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Latent profiles of university teachers' occupational well-being in the digital-intelligence era: associations with psychological and contextual factors

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Abstract

Background

Digital-intelligence technologies are transforming university teachers' work demands, resources, and psychological experiences. However, previous research has mainly focused on overall levels or variable-centered relationships, leaving the heterogeneous patterns of teachers' occupational well-being insufficiently understood. This study aimed to identify distinct occupational well-being profiles among Chinese university teachers and examine associated contextual and personal factors.

Methods

A sample of 1,731 Chinese university teachers participated in this study. Latent profile analysis was conducted based on occupational stress, burnout, self-efficacy, work engagement, and job satisfaction. Bolck-Croon-Hagenaars analyses were performed to compare profile differences in contextual factors, and R3STEP analyses were conducted to examine predictors of profile membership.

Results

Four distinct occupational well-being profiles were identified: high well-being, moderate well-being, stress-burdened, and low well-being profiles. Significant differences were observed across profiles in technostress, teacher-student conflict, and perceived school support. Digital competence primarily distinguished teachers in the high well-being profile from those in the low well-being profile, whereas emotional intelligence exerts broad predictive effects across multiple profile comparisons.

Conclusions

The findings reveal substantial heterogeneity in university teachers' occupational well-being in the digital-intelligence era and highlight the importance of considering individual differences when developing teacher support strategies. Tailored institutional interventions targeting different occupational well-being profiles may contribute to promoting teachers' sustainable professional development.

1. Introduction

Rapid advancements in generative artificial intelligence (AI) and other digital-intelligence technologies are reshaping today's higher education. These technologies are growing increasingly embedded in pedagogical design, classroom interaction, learning assessment, academic research, and administrative work, thereby changing university teachers' professional roles and daily experiences with work (Xia et al., 2024; Buele & Llerena-Aguirre, 2025). AI tools can support instructional preparation, feedback generation, data processing, and research productivity. However, they may also require intense technological adaptation and high digital competence. They also necessitate new modes for governing academic integrity and the reconstruction of professional boundaries (Almisad & Aleidan, 2025; Verano-Tacoronte et al., 2025).

In this context, university teachers' occupational well-being has become a key issue. Occupational well-being is not defined merely by the absence of stress or burnout; it also includes positive psychological and work-related states such as self-efficacy, engagement, and job satisfaction (Hascher & Waber, 2021; Zhou et al., 2024). For university teachers, these dimensions are closely related to instructional quality, research performance, professional identity, and sustainable career development. The advent of the digital-intelligence era has brought new opportunities as well pressures into coexistence. Educators are expected to integrate new technologies into teaching and research while maintaining academic standards, responding to students' shifting expectations, and managing increasingly complex work-related tasks on a daily basis.

The Job Demands-Resources model provides a useful framework for understanding these issues. It suggests that occupational demands may lead to stress or burnout by consuming teachers' psychological and physical resources, whereas possession of such resources supports goal achievement, reduces the burden of demands, and promotes deeper engagement with one's work (Bakker & Demerouti, 2007). According to the Conservation of Resources theory, individuals seek to obtain, retain, and protect valuable resources, and stress arises when resources are threatened, lost, or insufficiently replenished (Hobfoll et al., 2018). In the dual context of digital-intelligence and higher education, "technostress" and teacher-student conflict can be viewed as critical demands, while perceived administrative support, digital competence, and emotional intelligence can serve as resources that help teachers meet these demands while maintaining their personal and professional well-being.

Previous studies have examined teachers' stress, burnout, engagement, and job satisfaction, but most have adopted variable-centered approaches. Such approaches are useful for identifying general relationships among variables but may overlook heterogeneous patterns within the teacher population. For example, some teachers may experience high stress and high levels of engagement at the same time, while others may show low efficacy, low satisfaction, and high burnout simultaneously (Collie et al., 2020; Holmström et al., 2023; Pöysä et al., 2021). In the digital-intelligence era, university teachers' occupational well-being may therefore be better understood as a configuration of multiple indicators rather than a singular, linear trajectory.

In efforts to narrow this knowledge gap, the present study uses latent profile analysis to identify distinct occupational well-being profiles among Chinese university teachers. Occupational stress, burnout, self-efficacy, engagement, and job satisfaction were selected as profile indicators. This study also examines whether the identified profiles differ in terms of technostress, teacher-student conflict, and perceived administrative support, and further, whether digital competence and emotional intelligence can predict profile membership. By integrating the Job Demands-Resources model and Conservation of Resources theory, this study aims to gain a highly differentiated understanding of university teachers' occupational well-being in the digital-intelligence era.

2. Literature Review

2.1 Theoretical Foundations: Job Demands-Resources Model and Conservation of Resources Theory

The Job Demands-Resources (JD-R) model divides work-related characteristics into "job demands" and "job resources". Job demands refer to aspects of work that require sustained physical, cognitive, or emotional effort and, if they become excessive, create undue strain. Job resources are aspects of work that help individuals achieve professional goals, reduce the toll of job demands, and stimulate personal growth and motivation (Bakker & Demerouti, 2007). According to this model, job demands are mainly associated with the health-impairment process; job resources are associated with the motivational process. For teachers, high workload, emotional labor, student-related difficulties, administrative pressure, and technology-related pressure can function as job demands. Organizational support, autonomy, professional development opportunities, and personal capacities can function as job resources (Han et al., 2020).

