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Activity theory as a lens on teachers' adoption of AI technologies: A structural equation modeling

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ABSTRACT

Despite the growing use of Artificial Intelligence (AI) technologies in education, the underlying mechanisms that account for why some educators are inclined to adopt AI while others remain reluctant to do so remain unclear. The present study examined primary, secondary, and pre-service teachers' intentions to use AI tools in K-12 educational settings. Drawing from Activity Theory, we tested six hypotheses illustrating the complex interrelationships among AT-related components linked to teachers' intentions. Our factor analysis and structural equation modeling (SEM) demonstrated that AT components can be reliably measured and have explanatory power regarding teachers' intentions to adopt AI-driven tools. In the full sample analysis (N = 557), both *Individual* and *Community* components played significant roles in explaining teachers' *Intention. Objectives* and *Division of Labor* were directly linked to *Individual* and indirectly associated with *Intention. Community* was linked to *Rules/Regulations* and *Government*, which were indirectly associated with *Intention*. We also found notable differences when comparing secondary and primary school teachers. *Division of Labor* and *Community* had stronger effects among secondary teachers. On the other hand, *Objectives* and *Individual* played more prominent roles among primary teachers in their intention to use AI tools. The results for pre-service teachers resembled those of primary school teachers. Overall, the present study highlights the complex mechanisms through which teachers at different career stages and teaching levels may adopt AI-driven tools. Theoretical and practical implications are discussed in conclusion.

Introduction

The rapid development of Artificial Intelligence (AI) technology in recent years has created an urgent need for evidence-based guidance to support educational communities. The present study, drawing on Activity Theory (AT; [1,2]), also known as Cultural-Historical Activity Theory (CHAT), aims to examine how teachers may intend to use AI-driven tools in their professional settings. AT is one of the leading theoretical frameworks in the fields of human-computer interactions [3] and educational technology [4]. Its application spans across the topics of technology professional development for teachers [5], computer-assisted language learning [6], and practical challenges associated with digital technologies [3].

AT consists of six key components: (1) *Individual/Subject*, (2) *Objectives/Object*, (3) *Division of Labor*, (4) *Community*, (5) *Rules/Regulations*, and (6) *Tools*. It explains how these components interact to shape human activity of both individuals (*Individual*) and their social group (*Community*), offering insight into the role of technologies (*Tools*) within sociocultural and educational contexts. Interactions between individuals and tools in pursuit of their objectives (*Objectives*) are further mediated by the tools' potential to enhance the division of labor (*Division of Labor*) and by the community's consensus regarding the use of the tools (*Rules/Regulations*). In short, Activity Theory seeks to explain how technology use is shaped by socially and culturally mediated norms and practices (*Community*) within objective-oriented human activity (*Objectives*), highlighting its meaning and clarifying how and why individuals and communities engage with technology.

Educators' adoption of AI tools through the lens of activity theory (AT)

The present study, theoretically, seeks to evaluate the utility of Activity Theory (AT) in explaining teachers' intentions to use AI-driven tools. Practically, it seeks to provide insights for school leaders and policymakers to facilitate the effective integration of AI technologies for teaching workforce. In this study we conceptualize each of AT's six components in the following ways:

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1. *Individual* encompasses both in-service and pre-service teachers who may consider using AI tools in educational settings. It emphasizes the personal aspects of tool use, including current practices, individual engagement, and enjoyment derived from interacting with AI-driven technologies.
2. *Objectives* refer to the overarching motives or goals of an intended activity [3]. In this study, they represent the broad educational aims of enhancing teaching and learning through AI-driven technologies.
3. *Tools* serve as central medium in the activity system [7]. In this study, they refer to AI-driven digital mediums that teachers may use in the educational settings. Common examples of AI technologies include conversational chatbots, digital pedagogical agents, and adaptive learning platforms [8,9].
4. *Community* refers to the social network where the intended activity occurs (i.e., teachers' adoption of AI tools). Educational community network comprises teachers, their peers, school leaders, administrators, students, parents, and young children [4]. The extent to which a community engages with AI reveals how its members perceive, adopt, and embed these tools within their collective practices [10,4].
5. *Division of Labor* can occur amongst any members of the community (e.g., between teacher and student, and amongst teacher colleagues). In the present study, it pertains division of labor between teachers and AI technologies. This concept represents teachers' delegation of their routine tasks to AI tools and their willingness and inclination to use AI-driven tools to manage their work and enhance overall efficiency.
6. *Rules/Regulations* define the guidelines and frameworks for an activity to unfold. Rules about technology use for educational purposes typically include who may use the tools, for what purposes and tasks, where usage is permitted, and how such us is expected to support educational outcomes [7,9].

Roles of individuals, objectives, and division of labor

Teachers' intention to use AI tools primarily depends on their perception that such tools would lead to improvements in teaching efficiency and learning outcomes [11,8,12,13]. The premise of AI-driven tools is to provide more personalized learning platforms, increase teaching effectiveness, and enhance learning experiences for students with differing learning styles [11,8,14]. However, not all teachers fully embrace or recognize the affordances of AI technologies [15]. Only those who perceive AI tools as supporting educational objectives are more likely to integrate them into their current practice. Therefore, Hypothesis 1 (H1) proposes that when teachers perceive AI tools as beneficial for achieving educational objectives, they are more likely to use these tools (*Objectives → Individual*).

Teachers may also evaluate whether the adoption of new methods of teaching could yield personal benefits [16], such as reducing their workload and streamlining task management. For example, AI can automate administrative and repetitive tasks as well as more complex tasks such as lesson preparation, content creation, and grading [17,18]. Given the widespread challenges of teachers' workload and time constraints [12], AI-driven tools may be perceived as supporting their work, enhancing efficiency, and allowing greater focus on pedagogical and student-centered activities [12,18]. Therefore, Hypothesis 2 (H2) proposes that when teachers perceive AI tools as facilitating division of labor, they are more likely to use these tools (*Division of Labor → Individual*). Finally, teachers' current use of AI tools, shaped by their recognition of these tools' utility in achieving educational objectives and managing workload, are expected to be associated with their intention to adopt AI-driven technologies [18,14]. Therefore, Hypothesis 3 (H3) proposes that teachers' current use of AI tools (*Individual*), potentially shaped by their perceived educational benefits (*Objectives*; H1) and workload reduction (*Division of Labor*; H2), are positively associated with their future intention to adopt these technologies (*Individual → Intention*).

Roles of community, rules/regulations, and government intervention

AT posits that a community's engagement with technology shapes how its members adopt and develop diverse practices for using tools. The community's use of tools signals their utility in achieving collective objectives, while shared practices are continuously refined based on feedback and perceptions of the tools' effectiveness, contributing to the community's socio-cultural norms for technology use [11]. When a school community fosters AI–human collaboration, teachers are more likely to feel confident and find ways to integrate AI tools into their practice [14,13,19]. Moreover, collective expectations and shared experiences within the community can create additional opportunities and motivation for individual teachers to engage with AI technologies, while community pressure to avoid AI may discourage educators from adopting these technologies [3,7,4]. Therefore, Hypothesis 4 (H4) proposes that community engagement with AI is positively associated with teachers' intention to adopt these tools (*Community → Intention*).

