IRMM
INTERNATIONAL REVIEW OF MANAGEMENT AND MARKETING
EJ EconJournals
ISSN: 2146-4405

International Review of Management and Marketing

ISSN: 2146-4405

available at http: www.econjournals.com

International Review of Management and Marketing, 2026, 16(3), 317-325.

EJ EconJournals

From Classroom Care to Digital Support: Ecological Foundations for Teacher-Responsibility, AI-Integration and Student Well-Being Framework

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Received: 23 September 2025 **Accepted:** 18 January 2026 **DOI:** https://doi.org/10.32479/irmm.22934

ABSTRACT

This theoretical article develops a lean conceptual framework describing how the teacher responsibility can promote student mental health in higher education by the mediating factor of AI integration in learning. The model is based on the Ecological Systems Theory (PPCT), which places teacher responsibility as a proximal classroom factor that organizes facilitating processes, such As clear guidance, formative feedback, and scaffolding, and responsibly deployed AI tools (adaptive practice, intelligent tutoring, conversational agents) offer timely and personalized support, which decreases cognitive load and enhances autonomy and competence. We formulate testable hypotheses that state that (a) there exists a direct positive correlation between teacher responsibility and student mental well-being and (b) there is an indirect impact through the adoption of AI. The paper describes suggested operational definitions and reflective scales (adapted teacher responsibility, Warwick-Edinburgh Mental Well-Being Scale (WEMWBS), and AI-integration scales), provides a procedure/statistical solution to method bias, and provides a roadmap to empirical validation (using a cross-sectional survey and mediation analysis). In theory, the work incorporates both human and technological support into an ecological framework, beyond siloed approaches to education and ed-tech. In practice, the work supports educators and institutions in co-designing responsibility-informed teaching with the use of ethically governed AI used to create inclusive and supportive learning environments to meet emerging student mental-health issues. The framework is designed to guide evidence-based policy and course design in fast-digitizing systems, with China being a topical setting to be tested in the future.

Keywords: Teacher Responsibility, AI Integration, Student Mental Well-being, Higher Education, Ecological Systems Theory
JEL Classifications: I21, I23, I31, O33

1. INTRODUCTION

There has been a rise in concerns about university students' mental health and wellbeing in the higher education agendas around the world (Baik et al., 2019; Parmar et al., 2025). As academic pressures and competition increase, mental health problems are becoming increasingly problematic in limiting students' ability to reach their academic and personal potential, and are regularly associated with poor performance, disengagement, and the risk of dropout (Jones, 2019; Pointon-Haas et al., 2023; Zajac et al., 2024). Outside of the university, untreated mental ill-health has considerable economic cost (loss of productivity, increased healthcare costs) which highlights the societal benefit of early, embedded support through education (Correa et al., 2020). At the individual level, mental wellbeing fosters self-confidence, self-efficacy, and personal development that enable students to excel academically and professionally (Lister et al., 2023). It is therefore both a moral and pragmatic imperative for institutions to place student wellbeing at the heart of their work to prepare learners to be able to cope with difficulties and take advantage of opportunities (Hill et al., 2024; Prinsloo, Slade, & Khalil, 2024). In keeping with this trend, wellbeing is increasingly conceptualized as part of an inclusive supportive learning environment rather than something that is an optional extra (Baik et al., 2019). In light of this view, a holistic approach to technology integration that incorporates teacher scaffolding as well as reasonable inclusion of innovative technologies can offer a sensible framework for the holistic development of students (Bronfenbrenner, 2000; Tudge et al., 2009).

The ecological perspective is used to describe the reasons multi-level, proximal supports in the classroom are particularly effective. Bronfenbrenner's bioecological theory is focused on the idea that the development and wellbeing of students is based on complex proximal processes among individuals and their environments over time (Bronfenbrenner, 2000; Rosa and Tudge, 2013). In the case of higher education, this perspective calls for designs that intensify teacher-student relations and ethically integrate the technology into the everyday learning as part of the immediate microsystem while being aligned with the institutional conditions (El Zaatari, 2022; Tong et al., 2024). More recent uses of the PPCT model in education suggest that these structures promote sense of belonging and support in rapidly changing learning ecologies (Rosa and Tudge, 2013; Tong et al., 2024), precisely the places where wellbeing is at stake.