The Conservation of Resources (COR) theory offers a complementary explanation. It argues that individuals strive to acquire, maintain, and protect valued resources including objects, personal characteristics, conditions, and energies. Stress occurs when these resources are threatened, lost, or insufficient to meet demands. In organizational contexts, loss of resources can increase vulnerability, while resource gain can help individuals satisfy various demands and maintain well-being (Hobfoll et al., 2018). For university teachers managing today's advent of digital-intelligence technologies, resources such as institutional support, digital competence, and emotional intelligence may help them cope with technological as well as relational challenges.

Integrating the JD-R model and COR theory enables a thorough analysis of university teachers' occupational well-being, considering it a balance between demands and resources. The JD-R model creates a functional distinction between demands

and resources, while the COR theory explains why resource sufficiency (and resource depletion) can shape teachers' stress, burnout, engagement, self-efficacy, and satisfaction with their work.

2.2 Job Demands: Technostress and Teacher-Student Conflict

"Technostress" refers to the stress individuals experience when they are unable to adapt effectively to information and communication technologies (Ragu-Nathan et al., 2008). In higher education, digital-intelligence technologies have changed the manner in which teachers prepare, deliver instruction in the classroom, conduct research work, and navigate administrative procedures. Teachers are required to learn new platforms, evaluate AI-generated content, adjust assessment methods, and respond to institutional expectations for digital transformation. These requirements may increase workload, time pressure, uncertainty, and role ambiguity, particularly when technical support and training are insufficient (Khlaif et al., 2023; Yang et al., 2025). Recent studies have shown that technostress directly relates to teachers' burnout, job satisfaction, and performance (Tu et al., 2025).

Teacher-student conflict is another important job demand. It refers to tension, disagreement, or negative interactions between teachers and students, which may arise from classroom management problems, differences in expectations, academic disputes, communication difficulties, or inappropriate behavior. Student misbehavior and relational conflict are associated with teachers' emotional exhaustion and reduced well-being (Tsouloupas et al., 2010; Aldrup et al., 2018). In teaching environments supported by digital-intelligence technologies, teacher-student interactions may grow increasingly complex due to changes in students' learning behaviors, technology use, and expectations for instant feedback.

Accordingly, technostress and teacher-student conflict are crucial demands to consider when examining university teachers' occupational well-being.

2.3 Job Resources: Perceived School Support

Perceived administrative support (or "school support") refers to teachers' belief that their institution values their contributions, cares about their well-being, and provides recognition, assistance, and resources for effective work (Hsieh et al., 2022). As a school-specific form of organizational support, it represents an important job resource for teachers' occupational well-being (Hsieh et al., 2022; Admiraal & Røberg, 2023). In higher education, school support is reflected in administrative assistance, collaboration among colleagues, professional development opportunities, participation in decision-making, and responsiveness to stated needs (Honingh & Hooge, 2014; Peng et al., 2022).

From the perspective of the JD-R model, perceived school support influences occupational well-being through motivational and buffering processes. A supportive school environment can strengthen teachers' sense of belonging, competence, and value in their work, thereby improving self-efficacy, engagement, and job satisfaction (Skaalvik & Skaalvik, 2014; Olsen & Huang, 2019). Practical assistance, emotional support, and institutional resources can further help to replenish resources depleted by occupational stress, technostress, and interpersonal conflict, thereby lowering the risk of burnout (Wang et al., 2023).

From the perspective of COR theory, perceived school support functions as an external resource-replenishment mechanism. Teaching, researching, adapting to new technologies, and interacting with students place educators under pressure; school support can help protect, restore, and replenish the cognitive, emotional, time, and relational resources expended under these pressures. Supportive school environments are associated with lower burnout, lower emotional exhaustion, and higher job satisfaction, especially when technostress or time pressure are particularly high (Schulze-Hagenest et al., 2023; Wang et al., 2023). Accordingly, this study treats perceived school support as a profile-differentiating variable to examine contextual resource differences across occupational well-being profiles.

2.4 Personal Resources: Digital Competence and Emotional Intelligence

"Digital competence" refers to university teachers' ability to use digital technologies effectively and integrate them into their teaching to solve instructional and technological problems (Basilotta-Gómez-Pablos et al., 2022). The digital transformation of higher education requires operating various technologies effectively, evaluating various tools, adjusting classroom practices, problem-solving, and sustaining high performance within changing technological environments (Basilotta-Gómez-Pablos et al.,

2022). Teachers with stronger digital competence tend to show higher technology-related self-efficacy, better technology integration, lower emotional exhaustion, and higher occupational well-being (Shi et al., 2025). Digital competence can also enhance teachers' sense of control and overall competence, reduce technostress, and protect job resources that would be otherwise lost due to insufficient technological adaptation (Truța et al., 2023).

"Emotional intelligence" refers to individuals' ability to perceive, understand, regulate, and express emotions in themselves and others (Mayer & Salovey, 1990). In higher education, where teaching involves intensive interpersonal interaction, emotional intelligence serves a crucial personal resource that protects teachers' occupational well-being (Mérida-López & Extremera, 2017). Teachers with higher emotional intelligence generally report lower burnout, especially emotional exhaustion and depersonalization, as well as higher career adaptability, engagement with work, self-efficacy, perceived social support, and job satisfaction (Geraci et al., 2023; Mérida-López & Extremera, 2017; Mérida-López et al., 2020). From JD-R and COR perspectives, emotional intelligence helps teachers cope with conflict, teaching pressure, and organizational communication pressure while protecting their personal resources and gaining interpersonal resources (Mérida-López & Extremera, 2017; Mérida-López et al., 2020; Valente & Lourenço, 2020).

Therefore, this study includes digital competence and emotional intelligence as personal resources in the R3STEP analysis.