AT also posits that rules and regulations regarding tool use directly shape how communities adopt and utilize these technologies. These rules not only provide guidelines for tool usage but also influence the availability, adoption, and dissemination within the community. When the rules of educational institutions endorse AI tools and make them widely accessible, educators are more likely to integrate them into their classrooms [11,3,20]. The use of tools, shaped by social rules and regulations, also reflects the evolving nature and modes of social communication and norms [11,9]. While international organisations (e.g., UNESCO) have issued AI policy guidelines, the extent to which these frameworks are implemented at the local school level remains unknown [21]. In cases where government-level regulations have not been set up, rules at the school-level play a critical role in guiding its community members about how and when AI use is permitted, e.g., generating novel content [13] or automating grading tasks [12]. Such rules create community of practice, establishing social expectations and guiding shared experiences with the tools [4]. Therefore, Hypothesis 5 (H5) proposes that *Rules and Regulations* governing tools encourages community engagement with AI technologies (*Rules/Regulations → Community*).

Role of school level and career stage

While AT emphasizes relational influences through systemic mediation of rules, tools, and collaboration within communities, individuals' demographic factors such as gender, age, or years of teaching experience are not explicitly incorporated. However, each of the AT core constructs—subject, tool, community, rules, and division of labor—can be influenced by teachers' demographic and professional settings. Research has long claimed that teachers' backgrounds, teaching levels, and professional experience with technology are related to their classroom technology integration [22,23]. Studies investigating the effects of such background variables on teachers' technology use have provided mixed results. Some studies indicate that teachers in primary school settings are more likely to adopt technology because their pedagogical approaches to incorporate technology are practices in multiple subject areas, enhancing the opportunity to utilise technology in diverse ways [24,25]. In contrast, other studies indicate secondary teachers value AI more highly as they focus on their area of expertise which may form community of practice to interact with specific AI tools, thereby influencing access, engagement, and adoption patterns [26].

Career stage also appears relevant: pre-service teachers, who are generally younger and more familiar with new digital tools, tend to view AI positively [27], while some early-career in-service teachers may feel constrained by administrative demands and limited pedagogical confidence and thus may be hesitant to experiment with new tools [23]. In contrast, more experienced teachers may adopt new forms of digital tools successfully as they have gained classroom management expertise and familiarity with a range of pedagogical approaches and feel ready to experiment with new technologies reshaping teaching [22]. These studies collectively suggest that contextual factors such as teaching level and career stage may moderate the relationships among subjects, tools, and community, shaping how educators may engage with AI technologies. Therefore, Hypothesis 6 (H6) posits that the relationships among the core elements of AT may unfold differently depending on teaching level (primary vs. secondary) and career stage (pre-service vs. in-service).

The present study

AT has been increasingly applied to examine the processes and system-level educational outcomes underpinning the use of AI-driven tools. However, existing studies on this topic have been primarily conceptual or review-based (e.g., [11,3,7,4]), with only a few empirical studies—mostly qualitative —examining real-world practices (e.g., [28]). Qualitative studies with small size samples, while informative, often limit generalizability and applicability. There is a notable lack of psychometrically sound instruments for measuring AT components in the context of AI-powered technology use in educational settings ([4], p. 192). As a highly abstract framework, AT's core components have yet to be tested by using psychometrically sound instruments. Moreover, most research applying AT to AI-enhanced teaching and learning has focused on higher education [4,29], leaving a significant gap in its application to K-12 settings.

The present study aims to address these gaps by quantitatively operationalizing AT using structural equation modeling (SEM), to test a hypothesis-driven theoretical model against empirical data collected from K-12 educators. Given the multiple interconnections among AT's core components, SEM is well suited for theorizing and empirically testing these links. The current study focuses on testing six hypotheses, as outlined above, to quantitatively assess AT components and their relationship to K–12 educators' intentions to adopt AI technologies. We also test whether the hypothesized relationships would differ by teaching level (primary vs. secondary) and career stage (pre-service vs. in-service). Together, these hypotheses form an AT-based framework to understand how teachers' perceptions of educational objectives, workload management, community norms, institutional rules, and career stage context are collectively associated with their intention for AI adoption (see Fig. 1 for the hypothesized model).

Methods

Data collection & participants

Data for this study were obtained from educators working/living in the state of New South Wales (NSW), Australia. Multiple strategies were employed to recruit participants, including advertising the study within the School of Education at the authors' institution via students' official email addresses, utilizing snowball sampling through participant referrals, and engaging the research company Qualtrics to distribute the

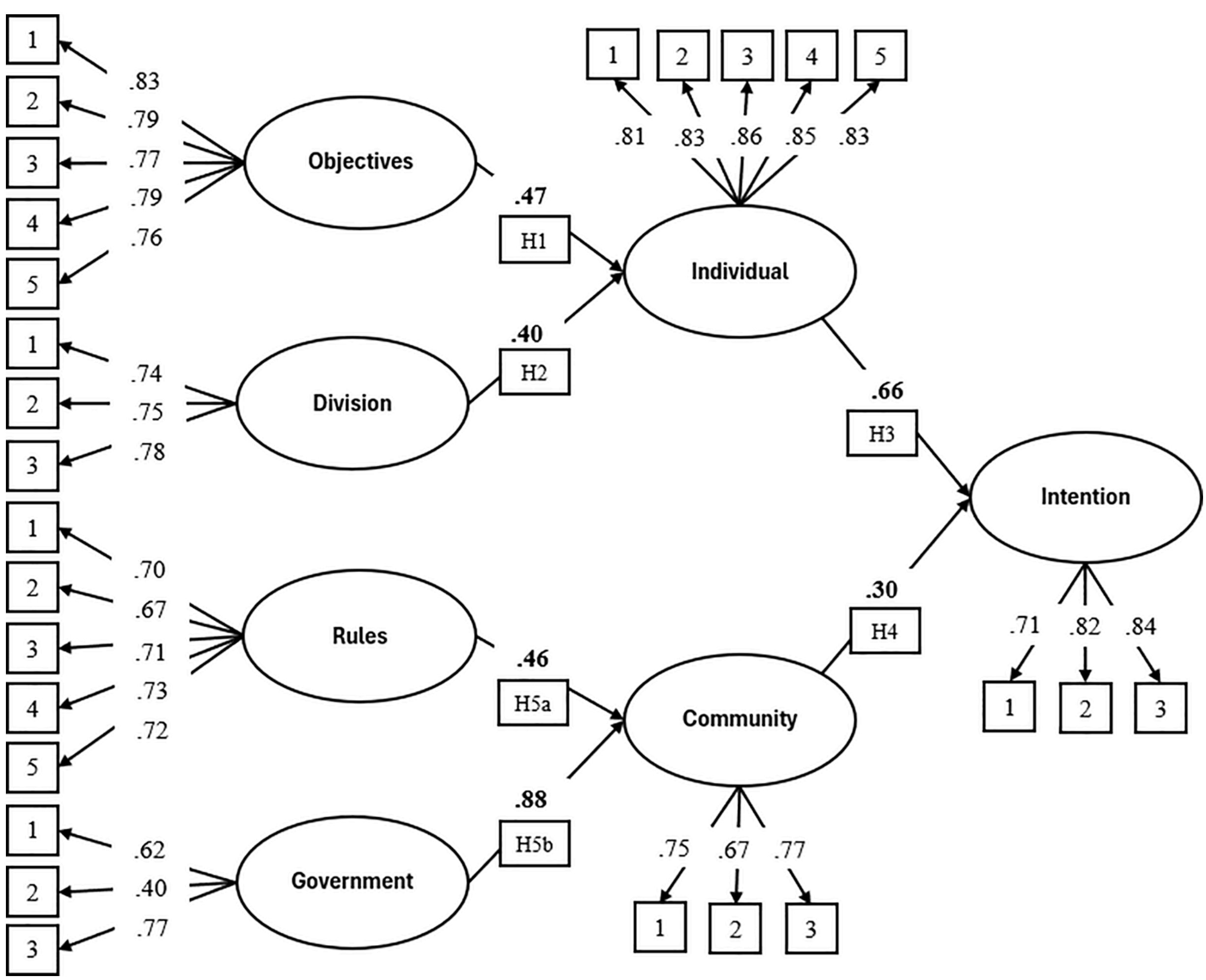

Fig. 1. Structural Equation Modelling Results based on the Full Sample ($N = 557$). Notes. The indicator numbers (in rectangular boxes) represent the item numbers for each factor listed in Table 3. The coefficients between the observed items and their corresponding factors are also reported in Table 3, while the structural relationships are presented in Table 4.

