

Empowerment or burden? Dual pathways linking school digitalization orientation to physical education teachers' AI-collaborative teaching behavior: a three-wave time-lagged study

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Article

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Abstract

Background

School digitalization and artificial intelligence (AI) are reshaping teaching, yet their implications for physical education teachers may be both enabling and burdensome. Because physical education is embodied, mobile, and safety-sensitive, digitalization may provide conditions that support pedagogically meaningful AI use while also increasing reporting, coordination, and device-management demands. This study examined whether school digitalization orientation was associated with teachers' later AI-collaborative teaching behavior through positive AI attitude and digital stress, and whether digital self-efficacy conditioned these pathways.

Methods

Matched three-wave survey data were collected from 638 physical education teachers in 80 schools across primary, secondary, and higher education settings in China. School digitalization orientation and digital self-efficacy were measured at Time 1, positive AI attitude and digital stress at Time 2, and AI-collaborative teaching behavior at Time 3. Measurement quality was assessed using confirmatory factor analysis, and the hypothesized direct, indirect, and moderated indirect associations were tested with structural equation modeling, bias-corrected bootstrapping, and school-clustered robustness checks.

Results

School digitalization orientation was positively associated with later AI-collaborative teaching behavior. It also showed a positive indirect association through positive AI attitude and a negative indirect association through digital stress. Digital self-efficacy moderated these pathways such that school digitalization orientation was more positively associated with positive AI attitude and less positively associated with digital stress when digital self-efficacy was higher. The overall pattern remained stable after additional covariates and school-clustered robust standard errors were introduced.

Conclusions

In physical education, school digitalization orientation appears to function as a dual-path organizational condition that can both enable and constrain teachers' later AI-collaborative practice. Digitalization is more likely to support pedagogically meaningful AI use when schools pair digital investment with context-sensitive implementation, realistic workload expectations, reliable technical support, and opportunities to build teachers' digital self-efficacy.

Background

School digital transformation has moved beyond equipment provision and platform deployment to reshape curriculum implementation, assessment, teacher decision making, and school governance. With the rise of generative AI, motion capture, learning analytics, wearables, and video recognition, AI can increasingly support diagnosis, feedback, and instructional decision making [1–3]. This shift is especially important in physical education (PE), where teaching is embodied, dynamic, and safety-sensitive and where AI may support movement analysis, fitness monitoring, risk identification, differentiated feedback, and real-time pedagogical adjustment [4–6].

Yet school digitalization and AI do not necessarily produce only positive consequences in PE. The same digital agenda that expands access to platforms, devices, training, and instructional support may also increase data-reporting requirements, device-management burdens, continuous-availability expectations, and metric-based evaluation. A key unanswered question, therefore, is whether school digitalization orientation helps PE teachers collaborate with AI more effectively or instead increases the strain that undermines such collaboration.

Three gaps remain. First, AI-in-education research has emphasized learning outcomes, trust, and general adoption intentions more than the organizational conditions surrounding teachers' everyday work [7, 8]. Second, studies of teacher technology use still provide limited PE-specific evidence, even though emerging PE-focused work shows that instruction is mobile, interactive, and highly dependent on immediate judgment [9–11]. Third, research seldom explains how school digital transformation simultaneously creates empowering and burdening pathways for teachers' later AI-related behavior.

This gap is theoretically meaningful rather than merely contextual. PE teachers must manage moving bodies, changing activity intensity, open spaces, equipment reliability, and ever-present safety responsibilities. In such environments, willingness to let AI enter movement analysis, feedback, assessment, class organization, or risk monitoring is shaped not only by teachers' personal preferences but also by the organizational signals, resources, and demands created by school digitalization orientation.

Guided by the Job Demands-Resources (JD-R) model, we conceptualize school digitalization orientation as a school-referent context that may contain both resource and demand properties. We test a moderated dual-mediation model in which school digitalization orientation is linked to PE teachers' AI-collaborative teaching behavior through positive AI attitude and digital stress, with digital self-efficacy as a boundary condition, using a three-wave time-lagged survey design.

This study makes three contributions. First, it extends JD-R reasoning to PE contexts marked by embodiment, outdoor implementation, and high situational volatility. Second, it moves teacher-AI research beyond general acceptance to a practice-oriented outcome centered on whether AI is used in pedagogically meaningful PE tasks. Third, it shows how digital self-efficacy helps determine whether the same school digitalization context is experienced more as a resource or as a burden.

Literature review and hypotheses development

Research already shows that digital technologies and AI are reshaping school teaching, but evidence remains fragmented on how school digital transformation affects teachers' AI-collaborative teaching behavior. Existing studies typically emphasize trust, acceptance, and readiness to use AI or, separately, technology-related stress and overload. These lines of work are rarely integrated, and even more rarely examined in the embodied, outdoor, and dynamic context of physical education. The present study addresses this gap by explaining how school digitalization orientation shapes PE teachers' AI-collaborative teaching behavior through positive AI attitude and digital stress.

Theoretical foundation

JD-R theory suggests that job resources support motivation and performance, whereas job demands consume energy and trigger strain [12–14]. Under digital transformation, the same organizational context may contain both properties. Whether teachers experience digitalization as supportive or burdensome depends on how it is implemented and interpreted.

School digitalization orientation captures how strongly a school prioritizes digital transformation in strategy, resource allocation, capability building, and coordination. In school settings, it reflects whether digitalization is treated as a core direction for curriculum, teaching, assessment, and governance, and whether teachers receive infrastructure, support, and space for experimentation. For this reason, it may simultaneously provide resources and create demands.

This duality is amplified in PE. Compared with general classrooms, PE depends more on open spaces, bodily activity, equipment reliability, and real-time judgment. Technology integration must therefore contend with weak outdoor signals, device calibration, safety responsibility, and hard-to-interrupt class rhythms. In this study, school digitalization orientation is defined as PE teachers' perceived school-level strategic and institutional orientation toward digitalization.

School digitalization orientation and AI-collaborative teaching behavior

AI-collaborative teaching behavior is not simply equivalent to whether teachers use AI tools. Rather, it refers to teachers' integration of AI as a functionally complementary collaborator rather than a mere external tool in processes such as lesson preparation, movement analysis, learning diagnosis, risk identification, feedback optimization, and instructional decision making. Kong et al. [15] argue in research on employee-AI collaboration that the essence of human-AI collaboration lies not in mere exposure to technology, but in whether AI genuinely enters the task workflow and participates in judgment, prediction, and problem solving. Applied to PE, AI-collaborative teaching behavior therefore means that teachers do not merely use a piece of software occasionally, but instead incorporate AI into the operational and decision-making chain of classroom instruction.

Overall, school digitalization orientation should encourage PE teachers' AI-collaborative teaching behavior. A clear digital agenda reduces ambiguity about whether AI use is expected, usually comes with infrastructure, training, and support, and lowers the threshold for embedding video analysis, wearables, movement recognition, and learning-data feedback into lesson preparation, diagnosis, and formative assessment. Thus, school digitalization orientation provides a practical context for AI collaboration rather than merely an abstract stance.

H1: School digitalization orientation positively predicts physical education teachers' AI-collaborative teaching behavior.

