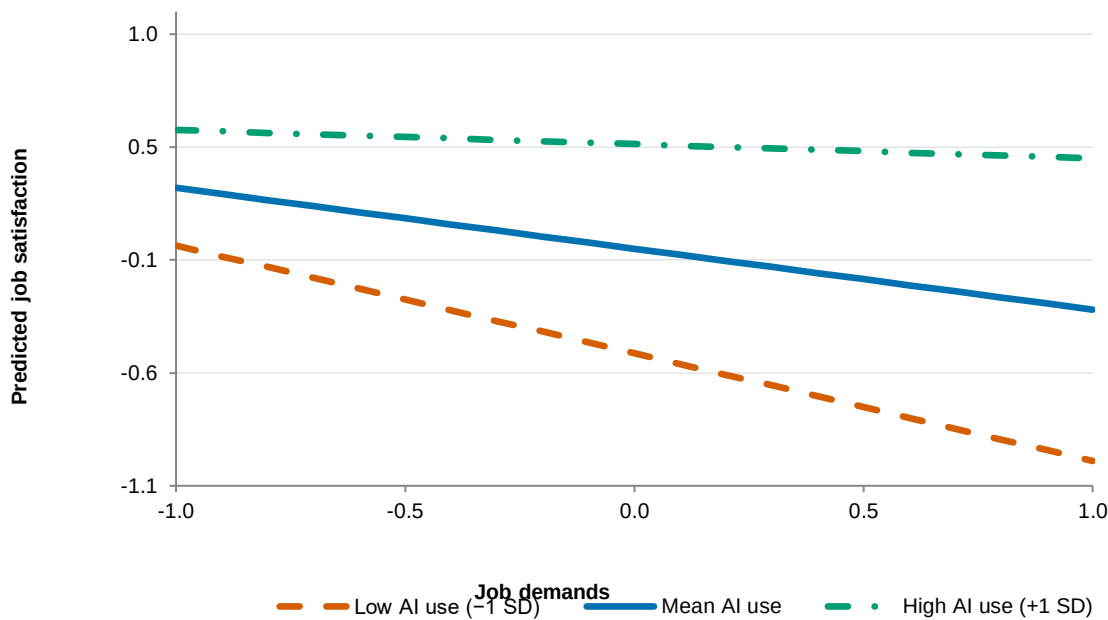


Figure 2. Moderating effect of AI use on the relationship between job demands and job satisfaction



Figure 3. Moderating effect of AI use on the relationship between interpersonal job resources and job satisfaction

DISCUSSION

This study examined the association between job satisfaction and job demands and interpersonal job resources among Chinese university faculty, and whether the use of AI changes the strength of these relationships. The findings revealed a clear pattern. Job demands were found to be negatively associated with job satisfaction, whereas interpersonal job resources were found to be positively associated with it. Furthermore, AI use was found to significantly moderate both relationships. Higher levels of AI use were found to weaken the negative association between job demands and job satisfaction, while strengthening the positive association between interpersonal job resources and job satisfaction. These results imply that AI use should not be considered solely as an independent technological factor, but rather as something that can alter the way in which existing academic working conditions are associated with faculty members' evaluations of their jobs.

Firstly, the negative correlation between job demands and job satisfaction aligns with the JD-R perspective and recent findings in Chinese higher education. University faculty members are required to manage multiple responsibilities involving teaching, research, administration, performance evaluation and interpersonal coordination. When these demands require sustained effort, time and energy, they can lead to a reduction in faculty members' positive evaluations of their work. Previous studies have similarly demonstrated that time pressure, research stress and other challenging working conditions are linked to poorer well-being and lower job satisfaction among Chinese university teachers (Chen et al., 2022; Xu et al., 2023; Zhao et al., 2024). In contrast, interpersonal job resources were positively associated with job satisfaction. Supportive relationships with colleagues and supervisors can provide faculty members with information, feedback, emotional support, and practical assistance when dealing with teaching, research, and administrative issues. This finding is consistent with recent studies showing that social and organisational support positively contributes to university teachers' work experiences and job satisfaction (Chen, 2025; Virtanen et al., 2026). Taken together, these results reinforce the importance of considering the demanding and supportive features of the academic work environment.