2.5 Present Study

Research on teachers' well-being generally includes both negative indicators (e.g., stress and burnout) and positive indicators (e.g., job satisfaction, work engagement, positive emotions, meaning, and self-efficacy) (Hascher & Waber, 2021). Occupational stress, burnout, self-efficacy, work engagement, and job satisfaction are closely connected and jointly reflect the job-related demands, resource depletion, competence-related beliefs, motivational investment, and occupational evaluation faced by practicing educators (Klassen & Chiu, 2010; Skaalvik & Skaalvik, 2014; Zhou et al., 2024). Teachers' occupational well-being should be understood as a multidimensional structure rather than a singular level of stress or satisfaction.

Person-centered studies have characterized various heterogeneous teacher profiles differently. Some are defined by being "highly engaged", others by "engagement-burnout coexistence" or "burnout" (Abós et al., 2019; Holmström et al., 2023). Research suggests that teachers differ not only in their levels of well-being but also in the configuration of multiple psychological indicators. Latent profile analysis can therefore capture meaningful group-wise patterns, including at-risk groups with high stress, high burnout, low efficacy, low engagement, and low satisfaction, as well as adaptive groups with relatively high efficacy, engagement, and satisfaction.

Despite these and other valuable contributions, there are three main limitations in existing studies. First, person-centered studies have focused on primary and secondary school teachers, giving less attention to university teachers, who face complex demands from teaching, research, administration, student support, and digital transformation. Second, many studies have adopted variable-centered approaches and examined single outcomes, gaining limited evidence on overall occupational well-being profiles. Third, in the context of AI and digital transformation, technostress, teacher-student conflict, school support, digital competence, and emotional intelligence have become increasingly relevant to university teachers' daily work; however, their roles in distinguishing or predicting well-being profiles remain under-explored.

Considering these limitations, this study integrates the JD-R model and COR theory in utilizing latent profile analysis to identify university teachers' occupational well-being profiles. Occupational stress, job burnout, self-efficacy, work engagement, and job satisfaction were selected as profile indicators. After identifying the profiles, this study compared differences in technostress, teacher-student conflict, and perceived school support across profiles, then further examined whether digital competence and emotional intelligence predict profile membership through R3STEP analysis.

Based on the above analysis, this study aims to answer three key research questions.

RQ1: With occupational stress, job burnout, self-efficacy, work engagement, and job satisfaction as core indicators, what latent profiles of occupational well-being can be identified among Chinese university teachers?

RQ2: Are there significant differences across occupational well-being profiles in technostress, teacher-student conflict, and perceived school support?

RQ3: Can digital competence and emotional intelligence significantly predict the likelihood of university teachers belonging to certain occupational well-being profiles?

3. Methodology

3.1 Research Procedure and Sample

This study focused on Chinese university teachers and adopted a cross-sectional survey design. Data were collected from October 2025 to January 2026 through online questionnaires and offline, paper-based questionnaires. The research protocol was approved by the ethics committee. Participants were informed of the research content, data-use procedures, anonymity, and confidentiality principles, and all provided informed consent prior to participating.

Purposive sampling and random sampling were combined. Online questionnaires were distributed through Wenjuanxing, and offline questionnaires were distributed to selected universities. A pilot test was used to revise the initial item wording and response logic. A total of 1,926 questionnaires were collected. After excluding invalid questionnaires (i.e., those with insufficient response time or patterned responses), the final valid sample included 1,731 questionnaires, with an effective response rate of 89.88%. Among them, 652 teachers were male and 1,079 were female.

Due to sampling limitations, teachers from normal universities were overrepresented while those from comprehensive and engineering-oriented universities were underrepresented. Therefore, the findings should be interpreted with caution in terms of generalizability. In addition, institutional level information was not collected, so potential clustering effects among teachers from the same university could not be controlled.

3.2 Measures

This study used a structured self-report questionnaire to measure variables related to university teachers' occupational well-being. All items were drawn from internationally validated scales and translated into Chinese through a translation and back-translation procedure. While retaining the core meanings of the original scales, this study localized the wording of some items before inviting experts in relevant fields to review the content. All items were scored on a 5-point Likert scale, ranging from 1 = "Strongly disagree" to 5 = "Strongly agree", where higher scores indicate higher levels of the corresponding variables. The items are listed in Appendix 1.

This study included occupational stress (10 items, $\alpha = 0.944$), job burnout (7 items, $\alpha = 0.928$), self efficacy (6 items, $\alpha = 0.909$), work engagement (9 items, $\alpha = 0.899$), and job satisfaction (5 items, $\alpha = 0.896$) as indicators for latent profile analysis. Technostress (7 items, $\alpha = 0.914$), teacher-student conflict (7 items, $\alpha = 0.928$), perceived school support (7 items, $\alpha = 0.897$), digital competence (9 items, $\alpha = 0.925$), and emotional intelligence (7 items, $\alpha = 0.849$) were used as external correlates.

In alignment with JD-R and COR, this study classified technostress and teacher-student conflict as job demands, perceived school support as a job resource, and digital competence and emotional intelligence as personal resources.

3.3 Data Analysis

SPSS 25.0 and Mplus 8.3 were used for data management and statistical analysis. First, confirmatory factor analysis was conducted to examine the structural validity of the scales. The WLSMV estimator and THETA parameterization were appropriate given that all items were 5-point Likert-type ordinal variables. Model fit was evaluated by CFI, TLI, RMSEA, and SRMR; CFI and TLI values above 0.90 and RMSEA and SRMR values below 0.08 indicate acceptable fit. The 10-factor measurement model showed a good fit: $\chi^2(2582) = 11968.809$, $p < 0.001$, RMSEA = 0.046, 90% CI [0.045, 0.047], CFI = 0.946, TLI = 0.944, SRMR = 0.038. Composite reliability (CR) ranged from 0.887 to 0.962, and average variance extracted (AVE) ranged from 0.529 to 0.742. The five-factor model for the profile indicators also showed acceptable fit: $\chi^2(619) = 5169.788$, $p < 0.001$, RMSEA = 0.065, CFI = 0.956, TLI = 0.953, SRMR = 0.034.