The empowerment pathway: the mediating role of positive AI attitude

According to the JD-R model, organizational resources are translated into individual behavior not because resources operate automatically, but because individuals form positive cognitive evaluations and motivational responses to those resources. In the AI context, teachers' attitudes toward AI are a key psychological mechanism in this motivational conversion process. Recent research on AI applications in education consistently shows that teachers' trust in AI, perceived value, perceived usability, and perceived adaptability are closely related to their acceptance of AI, willingness to try it, and intention to integrate it into classroom practice [2, 7, 16]. Park et al. [17] further show that individuals who perceive AI as highly adaptive, high in quality, and personally useful are more likely to develop a positive orientation toward human-AI collaboration in actual work settings.

School digitalization orientation may enhance PE teachers' positive AI attitudes for at least three reasons. First, through institutionalized resource provision and cultural signaling, school digitalization orientation strengthens teachers' belief that AI is legitimate within the school and can be meaningfully implemented in teaching. Second, the clearer the digitalization orientation, the more likely teachers are to encounter positive cases of AI use through training, peer experiences, and organizational communication, thereby improving their subjective evaluations of AI quality and instructional fit. Third, under sustained school support, teachers are more likely to see AI as a beneficial tool that improves the precision of classroom feedback, the efficiency of diagnosing student movement, and the capacity for differentiated instruction, rather than as an uncontrollable source of external technological pressure. This is especially true in PE, where AI can support movement capture, training-load judgment, and classroom risk identification, making it easier for teachers to view AI as pedagogically useful and worth integrating.

Positive AI attitude, in turn, is likely to promote AI-collaborative teaching behavior. Only when teachers endorse the pedagogical value, reliability, and contextual fit of AI are they more likely to assign it a collaborative role in authentic teaching tasks rather than confine it to symbolic trials or low-intensity exposure. For PE teachers, a positive AI attitude means a greater willingness to let AI participate in movement recognition, feedback generation, differentiation, assessment, and instructional judgment, as

well as a stronger readiness to work with AI in uncertain classroom situations. Therefore, the positive effect of school digitalization orientation on AI-collaborative teaching behavior is likely to be partially realized through the motivational mechanism of positive AI attitude.

H2a: School digitalization orientation positively predicts physical education teachers' positive AI attitude.

H2b: Physical education teachers' positive AI attitude positively predicts their AI-collaborative teaching behavior.

H2c: Positive AI attitude significantly and positively mediates the relationship between school digitalization orientation and physical education teachers' AI-collaborative teaching behavior.

The burden pathway: the mediating role of digital stress

School digitalization orientation may also increase digital stress through a demand-depletion pathway. Digital stress refers to tension and burden arising from constant connectivity, immediate feedback, information tracking, and expectations of availability [18–20]. Empirical work with teachers and academics further links technostress to higher burnout and lower well-being and resilience [21, 22]. For PE teachers, these demands are intensified when platform messages, wearable devices, and AI systems must be managed alongside fast-moving lessons and safety responsibilities.

In school settings, stronger digitalization orientation can mean more platform logins, denser data recording, and stronger expectations for responsiveness. In PE, these demands are especially salient because device calibration, data transmission, and class transitions often happen in open environments with unstable connectivity. Teachers must manage students' activity and digital-system feedback simultaneously, so digitalization can create real operational overload rather than only abstract concern.

Digital stress is likely to further inhibit AI-collaborative teaching behavior. Research on technostress and teachers' technology use has shown that sustained digital burdens weaken teachers' sense of control, reduce their willingness to continue investing in innovative teaching, and induce coping-oriented use or avoidance behavior [23, 24]. This inhibitory effect may be even more pronounced in PE: when teachers experience AI systems as sources of pressure that slow classroom rhythm, increase monitoring burdens, and occupy instructional attention, they are more likely to minimize their use, use them only formally, or avoid collaboration altogether. Thus, school digitalization orientation may promote AI-collaborative teaching on the one hand while simultaneously producing a negative indirect association through digital stress on the other, resulting in a masking effect.

H3a: School digitalization orientation positively predicts physical education teachers' digital stress.

H3b: Physical education teachers' digital stress negatively predicts their AI-collaborative teaching behavior.

H3c: Digital stress significantly and negatively mediates the relationship between school digitalization orientation and physical education teachers' AI-collaborative teaching behavior.

The moderating role of digital self-efficacy

The JD-R model also emphasizes that personal resources shape how individuals interpret and cope with the same work context. Digital self-efficacy refers to individuals' beliefs in their ability to use digital tools to accomplish work tasks [25]. In essence, it is a key personal resource that strengthens perceived control, reduces threat appraisal, and improves adaptive behavior. Research on teachers shows that ICT self-efficacy is not only related to technology integration and classroom innovation, but also influences whether digital demands are interpreted as challenges or burdens [26, 27]. In AI-related educational contexts, the stronger teachers' confidence in their abilities and their technical preparedness, the more likely they are to view AI as a tool that can be learned, controlled, and transformed into an instructional advantage [28, 29].

Based on this logic, digital self-efficacy should strengthen the positive effect of school digitalization orientation on positive AI attitude. For teachers with high digital self-efficacy, the digital resources, AI tools, and reform signals provided by schools are more likely to be interpreted as opportunities for growth and capability expansion. Consequently, they are more likely to develop positive evaluations of AI adaptability and personal utility under organizational support. In contrast, even in the same digital environment, teachers with low digital self-efficacy may fail to transform organizational resources into positive attitudes because they lack a sense of competence.

At the same time, digital self-efficacy should buffer the positive effect of school digitalization orientation on digital stress. Teachers with high digital self-efficacy typically possess stronger problem-solving beliefs, greater control over digital tasks, and more proactive coping tendencies. Therefore, when facing device calibration, platform switching, data recording, and classroom integration demands, they are more likely to respond through active adaptation and strategic handling rather than experiencing these requirements as overwhelming digital burdens. By contrast, teachers with low digital self-efficacy are more likely to feel intense tension and depletion under the same digital demands. Accordingly, digital self-efficacy should constitute a key boundary condition in the dual-path mechanism.

H4a: Digital self-efficacy positively moderates the relationship between school digitalization orientation and positive AI attitude, such that this positive relationship is stronger among teachers with high digital self-efficacy.

H4b: Digital self-efficacy negatively moderates the relationship between school digitalization orientation and digital stress, such that this positive relationship is weaker among teachers with high digital self-efficacy.

Moderated mediation effects

If digital self-efficacy strengthens the resource-motivation pathway while weakening the demand-depletion pathway, then it changes not merely the magnitude of individual path coefficients but also the overall mechanism through which school digitalization orientation influences AI-collaborative teaching behavior. Specifically, under high digital self-efficacy, school digitalization orientation is more likely to translate into higher levels of AI-collaborative teaching behavior through positive AI attitude; under low digital self-efficacy, by contrast, school digitalization orientation is more likely to weaken teachers' subsequent collaborative engagement through digital stress. Based on this reasoning, we further propose the following moderated mediation hypotheses.

H5a: Digital self-efficacy moderates the positive mediating effect of positive AI attitude in the relationship between school digitalization orientation and AI-collaborative teaching behavior.

H5b: Digital self-efficacy moderates the negative mediating effect of digital stress in the relationship between school digitalization orientation and AI-collaborative teaching behavior.