Secondly, the use of AI weakened the negative association between job demands and job satisfaction. This is particularly relevant because AI does not necessarily reduce the objective level of job demands. Faculty members may still be faced with the same teaching responsibilities, research targets, deadlines and performance expectations. However, greater AI use may reduce the personal effort required to respond to some of these demands. AI can assist with tasks such as information retrieval, drafting, data processing, summarisation and other routine or cognitively intensive activities, potentially enabling faculty to manage demanding workloads more efficiently. This interpretation is consistent with recent evidence suggesting that AI adoption can reduce stress and improve aspects of faculty well-being (Cambra-Fierro et al., 2025; Liu et al., 2025). Nevertheless, this result should not be interpreted as evidence that AI simply reduces academic workload. Recent research shows that AI may also create new responsibilities related to verification, ethical judgement, academic integrity and technological adaptation, and may contribute to higher productivity expectations (Su et al., 2026). The present findings therefore suggest that, within this sample, AI use appears to reduce the extent to which job demands are associated with lower job satisfaction, rather than eliminating those demands themselves.

Thirdly, AI use strengthened the positive association between interpersonal job resources and job satisfaction. This result suggests a complementary relationship between technological and interpersonal resources. While support from colleagues and supervisors can offer direction, experience, feedback, and problem-solving assistance, AI can help faculty translate this support into more efficient task completion. For instance, suggestions from colleagues or supervisors could be more easily implemented with the help of AI for tasks such as searching, drafting, analysis, or revision. Thus, the usefulness of interpersonal support may increase when faculty can also effectively employ AI in their work. This finding extends the JD-R perspective by suggesting that the benefits of traditional job resources depend partly on the technological context in which they are used. It also provides a more nuanced interpretation of concerns that AI may replace human interaction entirely. While previous research has demonstrated that extensive interaction with AI can lead to feelings of social disconnection when it replaces interaction with colleagues (Tang et al., 2023), the current findings imply that AI and interpersonal support can coexist rather than compete.

Finally, the two moderating effects highlight the dual role of AI in contemporary academic work. While existing research often asks whether AI is beneficial or harmful to employees, the present findings suggest that this question may be too simplistic. AI may be more appropriately understood as a contextual factor that changes how faculty respond to existing job conditions. In demanding work environments, using AI may reduce the negative correlation between job demands and job satisfaction, whereas in supportive environments, it may increase the positive correlation between interpersonal job resources and job satisfaction. This interpretation is consistent with recent Job Demands-Resources (JD-R) research emphasising that AI can generate both resource-enhancing and demand-generating processes simultaneously (Chuang et al., 2025; Y. Zhang et al., 2026). However, as the present study used cross-sectional and self-reported data, these findings should be interpreted as associations rather than causal effects. Future longitudinal or experimental research could more directly examine whether AI use changes faculty workload, resource utilisation, and job satisfaction over time.

CONCLUSION

Drawing on the JD-R framework, this study examined how job demands, interpersonal job resources, and AI use relate to job satisfaction among Chinese university faculty. Job demands were negatively associated with job satisfaction, whereas interpersonal job resources were positively associated with it. AI use weakened the negative relationship between job demands and job satisfaction and strengthened the positive relationship between interpersonal job resources and job satisfaction.

Theoretical Implications

Firstly, this study extends the JD-R framework by positioning the use of AI as a contextual boundary condition surrounding established job demands and resources. Recent research increasingly conceptualises AI as a potential job resource and source of new demands. These include enhanced autonomy and efficiency, as well as insecurity, verification requirements and technological adaptation (Chuang et al., 2025; Y. Zhang et al., 2026). The present study adopts a different but complementary perspective. Rather than redefining existing job characteristics as AI-related demands or resources, it keeps job demands, interpersonal job resources and AI use distinct and examines whether AI use alters the relationship between these work characteristics and job satisfaction. This provides a more nuanced approach to incorporating AI into JD-R research.