survey link. The recruitment yielded a total of $N = 630$ responses, of which $N = 557$ were complete and included in the final analysis. Most participants were in-service teachers with a small group of pre-service teachers ($n = 81$) working towards entering the teaching profession. The in-service teachers ($n = 439$) comprised of secondary teachers ($n = 226$; 51%), primary teachers ($n = 126$; 29%), early childhood teachers ($n = 38$; 9%), and those identifying as "other teaching" professionals ($n = 49$; 11%). A small number of participants ($n = 37$) indicated they were neither in-service teachers nor pursuing a teaching qualification. Demographic details of the study participants are presented in Table 1. The survey was administered between November 2024 and January 2025.

Data collection instrument

The participants were asked to response to an online survey designed to examine the relationships among AT components in explaining teachers' intention to use AI-driven technologies. The online survey began with demographic questions (e.g., gender, school level, years of teaching experience, and school location). This section was followed by a total of 46 items measuring seven constructs: six based on Activity Theory and one representing the outcome variable, *Intention* ("intention to use AI-driven tools in future"). All items employed a five-point Likert-type response format, ranging from "strongly disagree" [1] to "strongly agree" [5]. The outcome variable was measured using three items adapted from the behavioral intention subscale of the Theory of Planned Behavior, which has been widely used in recent studies on AI literacy and attitudes toward AI (e.g., [24]).

The survey items to measure the six components of AT were drawn from Hajimaghsoodi and Maftoon [6] and Wang et al. [10]. A review of recent empirical studies that applied AT in digital, computer-assisted, or AI-supported learning environments identified the measures employed in these two studies to be most suitable for the purpose of the current study. However, their focus was on EFL learners' writing, and thus, the items were revised to broaden the scope to AI tool use for educational purposes (rather than EFL learning focused on writing). For instance, the items "My friends helped me to write better" and "I used online sources to write better" from Hajimaghsoodi and Maftoon [6] were adapted to

Table 1
Demographic information of the study participants ($N = 557$).

	All participants ($N = 557$)	In-service teachers overall ($n = 439$)	Secondary in-service teachers ($n = 226$)	Primary in-service teachers ($n = 126$)	Pre-service teachers ($n = 81$)
Gender					
Males	36% (202)	39% (172)	44% (100)	30% (38)	19% (15)
Females	63% (351)	61% (267)	56% (126)	70% (88)	78% (63)
Other	0.01% (4)	0%	0%	0%	0.03% (3)
Area of School					
Urban	45% (199)	45% (199)	51% (115)	36% (45)	n/a
Suburban	43% (188)	43% (188)	37% (83)	52% (65)	n/a
Regional/ Rural	12% (52)	12% (52)	12% (28)	13% (16)	n/a
Year of Teaching					
<1 year	6% (25)	6% (25)	4% (9)	6% (7)	n/a
1 to 5 years	27% (118)	27% (118)	22% (49)	33% (41)	n/a
6 to 10 years	28% (124)	28% (124)	35% (78)	19% (24)	n/a
>10 years	39% (172)	39% (172)	40% (90)	43% (54)	n/a

"My peers encourage me to use AI tools" and "I use AI tools to improve my work," respectively. The modified items underwent two rounds of focus group meetings in collaboration with two other academics serving as external item reviewers. During this process, items were presented without reference to their intended constructs (e.g., community), and discussions continued until consensus was reached regarding the alignment between the items and its associated construct. This process resulted in a total of 43 items to assess the six elements of AT: (1) *Individual* (9 items), (2) *Objectives* (5 items), (3) *Division of Labor* (6 items), (4) *AI tools* (8 items), (5) *Rules & Regulations* (9 items), and (6) *Community* (6 items).

Pilot study & measures

Given that the AT-related items were modified for the present study, a preliminary psychometric analysis was conducted to assess their suitability. In the first stage, an exploratory factor analysis (EFA) was carried out to examine whether the expected six AT factors would emerge (see Appendix for the EFA results on the full item set). While six factors did emerge, they partially reflected the theoretical expectations. That is, the factors corresponded to *Individual, Rules/Regulations, Community*, and *Division of Labor*, as expected. However, the items for *Objectives* and *Tools* were loaded onto a single factor. The evaluation of the scale items indicated that the *Objectives* associated with AI tools use and the items about the use of *Tools* were difficult to separate empirically and conceptually; it was reasonable to combine them into a single factor.

Additionally, the items for *Rules/Regulations* were split into two distinct factors: one reflecting perceived need for rules and regulations, and the other one capturing concern specifically towards government intervention. Similarly, *Rules/Regulations* were separated into two dimensions, one reflecting a general perceived need for rules, and the other capturing government-specific concerns, which was also conceptually justifiable. Accordingly, six factors— *Individual, Objective, Community, Rules/Regulations, Division of Labor*, and *Government*—were considered conceptually relevant and empirically supported and were retained for the subsequent stage of analysis.

In the process of refining the scales for the six components of AT, only psychometrically robust items—those with factor loadings of 0.40 or higher—were retained. This resulted in a final set of 24 items, which were then organized into a six-factor structure based on the item groupings identified in the EFA. The six-factor structure was tested using confirmatory factor analysis (CFA) on the full sample ($N = 557$). The six-factor CFA model demonstrated satisfactory fit, with a Comparative Fit Index (CFI) of 0.944, Tucker-Lewis Index (TLI) of 0.935, Root Mean Square Error of Approximation (RMSEA) of 0.055, and Standardized Root Mean Square Residual (SRMR) of 0.042. Each scale was evaluated for factor loadings, internal consistency reliability (Cronbach's alpha and McDonald's omega), and average variance extracted (AVE, indicating the extent to which a construct explains the variance of its indicators). Common thresholds for acceptable scale properties include reliability coefficients of 0.70 or higher and an AVE of 50% or higher [30]. As a result of this factor analytic process, seven scales were constructed: six corresponding to the refined components of AT and one representing the outcome variable, *Intention* ("intention to use AI-driven tools in future"). Overall, the seven scales demonstrated acceptable psychometric properties and factor interpretabilities. Table 2 summarises details of the final set of measures, including example items and scale reliability.

Data analysis

As mentioned above, the six-factor structure was tested using CFA with each factor corresponding with the six components of AT Subsequently, structural equation modelling (SEM) was employed, which is the main analysis in this study. An SEM in this study aimed to examine the interrelationships among the six elements of AT and their relevance

Table 2
Scales of the study variables.