Within this ecology, one of the critical, direct, proximal influences on student wellbeing is teacher responsibility--the felt accountability by the teacher for student academic and emotional success (Lauermann and Karabenick, 2013). Teachers who take responsibility are more likely to implement active, student-based practices (e.g., early identification, customized feedback, regular encouragement) that develop resilience, self-efficacy, and emotional balance (Matteucci et al., 2017; Hagenauer and Volet, 2014). There is some empirical support that caring, informal teacher-student relationships moderate academic stress and nurture positive affect to promote mental health (Roorda et al., 2011; Wang et al., 2020; Frommelt et al., 2021). In support of this evidence, we further the assumption that teacher responsibility directly impacts student mental wellbeing through mediating daily classroom processes in the classroom to mitigate stressors and develop supportive classroom climates (Lauermann and Karabenick, 2013; Roorda et al., 2011).

At the same time, advances in artificial intelligence are transforming learning environments in ways that may carry--and magnify--teachers' supportive intent (Chiu et al., 2024). AI-enabled learning tools like intelligent tutoring systems, adaptive practice, and conversational agents can provide on-demand, personalized feedback, reduce cognitive load, and enable self-paced learning when judiciously embedded into coursework and advising--all of which map to autonomy and competence needs related to better psychological outcomes (Wilson-Trollip, 2024; Zawacki-Richter et al., 2019; Zhou et al., 2025). Recent reviews report increasing engagement and self-management benefits, and some studies report wellbeing benefits from AI-mediated support where tools are embedded within human-led, ethical frameworks (Wang et al., 2024; Bond et al., 2024; Stohr et al., 2024; Klimova, 2025). On this basis, we hypothesize that AI integration works as a mediating process through which teacher responsibility exerts a positive influence on students' mental wellbeing in their everyday learning (Wu & Yang, 2022; Ulagammal and Ramesh, 2023; Wang et al., 2023; Xu et al., 2025; Li et al., 2025).

China is a very relevant background. Rapid higher education growth accompanied by a persistent presence of stress, anxiety and depression among university students which has recently been analyzed for the need of campus-embedded interventions (Guo et al., 2019; Meirun et al., 2022; Zhao et al., 2021). At the same time, national level efforts are made to bolster mental health services, and universities are speeding up digital innovation - two conditions that make responsible informatization of education both relevant and timely (Guo et al., 2019; Meirun et al., 2022). Against this background, this study explores the direct and indirect relationships between teacher responsibility and student mental wellbeing in the context of the integration of Artificial Intelligence (AI) in learning in Chinese higher education (Zhao et al., 2021; Li et al., 2025). Despite the heavy investment made in the infrastructure of e-learning, along with the growing interest in digital education, China has not yet reached the full capacity to adopt e-learning systems at higher learning institutions (Ma et al., 2025). The aim is to produce practical recommendations for teachers and policy makers as to how they might develop culturally sensitive, developmentally appropriate interventions that enhance mental health in the context of teaching and learning daily (Tong et al., 2024; Ulrich, Way, & Wright, 2024).

Despite an emerging body of literature on student mental wellbeing, there are important gaps. Whilst there is a wide literature linking teacher accountability to educational outcomes, comparatively little research has examined its direct effects on psychological wellbeing in the context of university (Lauermann and Karabenick, 2013; Lauermann and Berger, 2021; Maclean and Law, 2022). Second, the cognitive focus of AI in education scholarship means that little attention has been given to the role of AI in promoting student wellbeing; the mediating mechanism of teacher responsibility and wellbeing is not well theorized nor empirically tested (Zawacki-Richter et al., 2019; Fitria, 2021; Wang et al., 2024). By paying attention to these two variables and stating a mediation model embedded in China's higher-education system, this study adds a theoretically grounded and contextually relevant explanation of how responsible pedagogy can be used in conjunction with pedagogically informed AI use in order to foster student mental wellbeing (Rosa and Tudge, 2013; Tong et al., 2024).