Second, the study identifies an asymmetric moderating pattern. Higher AI use was associated with a weaker negative relationship between job demands and job satisfaction and a stronger positive relationship between interpersonal job resources and job satisfaction. This pattern suggests that AI may simultaneously weaken the negative association between job demands and job satisfaction, while amplifying the positive association between interpersonal job resources and job satisfaction. Therefore, the findings move beyond the simple argument that AI itself functions as a job resource. Its value may depend on the work environment in which it is used and the resources already available to faculty members.

Thirdly, the study extends research on AI-enabled work to the context of Chinese higher education. Faculty work differs from many other occupations in that teaching, research, administrative responsibilities, performance evaluation and professional collaboration are often carried out simultaneously. AI is becoming increasingly embedded in these activities, but its impact on faculty job satisfaction is not well understood. By examining AI use alongside established academic job demands and interpersonal resources, this study provides a more contextualised account of how technology is associated with faculty work experiences in Chinese universities.

Practical Implications

Firstly, rather than treating efficiency gains as an automatic basis for increasing performance expectations, universities should integrate AI adoption with workload management. AI can reduce the time and effort needed for activities such as information retrieval, drafting, data processing and routine administrative tasks. However, if these efficiency gains lead to higher research targets, faster deadlines or additional responsibilities being imposed immediately, AI may contribute to work intensification rather than reducing workload.

Therefore, university administrators should evaluate whether AI actually reduces the effort required for specific academic tasks, and monitor whether new expectations offset these benefits.

Secondly, universities should preserve and strengthen interpersonal support in AI-enabled work environments. Findings show that the positive relationship between interpersonal job resources and job satisfaction is stronger at higher levels of AI use. This suggests that AI does not necessarily replace the value of colleagues and supervisors. In fact, guidance from supervisors, support from colleagues, feedback and professional discussion may become even more valuable when faculty use AI to support teaching, research and administrative tasks. Universities should therefore avoid replacing human interaction with technological tools, instead encouraging opportunities for faculty to discuss, review and refine AI-assisted work collaboratively.

Thirdly, AI training should focus on integrating AI into academic tasks rather than on technical functions alone. Faculty development programmes should address how AI can be used for teaching preparation, research support, information processing and administrative work, while emphasising output verification, academic integrity, ethical judgement and appropriate human oversight. Such training could help faculty to use AI more effectively without creating unnecessary technological demands. In this way, AI implementation can be more closely aligned with workload management and supportive academic work practices.

LIMITATIONS AND FUTURE RESEARCH

This study has several limitations. First, the cross-sectional and self-report design limits causal inference because temporal ordering cannot be established and reverse relationships remain possible. All predictors, the moderator, and the outcome were measured simultaneously from the same respondents. Common method variance may therefore have influenced the strength of the observed structural relationships, and the full-collinearity VIF results cannot establish its absence. Accordingly, the relatively strong associations should be interpreted cautiously. Future research could use longitudinal and multi-source designs to clarify temporal relationships and reduce reliance on a single measurement source. Second, recruitment through online and professional networks and respondent referrals may introduce selection bias. Moreover, 85.8% of respondents worked at public universities. Although the sample met the specified power-analysis requirement, it cannot be considered representative of all Chinese university faculty. Future studies could employ probability-based sampling and examine the stability of the relationships across academic ranks, experience, university types, disciplines, and administrative responsibilities. Third, the measures impose conceptual boundaries. Job demands captured work intensity, time pressure, and team conflict, while job resources focused on interpersonal support. AI use combined reported behaviours with confidence and perceived importance. Future research could distinguish different demands and resources and separately assess AI-use frequency, self-efficacy, and perceived usefulness. Finally, the study did not distinguish generative AI from other AI applications or directly assess the mechanisms underlying the moderation effects. Future studies could compare different forms of AI use and examine mechanisms such as workload reduction, cognitive offloading, task efficiency, and the effective use of social support.

