Journal of Inclusive Methodology and Technology in Learning and Teaching
ISSN 2785-5104
Anno 6 n. 3 (2026)

EDIZIONI UNIVERSITARIE ROMANE
editoria scientifica dal 1952

From Acceptance to Co-Creation: Generative Artificial Intelligence as Reflective Mediation for the Development of Evaluative Competencies in Initial Teacher Education

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Abstract: The integration of generative artificial intelligence into teacher education raises questions about how technology acceptance, human–AI interaction and professional learning are related. This exploratory study investigates the factors associated with pre-service teachers' intention to use generative AI, how they work with its outputs and the perceived development of their evaluative competencies. An anonymous questionnaire was completed by 113 trainees in university teacher qualification pathways who had built assessment rubrics with AI assistants; 100 valid responses were analysed in jamovi using descriptive statistics, reliability indices, Spearman correlations and multiple regressions. Trust and performance expectancy are most strongly associated with behavioural intention, including when the other factors are considered jointly, whereas AI Literacy is associated with active co-construction and trust with passive acceptance of outputs. Active co-construction shows the strongest association with Evaluative Competency Development (β = .520), followed by AI Literacy (β = .238). Unexpectedly, passive acceptance is also positively associated with perceived learning, and the link between active co-construction and perceived competencies is stronger among trainees with lower AI Literacy. The findings suggest fostering critical interaction, professional judgement and reflective reworking of AI outputs in initial teacher education. The cross-sectional, self-report design does not allow causal interpretations.

Keywords: generative artificial intelligence; UTAUT; AI Literacy; human–AI co-creation; initial teacher education

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1. Introduction

The spread of generative artificial intelligence is changing the way in which pre-service teachers build assessment tools. Building an assessment rubric requires two decisions that embody a specific pedagogical vision: choosing *what* to assess, that is, the dimensions, and describing the *observable evidence* that makes it possible to recognise the different levels of mastery. Within seconds, an AI assistant proposes neatly structured dimensions, levels and descriptors, which the pre-service teacher may accept as they stand or question and adapt to their own class. If the teacher accepts the proposal without intervening, the assistant takes over part of the

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evaluative reasoning that questioning and adapting the proposal would otherwise exercise.

Research on AI in education has focused mainly on acceptance. A systematic review of 60 studies conducted in different sectors finds that performance expectancy, attitudes, trust and effort expectancy are positively associated with the intention to use AI and with its use (Kelly et al., 2023). Studies involving university students, university educators and pre-service teachers generally stop at behavioural intention or frequency of use (Adigun et al., 2025; Strzelecki, 2024; Xu et al., 2024). What happens after adoption remains under-investigated: how people work with the assistant and what they believe they have learned.

The present study addresses this gap, focusing on trainees enrolled in the 60-, 30- and 36-credit (CFU) university teacher qualification pathways who, during their training, built assessment rubrics with the help of AI assistants suitably designed by their practicum tutors. It is guided by three research questions:

- which factors are associated with the intention to continue using the assistant in assessment design;
- which factors are associated with active work on AI outputs and which with their passive acceptance;
- how these two ways of working and AI Literacy are associated with the perceived development of evaluative competencies.

The theoretical framework is the UTAUT model (Unified Theory of Acceptance and Use of Technology), which brings together eight earlier models of technology acceptance and identifies four factors (Venkatesh et al., 2003). Three of them shape the intention to use a technology: performance expectancy, effort expectancy and social influence. The fourth, facilitating conditions, shapes use behaviour together with intention. The UTAUT2 extension adds, among others, hedonic motivation, that is, the gratification that use provides (van der Heijden, 2004; Venkatesh et al., 2012). A review of studies applying UTAUT2 to AI in higher education identifies performance expectancy and hedonic motivation as the factors associated with intention and use, and distrust and limited knowledge of AI as persisting barriers (Acosta-Enriquez et al., 2024).

Two extensions of the model are relevant to this study: trust and AI Literacy. Trust is understood as the belief in the "competence, benevolence, and integrity" of the other party and as the willingness to rely on it, following a typology developed for e-commerce (McKnight et al., 2002, p. 352); in studies of digital services, trust has been added to UTAUT2 (Alalwan et al., 2017). In the case of AI, trust that exceeds the actual capabilities of the system can translate into overreliance (Glikson & Woolley, 2020). A study close to ours in scope, conducted with university students who use ChatGPT to support their own assessment tasks, identifies trust and performance expectancy as the strongest predictors of behavioural intention (Lai et al., 2024). AI Literacy is the set of competencies that enables people to understand AI, use it, evaluate it critically and consider its ethical implications (Long & Magerko, 2020; Ng et al., 2021). Among university students, it is associated with a greater intention to adopt AI (Ke et al., 2025). This study also explores its link with the quality of the interaction with the assistant; to describe this interaction, it proposes the construct of Human–AI Co-Creation (HAICC), which draws on studies of creative collaboration between people and computer systems (Lubart,