Construct (Number of Items)	Description	Example Item	Mean (S.D.)	Reliability Alpha/ Omega	AVE
Individual (5 items)	Current use of and interest in AI tools.	"Using AI tools is part of my regular practice."	3.34 (1.15)	.920/0.921	70%
Objectives (5 items)	Perceived educational benefits and purpose of using AI technologies	"AI makes teaching and learning more engaging."	3.58 (0.96)	.891/0.892	62%
Division of Labor (3 items)	Willingness to adopt AI to alleviate workload.	"I would like AI to take on some of my workload."	3.62 (0.98)	.802/0.800	57%
Community (3 items)	Perceptions of peers' engagement with and interest in AI.	"People that I know show interest in AI."	3.68 (0.94)	.776/0.778	54%
Rules & Regulation (5 items)	Perceived urgency for establishing rules and regulations in AI use.	"It is necessary to define which AI tools are appropriate for which purposes."	3.89 (0.92)	.831/0.831	50%
Government (3 items)	Skepticism regarding government restrictions on AI use.	"People should be free to use AI without government-imposed restrictions."	3.28 (1.08)	.639/0.649	40%
Intention (3 items)	Intention to use and stay updated on AI technologies in future.	"I will continue to apply AI technology to solve problems I encounter in my life."	3.65 (1.02)	.827/0.832	63%

to teachers' intention to use AI-driven tools. SEM integrates both confirmatory factor analysis (the measurement component) and regression analysis (the structural component). In this study, covariance-based SEM (CB-SEM) was employed because it aimed to test a theoretically specified model rather than maximise predictive variance, for which partial least squares SEM (PLS-SEM) is typically recommended (cf [31,32]). The measurement component models the correspondence between observed items and their underlying latent constructs, while the structural component estimates the relationships among the latent constructs [33]. SEM offers a more precise representation of the relationships among the constructs (e.g., compared to regression) because it accounts for measurement error by modeling the shared variance among observed indicators to define each latent construct, thereby excluding random error that can bias estimates in traditional regression models.

To determine the appropriate estimation method, both univariate and multivariate normality of the items were assessed. Univariate normality (skewness and kurtosis) was within the acceptable range (between -1 and $+1$) for all 24 items, suggesting no violation of univariate normality. However, Mardia's multivariate normality test [34, 35] indicated significant departures from multivariate normality, with multivariate skewness = 6837.90 ($p < .001$) and multivariate kurtosis = 39.31 ($p < .001$). Therefore, to adjust non-normality, robust maximum likelihood estimation (MLR), robust standard errors, and chi-square test statistic with the Yuan–Bentler correction were applied in SEM.

Hypothesised models were evaluated based on overall goodness-of-fit, effect sizes (path coefficients) and statistical significance of the exogenous variables, and conceptual interpretability. The overall goodness-of-fit was assessed using multiple indices with established benchmarks for acceptable fit: Comparative Fit Index (CFI > 0.90), Tucker–Lewis Index (TLI > 0.90), Root Mean Square Error of Approximation (RMSEA < 0.05), and Standardized Root Mean Square Residual (SRMR < 0.08), in accordance with recommendations by Hu and Bentler [36] and Kline [33]. SEM analyses were conducted across the full sample ($N = 557$), all in-service teachers ($n = 439$), in-service secondary school teachers ($n = 226$), in-service primary school teachers ($n = 126$), and pre-service teachers ($n = 81$). Both direct and indirect effects are calculated and discussed in the main text, whereas tables and figures present only the direct effects for conciseness. The analyses were conducted in RStudio: *psych* package (version 2.3.6; [37]) for descriptive statistics, and *lavaan* package (version 0.6.19; [38]) for CFA and SEM analyses. Various rules-of-thumb have been proposed for CFA/SEM sample size, such as a minimum of 100 or 200 [39], 5 to 10 observations per estimated parameter [40], and 10 cases per variable [41]. According to the simulation study by Wolf et al. [42], the recommended sample size is about 180 for a SEM with the three direct and indirect relationships among three factors with around 0.40 path coefficients.

Results

Overall model fit & measurement components of structural equation modeling (SEM)

The hypothesized model, incorporating Hypotheses 1 to 5, is presented in Fig. 1. The path coefficients shown in Fig. 1 are based on the overall sample ($N = 557$). As described in the Methods section, the items initially expected to load onto the *Rules/Regulations* factor were split into two distinct factors: *Rules/Regulations* and *Government*. As a result, the original Hypothesis 5 (H5) was revised and divided into two sub-hypotheses: H5a, examining the relationship between *Rules/Regulations* and the outcome variable, and H5b, examining the relationship between *Government Intervention* and the outcome variable. The strength of the relationships between items and their corresponding latent constructs, based on CFA, are shown in Table 3 (obtained from the full sample, $N = 559$). All factor loadings were statistically significant ($p < .001$), with most falling within the 0.60 to 0.80 range, indicating strong item–construct alignment. Furthermore, full collinearity assessment was conducted using variance inflation factors (VIFs). VIF values for all pairs of the variables were below the recommended threshold of 3.3 (cf, [43]), with the exception of one pair between *Objective* and *Community*, which showed 3.374 (which is also an acceptable range). Therefore, there was strong evidence that common method bias (CMB) is unlikely to threaten the validity of the CFA findings. The Fornell–Larcker [44] test for discriminant validity was also conducted on all six CFA constructs. The results showed that the square root of AVE values exceeded the inter-construct correlations [$\sqrt{\text{AVE}}$ for *Individual* = 0.84.; $\sqrt{\text{AVE}}$ for *Objectives* = 0.70; $\sqrt{\text{AVE}}$ for *Rules* = 0.71; $\sqrt{\text{AVE}}$ for *Community* = 0.73; $\sqrt{\text{AVE}}$ for *Division of Labor* = 0.76; and $\sqrt{\text{AVE}}$ for *Government* = 0.62. The only exception, which was very close was between *Community* $\sqrt{\text{AVE}}$ (0.731) and the correlation between *Community* and *Individual* ($r = 0.734$). Overall, the Fornell–Larcker test results showed an adequate level of discriminant validity.

Table 4 included the SEM results —overall model fitness and standardised path coefficients obtained for the structural components of the SEM—of all subgroups. Overall, the model demonstrated excellent fit for the full sample (CFI = 0.92; TLI = 0.91; RMSEA = 0.059; SRMR = 0.051) and acceptable fit across subsamples. The SEM results based on the full sample showed the best fit while the model fit results on the pre-service teachers (with the smallest sample size) yielded the weakest fit. Nonetheless, the model exhibited satisfactory or near-satisfactory fit

Table 3
Results from confirmatory factor analysis ($N = 557$).