In summary, the hypothesized model is presented in Fig. 1.

Methods

Sample and procedure

To improve temporal separation among the focal variables and reduce common method bias (CMB) [30, 31], this study used a three-wave time-lagged survey design. At Time 1, we measured school digitalization orientation, digital self-efficacy, and key control variables, including teaching tenure, school digitalization investment level, prior technological experience, school type, AI training experience, gender, and school level. Approximately six weeks later, Time 2 measured the two mediators: positive AI attitude and digital stress. Approximately six weeks after Time 2, we measured AI-collaborative teaching behavior. The six-week lag was chosen to provide meaningful temporal separation while keeping PE teaching routines, digital workload, and school reform conditions sufficiently comparable across waves.

Data matching and cleaning followed standard procedures for time-lagged survey research. The archived analytic dataset used in the present manuscript comprised 638 matched three-wave cases. Because the archived file preserved the final matched sample rather than the full wave-specific screening records, the exact numbers of distributed questionnaires, valid cases at each wave, and unmatched cases across waves cannot be reconstructed from this version alone. The present manuscript therefore reports the characteristics of the matched analytic sample and treats the absence of wave-specific attrition information as a limitation.

The final sample came from 80 schools, with cluster sizes ranging from 3 to 19 teachers (median = 8). The participating teachers were distributed across primary schools (n = 205), junior high schools (n = 157), high schools (n = 139), and universities (n = 137), and were located in eastern (n = 264), central (n = 160), western (n = 156), and northeastern (n = 58) regions of China. Of the 638 teachers, 352 were men

(55.17%) and 286 were women (44.83%). The mean age was 39.41 years ($SD = 8.75$), the average teaching tenure was 15.06 years ($SD = 9.00$), the mean level of school digitalization investment was 2.90 ($SD = 1.08$), and the mean level of prior technological experience was 4.24 ($SD = 1.18$).

Control variables were coded as follows: gender was dummy coded, with women coded as 1 and men as 0; AI training experience was coded as 1 = having relevant training experience and 0 = no relevant training experience; and school type was coded as 1 = private school and 0 = public school. School level was converted into three dummy variables (university, high school, and junior high school), with primary school as the reference group. Teaching tenure, school digitalization investment level, and prior technological experience were treated as continuous variables. Because school digitalization orientation was operationalized as teachers' perceptions of a school-referent context and the mediators and outcome were theorized at the teacher level, the focal model used the teacher as the unit of analysis. School identifiers were nevertheless available, so the robustness tests additionally included age and estimated school-clustered robust standard errors. Null random-intercept models for the five composite scores (T1 SDO, T2 AIA, T2 DS, T1 DSE, and T3 AI-CTB) produced between-school variance estimates at the boundary, with ICC(1) values that rounded to .00 for all five composites. We therefore retained the teacher-level focal model and treated clustered standard errors as a conservative adjustment rather than imposing a multilevel SEM with negligible random-intercept variance.

Contextualization of the measures

Scale selection and translation and back-translation procedure

For all core variables, we selected established English-language scales with strong recent validation and clear transferability to PE contexts. Because the model links a school-referent digitalization context to teacher-level appraisal, stress, and behavior, special attention was paid to referent consistency. School digitalization orientation was therefore operationalized as teachers' perceptions of their school's digitalization orientation, whereas the remaining constructs were treated as teacher-level psychological or behavioral variables.

All scales were adapted into Chinese through translation, back-translation, expert review, and pilot revision. Two bilingual researchers independently translated the items, a third bilingual scholar performed the back-translation, and experts in PE, psychometrics, organizational behavior, and educational technology reviewed semantic equivalence and contextual fit. Cognitive interviews were then used to refine wording for the outdoor, dynamic, and safety-sensitive character of PE lessons. Unless otherwise specified, scale scores were computed as item means.

School digitalization orientation

School digitalization orientation was measured with the 19-item digital orientation scale developed by Kindermann et al. [32]. The scale captures technological scope, capability building, ecosystem

collaboration, and digital architecture and was selected because it aligns closely with the JD-R premise that organizational resources and demands may coexist. Because the level of analysis was the individual teacher, the construct was defined as PE teachers' perceptions of their school's digital strategy, resource investment, and governance arrangements rather than as an objective school-level index.

In contextualizing the measure, the research team replaced terms such as "company" and "organizational processes" with school-specific wording while retaining the original content domains. The scale used a 7-point response format ranging from 1 (strongly disagree) to 7 (strongly agree). Representative adapted items are reported in Appendix A.

Positive AI attitude

Positive AI attitude was adapted mainly from the workplace AI attitude scale developed by Park et al. [17]. In line with this study's theoretical model, we retained only the dimensions corresponding to the resource-motivation pathway: perceived AI adaptability, perceived AI quality, and personal utility (13 items in total). The anxiety and job-insecurity components were excluded to avoid conceptual overlap with digital stress. The measure therefore captures the positive evaluative component of teachers' AI attitudes rather than the full attitudinal domain.

In adapting the scale to PE, the items were shifted from a general work context to PE teaching tasks and emphasized the value of AI for feedback, movement analysis, and instructional optimization. The scale used a 5-point response format ranging from 1 (strongly disagree) to 5 (strongly agree). Representative adapted items are reported in Appendix A.

Digital stress

The conceptualization of digital stress drew on Steele et al.'s [18] review and was based primarily on the multidimensional Digital Stress Scale developed by Hall et al. [19]. Following the item-selection logic of the short version proposed by Funke et al. [20] and subsequent validation work by Geris et al. [33], we used 10 items to capture PE teachers' stress experiences in digitalized and AI-integrated teaching. The scale retained five dimensions with two items each and was suitable for the school digital platform, AI tool, and classroom data-system environment examined here.

In contextualizing the measure, general digital disturbances were translated into PE-relevant situations involving outdoor teaching, equipment dependence, and rapid class rhythm. The scale used a 5-point response format ranging from 1 (never) to 5 (always), with higher scores indicating greater digital strain during digitally and AI-integrated PE teaching. Representative adapted items are reported in Appendix A.

Digital self-efficacy

Digital self-efficacy was adapted from Hatlevik and Hatlevik's [26] measure of teachers' ICT self-efficacy for instructional purposes and revised for AI-collaborative teaching tasks, yielding a four-item scale. This approach was chosen because it captures teachers' perceived competence in handling complex digital

teaching tasks and aligns closely with the buffering and strengthening mechanisms examined in this study, while remaining conceptually consistent with foundational computer self-efficacy research [25].

The revised items focused on instructional design, learning monitoring, classroom diagnosis, and learning assessment with AI support. The scale used a 7-point response format ranging from 1 (strongly disagree) to 7 (strongly agree), with higher scores indicating stronger confidence in meeting the demands of digitally and AI-integrated teaching.

AI-collaborative teaching behavior

AI-collaborative teaching behavior was measured with the employee-AI collaboration scale developed by Kong et al. [15], adapted to PE teaching tasks, and consisted of five items. The scale was selected because it captures the extent to which AI participates in decision making, problem solving, information recognition, and risk judgment within actual work processes rather than merely measuring general adoption intention.