2. LITERATURE REVIEW

2.1. Ecological Systems Theory

Ecological Systems Theory (Bronfenbrenner, 2000) describes development as a multi-layered, reciprocal process influenced by interactions among layered systems -- the micro-, meso-, exo-, macro-, and chronosystems. Later refinements focus on the PPCT model (Process-Person-Context-Time) with proximal processes at the heart of development and the clarification of the role of individual characteristics in their transactions with the layers of context over time (Correa, 2020; Tudge et al., 2009; Rosa and Tudge, 2013). Contemporary syntheses give credit to the theory's value for education, emphasizing PPCT as a powerful lens for understanding school belonging and wellbeing in rapidly changing learning ecologies (El Zaatari, 2022; Tong et al., 2024). In the framework of this study, the teacher's responsibility lies within the microsystem, as a proximal interaction, influencing the emotional and academic functioning of children (Roorda et al., 2011). Peer collaboration is also part of the microsystem and an important source of social and emotional support which buffers stress and contributes to engagement (Furrer and Skinner, 2003; Smithikrai and Smithikrai, 2024). While thinking processes about AI are sometimes arranged on institutional or policy levels (exosystem), its enactments in classrooms bring the advanced resources into students immediate learning processes, which tight links between micro- and exosystems (Dai et al., 2021; Holmes et al., 2019). This multi-level view is an appropriate one for China's collectivist culture and rapidly changing higher education environment in which the systemic interactions of teacher practices, technological infrastructures and peer interactions exert a co-production of the mental wellbeing of the student (Khatri et al., 2024). Thus, Ecological Systems Theory justifies our moderated mediation framing of the research whereby individual (teacher responsibility), technological (AI integration) and social (peer collaboration) factors interlock to influence university students' mental wellbeing.

2.2. The Role of Teacher Responsibility in Student Mental Well-Being

According to the previous researchers, teachers provide students with high-quality instruction, nurturing relationships, and inclusive classroom climate, which consistently determine the academic, social, and emotional results of students (García-Moya and García-Moya, 2020; Frommelt et al., 2021). In this environment, the role of teacher responsibility, i.e. teacher perceived responsibility in both the academic and emotional success of the students, acts as the proximal influence of good practice. Educators who support high responsibility are more likely to be involved in early warning of learning and wellbeing vulnerabilities, personalized support, and continuous, formative feedback that perpetuates improvement and builds self-confidence (Lauermann and Karabenick, 2013; Matteucci et al., 2017). The further validation efforts on the Teacher Responsibility Scale in various programs and cultural contexts only enhance the uniqueness of the scale over related beliefs (e.g., efficacy, locus of control) and establish its positive correlations with engagement and achievement (Lauermann and Karabenick, 2013; Chen & Tsai, 2021). These results are consistent with education-management ideals of accountability and whole-person growth, which introduce responsibility not as a disposition, but as a practical framework in everyday pedagogy (Hagenauer and Volet, 2014).

Mechanically, responsibility-based teaching works in relational and instructional streams that are directly aligned with mental health support (Lee et al., 2022). Happy teacher-student relations cushion academic stressors and enhance perceived belonging and security, as well as positive affect--important antecedents of psychological wellbeing (Roorda et al., 2011). As a matter of practice, conscientious teachers establish explicit expectations, tinker workload and pace, habituative help-seeking and incorporate low-stakes feedback loops that lower uncertainty and cognitive load. Through these classroom processes, motivation and self-efficacy are encouraged, which subsequently result in improved emotion regulation and more adaptive coping to academic challenges (García-Moya and García-Moya, 2020; Frommelt et al., 2021). The combination of the literature shows that teacher responsibility has a direct and positive relationship with student mental wellbeing that supports our first hypothesis to a considerable degree on both theoretical and empirical levels.

