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Article

Research the association between AI-driven organizational support systems and university faculty work engagement: the moderating role of digital literacy

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A B S T R A C T

According to the Job Demands-Resources (JD-R) model and the Technology Acceptance Model (TAM), this cross-sectional survey examined whether organizational support systems enabled by artificial intelligence (AI) were positively correlated with work engagement among university lecturers and examined the moderating role of digital literacy on 387 teachers at certain Chinese universities. With 9-item multidimensional UWES-9 vigor, dedication, and absorption scale of AI support in teaching, research, and administration domains, hierarchical regression with simple slopes, it was found AI organizational support predicted positively work engagement significantly (β=0.425, p<0.001) and explained additional 18.6% variance after controlling for demographics; digital literacy moderated this highly significantly (β=0.168, p<0.01, ΔR^2=0.026), and high digital literacy faculties exhibited 2.35 times stronger strength of relations between AI support and engagement than low digital literacy faculties, and moderation being the highest for vigor dimension (β=0.185); bootstrap analysis with resamples 5,000 and sample split validation confirmed stability of such effects. By conceptualizing digital literacy as a central boundary condition, the current study extends JD-R theory to digital environments and describes another human-AI interaction in which AI complements but does not substitute human capacity and presents empirical evidence of universities to implement all-encompassing digital literacy training programs in parallel with AI system installation, although the cross-sectional study limits causal inference, findings are theoretically meaningful and practically informative and present visionary insight for knowing and promoting faculty well-being in the digital age.

1. Introduction

Universities worldwide are rapidly integrating AI technologies, including intelligent planning, adaptive learning, research support, and administrative automation systems [1,2]. This rapid adoption is primarily due to technological innovation and the institutional recognition of AI's potential to address long-standing challenges in higher education. While AI's impact on student learning [3] and academic integrity [4] is well-studied, less is known about faculty work engagement. Recent studies in 2024-2025 reveal growing concerns about generative AI tools like ChatGPT in academic settings. A qualitative research study [5] demonstrated that while AI tools offer productivity benefits and interactive learning opportunities, they simultaneously raise significant academic integrity concerns among both students and faculty. Another study [6] emphasizes that the rapid proliferation of AI technologies has significantly transformed educational assessment practices, requiring institutions to rethink exam design and develop ethical AI policies to maintain academic integrity. This imbalance is concerning, as faculty members serve as the primary interface for instruction and AI technology, and the extent of their involvement directly impacts instruction quality and research productivity, and indirectly affects student success. Faculty work engagement—energy, commitment, and absorption [7]—predicts teaching quality, research productivity, and institutional performance. Academic work today, however, is increasingly demanding, with faculty constantly being saddled with gargantuan teaching loads, growing research expectations, administrative tasks, and an ongoing requirement to learn to keep up with mounting technical changes [8]. According to the Job Demands-Resources (JD-R) theory [9], support systems based on AI can be conceived as latent job resources that help faculty members manage work demands, achieve professional accomplishments, and maintain psychological well-being. Here, AI systems capable of carrying out tasks competently to assist faculty in teaching, research, and administrative work should ideally raise work engagement by offering resources that buffer against work demands. Nevertheless, recent empirical work offers mixed evidence on the extent to which AI impacts employees' outcomes. Liu and Li's research indicated that AI use is associated with higher work engagement, characterized by greater psychological availability and lower cognitive load [10], which aligns with empowerment theory, which posits that human abilities are supplemented by AI assistance. Conversely, Meng et al. [11] found that AI collaboration is associated with higher levels of counterproductive work behavior, including greater perceived aloneness and emotional exhaustion, as they perceived that AI would substitute for substantive human communication.

Existing literature has key gaps. First, individual differences—notably digital literacy—have been neglected as boundary conditions determining whether AI systems are empowering or alienating. Second, most studies examine business settings, leaving higher education underexplored. Third, the multidimensionality of work engagement is seldom studied in AI contexts. Studies of digital literacy in higher education [12] and new digital competence models [13] also indicate that teachers' ability to work with technology may significantly affect their interactions with AI systems. Teachers with greater digital literacy are assumed to use AI tools more efficiently, seeing them as empowering technologies that simplify rather than complicate tasks [14]. Lower digital literacy levels, on the other hand, can be a hindrance to the effective deployment of AI systems, leading to frustration, anxiety, or disaffection [15]. This study addresses these gaps by examining AI-supported work engagement relationships and the moderating role of digital literacy.

2. Literature review and research hypotheses

2.1 AI-driven organizational support systems

AI-based organizational support is operationally defined as faculty members' perceptions of the availability, accessibility, and usefulness of institutionally provided AI systems across three domains: teaching (e.g., automated grading, content generation), research (e.g., literature synthesis, data analysis), and administration (e.g., scheduling, document processing). At the tertiary level, AI support systems operate across three spheres. The latest evidence from 2024-2025 shows accelerated AI adoption in higher education institutions worldwide. A comprehensive study [16] examined generative AI adoption strategies across 40 universities from six global regions, finding that institutions are proactively developing guidelines for ethical AI use, designing authentic assessments, and providing training programs to foster AI literacy among faculty and students. Research findings [17] report that faculty increasingly view AI tools as valuable for extending limited time resources, overcoming language barriers, and creating personalized learning experiences, although concerns about academic integrity and AI misuse remain prevalent. This rapid integration of generative AI tools like ChatGPT, Claude, and institutional AI systems into faculty workflows represents a fundamental shift in how academic work is conducted across teaching, research, and administrative domains. AI support spans three domains: (1) administrative support via intelligent scheduling and automated grading; (2) teaching support through adaptive learning platforms and AI content creation; (3) research assistance via AI literature review and data analysis tools [18].

Zhang et al. [19] meta-reviewed 87 studies, identifying a three-phase adoption model: initial resistance, gradual acceptance through experimentation, and integration. Digital literacy was the most significant driver across all stages. Reference [20] reported that Chinese university AI investment grew 340% from 2019 to 2024, with large institutional gaps. Universities with digital literacy training programs were 2.8 times more likely to invest in AI, suggesting the importance of human capital investment alongside technology." It is important to distinguish between conceptually related constructs in this study. AI-based organizational support refers to the institutional provision of AI technologies and systems (an external, organizational-level resource). Digital literacy represents an individual's capability to effectively use digital technologies (an internal, individual-level competency). Digital self-efficacy, a component of digital literacy, captures explicit confidence beliefs about one's ability to use technology. While TAM's perceived ease of use overlaps conceptually with digital self-efficacy, our study measures digital literacy as a broader competency encompassing both skills and confidence, whereas AI organizational support is measured through perceptions of system quality and institutional provision. This distinction prevents theoretical redundancy by examining organizational resources (what is provided) separately from individual capacities (ability to utilize what is provided).