Next, descriptive statistics and Pearson correlations were conducted. The five profile indicators were then standardized and treated as continuous observed variables for latent profile analysis. In Mplus 8.3, TYPE = MIXTURE and robust maximum likelihood estimation were used to fit one- to five-class models. Model selection was based on AIC, BIC, SaBIC, Entropy, LMR, BLRT, theoretical interpretability, class size, and practical significance (Spurk et al., 2020).

Lastly, the BCH method was used to compare differences across profiles in technostress, teacher-student conflict, and perceived school support, and the R3STEP method was used to examine the predictive effects of digital competence and emotional intelligence on profile membership.

4. Results

As shown in Table 1, the descriptive statistics showed mean values for occupational stress (M = 2.62, SD = 0.85), job burnout (M = 2.50, SD = 0.84), teacher-student conflict (M = 2.21, SD = 0.77), and technostress (M = 2.82, SD = 0.75) below or close to a midpoint of 3. The means for work engagement (M = 3.41, SD = 0.65), job satisfaction (M = 3.50, SD = 0.70), self efficacy (M = 3.59, SD = 0.65), emotional intelligence (M = 3.69, SD = 0.53), perceived school support (M = 3.31, SD = 0.67), and digital competence (M = 3.78, SD = 0.57) all fell above above this midpoint. Overall, the sample scored higher on resource-related and positive variables than on demand-related and exhaustion-related variables.

The correlation analysis showed significant and positive correlations with occupational stress and job burnout ($r = 0.795$, $p < 0.01$), both of which were significantly and negatively correlated with work engagement, job satisfaction, and self-efficacy ($|r| = 0.251–0.481$, $ps < 0.01$). Work engagement, job satisfaction, and self-efficacy were significantly and positively correlated with each other ($r = 0.403–0.710$, $ps < 0.01$). Teacher-student conflict was significantly and positively correlated with technostress ($r = 0.392$, $p < 0.01$), and both were significantly and negatively correlated with perceived school support, digital competence, emotional intelligence, and job satisfaction ($|r| = 0.099–0.370$, $ps < 0.01$). These correlation patterns are consistent with the core assumptions of the JD-R model, where higher job demands were associated with lower levels of positive psychological resources and occupational adaptation. It is important to note, however, that the correlation analysis in this study yielded only directional support and did not directly test the JD-R mechanism itself.

Table 1
Means, standard deviations and correlations.

Variables	1	2	3	4	5	6	7	8	9	10
OS	—									
JB	.795**	—								
WE	− .407**	− .481**	—							
JS	− .312**	− .349**	.505**	—						
SE	− .251**	− .275**	.403**	.710**	—					
EI	− .184**	− .211**	.279**	.526**	.618**	—				
TSC	.242**	.259**	− .106**	− .247**	− .223**	− .267**	—			
PSS	− .252**	− .249**	.318**	.541**	.472**	.497**	− .099**	—		
DC	− .177**	− .211**	.244**	.420**	.508**	.541**	− .295**	.450**	—	
TS	.272**	.250**	− .179**	− .336**	− .296**	− .312**	.392**	− .370**	− .240**	
M	2.6193	2.4966	3.4078	3.5011	3.5906	3.6892	2.2116	3.3133	3.7761	2.8228
SD	0.8507	0.8449	0.6549	0.7047	0.6500	0.5321	0.7741	0.6687	0.5679	0.7542

Note. M and SD are based on unstandardized raw scale means; N = 1731; **p < 0.01; OS = Occupational Stress; JB = Job Burnout; WE = Work Engagement; JS = Job Satisfaction; SE = Self-Efficacy; EI = Eemotional Intelligence; TSC = Teacher-student Conflict; PSS = Perceived School Support; DC = Digital Competence; TS = Technostress; M = Mean; SD = Standard Deviations.

4.1 Identification and Description of Latent Profiles

Table 2 presents the fitting results for the latent profile models. AIC, BIC, and SaBIC continually decreased as the number of classes increased, indicating gradual improvement in model fit. Over the three-class model, both the LMRT and BLRT of the four-class model reached statistical significance (ps < 0.001). The Entropy value was 0.815, indicating acceptable classification quality. The proportions of the four profiles were 12.074%, 40.555%, 38.359%, and 9.012%, respectively, all of which indicate practical interpretability. Although the information criteria of the five-class model was relatively low, its LMRT was not statistically significant (p = 0.3609) and it included a small class accounting for only 2.657% of the sample. Considering these model fit indices, classification accuracy, class size, and theoretical rationality, the four-class model was ultimately selected a the optimal latent profile solution.

Table 2
Model-fit indices

Profile	Nfp	LL	AIC	BIC	SaBIC	Entropy	LMRT	BLRT	Percentage
1	10	−10481.930	20983.861	21038.426	21006.657	1	NA	NA	1.000
2	16	−9716.349	19464.698	19552.001	19501.171	.700	.000	.000	55.633 / 44.367
3	22	−9365.744	18775.487	18895.529	18825.638	.798	.0002	.000	28.365 / 59.908 / 11.727
4	**28**	**−9160.837**	18377.674	18530.454	18441.501	**0.815**	**0.000**	**0.000**	12.074 / 40.555 / 38.359 / 9.012
5	34	−8992.893	18053.785	18239.305	18131.290	.760	.3609	.000	22.819 / 39.053 / 2.657 / 22.704 / 12.767

Note. The black bold font represents the chosen optimal model; Nfp = number of free parameters; LL = Log-likelihood; AIC = Akaike's information criterion; BIC=Bayesian information criterion; SaBIC = sample-adjusted BIC; LMRT = Lo-Mendell Ruben likelihood ratio test; BLRT = bootstrapped likelihood ratio test; NA represented the model was not fitted.