H_1: Teacher responsibility has a significant positive effect on student mental wellbeing.

2.3. Teacher Responsibility and AI Integration in Learning

By personalizing the learning process and addressing knowledge gaps, as well as automating the repetitive processes (e.g., generating quizzes, providing feedback on drafts, finding course materials), AI can help to lessen intellectual load and academic demands and enhance the feeling of competence and agency, which are known antecedents of wellbeing (Zawacki-Richter et al., 2019; Zhou et al., 2025). The growing body of converging evidence shows that AI can positively affect academic outcomes and interaction in higher education (Wang et al., 2024; Bond et al., 2024). Other sources of emerging literature also indicate anxiety reduction and enhancement of self-help behaviors in the situation when AI-driven system provides support in a timely manner and is tailored to an individual, e.g., a conversational tutor that instructs how to approach a problem or an adaptive platform that changes its level of difficulty in real-time (Stohr et al., 2024; Klimova, 2025). Mechanistically, such tools have the potential to support self-regulated learning (planning, monitoring, reflection), offer just-in-time formative feedback, and generate a progress sense, which is associated with autonomy- and competence-supportive conditions of enhanced psychological results.

Concurrently, some level of caution is justified: mental-health experts argue that AI should not take the place of professional care and indicate that the application of the technology should be approached with a lot of care and ethically conscious consideration in educational institutions (Kumar, 2025). Practically, it would entail taking on human-in-the-loop designs (teacher supervision, explicit escalation options in the case of distress), ensuring privacy and data security, reducing bias and establishing a limit around academic integrity. Intelligently implemented within such guardrails, intelligently implemented teacher-guided AI, as a complement and not a replacement of human support, has potential to support the mental wellbeing of students by creating more flexible, open, and supportive learning environments.

H_2: Teacher responsibility has a significant positive effect on AI integration in learning.

2.4. AI Integration in Learning and Student Mental Well-Being

By personalizing the learning process and addressing knowledge gaps, as well as automating the repetitive processes (e.g., generating quizzes, providing feedback on drafts, finding course materials), AI can help to lessen intellectual load and academic demands and enhance the feeling of competence and agency, which are known antecedents of wellbeing (Byrne et al., 2022; Zawacki-Richter et al., 2019; Zhou et al., 2025). The growing body of converging evidence shows that AI can positively affect academic outcomes and interaction in higher education (Wang et al., 2024; Bond et al., 2024). Other sources of emerging literature also indicate anxiety reduction and enhancement of self-help behaviors in the situation when AI-driven system provides support in a timely manner and is tailored to an individual, e.g., a conversational tutor that instructs how to approach a problem or an adaptive platform that changes its level of difficulty in real-time (Stohr et al., 2024; Klimova, 2025). Mechanistically, such tools have the potential to support self-regulated learning (planning, monitoring, reflection), offer just-in-time formative feedback, and generate a progress sense, which is associated with autonomy- and competence-supportive conditions of enhanced psychological results.

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H_3: AI integration in learning has a significant positive effect on student mental wellbeing.

2.5. The Mediating Mechanism of AI Integration in Learning

We theorize AI integration in learning as a mediating process in which teacher responsibility is transformed into more positive student mental wellbeing. This mediation is based on the pathways of pedagogical structured sequences. Highly responsible teachers do not sit back and wait without acting on technology; instead, they are the ones that establish the enabling conditions, e.g., the selective usage of the suitable AI tools, thorough onboarding experience, and the initiation of consistent feedback mechanisms, that will enable students to successfully appropriately new AI technology into their learning practices (Baker, 2024). This accountable scaffolding allows students to use AI to accommodate personalized practice, get formative feedback in real time, and study at their own pace, which are always correlated with lower levels of academic frustration and better affective states (Ulagammal and Ramesh, 2023; Wang et al., 2023).