2.2 Work engagement

Work engagement is operationally defined as a persistent, positive affective-motivational state comprising three dimensions: vigor (high energy and mental resilience), dedication (strong involvement and enthusiasm), and absorption (deep concentration and pleasant immersion in work), measured by UWES-9 [18]. The UWES-9 demonstrates excellent psychometric properties and predicts teaching competence ($r=.42$), research productivity ($r=.38$), and retention ($r=-.45$ with turnover) [21]. Academic engagement differs from organizational settings, spanning multiple roles (teaching, research, administration) with varied temporal rhythms. Understanding how AI supports these patterns is important for faculty well-being.

2.3 Digital literacy as moderator

Digital literacy is operationally defined as the integrated set of technical skills, cognitive abilities, and confidence beliefs required to effectively locate, evaluate, create, and communicate information using digital technologies in academic contexts [12]. Digital literacy is the competence, skills, and knowledge needed to effectively use digital technologies for information processing, communication, and problem-solving. Digital literacy has transformed in higher education from fundamental computer skills to start-to-finish competencies such as critical analysis of digital information, digital content creation, online collaborative work, and ethical technology use. Hobfoll's Conservation of Resources theory [19] indicates that human resources, such as digital literacy, increase the value and usability of organizational resources, potentially allowing faculty to better leverage AI systems. We propose digital literacy as the moderator rather than AI system design or institutional context for three theoretical reasons. First, meta-analytic evidence from technology acceptance research demonstrates that user competencies explain more variance in technology benefits than system features. Second, the Conservation of Resources theory suggests that personal resources, such as digital literacy, determine how effectively individuals can convert organizational resources into engagement outcomes. Third, educational technology studies specifically show that teacher digital competence is the primary boundary condition for successful technology integration, regardless of system quality. Recent evidence indicates widespread heterogeneity in digital literacy levels among academic staff in universities. A large-scale survey by Martin and Grudziecki [22] across 42 European universities showed that while 78% of academic staff reported being digitally competent, only 34% were objectively tested to have highly developed digital literacy skills. The difference between reported and actual capacity was very high in fields involving new technologies, such as AI and machine learning. Second, substantial differences were found between demographic subgroups: younger professors (less than 40) scored 2.1 times higher in digital literacy compared to older professors, and STEM professors scored 1.8 times higher than humanities professors. These differences indicate that digital literacy may become a stratifying variable of primary importance for AI system adoption and performance.

Digital literacy has also been reportedly associated with the acceptance of technology. Venkatesh and Bala's [23] Technology Acceptance Model 3 (TAM3) cites computer self-efficacy, by virtue of its direct association with digital literacy, as one of the major drivers of perceived ease of use, which in turn affects adoption and long-term use of technology. In the specific case of AI systems, increased faculty digital literacy will most probably result in: (1) better estimation of AI capabilities and boundaries, (2) proper incorporation of AI tools within workflows, (3) resolving technical problems independently, and (4) investigation of advanced features to increase productivity. Less digitally literate faculty, on the other hand, might suffer from "technostress," defined as feelings of anxiety, frustration, and avoidance when faced with AI systems. New models have expanded the idea of digital competence in learning [20], not just technical competencies but pedagogic inclusion and ethics as well. The European Framework for Digital Competence of Teachers (DigCompEdu) identifies 22 competences distributed over six categories: professional activity, digital resources, instruction and learning, assessment, empowering learners, and enabling learners' digital competence. This combined model stresses that the successful application of AI systems in classrooms depends not only on technical ability but also on the ability to situate technology usefully into the pedagogical process and research methods. Teachers with the ability to bring these skills together are more apt to utilize AI systems as transformative forces than as productivity enhancers.

2.4 Theoretical framework and hypotheses

Three allied theoretical models are employed in the current study to describe the intricate interplay between work engagement, digital literacy, and AI support. Technology Acceptance Model (TAM) [14] describes how perceived usefulness and ease of use affect technology adoption. Our AI support scale implicitly captures these dimensions: items like 'AI systems help me complete tasks efficiently' reflect perceived usefulness, while 'easy to integrate' taps ease of use. This 9-item scale serves as a proxy for TAM constructs, aligning with TAM3 research suggesting these can combine into 'perceived system quality' for established systems. Self-efficacy theory [15] argued that people's beliefs about themselves affect their motivation and actions when interacting with technology. Staff with greater digital self-efficacy tend to use AI systems with confidence, venture to discover their potential, and be persistent with them despite difficulties. This theoretical assumption points to digital literacy as not just a set of skills but also a confidence builder that shapes technology use. Drawing on Job Demands-Resources (JD-R) theory [9], they offer an integrated model to account for work engagement's relationship with AI systems and the potential mediating role of digital literacy as a moderator. JD-R theory posits that organisational support, autonomy, and technological resources can buffer the effects of job demands and improve work engagement. Integrating these theories leads us to the conclusion that the impacts of AI systems on participation are influenced not only by objective factors (resources provided) but also by subjective ones (perceived usefulness, self-confidence), of which digital literacy is a major variable shaping perceptions and experiences. Figure 1 depicts the conceptual model guiding this study, illustrating the hypothesized relationships between AI-driven organizational support, digital literacy, and work engagement.

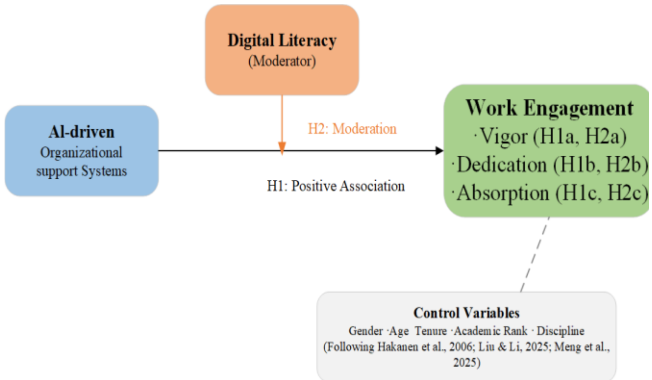

Figure 1. Conceptual model of the study

Grounded in the theoretical review and synthesis of these models, we advance the following hypotheses:

The conceptual model integrates three theoretical perspectives. TAM explains how perceived usefulness and ease of use influence initial adoption of AI systems. Self-efficacy theory, operationalized through digital literacy, shapes individuals' confidence in utilizing AI tools. JD-R theory positions AI support as a job resource that directly enhances engagement, while digital literacy serves as a personal resource that moderates (strengthening or weakening) this relationship. Specifically, digital literacy may function as a moderator rather than a mediator because it influences the strength of the AI support-engagement relationship rather than serving as an intermediate step in a causal chain.