Given the embodied and highly dynamic characteristics of PE classes, the items focused on movement feedback, learning diagnosis, risk identification, and support for training-related decisions. The scale used a 7-point response format ranging from 1 (strongly disagree) to 7 (strongly agree), with higher scores indicating a greater degree of AI collaboration in teachers' actual instructional activities.

Data analysis strategy

Data analysis followed a two-step sequence in which the measurement model was evaluated before the structural relationships were examined [34]. First, descriptive statistics and correlation analysis were used to assess distributional characteristics and bivariate associations among the study variables. Confirmatory factor analysis, composite reliability (CR), average variance extracted (AVE), and the Fornell-Larcker criterion [35] were then used to evaluate convergent and discriminant validity. Because SDO, AIA, and DS were intentionally broad constructs with multiple theoretically defined subdimensions, item diagnostics for the analytic sample were inspected before final model specification. The primary measurement model retained all items but allowed a limited set of 12 theory-consistent residual covariances within the same subdimension (Balanced-12) to account for localized item overlap while preserving content coverage. Because this study relied on teacher self-report data, common method bias was procedurally mitigated through three-wave temporal separation and further assessed with a supplementary parcel-level ULMC sensitivity test, following standard procedural and statistical recommendations [30, 31].

Second, after controlling for teaching tenure, school digitalization investment level, teachers' prior technological experience, school type, AI training experience, gender, and school level, we constructed a time-lagged association model in which Time 1 variables predicted the Time 2 mediators, which in turn predicted the Time 3 outcome. Time-lagged mediation, moderation, and moderated mediation effects were estimated using 5,000 bias-corrected bootstrap samples [36, 37], with bootstrap standard errors and 95% confidence intervals reported; effects were considered significant when the confidence interval

did not include zero. Because baseline mediator and outcome levels were not modeled, the estimates should be interpreted as time-lagged associations rather than change effects. To gauge whether a multilevel specification was empirically warranted, we also estimated null random-intercept models for the composite variables. Because the resulting between-school variance estimates were at the boundary and the ICC(1) values rounded to .00, we retained the teacher-level focal model and used school-clustered robust standard errors only as a conservative correction in the robustness tests. Finally, the statistical superiority of the hypothesized model and the stability of the core associations were further examined through comparisons with competing models and robustness checks.

Results

Measurement properties, common method bias, descriptive statistics, and discriminant validity

First, the measurement results showed acceptable internal consistency across the study variables. The AVEs for school digitalization orientation, positive AI attitude, and digital stress were 0.380, 0.445, and 0.339, respectively, which remain below conventional 0.50 benchmarks and thus warrant cautious interpretation of convergent validity. At the same time, these estimates were accompanied by satisfactory composite reliability and an acceptable item-level CFA once limited within-subdimension local dependence was modeled. Specifically, we retained the full item sets and estimated a theory-constrained Balanced-12 measurement model that added 12 within-subdimension residual covariances to absorb localized overlap without collapsing constructs into parcels. This approach preserved content coverage after PE contextualization while yielding an adequate basis for the subsequent structural tests; this caution is revisited in the limitations and Appendix A. (Table 1)

Table 1
Reliability and validity results for the study variables

Variable	No. of Items	Cronbach's α	Standardized Loading Range	CR	AVE
SDO	19	0.922	0.518–0.706	0.921	0.380
AIA	13	0.914	0.598–0.733	0.912	0.445
DS	10	0.848	0.507–0.633	0.836	0.339
DSE	4	0.852	0.722–0.858	0.853	0.593
AI-CTB	5	0.879	0.686–0.868	0.880	0.596
Note. SDO = school digitalization orientation; AIA = positive AI attitude; DS = digital stress; DSE = digital self-efficacy; AI-CTB = AI-collaborative teaching behavior. Cronbach's α = internal consistency coefficient; CR = composite reliability; AVE = average variance extracted.					

Further, a supplementary parcel-level ULMC sensitivity test did not show material fit improvement after a method factor was added, suggesting that same-source method variance did not appear dominant in this dataset. Taken together with the three-wave temporally separated design, this reduces but does not eliminate common method concerns. As further shown in Table 2, the diagonal values represent the square roots of the AVEs for each construct, and all were greater than the corresponding correlations with other variables, indicating acceptable discriminant validity. At the bivariate level, school digitalization orientation was significantly and positively correlated with positive AI attitude ($r = 0.480$, $p < .001$), digital stress ($r = 0.215$, $p < .001$), digital self-efficacy ($r = 0.281$, $p < .001$), and AI-collaborative teaching behavior ($r = 0.384$, $p < .001$). Positive AI attitude was significantly positively correlated with AI-collaborative teaching behavior ($r = 0.449$, $p < .001$), whereas digital stress was negatively correlated with both digital self-efficacy ($r = -0.134$, $p < .001$) and AI-collaborative teaching behavior ($r = -0.096$, $p < .05$).

Table 2
Descriptive statistics, correlations, and discriminant validity of the study variables

Variable	M	SD	1	2	3	4	5
1. SDO	4.194	1.079	0.617				
2. AIA	2.864	0.881	0.480***	0.667			
3. DS	2.323	0.755	0.215***	-0.021	0.582		
4. DSE	4.082	1.386	0.281***	0.357***	-0.134***	0.770	
5. AI-CTB	4.028	1.343	0.384***	0.449***	-0.096*	0.297***	0.772
Note. SDO = school digitalization orientation; AIA = positive AI attitude; DS = digital stress; DSE = digital self-efficacy; AI-CTB = AI-collaborative teaching behavior. The diagonal entries are the square roots of the AVEs for each construct; the lower triangle presents the correlations; N = 638. * $p < .05$. *** $p < .001$.							

Measurement model and comparison of competing models

As shown in Table 3, the five-factor item-level measurement model with the Balanced-12 within-subdimension residual specification demonstrated acceptable fit [38], chi-square = 2565.519, $df = 1202$, chi-square/ $df = 2.134$, CFI = 0.906, TLI = 0.901, and RMSEA = 0.042. Compared with the four-factor, three-factor, and single-factor models, the five-factor model showed clearly superior fit on all indices, indicating acceptable structural distinctiveness among school digitalization orientation, positive AI attitude, digital stress, digital self-efficacy, and AI-collaborative teaching behavior. Combined with the reliability indices and discriminant-validity evidence, these results indicate that the time-sequenced measurement model provided an adequate basis for testing structural relationships, while still warranting caution about the modest AVEs of the broader constructs.

Further comparison of competing models showed that the hypothesized model, which retained both a direct association and dual mediation pathways, fit slightly better than the full mediation and no-mediation models. Specifically, the hypothesized model yielded chi-square = 2571.017, $df = 1203$, chi-

square/df = 2.137, CFI = 0.906, TLI = 0.900, and RMSEA = 0.042, whereas the alternative models were marginally weaker. Because the differences were modest, the hypothesized model was retained as the focal structural specification rather than treated as decisively superior.