Based on the mean patterns of the five indicators, the profiles were labeled "high well-being", "moderate well-being", "stress-burdened", and "low well-being" (Fig. 1). The high well-being profile showed the lowest occupational stress and job burnout alongside the highest self-efficacy, work engagement, and job satisfaction relative to the remainder of the sample. Means for the moderate well-being profile, comprising the largest proportion of the sample, fell near the average. The stress-burdened profile showed relatively high occupational stress and job burnout with relatively low positive indicators. The low well-being profile showed the highest stress and burnout and the lowest positive indicators among these groups.

4.2 Differences in Job Demands and Job Resources Across Latent Profiles

Table 3 shows where there were significant between-group differences across the four latent profiles regarding technostress, teacher-student conflict, and perceived school support.

Technostress showed a step-wise increasing pattern across profiles: high well-being (M = 2.355, SE = 0.079), moderate well-being (M = 2.732, SE = 0.030), stress-burdened (M = 2.967, SE = 0.028), and low well-being (M = 3.257, SE = 0.068). The overall difference was significant at $\chi^2(3) = 115.218$, $p < 0.001$, and all pairwise comparisons were significant (ps < 0.001). Technostress provided the clearest distinction among the profiles, with the largest difference between the high well-being profile and the low well-being profile ($\Delta M = 0.902$), indicating a marked differentiation in the degree of exposure to job demands between these two groups of teachers.

Teacher-student conflict also increased gradually across profile types: high well-being (M = 1.649, SE = 0.052), moderate well-being (M = 2.148, SE = 0.030), stress-burdened (M = 2.401, SE = 0.033), and low well-being (M = 2.464, SE = 0.082). The overall difference was significant ($\chi^2(3) = 166.703$, $p < 0.001$). Excepting a non-significant difference between the stress-burdened profile and the low well-being profile ($\Delta M = 0.063$, $p = 0.490$), all other pairwise comparisons were significant (ps < 0.001). There were similar levels of teacher-student conflict between stress-burdened and low well-being profiles. In contrast, the high well-being profile maintained a clear distance from the other three profiles, suggesting that low teacher-student conflict is a typical characteristic of teachers in the high well-being group.

Perceived school support showed an opposite (decreasing) pattern relative to the two job demand indicators. The profile means from highest to lowest were, in order: high well-being (M = 3.791, SE = 0.057), moderate well-being (M = 3.394, SE =

0.025), stress-burdened (M = 3.152, SE = 0.028), and low well-being (M = 2.982, SE = 0.066). The overall difference was significant, $\chi^2(3) = 144.927$, $p < 0.001$, and all pairwise comparisons were significant. The difference between the stress-burdened profile and the low well-being profile was relatively slight ($\Delta M = 0.170$, $p = 0.022$), whereas the difference between the high well-being profile and the low well-being profile was substantial ($\Delta M = 0.809$, $p < 0.001$). This indicates that the distinguishing role of perceived school support manifested primarily in a contrast between the high well-being profile and the low well-being profile, while stress-burdened- and low well-being-profile members were similar in their perceived levels of resource access.

Overall, the external work environment characteristics of the four teacher profiles were clearly differentiated. Teachers with the high well-being profile were situated in an advantageous work environment characterized by low job demands and high school support, whereas teachers with the low well-being profile faced notable disadvantages concerning high job demands and less support from administration. The moderate well-being profile and the stress-burdened profile showed intermediate levels; the stress-burdened profile approached the low well-being profile in its levels of teacher-student conflict and perceived school support.

Table 3
Mean differences in technostress, teacher–student conflict, and perceived school support across the four latent profiles based on the BCH approach.

Variable	High Well-being Profile	Moderate Well-Being Profile	Stress-burdened Profile	Low Well-being Profile	Wald χ^2 (df)	p	Non-significant pairwise comparisons
Job Demands							
TS	2.355 (0.079)	2.732 (0.030)	2.967 (0.028)	3.257 (0.068)	115.218 (3)	<.001	None
TSC	1.649 (0.052)	2.148 (0.030)	2.401[a] (0.033)	2.464[a] (0.082)	166.703 (3)	<.001	P3 vs. P4, ns (p = .490)
Job Resources							
PSS	3.791 (0.057)	3.394 (0.025)	3.152 (0.028)	2.982 (0.066)	144.927 (3)	<.001	None

Note. Values are BCH-adjusted means, with standard errors (SEs) shown in parentheses. Wald χ^2 statistics test the overall differences across the four latent profiles for each variable, with df = 3. Means sharing the same superscript letter are not significantly different based on pairwise Wald tests in the BCH procedure.ns indicates a non-significant pairwise comparison. In the column "Non-significant pairwise comparisons," None indicates that all pairwise comparisons were statistically significant.