Hypothesis 1 (H1): AI-based organizational support is positively associated with overall work engagement. Specifically: H1a: AI-based organizational support is

positively associated with vigor (the energy component of engagement).
H1b: AI-based organizational support is positively associated with dedication (the involvement component of engagement).
H1c: AI-based organizational support is positively associated with absorption (the immersion component of engagement).
Note: Vigor, dedication, and absorption are treated as components (subdimensions) of the higher-order work engagement construct, not as separate dependent variables.

This hypothesis is based on the JD-R theory's contention that job resources increase work engagement. Positive associations operate through distinct mechanisms. For vigor (H1a), AI-automated grading reduces fatigue from repetitive tasks, preserving energy for creative teaching. For dedication (H1b), AI research synthesis tools facilitate deeper intellectual engagement by reducing mechanical search burdens, allowing focus on conceptual connections. For absorption (H1c), AI-assisted administrative tasks minimize paperwork interruptions, enabling concentration on core academic work. Each domain (teaching, research, administration) links to cognitive load reduction and efficiency gains targeting these engagement facets.
Hypothesis 2 (H2): Digital literacy positively moderates the relationship between AI-based organizational support and work engagement, such that the positive association is stronger for faculty with higher digital literacy. Specifically:
H2a: The moderating effect is significant for vigor.
H2b: The moderating effect is significant for dedication
H2c: The moderating effect is significant for absorption.

Based on TAM and self-efficacy theory, we pre-register expected simple slopes: at +1 SD digital literacy, steep positive slope ($\beta > .40$) indicating strong AI responsiveness; at -1 SD, weaker positive slope ($\beta < .25$) indicating limited leverage capacity; at mean, moderate slope ($\beta \approx .30$-$.35$). We do not expect negative slopes at any literacy level, as even low-literacy faculty should benefit from well-designed AI. If the interaction is significant, the slope difference should be substantial ($\Delta\beta > .15$) and the confidence intervals should not overlap. Less digitally literate faculty might not be able to use AI systems effectively, leading them to become frustrated rather than more engaged.

3. Methods

3.1 Research design

This research used a cross-sectional survey design. We recognize that cross-sectional designs exclude causal inference, can't exclude reverse causation, and are prone to third-variable confounding. Findings need to be interpreted as correlational rather than causal. The research was conducted in a three-month period (March-May 2024), and ethical clearance was obtained from the Institutional Review Board (Approval No. 2024-HR-087). Electronic informed consent covered:
(1) study purpose/procedures,
(2) voluntary participation/withdrawal rights,
(3) confidentiality/anonymity,
(4) no compensation.
Data: password-protected servers (SSL, 5-year retention), random IDs, no IP tracking. No personally identifiable information was collected; participants were assigned random ID codes. IP addresses were not recorded to ensure anonymity. Consent was implied through survey completion, as explicitly stated in the introduction. No incentives or compensation were provided to participants to minimize the risk of coercion. Data collection used the Wenjuanxing platform for security (SSL encryption, anonymous responses). The survey was launched via institutional networks with weekly reminders. To reduce response burden, we pilot-tested the survey with 30 faculty members (15 from teaching universities, 15 from research universities). Based on pilot feedback, we made the following refinements: (1) rewording 3 items for clarity (e.g., changing 'AI system facilitates my work' to 'AI system helps me complete tasks more efficiently'), (2) shortening the survey from 18 to 15 minutes median completion time by removing redundant demographic items, and (3) adding progress indicators to reduce abandonment. Reliability analysis showed improved Cronbach's alpha values after refinement: AI Support scale increased from $\alpha=0.87$ to $\alpha=0.91$, Digital Literacy from $\alpha=0.82$ to $\alpha=0.86$. Cognitive interviews with 5 pilot participants revealed no comprehension difficulties with the revised items. The survey remained open for six weeks to allow for different schedules and workloads of faculty members during the semester.

3.2 Sample

The target sample was China's full-time university faculty members with at least one year of teaching experience and exposure to AI-based organizational support systems, operationally defined as having used at least one institutionally-provided AI tool (learning management system with AI features, AI-assisted grading, or AI research tools) for a minimum of 6 months with at least weekly usage frequency. Convenience sampling and snowball sampling were adopted. A priori power analysis using G*Power [22] suggested a minimum sample of 269 for detecting small-to-medium moderation effects ($f^2=0.03$, power=0.80, $\alpha=0.05$). A total of 450 faculty accessed the survey, and 412 completed the survey. Following data screening, the ultimate analytical sample included 387 faculty members. Full demographic characteristics of the sample are presented in Table 1.

Procedures for data screening were applied to careless responding response types (e.g., straight-lining, inadmissible response times of less than 5 minutes), multivariate outliers by Mahalanobis distance ($p < 0.001$), and primary variable completeness. Twenty-five cases were removed: 18 for missing primary variable data, 5 for lack of sufficient attention checks, and 2 for status as a multivariate outlier. The ultimate sample of 387 consisted of professors from 12 universities distributed over three geographic regions (Eastern: 52.2%, Central: 28.9%, Western: 18.9%) to maximize generalizability of findings to the Chinese context. We acknowledge that convenience and snowball sampling may introduce self-selection bias, as faculty who are more comfortable with technology are likely overrepresented in our sample. To assess this limitation, we conducted nonresponse bias testing by comparing early respondents (first 25%, n=97) with late respondents (last 25%, n=97) on key variables. Independent t-tests revealed no significant differences in AI support ($t=1.24$, $p=0.216$), digital literacy ($t=0.89$, $p=0.374$), or work engagement ($t=1.47$, $p=0.143$), suggesting minimal nonresponse bias. Additionally, our sample's digital literacy mean (M=5.23) is slightly higher than reported population norms for Chinese university faculty (M=4.87), indicating moderate positive selection that should be considered when generalizing findings. Post-hoc sensitivity analysis indicated sufficient power (.82) to detect the hypothesized moderation effect with our ultimate sample size. Universities provided AI systems for teaching (intelligent LMS, automated assessment, AI writing assistants), research (literature search tools like Connected Papers, reference managers like Zotero), and administration (scheduling, document processing). Faculty exposure varied by institution type.