Construct/Items	Std. loading	Std. Err	z-value	$p(>\|z\|)$
Individual (Engagement and Interest in AI)				
1. Using AI tools is part of my regular practice.	0.81	n/a	n/a	n/a
2. I work more effectively with the help of AI.	0.83	0.03	32.4	< 0.001
3. My interest in learning increases, thanks to AI.	0.86	0.03	30.2	< 0.001
4. I become a more active learner with AI assistance.	0.85	0.03	35.1	< 0.001
5. I enjoy working with AI tools.	0.83	0.04	25.2	< 0.001
Objectives (Educational Goals Supported by AI)				
1. Learning becomes more enjoyable when guided by AI.	0.83	n/a	n/a	n/a
2. AI makes teaching and learning more engaging.	0.79	0.04	25.1	< 0.001
3. AI motivates students to stay involved in their learning.	0.77	0.04	22.0	< 0.001
4. Learning outcomes improve with AI support.	0.79	0.04	25.9	< 0.001
5. AI enhances efficiency in learning and work.	0.76	0.04	21.0	< 0.001
Division of Labor (Task Distribution Facilitated by AI)				
1. I would like AI to take on some of my workload.	0.74	n/a	n/a	n/a
2. People should assign some routine tasks to AI.	0.75	0.05	18.6	< 0.001
3. AI can handle some of my work efficiently.	0.78	0.06	17.8	< 0.001
Rules & Regulation (Guidelines for AI Use)				
1. There is an urgent need for government regulations on AI tool use.	0.70	n/a	n/a	n/a
2. Guidelines should specify who is allowed to use AI tools.	0.67	0.05	18.5	< 0.001
3. It is necessary to define which AI tools are appropriate for which purposes.	0.71	0.07	12.8	< 0.001
4. AI guidelines should specify how young children use AI at home.	0.73	0.07	14.1	< 0.001
5. Guidelines should help parents manage and support their children's AI use.	0.72	0.06	13.3	< 0.001
Community (Perceived Engagement and Interest of Others in AI)				
1. People that I know show interest in AI.	0.75	n/a	n/a	n/a
2. AI use is common among my peers.	0.67	0.06	15.1	< 0.001
3. My peers encourage me to use AI tools.	0.77	0.07	15.7	< 0.001
Government (Perceived Restrictions Imposed on AI Use)				
1. It is not feasible to develop effective government regulations for AI.	0.62	n/a	n/a	n/a
2. Government rules will not keep up with the speed of AI development.	0.40	0.07	7.5	< 0.001
3. People should be free to use AI without government-imposed restrictions.	0.77	0.15	8.3	< 0.001
Intention (Continued and Future Engagement and Interest in AI)				
1. I will regularly update the latest AI-related applications.	0.71	n/a	n/a	n/a
2. I plan to use AI to help me learn and work now and in the future.	0.82	0.06	18.4	< 0.001
3. I will continue to apply AI technology to solve problems I encounter in my life.	0.84	0.06	20.2	< 0.001

across all subgroups. Although additional post-hoc modifications just to improve the model fit could have been performed for subgroups (e.g., correlating residuals), the same model was retained by maintaining consistent measurement and structural specifications, to ensure direct comparisons of the path coefficients across groups.

Structural components of structural equation modeling (SEM)

Fig. 1 provides a visual representation of the SEM model, with path coefficients based on the full sample ($N = 557$). The results of the SEM structural component of each of the five groups are presented in Table 4. To maintain a logical and concise presentation of results, the findings based on the full sample are described first and in greater detail. Results for the in-service teachers overall ($n = 439$) are not discussed separately, as the result patterns are similar to those of the full sample. Results from the remaining subgroups are discussed in relation to one another, with an emphasis given to notable differences across subgroups; findings that closely align with the results of other subgroups are not reiterated to avoid redundancy.

Full sample (N = 557)

In the structural components of SEM conducted on the full sample, all hypothesised pathways illustrated in Hypotheses 1 to 5b were found to be statistically significant, $p < .001$ (see Fig. 1; Table 4). Both *Objectives* ($\beta = 0.467$, $p < .001$) and *Division* ($\beta = 0.398$, $p < .001$) were positively and directly associated with *Individual*, suggesting that individuals' current use and interest in using of AI tools (*Individual*) are predicted by their perceptions of AI's potentials to support educational goal achievement (*Objectives*; Hypothesis 1) and by the AI's potentials to facilitate task distribution between human and AI tools (*Division of Labor*; Hypothesis 2). Furthermore, both *Rules/Regulations* ($\beta = 0.460$, $p < .001$) and *Government* ($\beta = 0.882$, $p < .001$) were also positively associated *Community*, indicating that the perceived urgency for establishing guidelines for AI use (*Rules*; Hypothesis 5a) and governmental involvement in AI regulation (*Government*; Hypothesis 5b) could shape how community may adopt and engage with AI tools (*Community*). Finally, both *Individual* ($\beta = 0.660$, $p < .001$) and *Community* ($\beta = 0.298$, $p < .001$) were directly linked to the intention to use AI (*Intention*; Hypotheses 3 and 4, respectively), with the influence of *Individual* being much stronger. These findings indicate that all six AT-derived components were associated with teachers' intention to use AI, either directly or indirectly. *Individual* and *Community* emerged as significant direct predictors of teachers' intention to adopt AI tools, whereas *Objectives, Division of Labor, Government*, and *Rules/Regulations* exerted indirect effects by influencing *Individual* and *Community*.

Secondary school in-service teachers (n = 226)

Compared to the results based on the full sample, a few notable differences emerged in the results of the secondary school teachers. First, the predictive strengths of the two direct paths to the outcome variable (*Intention*) were similar for secondary school teachers: *Individual* → *Intention* ($\beta = 0.463$, $p < .001$; Hypothesis 3) and *Community* → *Intention* ($\beta = 0.451$, $p < .001$; Hypothesis 4), suggesting that both individual engagement with AI (*Individual*) and community's perceptions towards AI (*Community*) are equally important in shaping secondary teachers' intention to use AI (*Intention*). This result contrasted with the full sample results, where the role of individual was much stronger than community for *Intention* ($\beta = 0.660$ for *Individual* vs. $\beta = 0.298$ for *Community*). Second, the role of *Objectives* was minimal; neither the direct path from *Objectives* → *Individual* ($\beta = 0.252$, $p =$ ns; Hypothesis 1) nor the indirect path from *Objectives* → *Individual* → *Intention* ($\beta = 0.117$, $p =$ ns) was statistically significant. This result is also in contrast to the full sample result where the direct path of *Objectives* → *Individual* ($\beta = 0.467$, $p < .001$) were significant. Third, *Division*—the perceived efficiency or redistribution of labour through AI use—was a statistically significantly linked to individual teachers' current use of AI (*Division* → *Individual*; $\beta = 0.486$, $p < .01$; Hypothesis 2); this path was stronger in the secondary school teachers compared to the full sample. In summary, both *Individual* and *Community* factors played equally important roles in the intention to use AI (*Intention*) for secondary school teachers. *Intention* was also *indirectly* influenced by the perceived benefits by *Division* of labour ($\beta = 0.225$, $p = .001$), the need for *Rules/Regulations* ($\beta = 0.184$, $p = .005$), and *Government* involvement ($\beta = 0.375$, $p < .001$), with *Government* showing the strongest indirect effect on *Intention*.

Table 4
Structural components of structural equation modelling results across five groups.