Table 3
Fit indices for the measurement model and competing models

Model	χ^2	df	χ^2/df	CFI	TLI	RMSEA
Five-factor measurement model	2565.519	1202	2.134	0.906	0.901	0.042
Four-factor measurement model	3497.207	1206	2.900	0.843	0.834	0.055
Three-factor measurement model	4384.689	1209	3.627	0.782	0.770	0.064
Single-factor model	7056.844	1212	5.822	0.598	0.577	0.087
Hypothesized model	2571.017	1203	2.137	0.906	0.900	0.042
Full mediation model	2600.800	1204	2.160	0.904	0.898	0.043
No-mediation model	2621.891	1204	2.178	0.903	0.897	0.043
Note. CFA = confirmatory factor analysis; CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation. The measurement comparisons retained the same set of 12 theory-consistent within-subdimension residual covariances (Balanced-12) across models.						

Path tests in the time-lagged structural model

As shown in Fig. 2 and Table 4, after controlling for teaching tenure, school digitalization investment level, teachers' prior technological experience, school type, AI training experience, gender, and school level, the core paths of the time-lagged association model were all in the expected directions. Specifically, Time 1 school digitalization orientation was positively associated with Time 3 AI-collaborative teaching behavior (beta = 0.116, SE = 0.043, $p = 0.007$), supporting H1. Along the empowerment pathway, Time 1 school digitalization orientation was positively associated with Time 2 positive AI attitude (beta = 0.335, SE = 0.041, $p < .001$), and Time 2 positive AI attitude was positively associated with Time 3 AI-collaborative teaching behavior (beta = 0.240, SE = 0.041, $p < .001$), supporting H2a and H2b. Along the burden pathway, Time 1 school digitalization orientation was positively associated with Time 2 digital stress (beta = 0.274, SE = 0.046, $p < .001$), whereas Time 2 digital stress was negatively associated with Time 3 AI-collaborative teaching behavior (beta = -0.120, SE = 0.036, $p < .001$), supporting H3a and H3b. Thus, school digitalization orientation showed both a direct positive association and two indirect associations through positive appraisal and stress-related depletion.

Tests of moderation further showed that digital self-efficacy strengthened the positive association between school digitalization orientation and positive AI attitude (beta = 0.096, SE = 0.029, $p = 0.001$) and

weakened the positive association between school digitalization orientation and digital stress ($\beta = -0.125$, $SE = 0.037$, $p < .001$). These findings indicate that, under the same school digitalization context, teachers with higher digital self-efficacy are more likely to interpret organizational digital arrangements as resources for professional growth rather than primarily as additional technological burdens. Accordingly, both H4a and H4b were supported.

Table 4
Standardized path coefficients of the time-lagged structural model

Hypothesis	Path	β	Robust SE	z/t	p	95% CI
H1	T1 SDO -> T3 AI-CTB	0.116	0.043	2.676	0.007	[.031, .202]
H2a	T1 SDO -> T2 AIA	0.335	0.041	8.086	< .001	[.253, .416]
H2b	T2 AIA -> T3 AI-CTB	0.240	0.041	5.835	< .001	[.160, .321]
H3a	T1 SDO -> T2 DS	0.274	0.046	5.965	< .001	[.184, .364]
H3b	T2 DS -> T3 AI-CTB	-0.120	0.036	-3.309	< .001	[-.192, -.049]
H4a	T1 SDO x DSE -> T2 AIA	0.096	0.029	3.272	0.001	[.039, .154]
H4b	T1 SDO x DSE -> T2 DS	-0.125	0.037	-3.370	< .001	[-.197, -.052]
Note. SDO = school digitalization orientation; AIA = positive AI attitude; DS = digital stress; DSE = digital self-efficacy; AI-CTB = AI-collaborative teaching behavior. Reported values are standardized path coefficients; SE = robust standard error; CI = 95% confidence interval.						

Direct, indirect, and moderated mediation effects

As shown in Table 5, Panel A, the bootstrap resampling results indicated that the direct association of school digitalization orientation with AI-collaborative teaching behavior remained significant (direct effect = 0.116, Boot SE = 0.043, 95% CI [0.034, 0.200]), suggesting partial mediation. Specifically, the positive indirect association through positive AI attitude was significant (indirect effect = 0.081, Boot SE = 0.017, 95% CI [0.051, 0.116]), and the negative indirect association through digital stress was also significant (indirect effect = -0.033, Boot SE = 0.011, 95% CI [-0.056, -0.013]). The total indirect effect across the two pathways was 0.048 (Boot SE = 0.020, 95% CI [0.009, 0.088]), and the total effect was 0.164 (Boot SE = 0.040, 95% CI [0.085, 0.243]). Therefore, H2c and H3c were supported.

As shown in Table 5, Panel B, and Fig. 3, digital self-efficacy significantly altered the strength of both indirect pathways. Under high digital self-efficacy, the indirect association of school digitalization orientation with AI-collaborative teaching behavior through positive AI attitude was stronger (indirect effect = 0.104, Boot SE = 0.021, 95% CI [0.066, 0.148]); under low digital self-efficacy, this empowerment pathway was relatively weaker (indirect effect = 0.058, Boot SE = 0.015, 95% CI [0.030, 0.091]). In contrast, the negative indirect association through digital stress was stronger under low digital self-efficacy (indirect effect = -0.048, Boot SE = 0.016, 95% CI [-0.082, -0.020]) and was substantially weaker under high digital self-efficacy (indirect effect = -0.018, Boot SE = 0.009, 95% CI [-0.038, -0.003]). Moreover, the indices of moderated mediation for the empowerment pathway and burden pathway were 0.023 (Boot SE = 0.008, 95% CI [0.008, 0.040]) and 0.015 (Boot SE = 0.006, 95% CI [0.004, 0.030]), respectively, and neither 95% confidence interval included zero. These findings indicate that digital self-efficacy altered the time-lagged indirect associations of school digitalization orientation with AI-collaborative teaching behavior through the two psychological mechanisms, thereby supporting H5a and H5b.

Table 5
Bootstrap results for the direct, indirect, and conditional indirect effects

Effect Type	Path	Estimate	Boot SE	Boot LLCI	Boot ULCI
Panel A. Direct and mediation effects					
Direct effect	T1 SDO -> T3 AI-CTB	0.116	0.043	0.034	0.200
Mediation effect	T1 SDO -> T2 AIA -> T3 AI-CTB	0.081	0.017	0.051	0.116
Mediation effect	T1 SDO -> T2 DS -> T3 AI-CTB	-0.033	0.011	-0.056	-0.013
Total indirect effect	Total indirect effect across AIA and DS pathways	0.048	0.020	0.009	0.088
Total effect	Total effect	0.164	0.040	0.085	0.243
Panel B. Conditional indirect effects and indices of moderated mediation					
Conditional indirect effect	AIA pathway at low DSE (-1 SD)	0.058	0.015	0.030	0.091
Conditional indirect effect	AIA pathway at mean DSE	0.081	0.017	0.051	0.116
Conditional indirect effect	AIA pathway at high DSE (+ 1 SD)	0.104	0.021	0.066	0.148
Conditional indirect effect	DS pathway at low DSE (-1 SD)	-0.048	0.016	-0.082	-0.020
Conditional indirect effect	DS pathway at mean DSE	-0.033	0.011	-0.056	-0.013
Conditional indirect effect	DS pathway at high DSE (+ 1 SD)	-0.018	0.009	-0.038	-0.003
Index of moderated mediation	AIA pathway IMM	0.023	0.008	0.008	0.040
Index of moderated mediation	DS pathway IMM	0.015	0.006	0.004	0.030
Note. SDO = school digitalization orientation; AIA = positive AI attitude; DS = digital stress; DSE = digital self-efficacy; AI-CTB = AI-collaborative teaching behavior. Bootstrap resampling = 5,000 iterations; IMM = index of moderated mediation; Boot LLCI and Boot ULCI indicate the lower and upper bounds of the 95% confidence interval, respectively.					