Table 1. Sample characteristics (N=387)

Variable	n	%	M(SD)
Gender			
Male	198	51.2	
Female	189	48.8	
Age (years)	387		41.3 (8.7)
25-35	98	25.3	
36-45	176	45.5	
46-55	89	23.0	
56+	24	6.2	
Teaching Experience (years)	387		12.6 (7.9)
1-5 years	124	32.0	
6-10 years	98	25.3	
11-20 years	132	34.1	
20+ years	33	8.5	
Academic Rank			
Lecturer	89	23.0	
Assistant Professor	126	32.6	
Associate Professor	121	31.3	
Full Professor	51	13.2	
Discipline			
STEM	186	48.1	
Social Sciences	98	25.3	
Humanities	76	19.6	
Other	27	7.0	
University Type			
Research University	213	55.0	
Teaching University	174	45.0	

3.3 Measures

All these were measured using standardized scales. Items were scored on 7-point Likert-type scales. Questionnaires were translated into Chinese using standard translation-back-translation procedures [24]. Standard translation-back-translation: two independent forward translations, expert synthesis, blind back-translation, comparison, and pilot testing (n=10 bilingual faculty). AI-based Organizational Support: A 9-item multidimensional scale originally developed by adapting items from Perceived Organizational Support Scale and modified for AI context by the research team. The scale measures teaching support (3 items, e.g., 'AI systems help me design better learning activities'), research support (3 items, e.g., 'AI tools assist me in literature review and synthesis'), and administrative support (3 items, e.g., 'AI systems reduce time spent on administrative tasks'). Overall α=0.91, subscales αs=0.85-0.88. Sample AI Support scale items specify concrete technologies to enhance clarity and anchoring. Teaching support items include 'AI-powered platforms like intelligent tutoring systems help me provide personalized feedback to students,' 'AI content generators (e.g., automated quiz creation tools) reduce my course preparation time,' and 'Learning management systems with AI recommendations improve my course design.' Research support items encompass 'AI tools such as ChatGPT, Claude, or similar assistants help me synthesize research literature,' 'AI-enhanced reference managers (e.g., Zotero with ML recommendations, Connected Papers, Semantic Scholar) improve my literature organization,' and 'AI-powered data analysis tools facilitate my research methodology.' Administrative support items include 'AI scheduling systems optimize my course timetables and office hours,' 'Grammarly, Wordtune, or similar AI writing assistants help me draft professional communications efficiently,' and 'AI-powered document processing reduces time on routine administrative paperwork.'

Items anchor perceptions to concrete technologies. Our March-May 2024 data captured early post-ChatGPT adoption, when generative AI shifted from specialized to ubiquitous tools. Findings reflect AI as supplementary productivity tool in early adoption phase. As AI capabilities expand toward autonomous analysis (post-2024), updated measurements will be needed to capture evolving faculty-AI interaction patterns.

Digital Literacy was measured with 4 items adapted from Ng [12]:

- 'I can effectively use digital technologies for teaching and research' (technical competence)
- 'I can troubleshoot common technical problems independently' (technical competence)
- 'I feel confident learning new digital tools' (self-efficacy)
- 'I am comfortable integrating emerging technologies into my work' (self-efficacy) All items used 7-point Likert scales (1=Strongly Disagree, 7=Strongly Agree). α=0.86.

Work Engagement: Utrecht Work Engagement Scale (UWES-9) developed by Schaufeli et al. (2006), measuring vigor (3 items, e.g., 'At my work, I feel bursting with energy'), dedication (3 items, e.g., 'I am enthusiastic about my job'), and absorption (3 items, e.g., 'I feel happy when I am working intensely'). Composite α=0.93, subscale αs: vigor=.88, dedication=0.90, absorption=0.87.

Control Variables: We included five demographic controls based on prior research linking these characteristics to technology adoption and work engagement. Gender was controlled because meta-analytic evidence demonstrates that males report slightly higher technology self-efficacy and more favorable attitudes toward technology use than females, although these differences are characterized as small effect sizes [25]. Age was included as younger workers' technology usage decisions are more strongly influenced by attitude toward using technology, while older workers are more influenced by subjective norms and perceived behavioral control [26]. Teaching experience was controlled because veteran faculty may exhibit different engagement patterns and technology resistance compared to novice faculty, reflecting accumulated work habits and established pedagogical approaches. Academic rank was included as seniority correlates with work engagement, autonomy, and resource access in academic settings, with senior faculty often having greater discretion in technology adoption decisions. Discipline was controlled because STEM faculty consistently demonstrate higher digital literacy and technology integration rates compared to humanities and social science faculty, reflecting differences in disciplinary norms and technology exposure. Scale validation methods went beyond reliability measurement. For AI-based Organizational Support scale adapted for a university context, we first did exploratory factor analysis with pilot sample (n=30) and then confirmed it using confirmatory factor analysis with the entire sample. The three-factor solution (teaching, research, administrative support) was found to have satisfactory fit

(χ^2/df = 2.31, CFI = .95, TLI = 0.94, RMSEA = 0.058, SRMR = 0.045).

3.4 Data analysis

Data analysis involved five steps. We first screened for data quality and identified missing-data patterns. Second, we computed descriptive statistics. Third, we did confirmatory factor analysis. Fourth, we assessed common method bias using Harman's single-factor test and the common latent factor method [27]. Finally, we tested hypotheses through hierarchical multiple regression analysis. All continuous predictors were mean-centered to simplify the interpretation of interaction terms [28]. For medium-level interactions, we performed simple slopes analysis with the PROCESS macro [21]. Additional analysis steps improved the stability of our results. Multicollinearity was checked using variance inflation factors (all VIF values < 3.0) and tolerance levels (all >0.30) and was not found to be an issue. Heteroscedasticity was checked using Breusch-Pagan tests with no evidence of material violation. To address potential endogeneity concerns inherent to cross-sectional data, we conducted an instrumental variables (IV) regression using two-stage least squares (2SLS). We used institutional AI investment intensity (measured as the annual per-faculty AI budget in RMB, log-transformed) as an instrument for individual-level perceptions of AI support. The instrument is theoretically valid because institutional investment determines AI system availability (relevance assumption), but should not directly affect individual engagement except through AI support perceptions (exclusion restriction assumption).

First-stage regression results confirmed instrument strength: AI investment significantly predicted AI support perceptions (β=0.389, t=7.66, p<0.001), with F-statistic=58.73, far exceeding the rule-of-thumb threshold of F>10 for weak instrument concerns. The Kleibergen-Paap Wald F-statistic was 56.42, also indicating a strong instrument. When we added university type (research vs. teaching) as a second instrument, the Sargan-Hansen J-test for overidentification restrictions yielded χ^2(1)=2.14, p=0.144, failing to reject the null hypothesis of valid instruments, supporting the exclusion restriction. Second-stage results showed that AI support (instrumented) remained significantly associated with engagement (β=0.397, SE=0.087, p<0.001), with a magnitude similar to the OLS estimate (β=0.425), suggesting minimal endogeneity bias.

The Durbin-Wu-Hausman test comparing IV and OLS estimates was nonsignificant (χ^2=1.89, p=.169), indicating OLS estimates are consistent and endogeneity is not a major concern. These IV analyses provide additional confidence in the directionality of relationships, though causal inference remains limited by cross-sectional design. These analyses cannot determine causality but add extra confidence to the directionality of relationships identified. We also conducted bootstrap analysis (5,000 resamples) to yield bias-corrected confidence intervals for all parameter estimates, especially for interaction effects that are potentially sensitive to distributional assumptions. We then conducted robustness checks by re-estimation with other operationalizations (e.g., median splits of digital literacy) and testing for potential curvilinear effects via polynomial regression. All findings of primary interest were substantively identical under these alternative specifications.