All Participants (N = 557)			Std. Coeff.	s.e.	z-value	$p(>\|z\|)$	CFI	TLI	RMSEA	SRMR
Objectives	→	Individual (H1)	0.467***	0.096	5.78	< .001	.92	.91	.059	.051
Division	→	Individual (H2)	0.398***	0.103	5.13	< .001				
Individual	→	Intention (H3)	0.660***	0.042	11.43	< .001				
Community	→	Intention (H4)	0.298***	0.055	5.68	< .001				
Rules	→	Community (H5a)	0.460***	0.084	5.39	< .001				
Government	→	Community (H5b)	0.882***	0.161	7.46	< .001				
In-Service teachers overall (n = 439)										
Objectives	→	Individual (H1)	0.382**	0.149	3.21	0.001	.91	.90	.059	.054
Division	→	Individual (H2)	0.436***	0.158	3.99	< .001				
Individual	→	Intention (H3)	0.547***	0.046	8.18	< .001				
Community	→	Intention (H4)	0.396***	0.072	6.11	< .001				
Rules	→	Community (H5a)	0.454***	0.108	4.32	< .001				
Government	→	Community (H5b)	0.926***	0.215	5.72	< .001				
Secondary Teachers (n = 226)										
Objectives	→	Individual (H1)	0.252	0.225	1.43	0.153	.88	.86	.066	.071
Division	→	Individual (H2)	0.486**	0.244	3.27	0.001				
Individual	→	Intention (H3)	0.463***	0.056	5.66	< .001				
Community	→	Intention (H4)	0.451***	0.085	5.57	< .001				
Rules	→	Community (H5a)	0.408**	0.145	3.20	0.001				
Government	→	Community (H5b)	0.832***	0.190	4.95	< .001				
Primary Teachers (n = 126)										
Objectives	→	Individual (H1)	0.678***	0.216	3.86	< .001	.90	.88	.073	.063
Division	→	Individual (H2)	0.235		0.210	1.46	0.145			
Individual	→	Intention (H3)	0.741***	0.075	7.07	< .001				
Community	→	Intention (H4)	0.219		0.114	1.93	0.054			
Rules	→	Community (H5a)	0.800*	0.387	2.48	0.013				
Government	→	Community (H5b)	1.100*	1.085	2.08	0.037				
Pre-Service Teachers (n = 81)										
Objectives	→	Individual (H1)	0.676***	0.125	5.90	< .001	.84	.82	.097	.087
Division	→	Individual (H2)	0.326**	0.100	3.32	0.001				
Individual	→	Intention (H3)	0.918***	0.109	5.88	< .001				
Community	→	Intention (H4)	0.045		0.050	0.69	0.489			
Rules	→	Community (H5a)	0.305*	0.149	2.00	0.046				
Government	→	Community (H5b)	0.675**	0.296	2.92	0.004				

Primary school in-service teachers (n = 126)

A few aspects of the structural relationships in the SEM for primary school teachers differed notably from those observed in the secondary school teacher group. First, the model showed that only one direct pathway was statistically significant: *Individual → Intention* ($\beta = 0.741$, $p < .001$; Hypothesis 3). The other hypothesised direct path, *Community → Intention* ($\beta = 0.219$, $p = .054$; Hypothesis 4), approached but did not reach statistical significance. This suggests that primary school teachers' intention to use AI technologies (*Intention*) was primarily driven by their own engagement with AI (*Individual*), rather than by a sense of their perceptions about their community's engagement with AI (*Community*). Second, *Objectives* ($\beta = 0.678$, $p < .001$; Hypothesis 1), but not *Division* ($\beta = 0.235$, $p = .145$; Hypothesis 2), was linked to *Individual*. This pattern for primary school teachers was in contrast with the results for secondary school teachers. For primary teachers, their current engagement of AI (*Individual*) was shaped by perceived educational goals (*Objectives*) rather than perceptions of task distribution (*Division*). For secondary teachers, their perceptions of task distribution (*Division*), rather than perceived educational goals (*Objectives*) drives their current engagement of AI (*Individual*). In summary, only *Individual* had a direct path with *Intention* for primary school teachers. Among the indirect effects, only *Objectives* showed a statistically significant mediated relationship with *Intention* via *Individual* ($\beta = 0.502$, $p < .001$). The other three variables hypothesised to have indirect effects—*Division of Labor, Rules/Regulations*, and *Government*—were not statistically significant.

Pre-service teachers (n = 126)

Results obtained from pre-service teachers resembled those of primary school in-service teachers. In both groups, only *Individual* had a statistically significant direct effect on *Intention* although the effect size was greater for pre-service teachers ($\beta = 0.918$, $p < .001$; Hypothesis 3). As with the primary teacher group, the pathway from *Community* to *Intention* was not statistically significant (*Community → Intention*: $\beta = 0.045$, $p = .489$; Hypothesis 4), suggesting that community's roles in determining individuals' intention to use AI tools were not observed. On the other hand, *Objectives* played a strong role, both directly (*Objectives → Individual*: $\beta = 0.676$, $p < .001$; Hypothesis 1) and indirectly (*Objectives → Individual → Intention*: $\beta = 0.620$, $p < .001$), mirroring the pattern observed among primary school teachers.

However, unique characteristics of pre-service teachers were also noted. First, the predictive strength of *Individual* was even greater for pre-service teachers ($\beta = 0.918$, $p < .001$) compared to primary school teachers ($\beta = 0.741$, $p < .001$). Therefore, pre-service teachers' intention to use AI was primarily driven by their own current use and not influenced by their sense of community's involvement with AI. Second, pre-service teachers demonstrated statistically significant effects for *Division* in both direct (*Division → Individual*: $\beta = 0.326$, $p = .001$; Hypothesis 2) and indirect (*Division → Individual → Intention*: $\beta = 0.299$, $p = .005$) pathways to *Individual*, unlike primary teachers for whom *Division* was not statistically significant. This suggests that pre-service teachers are mindful of *Division of Labor* when they engage with AI tools. In summary, pre-service teachers placed the greatest emphasis on *Individual* among all subgroups, with no association between *Community* and *Intention* Their intention to use AI was also indirectly shaped by both *Objectives* and *Division*, mediated through their own current use of AI (*Individual*).

Discussion

Guided by Activity Theory [1,2], this study examined the mechanisms underlying teachers' intentions to use AI tools in educational settings. SEM was employed to test hypothesised relationships among Activity Theory (AT) components and their predictive roles in teachers' intentions to adopt AI. We also examined whether these relationships differed by teaching level (primary vs. secondary) and career stage or teaching experiences (pre-service vs. in-service). The overall SEM demonstrated satisfactory model fit for the full sample and across all subgroups. Although prior research has noted substantial conceptual overlap among AT components, complicating quantitative measurement [4], the present findings demonstrate that AT constructs can be reliably operationalised using quantitative methods, offering empirical support and informing future theoretical refinement.

Key findings and hypotheses

All hypothesised relationships among the AT components, *Objectives* → *Individual* (H1), *Division of Labor* → *Individual* (H2), *Individual* → *Intention* (H3), *Community* → *Intention* (H4), *Rules* → *Community* (H5a), and *Government* → *Community* (H5b), were supported in the full sample, with most also supported across subgroups.

Hypotheses 1 and 2: objectives, division of labor, and the individual

Results supported the link from *Objectives* to *Individual* (H1) and from *Division of Labor* to *Individual* (H2), highlighting the central role of individual teachers in AI adoption. These findings suggest that clearly articulated educational objectives (*Objectives*) drive teachers' interest in AI (*Individual*), while considering efficiency and task redistribution (*Division of Labor*) would further reinforce AI engagement among individual teachers. Therefore, *Division of Labor* appears to be conceptualised primarily at the individual level—between teachers and AI tools—rather than as a shared, community-based function, as originally proposed in second-generation Activity Theory [1]. This may also reflect the current policy environment, where AI-related rules and regulations are often unclear or absent [21,45,46], resulting in AI-supported task redistribution being considered and carried out, mostly through individual teachers. As [46] noted, community-level practices and formal policy frameworks often remain limited while individual teachers are increasingly using AI to optimise tasks such as administrative work, lesson differentiation, and assessment design. Studies continue to suggest that teachers' beliefs about whether technology will help them perform better in their work are among the most important predictors of their intention to use AI technologies in the future (e.g., [47]). However, caution is warranted: reliance on AI tools may increase when AI-supported task completion occurs largely in isolation and when teachers are not equipped with sufficient AI literacy [27,48]. Therefore, collaborative discussions and shared practices within professional communities regarding how AI can support teachers' work may be necessary to support educators with varying levels of AI literacy and to mitigate potential dependency on AI.