Robustness checks

As shown in Table 6, the robustness tests further supported the core conclusions of this study. First, the hypothesized model continued to fit the data slightly better than both the full mediation model and the no-mediation model, indicating that the direct-plus-dual-mediation structure retained somewhat stronger explanatory power than simpler alternatives. Second, after additionally including age and estimating a school-clustered stringent-control model based on school identifiers, the direct association of school digitalization orientation with AI-collaborative teaching behavior remained significant ($\beta = 0.114$, $p = 0.004$). The positive association of positive AI attitude with AI-collaborative teaching behavior ($\beta = 0.243$, $p < .001$) and the negative association of digital stress with AI-collaborative teaching behavior ($\beta = -0.123$, $p = 0.003$) were also retained, whereas the direct effect of digital self-efficacy remained nonsignificant. Model explained variance increased slightly from 0.324 to 0.326. This clustered strategy was also consistent with the null random-intercept diagnostics, which indicated negligible residual between-school variance in the composite scores once teachers were treated as the analytic unit. These results indicate that the core conclusions regarding the empowerment pathway, burden pathway, and their boundary conditions were robust to additional controls and school clustering.

Table 6
Robustness tests of the core paths under stringent controls

Core Path	Baseline Model beta	Baseline p	Clustered Model beta	Clustered Model p	Directional Consistency	Significance Retained
T1 SDO -> T3 AI-CTB	0.116	0.007	0.114	0.004	Yes	Yes
T2 AIA -> T3 AI-CTB	0.240	< .001	0.243	< .001	Yes	Yes
T2 DS -> T3 AI-CTB	-0.120	< .001	-0.123	0.003	Yes	Yes
T1 DSE -> T3 AI-CTB	0.036	0.396	0.039	0.386	Yes	No
Model explained variance R- squared	0.324	-	0.326	-	-	-
Note. SDO = school digitalization orientation; AIA = positive AI attitude; DS = digital stress; DSE = digital self-efficacy; AI-CTB = AI-collaborative teaching behavior. The clustered stringent-control model additionally included age and estimated school-clustered robust standard errors based on school identifiers (80 schools).						

Discussion

Main findings and theoretical interpretation

The present findings suggest that school digitalization orientation is positively associated with PE teachers' later AI-collaborative teaching behavior. This supports the view that teachers' engagement with AI is shaped not only by their individual preferences but also by organizational support, institutional signals, and the school's mode of digital governance [2, 3, 16]. In PE, this matters because AI-collaborative teaching behavior concerns concrete pedagogical work, including movement diagnosis, feedback, differentiation, safety monitoring, and real-time instructional adjustment, rather than generic technology use alone.

The results also support a qualified dual-path interpretation of school digitalization orientation. The same school context was associated with a more positive appraisal of AI and, in turn, more AI-collaborative teaching behavior, but it was also associated with more digital stress and, in turn, less AI-collaborative teaching behavior. This pattern is consistent with recent AI-in-education research showing that digitalization can expand instructional resources while also increasing complexity, workload, and implementation pressure [1–3]. The coefficients were meaningful but not large, suggesting that school digitalization orientation is one important organizational condition among several rather than a single dominant driver of AI-related pedagogical work in PE.

The PE context helps explain why these positive and negative pathways coexist. PE teachers evaluate AI not in the abstract, but in relation to whether it helps with movement observation, classroom organization, formative feedback, assessment, or risk identification, a pattern that is consistent with emerging qualitative evidence on PE teachers' perceptions of AI [39]. The same digital reform can therefore feel empowering when it improves pedagogical precision and coordination, yet burdensome when it adds device setup, unstable connectivity, data-entry work, or safety-management pressure in fast-moving lessons [5, 10, 11, 40].

It is also important that the negative association between digital stress and AI-collaborative teaching behavior was already visible at the bivariate level and remained stable in the multivariable and clustered models. This pattern strengthens the interpretation that digital burden inhibits pedagogically meaningful AI collaboration rather than merely emerging as a statistical artifact after controls are added. The practical implication is that apparently successful digital reform can still carry hidden pedagogical costs for teachers if strain accumulates beneath the surface.

Theoretical contributions

From a theoretical perspective, the study makes three modest but meaningful contributions. First, it extends JD-R reasoning to PE settings, where embodiment, spatial openness, and safety demands make the coexistence of resources and demands especially visible. This helps move AI-in-education research beyond overly generalized classroom assumptions.

Second, it advances teacher-AI research from acceptance-oriented outcomes to a collaboration-oriented outcome that is more directly tied to pedagogy. Rather than asking only whether teachers trust or use AI, the study asks whether AI is woven into decision making, diagnosis, feedback, differentiation, assessment, and risk monitoring in PE teaching.

Third, it shows that digital self-efficacy does more than encourage technology use in general. It helps determine whether the same school digitalization context is interpreted more through a growth-oriented pathway or more through a strain-oriented pathway, thereby clarifying why teachers respond differently to similar reform environments.

Practical implications

Practically, the findings suggest that digitalization in PE should not be evaluated only through equipment provision, platform activity, or data-upload frequency. Schools should also ask whether digital reform helps teachers deliver better movement feedback, differentiate tasks, monitor safety, and make timely instructional adjustments.

This issue is especially important in PE, where weak-network conditions, open spaces, device deployment, and safety supervision can quickly turn a promising tool into additional workload. Schools should therefore prioritize tools that are context-sensitive, mobile, reliable in outdoor settings, and capable of reducing rather than expanding data-entry burdens.

Teacher support should likewise move from feature-based demonstrations to task-embedded professional development. This recommendation is consistent with evidence that AI-focused professional development can improve teachers' implementation readiness and self-efficacy when it is anchored in concrete pedagogical tasks [41, 42]. Training is more likely to build durable digital self-efficacy when it focuses on recurring PE tasks such as movement analysis, class grouping, formative assessment, safety monitoring, and real-time feedback, and when schools pair that training with realistic trial opportunities and reasonable expectations for response speed and documentation. PE teacher educators and professional-development providers should therefore prepare teachers not only to operate tools, but also to judge when AI adds pedagogical value and when it disrupts lesson flow, embodied learning, or safe class management.

Limitations and future directions

This study has several limitations. First, although the three-wave design improved temporal separation, the study remained nonexperimental. Because baseline mediator and outcome levels were not modeled, the estimates should be interpreted as time-lagged associations rather than change effects or strong causal effects. Future studies should incorporate autoregressive controls, repeated-measures models, experience sampling, or field interventions.

Second, because the archived analytic dataset preserved only the matched final sample, exact wave-specific recruitment and attrition counts could not be reconstructed, and a formal attrition comparison

between retained and lost participants was not possible. Future data-management procedures should retain wave-specific screening files so that recruitment flow and attrition bias can be reported transparently.