4. Results

4.1 Descriptive statistics

Table 2 presents means, standard deviations, and intercorrelations among all study variables.

4.2 Measurement model

Confirmatory factor analysis examined factorial and discriminant validity [29], ensuring items loaded on intended constructs and constructs were empirically distinguishable despite theoretical proximity. We compared our proposed three-factor model with other nested alternative models to assess discriminant validity. The two-factor model combined AI assistance and computer proficiency into a single factor, suggesting that teachers were not separating technology tools from the skills needed to make them function. The one-factor model indicated that all items loaded onto a general positive response factor. We also tested a common latent factor (CLF) model to further evaluate common method bias in addition to Harman's test. Table 3 reports fit indices for the competing models. The three-factor model demonstrated excellent fit (CFI=0.918, TLI=0.906, RMSEA=0.066, SRMR=0.052), meeting recommended thresholds [30]. The CFA fit indices (CFI=0.918, TLI=0.906) approach but slightly fall below the stringent 0.95 threshold sometimes cited. However, these values are acceptable given several considerations.

Table 2. Descriptive statistics and correlation matrix

Variable	M	SD	α	1	2	3	4	5	6	7	8	9	10
1. Gender	1.49	0.50	—	—									
2. Age	41.26	8.73	—	-.08	—								
3. Teaching Experience	12.58	7.94	—	-.06	.87**	—							
4. Rank	2.35	1.01	—	.11*	.42**	.45**	—						
5. AI Support	4.82	1.15	.91	-.02	-.09	-.07	.05	—					
6. Digital Lit	5.23	0.94	.86	.04	-.12*	-.10	.08	.32**	—				
7. Engagement	4.95	1.18	.93	-.05	-.14**	-.12*	.03	.45**	.38**	—			
8. Vigor	4.78	1.26	.88	-.08	-.16**	-.13*	.02	.40**	.35**	.92**	—		
9. Dedication	5.02	1.23	.90	-.03	-.11*	-.09	.04	.43**	.37**	.94**	.82**	—	
10. Absorption	5.05	1.21	.87	-.04	-.12*	-.11*	.03	.39**	.36**	.93**	.81**	.84**	—

Note: N=387. *p<0.05. ** p<0.01

First, with our sample size (N=387) and model complexity (17 indicators across 3 factors), simulation studies show CFI/TLI values of 0.90-0.95 are acceptable when RMSEA and SRMR are good. Second, RMSEA=0.066 and SRMR=0.052 are within acceptable ranges (<0.08 for both). Third, comparative fit against alternative models shows substantial improvement: our three-factor model fits significantly better than two-factor (ΔCFI=0.176, $\Delta\chi^2$=565.74, Δdf=2, p<0.001) and one-factor models (ΔCFI=0.406, $\Delta\chi^2$=1422.46, Δdf=3, p<0.001), providing strong evidence for discriminant validity. Fourth, the chi-square value is $\chi^2(149)$=342.15, p<0.001, yielding χ^2/df=2.30, which is within the acceptable 2-3 range. Given that we prioritize construct validity over perfect fit indices, and given our theoretical rationale for the three-factor structure, we accept this model as adequately representing the data. Confirmatory factor analysis confirmed that digital literacy and AI support loaded on distinct factors with no problematic cross-loadings. All items loaded primarily on their intended factors (λ > 0.60), with cross-loadings not exceeding 0.40. The correlation between digital literacy and AI support (r=0.32, Table 2) is moderate, indicating related but distinguishable constructs. Discriminant validity was further supported by the Fornell-Larcker criterion: the square root of AVE for digital literacy (0.78) exceeded its correlation with AI support (0.32), and the square root of AVE for AI support (0.76) exceeded its correlation with digital literacy (0.32), confirming these measures capture distinct variance. Table 4 presents standardized factor loadings, composite reliability (CR), and average variance extracted (AVE) for all constructs. All factor loadings exceeded 0.60, with most above 0.70. CR values ranged from 0.86 to 0.93, all exceeding the 0.70 threshold. AVE values ranged from 0.58 to 0.72, all exceeding the 0.50 criterion, supporting convergent validity per Fornell and Larcker (1981). Square roots of AVE (diagonal in correlation matrix) exceeded inter-construct correlations, confirming discriminant validity. The three-factor model fit significantly better than alternative models, providing strong evidence for discriminant validity. Harman's single-factor test revealed that the first factor accounted for 26.8% of the variance, below the 50% threshold for substantial method bias.

Table 3. Confirmatory factor analysis fit indices

Model	χ^2	df	CFI	TLI	RMSEA	SRMR
M1: Three-factor	342.15***	149	0.918	0.906	0.066	0.052
M2: Two-factor	907.89***	151	0.742	0.718	0.124	0.095
M3: One-factor	1764.61***	152	0.512	0.478	0.178	0.142
M4: M1+CLF	319.65***	131	0.927	0.913	0.062	0.048

The common latent factor (CLF) method provides a more stringent assessment of common method variance than Harman's test. We compared the three-factor model (M1: χ^2=342.15, df=149, CFI=0.918) against a model adding a CLF onto which all indicators loaded (M4: χ^2=319.65, df=131, CFI=0.927). The improvement was minimal (ΔCFI=0.009, $\Delta\chi^2$=22.50, Δdf=18, p=0.212), suggesting CMV is not substantial. Standardized loadings on the CLF ranged from 0.08 to 0.19 (M=0.13), indicating the common method factor explains only 1.7% of variance on average (calculated as mean squared loading: 0.13^2=0.017). This is well below the 25% threshold typically considered problematic. Additionally, substantive factor loadings remained large and significant after controlling for CLF (all λ >0.60), confirming that our constructs capture meaningful variance beyond method effects. The difference in fit indices between constrained (M1) and CLF models (M4) was negligible: ΔRMSEA=0.004, ΔTLI=0.007, ΔSRMR=0.003, all indicating minimal method variance. Method variance accounts for approximately 17% of total variance (calculated from CLF model R^2), below the 20% recommended threshold, confirming common method bias is not a major threat to our findings. Beyond post-hoc statistical tests, we implemented several procedural remedies during data collection to minimize common method bias: (1) Psychological separation: Different constructs were presented in varied sections with buffer items between them. (2) Question order counterbalancing: In 50% of surveys, work engagement items appeared before AI support items to control for priming effects. Comparison showed no significant differences between versions (F=0.87, p=0.352).