Hypotheses 3 and 4: individuals versus community

Hypotheses 3 and 4 examined the relative roles of *Individuals* (H3) and *Community* (H4) in predicting AI adoption intentions. The results showed a much stronger effect for *Individual* ($\beta = 0.66$) than for *Community* ($\beta = 0.30$), indicating that intentions to adopt AI reside primarily at the individual level. This aligns with earlier findings highlighting individual teachers' agency in interpreting objectives and enacting AI-supported division of labor.

While previous studies emphasise the importance of both individual and community influences on AI adoption [17,18,15], community-level endorsement may not yet have reached sufficient critical mass. Ongoing concerns about ethical risks and distrust toward technology providers may inhibit collective uptake [45]. As AI adoption remains primarily individual-led, an imbalance has emerged between educators' interest in AI and the limited availability of institutionally supported professional development [46]. Schools seeking to promote AI adoption should therefore emphasise individual benefits while simultaneously strengthening community understanding through clearer rules and guidance [13,28]. Educators' community-based activities (cf, [49]) may include proactive teacher consultations, structured reflection, scenario-based activities, and peer exchange.

Hypotheses 5a and 5b: rules and government

Hypotheses 5a and 5b addressed the influence of *Rules* (H5a) and *Government* (H5b) on Community. Both pathways were statistically significant, with *Government* → *Community* emerging as the strongest relationship among all structural relationships tested in SEM. This suggests a strong expectation among educators for government involvement in safeguarding human-centred education and regulating AI use. Educators' concerns about data privacy, misinformation, and ethical risks appear to heighten demand for trusted authorities to provide oversight [7,28].

These findings also point to a potential extension of Activity Theory to include Government or Authority as a distinct component in AI-related activity systems. Government regulation does more than enforce compliance; it signals institutional legitimacy, shapes perceptions of acceptable use, and supports the dissemination and effective implementation of AI technologies. International organisations such as OECD and UNESCO consistently emphasise the role of governance frameworks in enabling safe and ethical AI adoption in schools [21,46,50]. Well-communicated rules that clarify age-appropriate uses and pedagogical purposes can increase educator confidence and support sustained integration [4,51].

Hypothesis 6: subgroup differences

Finally, Hypothesis 6 examined whether the relationships among AT components differed by teaching level and career stage (or teaching experience). The following section discusses notable subgroup variations observed across Hypotheses 1–5. Overall, there were some noteworthy subgroup differences, suggesting the importance of considering teaching context and career stage in implementation strategies for AI adoption. Firstly, the most salient differences were found in the relative role of *Individual* (H3) versus *Community* (H4). For secondary school teachers, both *Individual* and *Community* were significantly linked to their AI adoption intentions, with nearly equal strength of the path coefficients ($\beta = 0.46$, $p < .001$; $\beta = 0.45$, $p < .001$, respectively). In contrast, *Community* played a much smaller role among primary school teachers ($\beta = 0.22$, $p =$ *n*.s.) and its role was virtually nonexistent for pre-service teachers ($\beta = 0.05$, $p =$ *n*.s.). For pre-service teachers, intention to adopt AI tools was driven almost entirely by *Individual* ($\beta = 0.92$, $p < .001$), with no significant role played by community perceptions. It appears that a sense of professional community for AI use may be more strongly established among secondary school teachers, somewhat weaker among primary school teachers, and relatively scarce among pre-service teachers who have yet to enter the professional teaching environment. Secondly, subgroup differences also emerged in the influence of *Division of Labor* on current AI tool usage (H2). This factor played a stronger role for secondary school teachers ($\beta = 0.49$), compared to primary ($\beta = 0.24$) and pre-service teachers ($\beta = 0.33$). For primary and pre-service teachers, current AI use appeared to be more aligned with broader educational goals (H1) rather than specific task delegation (H2).

These results—showing stronger effects of *Community* and *Division of Labor* for secondary school teachers—may reflect differences in school structures and staff dynamics. Secondary teachers often work within subject-based teams, increasing their exposure to peer influence, professional discourse, and opportunities to develop subject-specific strategies for incorporating technology. Their engagement with technology can be effectively supported by subject-specialist communities within the school [26,29]. In contrast, primary school teachers typically manage a single class for the entire school year, which may limit collaborative opportunities for AI exploration. Primary teachers often recognize the potential of professional learning communities and express a strong need for structured opportunities focused on technology development [24,25]. Technology education in teacher training is generally given less emphasis than Science or Mathematics within STEM subjects, leaving many primary teachers with limited confidence in teaching or applying technology effectively [52]. Consequently, initiatives to enhance confidence, competence, and collaborative opportunities in AI use may be particularly critical for primary school teachers.

Limitations of the study & future study directions

Several limitations should be acknowledged to ensure a more accurate interpretation of the findings. First, the sample was drawn from Australian teachers, which limits the generalizability of the results to educators in other countries or broader international contexts. Future research may include teachers from multiple countries—particularly those with differing policies and cultural perspectives on AI tool adoption—to enhance the external validity of the findings. Second, a probability-based sampling method (e.g., stratified sampling) was not implemented. Although participants were recruited from diverse sources, future studies may benefit from more systematic recruitment strategies to ensure more representative demographic and professional diversity (e.g., teaching areas) among educators. Third, the overall SEM model was not modified to optimize model fit for each subgroup. While it was possible to improve the goodness-of-fit for each group, priority was given to maintaining the consistent model structure to allow the comparisons of the path strengths across subgroups. Future studies, with a greater number of subgroup samples, may pursue more tailored SEM models for each group. Fourth, educators' attitudes toward AI are influenced by external factors such as media coverage and government priorities, both of which can fluctuate over time. As such, the timing of data collection may reflect a particular climate around AI in education. Recognizing this temporal and contextual variability is essential for interpreting educators' current and future intentions for AI adoption. Finally, reciprocal relationships exist among AT components; for example, rules may shape community acceptance (*Rules → Community*), while community demand and feedback can, in turn, contribute to the establishment of rules (*Community → Rules*). Future longitudinal studies may explore these potential bidirectional associations.

Conclusion & practical implications

The present study demonstrated that *individual teachers*' understanding, valuation, and application of AI—particularly for enhancing teaching and learning and reducing workload—are the primary drivers of adoption. These findings highlight the value of targeted professional development to improve AI literacy at the individual level, addressing educators' confidence gaps [15]. Variations in AI use across teaching levels and career stages suggest that community-focused strategies may be more effective in secondary school settings. Across all groups, however, there is a clear demand for government guidance to shape broader community attitudes and support the use of AI tools, highlighting the importance of establishing clear boundaries for AI use at both school and governmental levels. In the absence of national policies, schools may need to develop internal guidelines to support educators in integrating AI tools effectively into their professional practice.