These can be reduced to several interrelated processes that constitute the mediating pathway. First, the responsible teachers reduce the anxiety and ambiguity connected with the new technologies, which creates the atmosphere of a psychological sense of security that promotes the experimental use of AI tools by students (Li and Chiu, 2025). Second, teachers make sure that such tools are used as prompts to learn but not another source of stress because they have been built into a coherent pedagogical model. An example of such evidence is that even with the positive impacts of recent interventions in assisting students with stress management, cognitive engagement, and proactive help-seeking behavior, AI-based coaching and chatbots can bring a lot of benefit only when they are incorporated into the pedagogically sound frameworks that incorporate ethical guardrails and striking human supervision (Xu et al., 2025; Li et al., 2025). These papers point to the fact that the presence of AI on its own is not enough but that the quality of its integration mediates the effects it has on wellbeing, which is a direct result of teacher responsibility.

Moreover, this mediation is compatible with the Ecological Systems Theory with a microsystem influence (the teacher) and an ecosystem influence (the institutional support of AI) as a joint catalyst of AI-mediated proximal processes which are the persistent forms of interaction leading to development. With the daily and supervised engagements with adaptive AI systems, learners develop competency and independence, both of which are fundamental psychological needs that are related to wellbeing (Ryan and Deci, 2024). With age (the chronosystem), these positive academic experiences and alleviation of chronic stresses come together to institute healthier and more stable affective conditions (Zhou et al., 2025). Essentially, the responsible teacher is an imperative mediator, who influences the possibility of AI into the reality of well-being-promoting learning processes of the student.

H_4: AI integration in learning mediates the relationship between teacher responsibility and student mental wellbeing.

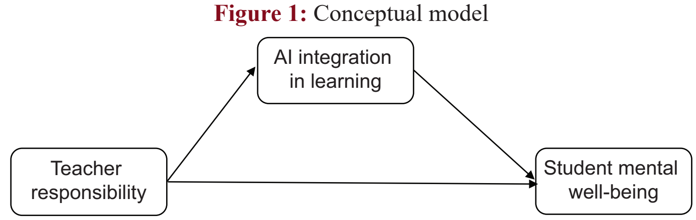
3. CONCEPTUAL MODEL

The model assumes the existence of a single mediator: teachers' responsibility (proximal classroom influence) increases AI integration in learning which, in turn, increases student mental well-being as demonstrated in Figure 1. Based on an ecological/PPCT perspective, accountable educators develop facilitative procedures, such as explicit instructions, summative feedback, and scaffolding, through which the daily application of AI tools is justified and facilitated. These interventions provide personalized and timely (e.g., adaptive practice, tutoring/chatbots) support, reducing cognitive load and reinforcing autonomy and mastery--critical to psychological well-being. In this way, responsible pedagogy becomes more well-being-oriented through the implementation of AI.

4. METHODOLOGY

Although this is a conceptual study, we outline a concrete methodological roadmap to guide future empirical testing of the proposed mediation model in which teacher responsibility influences student mental wellbeing via AI integration in learning.

Figure 1: Conceptual model



The framework emphasizes rigor, feasibility, and alignment with best practices in education, information systems, and behavioral research.

4.1. Research Design

Our proposed research design will be a quantitative, cross-sectional survey that would be suitable to test theory-driven hypotheses, with multiple latent constructs and a mediating mechanism (Creswell and Creswell, 2018). Quantitative methods allow estimating the direct impact of teacher responsibility on mental wellbeing and the indirect impact of teacher responsibility through AI integration using the validated multi-item scales and structural modeling. Cross-sectional data that is gathered at one specific time is appropriate to evaluate the perceptions, proximal learning experiences, and self-reported behaviors in higher education settings and is also cost-effective and efficient to administer. A longitudinal design would provide even greater leverage on causality and developmental patterns (e.g., change in wellbeing across semesters), but a cross-sectional design would provide a rigorous initial test of theory confirmation and also of the quality of measurement prior to panel extensions (Kline, 2015; Hair et al., 2019; Järvelä, Järvenoja, Malmberg, 2019).