4.3 Predictive Effects of Personal Resources on Latent Profile Membership

As shown in Table 4, the R3STEP results showed different predictive effects of digital competence and emotional intelligence on profile membership. With the low well-being profile as a reference group, digital competence only positively predicted the likelihood of teachers being classified into the high well-being profile group ($\beta = 0.686$, OR = 1.986, $p = 0.025$), whereas its predictive effects on moderate well-being and stress-burdened profile membership were not significant. In contrast, emotional intelligence showed a broader predictive effect: it significantly increased the likelihood of teachers being classified into high well-being profile ($\beta = 2.173$, OR = 8.784, $p < 0.001$), moderate well-being profile ($\beta = 0.564$, OR = 1.757, $p = 0.006$), and stress-

burdened profile (β = 0.411, OR = 1.509, p = 0.039) groups, effectively distinguishing these profiles from the low well-being profile.

Further pairwise comparisons showed that digital competence mainly distinguished the high well-being profile from the stress-burdened profile, the high well-being profile from the low well-being profile, and the moderate well-being profile from the stress-burdened profile. Emotional intelligence showed significant predictive effects across most comparisons when the low well-being profile was used as the reference group, with the only non-significant difference occurring between the moderate well-being profile and the stress-burdened profile. Overall, emotional intelligence had a broader and more stable predictive effect on occupational well-being profile membership, whereas the effect of digital competence was more selective.

Table 4
Multinomial Logistic Regression Estimates for Digital Competence and Emotional Intelligence Predicting Latent Profile Membership (R3STEP)

Comparison	Predictor	β	SE	OR	95%CI for OR	p
P1 vs. P2	DC	0.441	0.262	1.554	[0.930, 2.597]	.092
	EI	1.609	0.311	4.999	[2.717, 9.194]	< .001
P1 vs. P3	DC	0.986	0.256	2.679	[1.623, 4.427]	< .001
	EI	1.762	0.303	5.821	[3.216, 10.547]	< .001
P1 vs. P4	DC	0.686	0.307	1.986	[1.088, 3.625]	.025
	EI	2.173	0.343	8.784	[4.485, 17.206]	< .001
P2 vs. P3	DC	0.544	0.143	1.724	[1.302, 2.280]	< .001
	EI	0.152	0.159	1.164	[0.852, 1.590]	.339
P2 vs. P4	DC	0.245	0.213	1.278	[0.842, 1.940]	.250
	EI	0.564	0.206	1.757	[1.174, 2.632]	.006
P3 vs. P4	DC	-0.299	0.220	0.741	[0.482, 1.141]	.173
	EI	0.411	0.200	1.509	[1.019, 2.232]	.039

Note. P1 = high well-being; P2 = moderate well-being; P3 = stress-burdened; P4 = low well-being. DC = digital competence; EI = emotional intelligence. OR > 1 indicates that higher predictor levels are associated with greater odds of membership in the first-named profile.

5. Discussion

This study adopted a person-centered perspective to examine occupational stress, self-efficacy, job burnout, work engagement, and job satisfaction as core indicators in a latent profile analysis. Four latent profiles of university teachers' occupational well-being were identified: high well-being, moderate well-being, stress-burdened, and low well-being. Analysis of these profiles indicated that university teachers' occupational well-being in the digital-intelligence era should not be characterized a single, continuous state, but rather as a heterogeneous configuration shaped by job demands, internal and external conditions, and personal resources.

5.1 Heterogeneity in University Teachers' Occupational Well-Being

The moderate well-being profile accounted for the largest proportion of the sample, followed by the stress-burdened profile, while high well-being and low well-being profiles accounted for smaller proportions. This pattern suggests that most teachers were operating between stable adaptation and severe depletion. Their occupational well-being was neither uniformly positive nor uniformly negative, instead existing as a transitional state in which positive and negative experiences coexisted. Therefore, relying only on group-level averages may obscure meaningful internal differences among teachers.

From a JD-R perspective, the four profiles reflect different states of balance between personal health impairment and motivational processes. Teachers in the high well-being profile showed low levels of stress and burnout together with high self-efficacy, work engagement, and job satisfaction, suggesting that motivational resources were relatively strong and demand-related depletion was limited. In contrast, the low well-being profile showed high stress and burnout and low positive occupational indicators, reflecting a configuration in which job demands outweighed available resources.

The stress-burdened profile deserves particular attention because it combined relatively high depletion with weakened positive occupational functioning. Though this group may not have reached the most severe level of low well-being, it already showed clear vulnerability. Due to the cross-sectional design, this study could not determine whether this group would move toward recovery or further depletion over time (Ployhart & Vandenberg, 2010; Xie et al., 2022).

These results are also consistent with the COR theory. The high well-being profile can be understood as a state of relative resource sufficiency, whereas the low well-being profile is closer to continuous resource loss (Hobfoll et al., 2018; Salmela-Aro et al., 2019; Xie et al., 2022). In the moderate and stress-burdened profile groups, it appears that many teachers experienced unstable resource configurations wherein available resources could still support basic functioning but were insufficient to fully offset occupational demands. This explanation remains theoretical, however, as longitudinal data are needed to directly test resource gain or loss spirals.

5.2 Distinguishing Roles of Job Demands and Job Resources

The four profiles differed significantly in levels of technostress, teacher-student conflict, and perceived school support. These differences followed theoretically meaningful gradients, indicating that the latent profiles were not arbitrary statistical groupings and reflected distinct working conditions across participants.

Technostress increased from the high well-being profile to the low well-being profile, reflecting technology-related pressure as a critical job-related demand in contemporary higher education. Digital technologies may improve flexibility and efficiency, but when teachers are required to integrate new tools without adequate time, training, technical support, or clarity on relevant policies, technology can become burdensome. In such situations, teachers may experience increased workloads, uncertainty, and pressure to adapt, leading them to experience digital transformation as a source of resource loss rather than support (Khlaif et al., 2023). This finding is consistent with previous studies showing that technostress is associated with lower occupational well-being (Pagán-Garbín et al., 2024; Yang et al., 2025). It further suggests that technostress does not affect all teachers equally; instead, it helps distinguish different well-being profiles within the teacher population.