REFERENCES

1. Abdulkareem, A. K., Ishola, A. A., Bello, M. L., & Adejumo, A. (2024). The dark side of digitalization: Examining the impact of digital overload on job autonomy and job satisfaction. *Journal of Information, Communication and Ethics in Society*, 22(3), 354–371. <https://doi.org/10.1108/JICES-07-2023-0091>
2. Baciú, C., Mohan, G., & Wilson, J. (2026). Algorithmic scholarship and academic evaluation: Governance misalignment in the age of generative AI. *Frontiers in Artificial Intelligence*, 9, 1862980. <https://doi.org/10.3389/frai.2026.1862980>
3. Bakker, A. B., & Demerouti, E. (2024). Job demands–resources theory: Frequently asked questions. *Journal of Occupational Health Psychology*, 29(3), 188–200. <https://doi.org/10.1037/ocp0000376>
4. Cambra-Fierro, J. J., Blasco, M. F., López-Pérez, M. E., & Trifu, A. (2025). ChatGPT adoption and its influence on faculty well-being: An empirical research in higher education. *Education and Information Technologies*, 30(2), 1517–1538. <https://doi.org/10.1007/s10639-024-12871-0>
5. Cao, J., Dai, T., Dong, H., Chen, J., & Fan, Y. (2024). Research on the mechanism of academic stress on

- occupational burnout in Chinese universities. *Scientific Reports*, 14, 12166.
<https://doi.org/10.1038/s41598-024-62984-2>
6. Chen, M. (2025). Exploring the influencing effect of tertiary teachers' perceived organizational support and teacher self-efficacy on their job satisfaction: The mediating role of teacher work engagement. *Frontiers in Psychology*, 16, 1609824. <https://doi.org/10.3389/fpsyg.2025.1609824>
7. Chen, Z., Lee, T., Yue, X., & Wang, J. (2022). How time pressure matter university faculties' job stress and well-being? The perspective of the job demand theory. *Frontiers in Psychology*, 13, 902951. <https://doi.org/10.3389/fpsyg.2022.902951>
8. Chuang, Y.-T., Chiang, H.-L., & Lin, A.-P. (2025). Insights from the Job Demands–Resources Model: AI's dual impact on employees' work and life well-being. *International Journal of Information Management*, 83, 102887. <https://doi.org/10.1016/j.ijinfomgt.2025.102887>
9. Han, J., Yin, H., Wang, J., & Zhang, J. (2020). Job demands and resources as antecedents of university teachers' exhaustion, engagement and job satisfaction. *Educational Psychology*, 40(3), 318–335. <https://doi.org/10.1080/01443410.2019.1674249>
10. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135. <https://doi.org/10.1007/s11747-014-0403-8>
11. Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration*, 11(4), 1–10. <https://doi.org/10.4018/ijec.2015100101>
12. Li, X., Lin, Z., Huang, G., & Cui, H. (2026). Department-based need-supportive leadership and affective job satisfaction among Chinese university teachers: A cross-sectional serial mediation analysis of work-related basic psychological need satisfaction and work motivation. *Frontiers in Psychology*, 17, 1815184. <https://doi.org/10.3389/fpsyg.2026.1815184>
13. Liu, G., Lan, G., Nneli, N. C., Song, F., Xiao, Q., & Zheng, M. (2025). Balancing generative AI integration and faculty well-being: Evidence from Chinese higher education. *Frontiers in Education*, 10, 1688902. <https://doi.org/10.3389/feduc.2025.1688902>
14. Macdonald, S., & MacIntyre, P. (1997). The generic job satisfaction scale: Scale development and its correlates. *Employee Assistance Quarterly*, 13(2), 1–16. https://doi.org/10.1300/J022v13n02_01
15. Metzger, O. S. (2024). The impact of interacting with AI in the workplace on employees' job and life satisfaction [Master's thesis, Universidade Católica Portuguesa]. <https://hdl.handle.net/10400.14/45820>
16. Mudrak, J., Záborská, K., Květon, P., Jelínek, M., Blatný, M., Šolcová, I., & Machovcová, K. (2018). Occupational well-being among university faculty: A job demands-resources model. *Research in Higher Education*, 59(3), 325–348. <https://doi.org/10.1007/s11162-017-9467-x>
17. Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879–903. <https://doi.org/10.1037/0021-9010.88.5.879>
18. Soulami, M., Benchekroun, S., & Galiulina, A. (2024). Exploring how AI adoption in the workplace affects employees: A bibliometric and systematic review. *Frontiers in Artificial Intelligence*, 7, 1473872. <https://doi.org/10.3389/frai.2024.1473872>
19. Su, F., Beh, W. F., & Cheah, K. S. L. (2026). Efficiency or intensification? A systematic review of generative AI and academic workload in higher education. *Acta Psychologica*, 268, 107353. <https://doi.org/10.1016/j.actpsy.2026.107353>
20. Tang, P. M., Koopman, J., Mai, K. M., De Cremer, D., Zhang, J. H., Reynders, P., Ng, C. T. S., & Chen, I.-H. (2023). No person is an island: Unpacking the work and after-work consequences of interacting with artificial intelligence. *Journal of Applied Psychology*, 108(11), 1766–1789. <https://doi.org/10.1037/apl0001103>
21. Virtanen, V., Hailikari, T., Murtonen, M., Parpala, A., & Postareff, L. (2026). What challenges higher education teachers' teaching-related wellbeing? *Teacher Development*, 30(2), 414–432. <https://doi.org/10.1080/13664530.2025.2537056>
22. Wang, Q., & Yao, N. (2025). Understanding the impact of technology usage at work on academics' psychological well-being: A perspective of technostress. *BMC Psychology*, 13, 130.