To facilitate sound inferences, the empirical plan would involve close instrument adaptation (forward-back translation, expert review, and cognitive interviews), pilot test, and verification of reliability and validity before subjecting to hypothesis testing. Evaluation of the measurement model will be done through item loadings, internal consistency (CR), convergent validity (AVE) and discriminant validity (Fornell-Larcker and HTMT). Cronbach's alpha (a) values are critical for determining instrument reliability (Aman-Ullah et al., 2024). Once the measurement model is validated, PLS-SEM will then be used to estimate the structural model to facilitate complex mediation, non-normal variables, and focus on prediction followed by sensitivity checks with covariance-based SEM (CFA + path model) to assess global fit measures (CFI/TLI, RMSEA, SRMR) and compare the pattern of effects (Hair et al., 2019; Kline, 2015). Structural equations models have been demonstrated to be superior models to perform estimations better than regressions for assessing mediation (Saoula et al., 2019). Nonparametric bootstrapping (5,000 resamples) will be used to test mediation, which will give confidence intervals of the indirect effects.

To overcome common method variance, we shall use procedural remedies, including assured anonymity, neutral wording of items, proximal separating predictor/mediator/outcome blocks, and different item stem, as well as statistical diagnostics (a marker variable and/or latent method factor) (Podsakoff et al., 2003). Data quality checks (attention checks, response-time flags), principled management of missingness (e.g., FIML or pairwise deletion consistent with the estimator) will be defined. VIFs and influence diagnostics will be used to check assumptions (multicollinearity), and alternative specifications (inclusion of theoretically relevant covariates) will be used to check robustness. Where practicable, self-reports of AI integration will be triangulated with unobtrusive learning-analytics traces (LMS access, time-on-task). Ethical considerations will be applied to all procedures (informed consent, minimal risk, data privacy), hypotheses should be preregistered, and an analysis plan will be developed to improve the level of transparency and reproducibility (Creswell and Creswell, 2018; Hair et al., 2019).

4.2. Target Population and Sampling Strategy

The target population will include undergraduate and postgraduate students who are already studying in Chinese universities because they are the ones who are integrated into the learning ecologies where teacher responsibility and AI-assisted learning are to be implemented. Since students are distributed in a variety of different types of institutions (applied universities, vocational colleges), regions (East/Central/West/Northeast), and clusters of disciplines (STEM, social sciences, humanities), and due to the unavailability of a national sampling frame, we suggest nonprobability convenience sampling, with light stratification or quota targets (e.g., by institution type, region, and level of study) added in cases where feasible to increase the heterogeneity of the sample and minimize coverage bias (Et Recruitment will be based on official online (learning management systems/teaching platforms, department and program mailing lists), student digital communities (WeChat groups, QQ forums), and some offline posters, which will be organized via student affairs offices to reach the less digitally engaged students. This method is common in information-systems and higher-education research when access to the appropriate users is needed in a timely manner and probability sampling cannot be practiced (Sun et al., 2022).

To enhance validity amid convenience sampling, we will clarify transparent inclusion criteria, which are currently enrolled, age $\geq$ 18, and recent exposure to course-approved AI-supported tools/platforms and screen briefly at entry to the survey to eligibility (Etikan et al., 2016). We will also track basic distributional metrics (e.g discipline, year of study, gender, region) to prevent severe imbalances and, in the case of recruitment shortages in specific strata, will use program coordinators to send targeted reminders to enhance coverage. More specific data-quality controls will involve survey links that are unique, duplicate-response detectors (IP/device), attention checks, and response-time flags; incentives will be small, obviously non-coercive to restrict satisficing. Following fieldwork, we will record participation statistics (reach, click-through, completion, cooperation rates) and perform simple nonresponse checks (e.g. early late comparison; agreement between observable marginals and public enrollment statistics). In case of the existence of small discrepancies and the availability of auxiliary information allows sensitivity analyses with the light post-stratification weights may be reported, and primary hypothesis tests will not be weighted to avoid interpretation bias to test the theory (Hair et al., 2019). All research materials will be in Simplified Chinese, forward-back translation and cognitive interviewing to make sure that linguistic and cultural appropriateness is achieved, and the usual ethical considerations (informed consent, confidentiality, data minimization) will be followed.