CRediT authorship contribution statement

Jihyun Lee: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Helena Granziera:** Writing – review & editing, Writing – original draft.

Declaration of competing interest

I have nothing to declare. There is no conflict of interest with respect to this article. There is no financial or personal relationship with a third party whose interests could be positively or negatively influenced by the article's content.

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Appendix. Results of exploratory factor analysis (EFA) on the entire set of the items on the six components of activity theory and the behavioral intention variable

Initial Constructs	Items	Pattern Factor Matrix						
		1	2	3	4	5	6	7
Individuals	I feel confident using AI to complete a task.	0.06	0.76	0.08	0.02	−0.07	0.00	0.08
Individuals	**Using AI tools is part of my regular practice.**	−0.14	0.87	−0.02	0.04	0.11	0.01	0.01
Individuals	I use AI more frequently than my peers.	−0.07	0.84	0.05	0.15	0.12	−0.22	0.03
Individuals	**I work more effectively with the help of AI.**	0.04	0.80	−0.05	−0.10	−0.05	0.08	0.16
Individuals	I feel motivated when AI tools support my learning.	0.05	0.80	0.00	−0.05	−0.07	0.05	0.14
Individuals	**I become a more active learner with AI assistance.**	0.18	0.79	0.00	0.00	−0.11	0.00	−0.14
Individuals	**My interest in learning increases, thanks to AI.**	0.17	0.76	0.05	−0.01	−0.07	0.01	−0.14
Individuals	**I enjoy working with AI tools.**	0.17	0.72	0.03	−0.08	−0.03	0.01	0.07
Individuals	I stay updated on new AI tools.	−0.17	0.62	0.02	−0.02	0.43	0.02	−0.11
Objectives	**AI enhances efficiency in learning and work.**	0.81	0.07	−0.03	−0.06	−0.09	−0.07	0.11
Objectives	**Learning becomes more enjoyable when guided by AI.**	0.79	0.07	−0.01	−0.05	0.00	−0.01	−0.21
Objectives	Challenging tasks once thought unachievable are now doable with the help of AI.	0.74	−0.05	0.10	0.07	−0.06	−0.01	0.04
Objectives	**Learning outcomes improve with AI support.**	0.72	0.05	−0.03	−0.13	0.19	−0.04	−0.16
Objectives	Using AI in education is beneficial.	0.71	0.06	0.00	0.05	0.06	−0.13	0.13
Division of labor	AI allows for effective division of labor between humans and machines.	0.46	0.07	0.00	0.27	0.14	−0.08	0.07
Division of labor	Using AI reduces the time and effort needed to complete a task.	0.66	0.04	0.01	0.02	−0.11	0.03	0.30
Division of labor	**People should assign some routine tasks to AI.**	0.52	−0.08	−0.07	0.11	0.20	0.05	0.27
Division of labor	**I would like AI to take on some of my workload.**	0.50	0.01	−0.14	0.16	0.01	0.02	0.35
Division of labor	**AI can handle some of my work efficiently.**	0.49	0.12	0.00	0.11	−0.01	0.10	0.22
Division of labor	I consider which of my tasks to allocate to AI.	0.31	0.22	−0.01	0.03	0.02	0.13	0.32
Rules	**Guidelines should specify who is allowed to use AI tools.**	0.04	0.04	0.71	−0.03	0.06	−0.03	−0.21
Rules	**Guidelines should help parents manage and support their children's AI use.**	0.04	−0.04	0.68	−0.01	−0.04	0.10	0.17

(*continued on next page*)

(*continued*)

Initial Constructs	Items	Pattern Factor Matrix						
		1	2	3	4	5	6	7
Rules	**It is necessary to define which AI tools are appropriate for which purposes.**	0.09	−0.08	0.67	−0.11	0.03	0.09	0.05
Rules	**It is not feasible to develop effective government regulations for AI.**	0.10	0.09	−0.10	0.46	−0.15	0.17	−0.09
Rules	**Government rules will not keep up with the speed of AI development.**	0.00	−0.11	0.04	0.43	−0.04	0.19	0.15
Rules	**There is an urgent need for government regulations on AI tool use.**	−0.06	0.02	0.78	0.14	0.01	−0.09	−0.10
Rules	**AI guidelines should specify how young children use AI at home.**	0.02	0.08	0.71	−0.11	−0.06	0.05	0.02
Rules	Setting rules is the most important aspect of managing AI use.	−0.06	0.07	0.59	0.01	0.06	0.08	−0.30
Rules	**People should be free to use AI without government-imposed restrictions.**	0.04	0.20	−0.21	0.39	−0.08	0.24	−0.07
Community	AI makes learning communities more active.	0.50	0.22	0.00	−0.06	0.01	0.14	−0.15
Community	**My peers encourage me to use AI tools.**	0.01	0.14	0.05	0.28	0.04	0.59	−0.04
Community	AI enhances communication among learning communities.	0.46	0.21	−0.02	−0.03	0.05	0.15	−0.12
Community	Learning communities benefit from AI.	0.42	0.17	0.11	0.22	0.08	0.00	0.08
Community	**AI use is common among my peers.**	−0.06	0.06	0.05	0.22	0.10	0.59	0.08
Community	**People that I know show interest in AI.**	0.24	−0.10	0.07	0.13	0.09	0.53	0.12
Tools	**AI makes teaching and learning more engaging.**	0.89	−0.04	0.01	−0.02	−0.04	−0.01	−0.14
Tools	**AI motivates students to stay involved in their learning.**	0.83	−0.02	−0.02	0.03	−0.02	−0.04	−0.23
Tools	AI enhances digital skills, preparing learners for technology-driven environments.	0.81	−0.16	0.01	−0.05	−0.01	0.00	0.04
Tools	AI boosts people’s confidence in exploring new topics.	0.75	−0.02	0.05	−0.04	−0.07	0.02	0.06
Tools	AI supports independent learning.	0.73	0.05	0.00	−0.01	−0.07	−0.01	0.05
Tools	AI is helpful for brainstorming ideas with peers.	0.68	0.05	0.06	0.10	−0.12	−0.02	0.16
Tools	AI improves access to learning materials, making resources more available.	0.67	0.09	0.02	0.07	0.09	−0.14	0.08
Tools	The novelty of AI tools keeps learning engaging.	0.66	−0.15	−0.01	−0.02	0.24	0.10	−0.03
Behavioral intention	**I plan to use AI to help me learn and work now and in the future.**	0.40	0.27	−0.05	−0.13	0.16	0.03	0.29
Behavioral intention	**I will continue to apply AI technology to solve problems I encounter in my life.**	0.45	0.30	−0.09	−0.20	0.15	0.01	0.22
Behavioral intention	**I will regularly update the latest AI-related applications.**	0.12	0.14	−0.07	−0.17	0.71	0.14	−0.01
Behavioral intention	I will continue to keep an eye on the progress of AI-related technologies.	0.21	−0.08	0.14	−0.02	0.49	0.06	0.09
Eigenvalue		**19.42**	**3.50**	**2.12**	**1.52**	**1.44**	**1.14**	**1.06**

Notes. The items retained in the final set are in bold for emphasis. EFA was conducted with promax rotation and maximum likelihood estimation. Harman’s test result showed that common method bias (CMB) is not a concern because a single factor did not account for the majority of the variance (it was only at 19%).

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