<https://doi.org/10.1186/s40359-025-02461-1>

23. Xu, L., Guo, J., Zheng, L., & Zhang, Q. (2023). Teacher well-being in Chinese universities: Examining the relationship between challenge–hindrance stressors, job satisfaction, and teaching engagement. *International Journal of Environmental Research and Public Health*, 20(2), 1523.
<https://doi.org/10.3390/ijerph20021523>
24. Zhang, Y., Lai, Z., Liu, X., & Sun, H. (2026). How artificial intelligence (AI) usage affects employees' workplace well-being: A job demands-resources perspective. *Personnel Review*, 55(6), 1509–1526.
<https://doi.org/10.1108/PR-07-2025-0806>
25. Zhang, Z., Wang, Y., Zheng, M., Wan, X., & Bian, Y. (2026). How challenge and hindrance research stressors affect university teachers' research performance: The mediating role of researcher identity and the moderating role of research environment. *Frontiers in Psychology*, 17, 1786936.
<https://doi.org/10.3389/fpsyg.2026.1786936>
26. Zhao, P., Yuan, J., & Hu, Y. (2024). Work hours, job resources and subjective well-being of Chinese faculty: An empirical analysis based on a sequential mediation model. *Research in Higher Education*, 65(5), 965–988. <https://doi.org/10.1007/s11162-023-09770-7>

Ethical Approval

Chinese regulations permit studies using anonymised data to be exempt from ethical review when no physical harm, sensitive personal information, or commercial interests are involved. This study used an anonymous survey of adult faculty, with voluntary participation and informed consent.

Conflict of Interest

The authors declare that they have no conflicts of interest related to this study.

Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request. The dataset is not publicly available in order to protect participant confidentiality.

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