4.3. Sample Size Considerations

We would like to have 300-400 complete responses so that we have sufficient statistical power to perform the mediation analysis using Partial Least Squares-Structural Equation Modeling (PLS-SEM)

(Krejcie and Morgan, 1970; Hair et al., 2019). PLS-SEM is suitable for prediction and theory development, is strong with complex models and nonnormal data, and it is more robust to smaller samples than covariance-based SEM-indirect effect tests (mediational analysis) and the stability of path estimates still benefit from larger N (Hair et al., 2019; Kline, 2015). A sample in the 300-400 range will usually be adequate (0.80) for the detection of small-to-moderate indirect effects under typical measurement reliabilities and path sizes (For power analyses that are prospective, for instance, with G*Power, the N can be justified more fully based on anticipated effect sizes and numbers of predictors (e.g. Cohen, 1992). Larger samples would also allow for subgroup analyses (undergraduate vs. postgraduate; STEM vs. non-STEM), and cross-validation of the measurement model, further enhancing robustness and external credibility of results.

4.4. Proposed Measures and Operationalization

As a conceptual paper we indicate how the focal constructs would be operationalized in a later empirical investigation, drawing on established instruments which could be considered valid and reliable and outlining validation procedures appropriate to the Chinese higher education context.

4.4.1. Teacher responsibility (reflective)

We include 13-items adapted from the Teacher Responsibility Scale (TRS) (Lauermann and Karabenick, 2013). Material reflects teachers perceived responsibility for student achievement (academic and emotional) as experienced by students. An example sentence would be: *My teacher feels guilty if I fail to learn what I should know*. Adaptation will maintain the content domain of the original construct but will focus on classroom-level practices relevant in Chinese universities.

4.4.2. Student mental wellbeing (reflective)

We suggest 14 items drawn from the Warwick-Edinburgh Mental Well-Being Scale (WEMWBS) (Tennant et al., 2007) that are re-contextualized to academic life (e.g., “I feel optimistic about my academic future.”). The WEMWBS’s focus on positive functioning is in line with our theorized outcomes of supportive teaching and learning environments.

4.4.3. AI integration in learning (reflective)

We suggest 4 perception-based items borrowed from Stohr et al. (2024), centered on the utility of studying with AI tools as perceived by the students (e.g. “The chatbots I use make me more effective in my studies”). Items will capture more day-to-day, course-embedded use, rather than general attitudes towards AI.

4.4.4. Response format

All items will use a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). Scale anchors are chosen to balance discrimination and respondent burden and to align with prior validations of the source instruments (Lauermann and Karabenick, 2013; Tennant et al., 2007; Stöhr et al., 2024).

4.4.5. Cultural and linguistic adaptation (planned)

For deployment in Chinese universities, we both specify forward-back translation with bilingual experts, reconciliation by a panel and cognitive interviewing with a small group of students to ensure semantic equivalence and contextual relevance (Brislin, 1986). Expert review (subject-matter and methods experts) to review content validity (full coverage of each construct’s domain and clarity for target population).

5. CONCLUSION

In this conceptual paper, we provide a parsimonious explanation of the role of responsible teaching in promoting the mental well-being of students in a modern higher education system by projecting a mediating course through the use of AI-mediated learning. Using an ecological approach, we claim that the teacher responsibility (taken as referring to the affective responsibility of teachers to the academic and emotional success of students) is a proximal force that influences the enabling classroom processes. The combination of these processes with properly designed and ethically controlled AI tools (e.g., adaptive practice systems, intelligent tutoring, conversational agents) may give them feedback earlier, lessen cognitive load, and help students feel more self-reliant and competent, which in turn will lead to their psychological wealth. Placing this model within the framework of a fast-changing higher education system in China shows the dire need to pay attention to the issue of student mental health, at the same time not underestimating the topicality of the further institutional digitalization.