Third, the study relied primarily on teacher self-report data, which is useful for capturing perceived school digitalization orientation, positive AI attitude, and digital stress but cannot fully represent actual classroom practice. Multi-source evidence, such as classroom observation, platform logs, AI tool records, student feedback, and wearable-device data, would strengthen future work.

Fourth, the AVEs for school digitalization orientation, positive AI attitude, and digital stress were 0.380, 0.445, and 0.339, respectively, which remain below conventional 0.50 benchmarks. Although we retained the full scales to preserve content coverage and improved item-level fit through a theory-constrained within-subdimension residual specification, construct validity should still be interpreted cautiously. Future studies should report the full adapted item set as online supplementary material and continue comparing correlated-factor, higher-order, or shorter-form representations of these broader constructs.

Fifth, school digitalization orientation is school-referent in theory but was measured through individual perceptions and estimated in a teacher-level model. Although school identifiers allowed school-clustered robustness checks, future studies should combine teacher perceptions with administrator reports or archival school indicators and test the model in a multilevel framework.

Finally, although the study identified a negative pathway through digital stress, it did not directly observe how strain accumulates across device calibration, weak-network conditions, data-based evaluation, and safety management in PE lessons. Qualitative or mixed-method follow-up work could make these microprocesses more explicit.

Conclusions

Using matched three-wave time-lagged data and a JD-R framework, this study suggests that school digitalization orientation is one meaningful organizational condition associated with PE teachers' AI-collaborative teaching behavior. Its role is not uniformly beneficial: the same context is associated with coexisting empowering and burdening pathways via positive AI attitude and digital stress, and digital self-efficacy shifts the balance between these pathways. The main implication is that digitalization in PE should be organized not simply as technology deployment, but as the creation of context-sensitive tools, teacher capability support, and stress-buffering conditions that help AI contribute to pedagogically meaningful practice.

Abbreviations

AI
artificial intelligence
AI-CTB

AI-collaborative teaching behavior

AIA

positive AI attitude

AVE

average variance extracted

CFA

confirmatory factor analysis

CFI

comparative fit index

CMB

common method bias

CR

composite reliability

DS

digital stress

DSE

digital self-efficacy

ICC

intraclass correlation coefficient

JD-R

Job Demands-Resources

PE

physical education

RMSEA

root mean square error of approximation

SDO

school digitalization orientation

SEM

structural equation modeling

TLI

Tucker-Lewis index

ULMC

unmeasured latent method construct.

Declarations

Ethics approval and consent to participate

This study was conducted in accordance with the ethical principles of the Declaration of Helsinki. Under Article 32(2) of the Measures for Ethical Review of Life Sciences and Medical Research Involving Humans issued by the National Health Commission of the People's Republic of China, the Ministry of

Education, the Ministry of Science and Technology, and the National Administration of Traditional Chinese Medicine, research using anonymized information data may be exempt from formal ethical review when it does not cause harm to human participants and does not involve sensitive personal information or commercial interests.¹

This study met these exemption conditions because it used an anonymous voluntary questionnaire survey of adult physical education teachers, involved no clinical intervention, biological samples, human experimentation, minors, identifiable personal information, sensitive personal information, or commercial interests, and all data were de-identified before analysis. At the beginning of each survey wave, participants were informed of the study purpose, anonymous matching procedure, voluntary nature of participation, right to withdraw, and intended use of the data. Electronic informed consent was obtained from all participants before questionnaire completion.

<https://www.nhc.gov.cn/wjw/c100375/202302/902b4a1dc3af4aba862a6387e6e376dc.shtml>

Consent for publication

Not applicable.

Availability of data and materials

The raw data supporting the findings of this study have been uploaded as a Related File during submission and are available to editors and reviewers for assessment. The dataset contains the de-identified matched survey data used for the analyses reported in this manuscript. No personally identifiable information is included.

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Figures

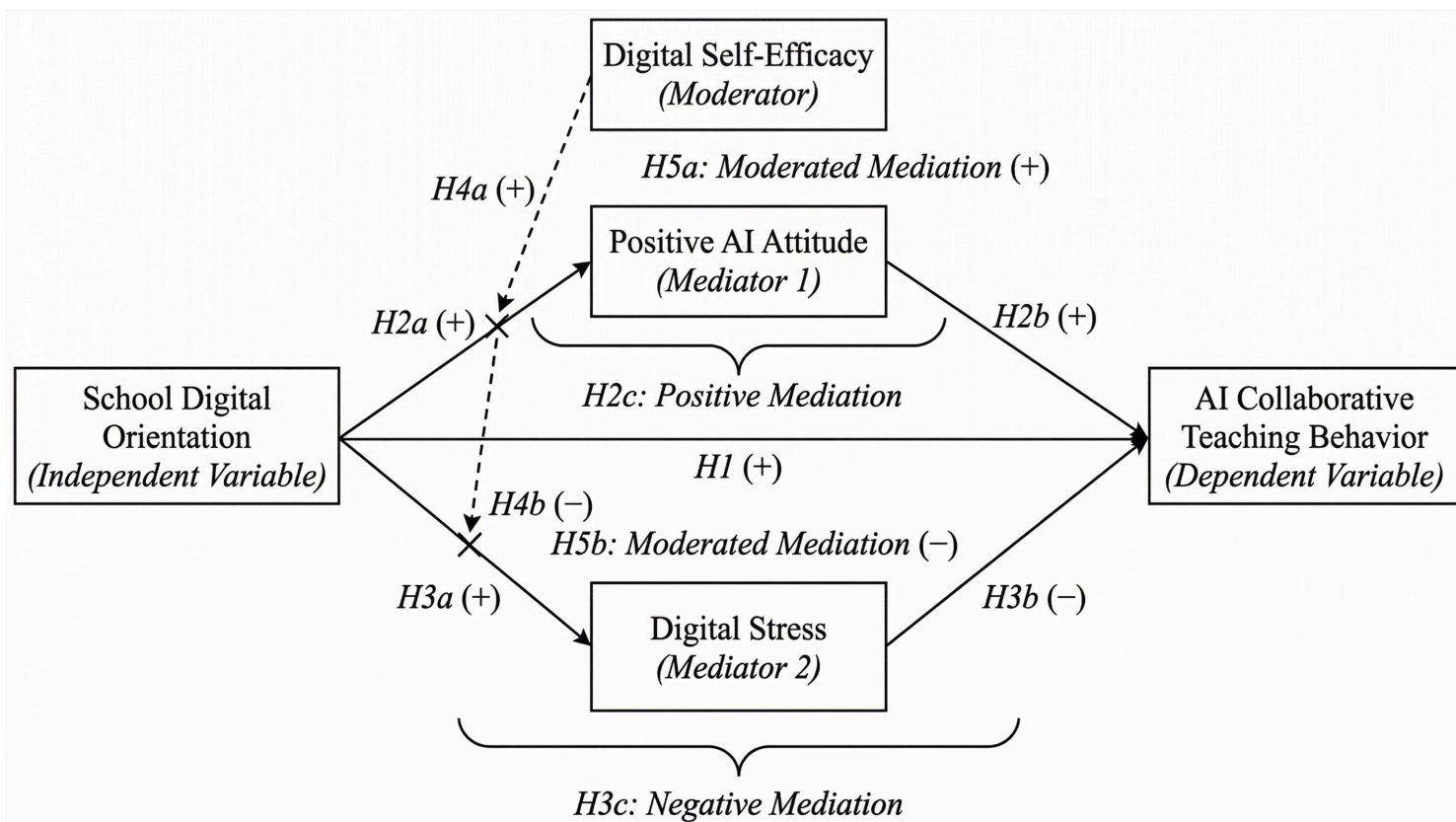
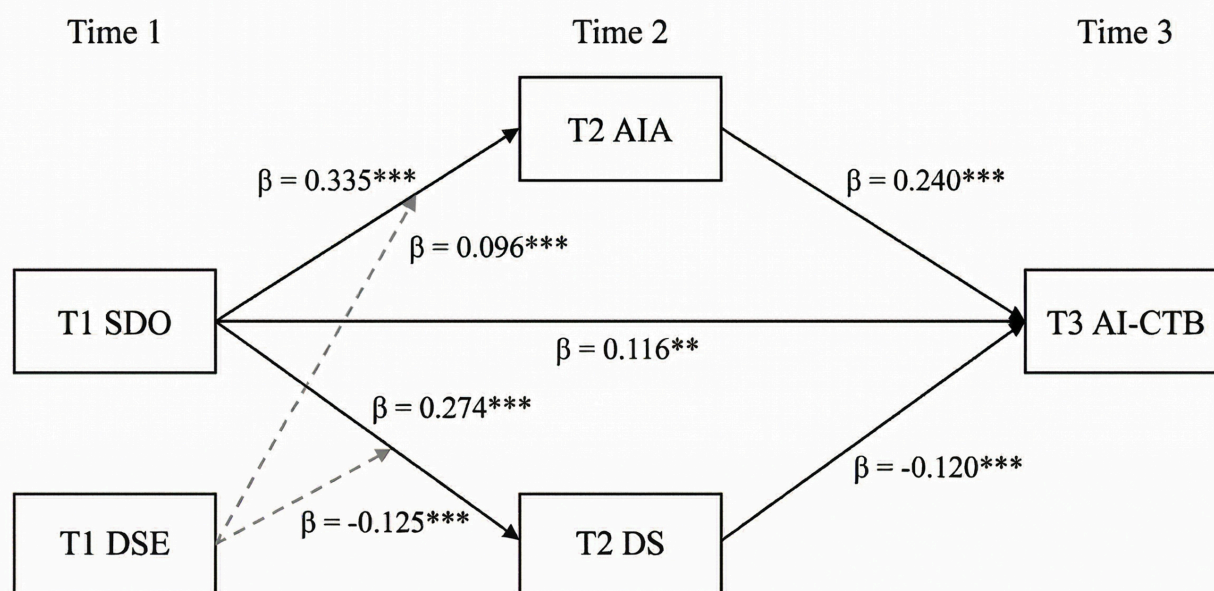