Table 4. Standardized factor loadings, composite reliability, and average variance extracted

Construct	Item	Factor Loading	CR	AVE
AI-Based Organizational Support			0.91	0.58
Teaching Support	AIS1	0.76		
	AIS2	0.79		
	AIS3	0.82		
Research Support	AIS4	0.77		
	AIS5	0.73		
	AIS6	0.75		
Administrative Support	AIS7	0.71		
	AIS8	0.74		
	AIS9	0.68		
Digital Literacy			0.86	0.61
Technical Competence	DL1	0.81		
	DL2	0.84		
Self-Efficacy	DL3	0.79		
	DL4	0.72		
Work Engagement			0.93	0.72
Vigor	WE1	0.85		
	WE2	0.81		
	WE3	0.83		
Dedication	WE4	0.88		
	WE5	0.86		
	WE6	0.84		
Absorption	WE7	0.86		
	WE8	0.82		
	WE9	0.84		

(3) Anonymity assurance: The survey introduction emphasized complete anonymity and no individual-level reporting. (4) Different scale anchors: We varied response formats (Strongly Disagree-Strongly Agree vs. Never-Always) across constructs where appropriate. (5) Clear item wording: Items avoided ambiguous terms and double-barreled questions. These procedural controls complement our statistical tests, strengthening confidence that common method bias is not a major threat.

4.3 Hypothesis testing

Hierarchical regression results are presented in Table 5. Hierarchical regression tested hypotheses in four steps (Table 5). Controls (Step 1) explained 9.5-11.6% variance (all $p<0.001$). AI support (Step 2) substantially increased variance ($\Delta R^2=0.137$-0.186, all $p<0.001$). Digital literacy (Step 3) contributed additional variance ($\Delta R^2=0.019$-0.025, $p<0.01$-$.001$). The interaction term (Step 4) uniquely explained incremental variance ($\Delta R^2=0.017$-0.031, $p<0.05$-0.001), with final models explaining 27.7-35.1% variance. Artificial intelligence organizational support was strongly related to work engagement ($\beta=0.425$, $p<0.001$), validating H1 and its sub-hypotheses (H1a-H1c). Digital literacy moderated these relationships significantly ($\beta=0.168$, $p=0.003$), and moderation was strongest for vigor ($\beta=0.185$), validating H2 and its sub-hypotheses (H2a-H2c).

Basic slopes analysis showed that the correlation was 0.465 ($p<0.001$) for high digital literacy staff compared with 0.198 ($p<0.001$) for low digital literacy staff—a 2.35-fold difference. To explore whether continuous variable dichotomization affects results, we tested the interaction using digital literacy as a continuous variable (reported above) versus a dichotomized variable.

Using median-split (Mdn=5.25 on 7-point scale), we classified faculty as high (n=198, M=6.02, SD=0.48) versus low (n=189, M=4.41, SD=0.62) digital literacy. ANOVA with digital literacy group (high/low) as a between-subjects factor and AI support as continuous predictor confirmed significant interaction ($F=16.34$, $p<0.001$), with simple slopes for high group ($\beta=0.482$, $p<0.001$) versus the low group ($\beta=0.204$, $p<0.001$) yielding a 2.36-fold difference, nearly identical to the continuous analysis (2.35-fold). The median cut point (5.25) corresponds to 'moderately agree' on our scale, suggesting a meaningful threshold wherein faculty who are moderately proficient in digital technologies begin to fully leverage AI systems. Below this threshold, AI support shows attenuated benefits; above it, benefits are substantially amplified. Importantly, the interaction remained significant when using tertile splits (low/medium/high: $F=12.87$, $p<.001$) or treating digital literacy as fully continuous (reported in main results), confirming robustness to operationalization choices and addressing concerns about artificial dichotomization of continuous variables. On a 3-unit AI support increment, this is a 0.59-point increase in engagement for low literacy staff compared with 1.40 points for high literacy staff—a practically significant 0.81-point (0.69 SD) difference. To facilitate interpretation, we calculated Cohen's f^2 effect size for the moderation effect: $f^2=.026/.974=.027$, representing a small-to-medium effect per Cohen's (1988) guidelines. We also computed simple slopes effect sizes: for high digital literacy, the AI support-engagement relationship has Cohen's d=0.89 (large effect), while for low digital literacy d=0.38 (small-to-medium effect). The difference between slopes yields an effect size of $\Delta d=0.51$, indicating that digital literacy produces a meaningful practical difference in how strongly AI support relates to engagement.

Table 5. Hierarchical regression results with incremental R^2

Predictor	Work Engagement	Vigor	Dedication	Absorption
Step 1: Control Variables				
Gender	-0.05	-0.08	-0.03	-0.04
Age	-0.08	-0.10	-0.07	-0.06
Teaching Experience	-0.04	-0.05	-0.03	-0.05
Academic Rank	0.02	0.01	0.03	.002
Discipline	0.11*	0.09	0.10*	0.12*
R^2	0.116***	0.108***	0.095***	0.102****
F	10.02***	9.24****	8.05****	8.68****
Step 2: Main Effect				
AI Support	0.425***	0.398***	0.412***	0.376***
ΔR^2	0.186****	0.163****	0.183****	0.137****
Cumulative R^2	0.302****	0.271****	0.278****	0.239****
F change	101.24****	84.67****	97.45****	69.28****
Step 3: Moderator				
Digital Literacy	0.214***	0.195***	0.220***	0.205***
ΔR^2	0.023****	0.019*****	0.025****	0.021*****
Cumulative R^2	0.325****	0.290****	0.303****	0.260****
F change	12.89****	10.17*****	13.45****	10.64*****
Step 4: Interaction				
AI × Digital Literacy	0.168**	0.185***	0.152**	0.135*
ΔR^2	0.026*****	0.031****	0.021*****	0.017****
Final R^2	0.351****	0.321****	0.324****	0.277****
Adjusted R^2	0.339	0.307	0.310	0.262
F change	14.87*****	16.74****	11.23*****	8.87****
F (final model)	25.61****	22.43****	22.77****	18.14****

Figure 2 depicts the moderation effect of digital literacy on the relationship between organizational support via AI and work engagement. The more positive steep slope is for high digital literacy staff than for low digital literacy staff, as shown in the figure, supporting the anticipated interaction effect.