Teacher-student conflict also showed a gradient pattern, where teachers with more adaptive profiles reported lower levels of conflict while those with less adaptive profiles reported higher levels. Notably, there was no significant difference between the stress-burdened profile and the low well-being profile, suggesting that elevated teacher-student conflict may be a shared feature of high-risk groups. Relational stress appears closely associated with teachers' emotional labor, perceived efficacy, and burnout. Repeated conflict, incivility, or emotionally demanding interactions may consume teachers' emotional and interpersonal resources, reduce their sense of professional effectiveness, and increase their risk of burning out (Aldrup et al., 2018; Jiang et al., 2016; Tsouloupas et al., 2010). In today's higher education contexts, educators are expected not only to complete teaching tasks but also to effectively support their students' academic, emotional, and technological needs. When these expectations fall beyond a teacher's available resources, teacher-student relational stress may become a major source of depletion (Trillo et al., 2025; Porter et al., 2025).

Perceived school support showed an opposite pattern. Teachers in the high well-being profile reported the highest levels, whereas those in the low well-being profile reported the lowest levels of perceived support. This result aligns with the JD-R model, which regards job resources as important conditions for motivation and adaptation (Hakanen et al., 2006), and with the COR theory, which emphasizes the role of external resources in mitigating resource depletion (Hobfoll et al., 2018). School support may influence well-being not only by providing concrete assistance but also by shaping the ways that teachers understand and cope with the demands placed upon them at work. When teachers perceive that their institution values them, can and will respond to difficulties, and provides practical resources, stressors are less likely to develop into dissatifaction or

burnout (Kurtessis et al., 2017; Hsieh et al., 2022; Wang et al., 2024; Kinder et al., 2023). Therefore, perceived school support appears to be a key contextual resource that differentiates adaptive from less adaptive or maladaptive profiles.

5.3 Predictive Effects of Personal Resources

The R3STEP results indicated varying roles for digital competence and emotional intelligence. Unlike the low well-being profile, digital competence significantly increased the likelihood of membership to the high well-being profile. However, it did not significantly distinguish moderate or stress-burdened profiles from the low well-being profile. This suggests that digital competence is particularly important for reaching a highly adaptive state, as teachers with stronger digital competence may use digital tools more efficiently, experience greater control, and perceive technology-related tasks as less threatening (Yang et al., 2025; Wang et al., 2023). However, digital competence alone may not be sufficient to shift teachers out of moderate or stress-burdened configurations if other demands, such as workload or relational conflict, remain excessive.

Emotional intelligence, conversely, showed broader predictive effects. Teachers with higher emotional intelligence were more likely to belong to the high, moderate, or stress-burdened groups rather than the low well-being group. This indicates that emotional intelligence may function as a more general personal resource. Teachers who can perceive, understand, and regulate emotions are better able to manage classroom tension, cope with work-related pressure, maintain constructive relationships, and preserve psychological stability under demanding conditions (Liu et al., 2026; Mérida-López & Extremera, 2017). Compared to digital competence, emotional intelligence may operate across a wider range of work situations because university teaching involves continuous interpersonal communication, emotional regulation, and organizational interaction.

5.4 Practical Implications

The findings of this study suggest that support for university teachers should be tailored to specific profiles rather than uniformly deployed. Teachers with low well-being and stress-burdened profiles require targeted support to reduce technostress, manage teacher-student conflict, and protect resources from undue depletion. Those with moderate well-being profiles also merit careful attention as they represent the largest group within the teacher population and may shift toward either adaptation or depletion depending on future demands and resources.

Universities should reduce unnecessary digital burdens, clarify technology-use expectations, strengthen training and technical support, and establish mechanisms for handling teacher-student relational difficulties. Institutional support should also be combined with personal resource development. Digital competence and emotional intelligence training are more likely to be successful when embedded in a supportive organizational environment rather than treated merely as individual responsibilities.

6. Conclusion

This study examined heterogeneity in university teachers' occupational well-being from a person-centered perspective based on indicators of occupational stress, burnout, self-efficacy, engagement with work, and job satisfaction. Four distinct profiles were identified: high well-being, moderate well-being, stress-burdened, and low well-being. The results show that university teachers' occupational well-being cannot be represented by a single average score. The profiles also differed significantly in technostress, teacher-student conflict, and perceived school support. Digital competence selectively predicted profile membership, while emotional intelligence showed broader predictive effects. Overall, university teachers' occupational well-being in the digital-intelligence era appears to be shaped by a dynamic configuration of job demands, supportive resources, and personal resources.

7. Limitations and Future Directions

This work was not without noteworthy limitations. First, the cross-sectional design precluded causal inference and prevented examination of transitions among profiles. Longitudinal studies are yet needed to test whether and how teachers move across profiles and to determine if theoretical explanations of resource maintenance and resource loss are empirically supported (Ployhart & Vandenberg, 2010; Xie et al., 2022). Second, although the sample size was large, demographic and institutional

heterogeneity was not fully considered. Future studies could include gender, professional experience, disciplinary background, university type, and institutional level as covariates or grouping variables. Third, this study focused on select demands, external supports, and personal resources. Future research could include family support, organizational climate, workload structure, leadership practices, and AI governance arrangements as potential variables of interest. Finally, the use of self-report data may have introduced common method bias. Future studies could combine self-report scales with multi-source or longitudinal data to enhance generalizability.