Figure 1

Hypothesized research model



Abbrev.: SDO = school digitalization orientation; AIA = positive AI attitude; DS = digital stress; DSE = digital self-efficacy; AI-CTB = AI-collaborative teaching behavior.

Figure 2

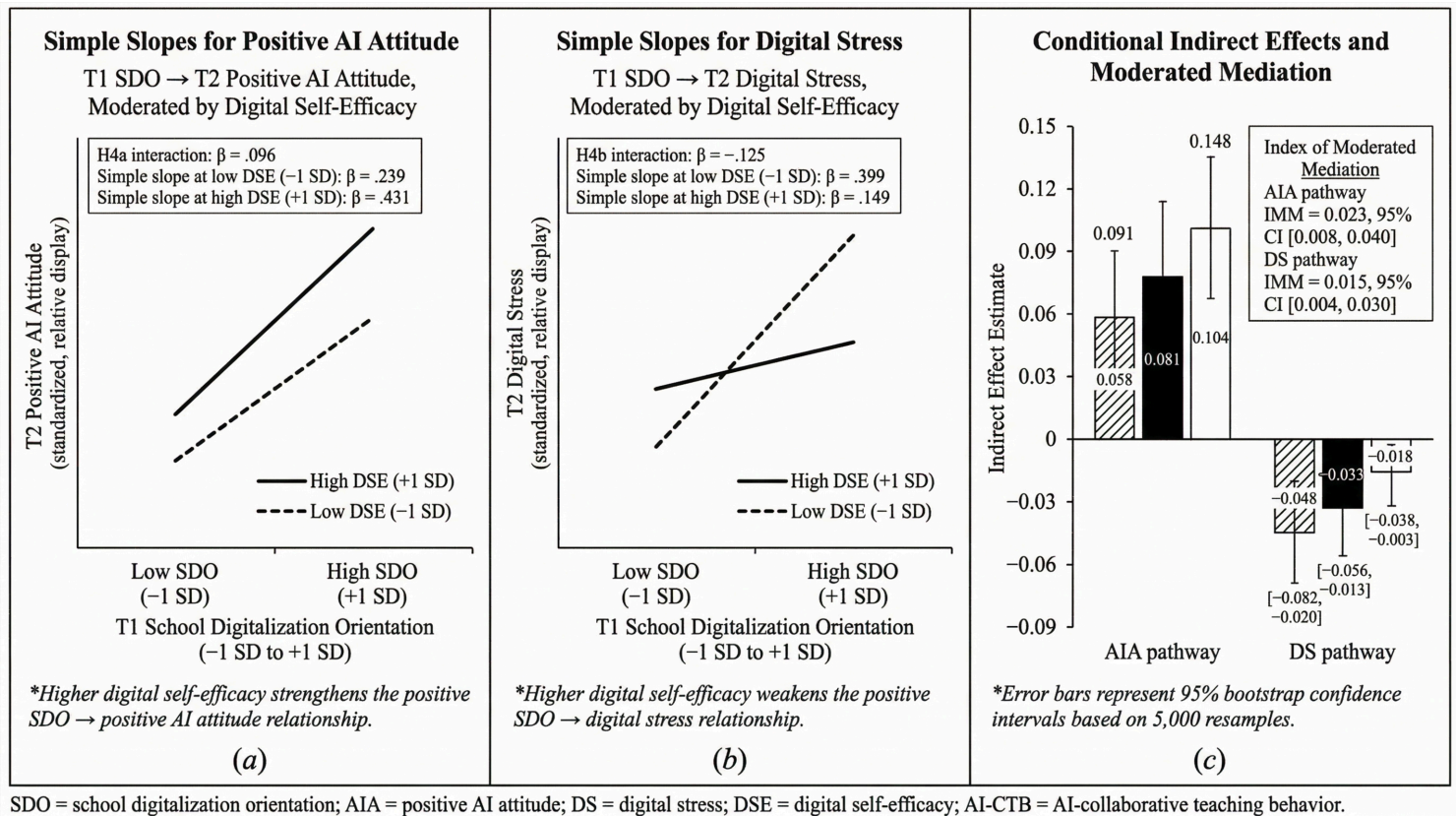


Figure 3

Simple slopes of digital self-efficacy and moderated mediation effects

Supplementary Files

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- Supplementaryinformation.docx