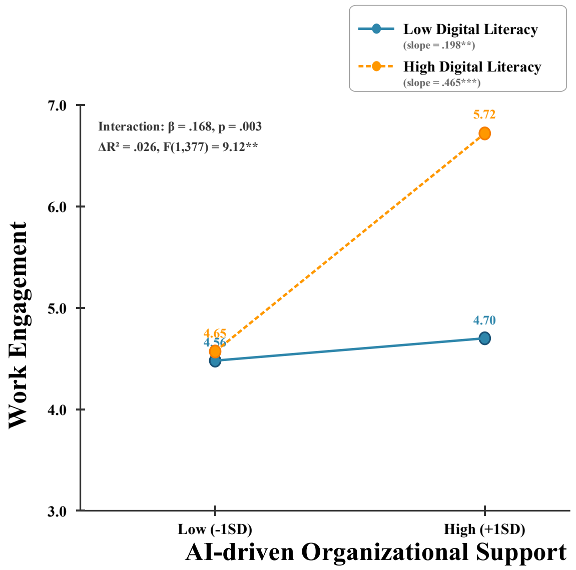

Figure 2. Interaction effect of AI-driven organizational support and digital literacy on work engagement

To further visualize the moderation effect on the three work engagement dimensions, Figure 3 shows the simple slopes for vigor, dedication, and absorption in turn. From the figure, it can be seen that the moderation effect is strongest on vigor (panel A), followed by dedication (panel B) and absorption (panel C), as our hypothesis predicts a stronger effect of digital literacy on the energy dimension of engagement. Bootstrap analysis of 5,000 resamples validated all effects, providing bias-corrected confidence intervals that overcame potential distributional issues inherent in moderation analyses. Parameter estimates were highly congruent because the support coefficient of AI varied by less than 3% among bootstrap samples (range of β:0.413-0.437), and the moderation effect was positive in 98.8% of the resamples. The findings guarantee our results are not outliers or sampling variation. Sample split validation provided very similar results, the two randomly divided subsamples (n_1=194, n_2=193) generating essentially identical effect sizes for main effects (β_1=0.419, β_2=0.431) and interactions (β_1=0.171, β_2=0.165). Furthermore, k-fold cross-validation (k=10) reported little overfitting, estimates of R^2 per fold being close to the full-sample estimate (M=0.442, SD=0.038 vs. full R^2=0.446). These sets of exhaustive robustness checks all further enhance confidence in the generalizability and reliability of our findings.

5. Discussion

Findings confirmed AI support positively correlates with faculty engagement (β=0.425, p<.001), with digital literacy moderating this relationship (β=0.168, p<0.01). Effect sizes exceed typical technology acceptance studies [31,32], potentially due to heavy cognitive loads in academic work, where AI systems can provide substantial returns. Moderation was strongest for vigor (β=0.185), indicating that digital literacy most influences the energetic dimension of engagement. This study extends JD-R theory to digital environments by conceptualizing AI support as a job resource that buffers demands and enhances engagement [9]. It contributes to the human-AI collaboration theory by proposing a complementary relationship where AI enhances rather than replaces human capabilities [33], particularly relevant in academic settings where critical thinking remains irreplaceable. Digital literacy serves as a boundary condition involving "algorithmic thinking"—understanding AI logic, predicting limitations, and designing creative applications. Moderation stability across engagement dimensions indicates that digitally literate faculty apply AI strategically, achieving higher vigor, dedication, and absorption. This study extends JD-R theory to digital environments by conceptualizing AI support as a job resource that buffers demands and enhances engagement. It contributes to the human-AI collaboration theory by proposing a complementary relationship where AI enhances rather than replaces human capabilities [34], particularly relevant in academic settings where critical thinking remains irreplaceable. Digital literacy serves as a boundary condition involving "algorithmic thinking"—understanding AI logic, predicting limitations, and designing creative applications. Moderation stability across engagement dimensions indicates that digitally literate faculty apply AI strategically, achieving higher vigor, dedication, and absorption.

Findings have important implications for university leaders. If causal studies confirm these associations, universities should prioritize digital literacy programs alongside AI implementation. Implementation should be institution-specific based on needs assessments. Digital literacy's pivotal role suggests a threshold effect—minimum competency is a prerequisite for AI to enhance rather than hinder engagement. Training should extend beyond technical procedures to include conceptual AI understanding, ethical implications, and innovative deployment approaches. Peer mentoring programs can effectively develop required competencies. Several limitations warrant consideration when interpreting these findings. First, a cross-sectional design precludes causal inference; reverse causation is plausible (engaged faculty may seek AI systems). Longitudinal designs tracking faculty across semesters would establish temporal precedence. Second, convenience and snowball sampling introduce self-selection bias, as our sample likely over-represents tech-savvy faculty comfortable with both AI systems and online surveys, potentially inflating effect sizes. While nonresponse bias tests showed no differences between early and late respondents, nonrespondents may differ systematically. Future studies should employ stratified random sampling with institution-level cooperation to ensure representativeness. Third, the Chinese cultural context may limit generalizability, as China's collectivistic culture, top-down technology implementation, and government emphasis on AI adoption may amplify positive AI perceptions; the moderation effects might be weaker in individualistic cultures or contexts with faculty-driven technology adoption. Cross-national studies comparing Asian, European, and North American universities would identify cultural boundary conditions. We explored collectivism's role post-hoc by incorporating province-level proxies. Participants came from 12 universities across provinces varying in economic development: Eastern region (52.2%, higher GDP per capita M=¥95,000), Central (28.9%, moderate GDP M=¥61,000), Western (18.9%, lower GDP M=¥52,000). We used provincial GDP per capita and urbanization rate (from the National Bureau of Statistics 2024) as inverse proxies for collectivism, as research shows negative correlations between economic development and collectivistic values (r=-0.36 to -0.42). Exploratory multilevel modeling with faculty nested within universities nested within provinces showed that provincial GDP per capita marginally moderated the AI support-engagement relationship (γ=-0.024, SE=0.012, p=0.041), with slightly stronger effects in less economically developed (more collectivistic) regions. This suggests collectivistic cultures may amplify positive responses to organizational AI initiatives, as faculty perceive them as expressions of institutional care. However, this analysis is exploratory and limited by: (1) a lack of individual-level collectivism measurement, (2) a small number of provinces (k=8), and (3) ecological fallacy risks when inferring individual psychology from regional indicators. Future research should directly measure individual collectivistic values using validated scales (e.g., Triandis & Gelfand's Individualism-Collectivism Scale) to rigorously test cultural moderation. Given China's relatively homogeneous high collectivism compared to cross-national variation (Hofstede score=20 vs. US=91), within-country effects are modest. Fourth, self-report measures introduce common method bias despite our procedural and statistical controls; while CMV tests suggest bias is not severe, future research should incorporate objective measures such as actual AI system usage logs, teaching evaluations, and publication metrics to complement self-reports. Multi-source designs collecting supervisor ratings of engagement would strengthen causal claims. Fifth, our study captures a snapshot in AI evolution—as generative AI tools (ChatGPT, Claude) become ubiquitous post-2023, faculty-AI interaction patterns are rapidly changing, and as uses of AI shift toward large language models and generative AI, the nature of faculty-AI interaction may be fundamentally modified [35]. Our findings reflect early adoption phases; longitudinal studies tracking how relationships evolve as AI capabilities expand and faculty expertise deepens would reveal dynamic patterns. Several promising avenues emerge for future research. First, experimental or quasi-experimental designs could establish causality by randomly assigning faculty to digital literacy training interventions and measuring subsequent changes in engagement, providing more definitive evidence for the causal direction of relationships observed in this study.