The paper makes three contributions. Theoretically, it weaves together strands of work on teacher responsibility, AI-enhanced learning and student wellbeing into a single mediation framework, explaining how human and technological supports can be co-designed, rather than studied in isolation. Conceptually, it defines clear construct boundaries and suggests operational definitions and reflective measures appropriate for further empirical study. Methodologically, it provides a specific roadmap (which centers on a quantitative, cross-sectional survey and PLS-SEM) based on testing direct and indirect effects, cultural adaptation, procedures for measurement quality, and common-method mitigation procedures.

In practice the model points out priorities for universities (and faculties) to act upon. Step 1: Hold everyone accountable by creating a culture of teacher development through relational pedagogy, early identification, and formative feedback. Second, link instructional design to accountable AI use -- choose tools that are proven to positively affect learning, have human-in-the-loop oversight, and provide clear governance on transparency, privacy, and academic integrity. Third, implement wellbeing goals at a course level (e.g. pacing, assessment load, reflective check-ins) so that the psychological benefits of AI-supported learning are realized as part of day-to-day pedagogy.

We know there are significant limitations. As a conceptual claim, causal claims need to be empirically verified. Cross-sectional tests should be followed by more robust designs - longitudinal panels to measure change over the course of semesters, multilevel models to capture the influence of classroom and institutional factors, and, where possible, field experiments or quasi-experiments to investigate causality. Future research should address measurement invariance across subgroups (e.g., undergraduate/postgraduate, STEM/non-STEM), test robustness to indirect-effect specifications, and consider ethical and equity issues (access, bias, over-reliance on automation). Mixed-methods extensions - connecting quantitative impacts and qualitative descriptions of students lived experiences - will enhance explanatory power and guide implementation.

In a future empirical study, we are going to test the proposed mediation model (teacher responsibility predicts student mental wellbeing through AI integration in learning) by conducting a multi-site survey across Chinese universities. We will aim at both undergraduate and postgraduate students who have been introduced to AI-assisted coursework recently (e.g., adaptive practice, intelligent tutoring, or course-approved chatbots). To achieve sufficient heterogeneity, recruitment will be done through official university channels and student groups (WeChat/QQ), with defined inclusion criteria (enrolled students; age ≥18; use of AI in current or most recent semester). A priori power analysis will be used to determine sample size with a goal of 300-400 valid responses that will provide robust estimation of mediation and subgroup checks.

Constructs will be operated through validated reflective scales: perceived teacher responsibility (adapted from available teacher responsibility tools), student mental wellbeing (adapted for academic setting from an existing, well known wellbeing scale), and AI integration in learning (items based on perception of utility and uptake in coursework). Instruments will be forward-back translated, reviewed by experts and cognitively interviewed to ensure cultural and linguistic appropriateness. We will introduce procedural solutions to minimize common method variance (guaranteed anonymity, neutral language, proximal separation of predictors/mediators/outcomes), and a theoretically independent marker will be included to measure residual bias. Pilot testing will be used to check for clarity and timing, and minor items will be adjusted as necessary.

Data analysis will be carried out in two stages. First, we will confirm the measurement model (item loadings, reliability, convergent and discriminant validity) and assessment of measurement invariance by key groups (undergraduate/postgraduate; STEM/non-STEM) as a way to ensure comparability. Second, we will estimate the structural model and the indirect effects by PLS-SEM approaches (predictive emphasis and distributional robustness) with a bootstrapped confidence interval for the mediating pathway. As a sensitivity check, we will re-estimate the model using covariance-based SEM (CFA + path model) to investigate fit indices and compare effect patterns. Where possible we will triangulate self-report indicators of AI integration with unobtrusive traces of learning analytics (LMS time-on-task, tool access logs) to enhance validity.

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