Declarations

Ethics approval and consent to participate

Ethical approval for this study was obtained from the Ethics Committee of Central China Normal University (Institutional Review Board, IRB Number: CCNU-IRB-202509144b) on September 10 2025. All procedures involving human participants were conducted in accordance with the ethical guidelines and regulations of the committee. Before completing the questionnaire, all participants were provided with detailed information regarding the objectives, procedures, potential benefits, and confidentiality measures of the study. Participation was entirely voluntary, and informed consent was obtained from all participants prior to data collection. Participants were assured that their personal information and responses would remain confidential and would only be used for academic research purposes. They were also informed of their right to discontinue participation at any stage without any consequences.

Consent for publication

Not Applicable

Data availability statement: The datasets generated or analysed during the current study are not publicly available due to participant privacy and ethical restrictions, but are available from the corresponding author on reasonable request.

Conflict of interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Author Contributions

Xiaoxuan Zhang and Si Xu contributed equally to this work. Xiaoxuan Zhang, Si Xu, and Yinguang Sun conceived and designed the study, developed the research framework, and provided theoretical guidance. Xiaoxuan Zhang and Si Xu conducted the literature review, collected and organized the data, and contributed to the initial drafting of the manuscript. Yinguang Sun supervised the research process, provided critical methodological advice, and substantially revised the manuscript. Yuchan Zhang and Xiang Li assisted with data collection, data management, and manuscript revision. Kai Wang conducted the statistical analyses, interpreted the findings, prepared the tables and figures, and contributed to the revision of the manuscript. All authors reviewed and approved the final version of the manuscript.

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Figures

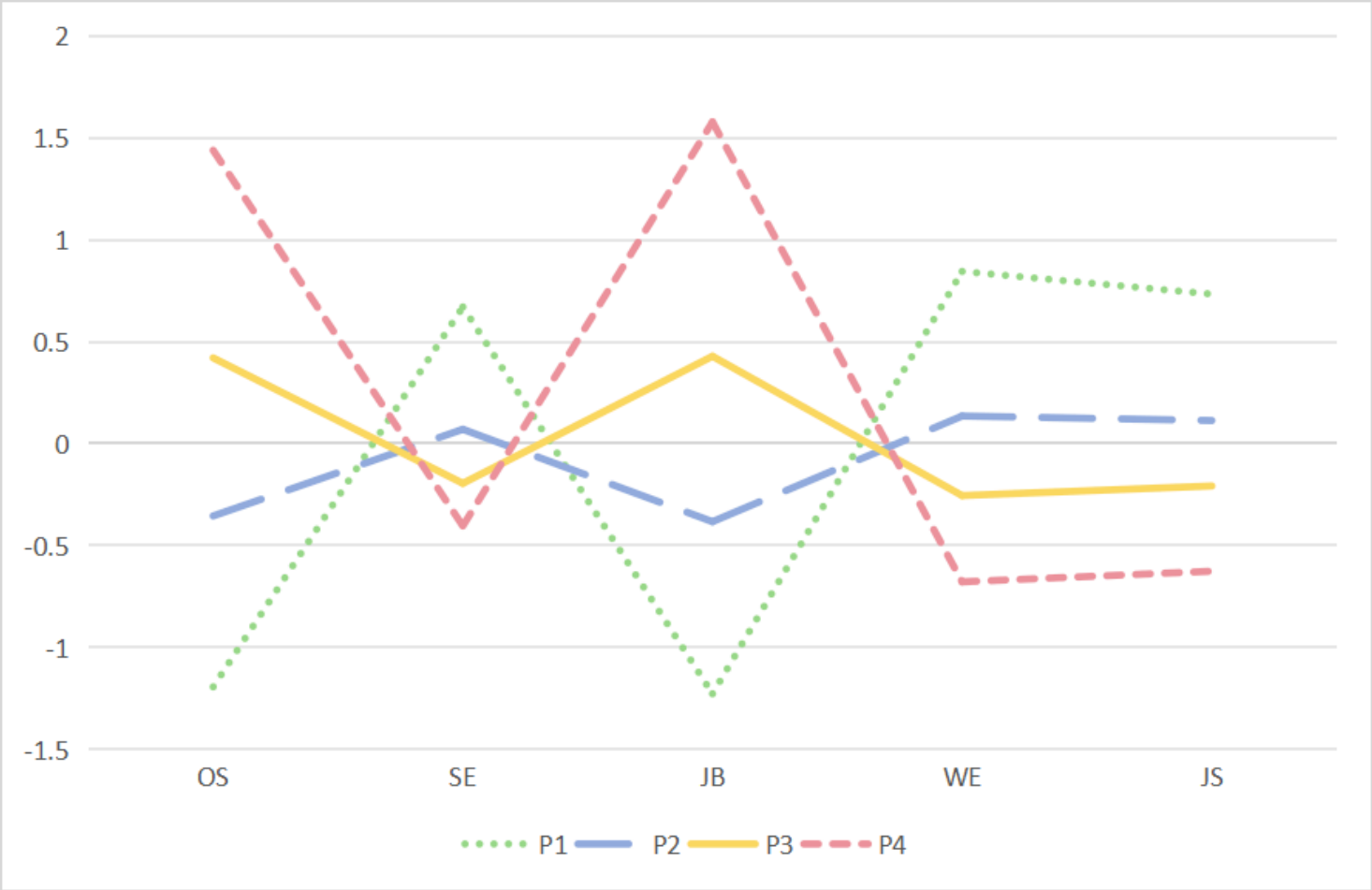


Figure 1

our profiles of the best-fitting solution.

Supplementary Files

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- Appendix1.docx