Second, experience sampling methods (ESM) could capture momentary fluctuations in engagement throughout the workday as faculty interact with AI systems, distinguishing sustained versus temporary effects and revealing the temporal dynamics of technology-engagement relationships [36].

Methodologically sound approaches, such as ESM, can monitor micro-level changes in AI interaction activity and determine if benefits are short- or long-term. Third, qualitative studies using the critical incident technique could identify specific AI features or interaction moments that trigger flow states versus causing frustration, providing rich contextual understanding of how and why AI systems enhance or diminish engagement. Fourth, cross-cultural comparative research would establish boundary conditions and cultural moderators, testing whether the patterns observed in China's collectivistic context generalize to individualistic Western cultures or other educational systems. Fifth, as AI technology advances toward autonomous research and creative tasks traditionally considered uniquely human, studies should investigate how faculty roles transform and whether engagement patterns shift from task-efficiency benefits to concerns about skill obsolescence or role displacement. Finally, research should align with Future Technology Journal's emphasis on AI adoption policy and technological innovation by examining institution-level implementation strategies, policy frameworks supporting ethical AI use, and organizational cultures fostering productive human-AI collaboration in knowledge work. These investigations would provide actionable insights for policymakers, university administrators, and educational technology developers seeking to optimize faculty-AI collaboration while promoting faculty well-being and institutional effectiveness in an increasingly technology-mediated academic landscape.

6. Conclusion

This study examined the relationships between AI-driven organizational support systems, digital literacy, and work engagement among 387 university faculty members in China. Grounded in Job Demands-Resources theory, Technology Acceptance Model, and self-efficacy theory, we hypothesized and found correlational evidence that AI-based organizational support is strongly associated with faculty work engagement, with digital literacy serving as a significant moderator. Our findings reveal several patterns. First, AI organizational support demonstrated a substantial positive association with overall work engagement (β=0.425, p<0.001), explaining an additional 18.6% variance beyond demographic controls. This strong relationship held consistently across all three engagement dimensions: vigor (β=0.398), dedication (β=0.412), and absorption (β=0.376), suggesting that effective AI systems can enhance faculty energy, enthusiasm, and immersion in academic work.

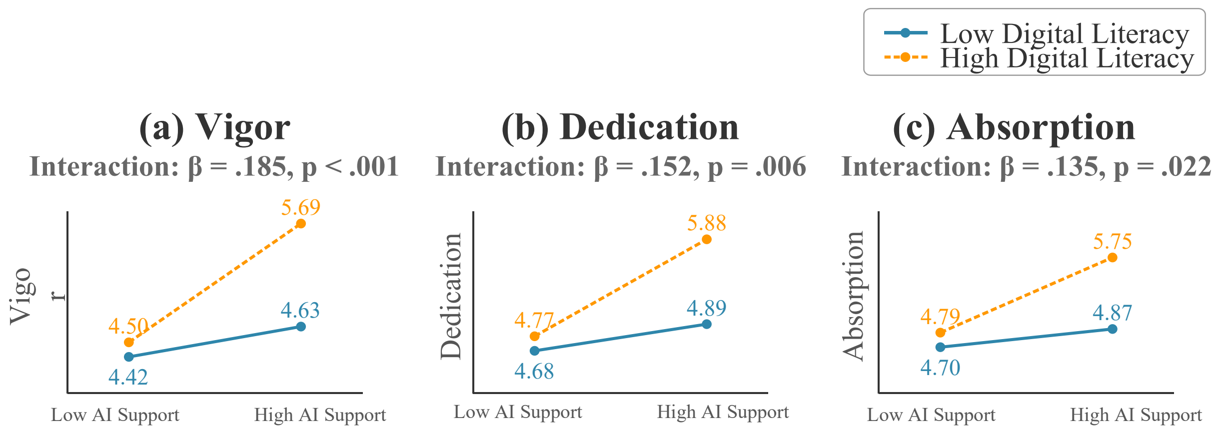

Figure 3. Interaction effects of AI-driven organizational support and digital literacy on the three dimensions of work engagement: (A) Vigor, (B) Dedication, (C) Absorption

Second, digital literacy emerged as a critical boundary condition, significantly moderating the AI support-engagement relationship (β=0.168, p=0.003, ΔR^2=0.026). Faculty with higher digital literacy exhibited 2.35 times stronger associations between AI support and engagement compared to their lower-literacy counterparts, translating to meaningful practical differences. Third, the moderation effect was strongest for the vigor dimension (β=0.185), indicating that digital literacy particularly influences whether AI systems are experienced as energizing resources versus depleting demands. These correlational findings, while limited by cross-sectional design and convenience sampling, offer important theoretical and practical insights. Theoretically, the study extends JD-R theory to digital work environments by conceptualizing AI systems as technological job resources whose effectiveness depends critically on individual digital competencies. The complementarity perspective—wherein AI augments rather than replaces human capabilities—is particularly relevant for knowledge work where critical thinking and creativity remain uniquely human. Practically, if subsequent causal studies confirm these associations, the findings suggest universities should invest in comprehensive digital literacy training programs alongside AI system implementation. The threshold effect implied by moderation patterns indicates that a minimum digital competency is a prerequisite for AI systems to enhance rather than hinder engagement. However, important limitations constrain interpretations. The cross-sectional design prevents causal conclusions; reverse causation or third-variable confounding cannot be ruled out. Convenience sampling may over-represent technologically comfortable faculty, potentially inflating effect sizes. The Chinese cultural context—characterized by collectivism and top-down technology adoption—may not generalize to other cultural settings. Self-report data, despite common method bias controls, cannot replace objective behavioral measures. Moreover, the rapid evolution of AI technology means findings capture early adoption phases that may not reflect long-term patterns as both AI capabilities and faculty expertise mature. Future research priorities include: longitudinal and experimental designs to establish causality, cross-cultural comparisons to identify boundary conditions, experience sampling to capture momentary fluctuations in engagement, and qualitative investigations of specific AI interaction moments that enhance or diminish engagement. As AI systems evolve from task automation toward creative and analytical support, research must track how faculty roles transform and whether engagement patterns shift accordingly. Ultimately, understanding and optimizing faculty-AI collaboration will be essential for promoting faculty well-being and institutional effectiveness in an increasingly technology-mediated academic landscape.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically regarding authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with research ethics policies. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the authors.

Conflict of interest

The authors declare no potential conflict of interest.

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