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2005; Rezwana & Maher, 2025). The construct distinguishes two ways of working with the assistant. Active co-construction comprises three components: critical review of the outputs, iterative interaction with the assistant through successive prompts, and the integration of one's own professional knowledge into the generated content. Passive acceptance, by contrast, consists in accepting the assistant's proposals with minimal or no reworking.

The outcome considered is the development of evaluative competencies, framed within the literature on teachers' assessment literacy (DeLuca et al., 2016; Popham, 2009) and measured as development perceived by the trainees (Evaluative Competency Development, ECD; hereafter, perceived competencies). The underlying idea is that this development depends more on the quality of the mediation between teacher and assistant than on use as such. Fifteen hypotheses had been formulated before data collection; they are treated here as exploratory expectations. In summary, performance expectancy, effort expectancy, social influence, hedonic motivation and trust were expected to be associated with behavioural intention; use behaviour and trust with co-creation; and co-creation with perceived competencies, more strongly for those with higher AI Literacy.

2. Materials and Methods

The study was correlational and based on a single data collection at the end of the training experience, with no baseline measure and no comparison group. Participants were 113 trainees enrolled in the university teacher qualification pathways (*Percorsi Universitari Abilitanti*) of the Università Europea di Roma, who completed an anonymous and voluntary online questionnaire between 19 June and 24 July 2026 (210 trainees invited; response rate 53.8%). The analyses concern the 100 trainees retained after the quality check: 61 women, 37 men and 2 people who did not report their gender; 70 from the 60-credit pathway, 28 from the 30-credit pathway and 2 from the 36-credit pathway. Of these, 53% had less than two years of teaching experience and 69% had never, or only rarely, built an assessment rubric.

During the pathway, the trainees built assessment rubrics with AI assistants set up by the practicum tutors on ChatGPT (custom GPTs) and on Gemini (Gems). Each assistant operated on the basis of a prompt written in advance by the tutors and grounded in three references: theoretical constructs on assessment; the guidance offered by the literature on how to identify the dimensions of a rubric and describe its levels of mastery, set at four (Castoldi, 2016; De Mutiis & Rosa, 2024; Pilotti, 2021; Trinchero, 2017); and the national competency certification templates adopted by Ministerial Decree No. 14/2024 (Ministero dell'istruzione e del merito, 2024), together with the Council Recommendation on key competences for lifelong learning (Council of the European Union, 2018). The activities took place during the module on the design of the simulated lesson, in its assessment phase (8 hours, in person). Trainees created the rubric using the AI assistants (GPTs and Gems) and were asked to produce a critical analysis of the rubric obtained and to adapt it to their own subject. The questionnaire comprised 77 questions (60 items rated on a 7-point Likert scale; 2 items on use behaviour with five ordered response categories; 7 background questions; 3 on previous experience with AI; 3 on how the assistant was used; 2 open-ended questions) and brought together three types of constructs with differing levels of prior empirical support. The scales of the acceptance model and of trust were adapted from validated scales, for which, however, no validated Italian

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version exists. The AI Literacy scale was developed from conceptual frameworks found in the literature (Long & Magerko, 2020; Ng et al., 2021), whereas Human–AI Co-Creation and perceived competencies are original constructs, which draw on studies of co-creativity (Lubart, 2005; Rezwana & Maher, 2025) and of assessment literacy (DeLuca et al., 2016; Popham, 2009). The results for the adapted constructs therefore rest on scales already used in other studies, whereas those for the original constructs rest on scales applied here for the first time (Table 1).[1]

Table 1. Origin of the questionnaire constructs (the count includes the two use behaviour indicators and the two items excluded from the scores after the reliability analysis).

Origin	Constructs	References	Items
Drawn from the literature and adapted	Performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, behavioural intention, use behaviour; trust in AI	Venkatesh et al. (2003, 2012); van der Heijden (2004); McKnight et al. (2002); Martins et al. (2014); Slade et al. (2015); Lai et al. (2024)	30 (of which 4 translated almost literally, 20 adapted and 6 newly developed)
Developed from the literature	AI Literacy	Ng et al. (2021); Long and Magerko (2020)	6 (all newly developed)
Original	Human–AI Co-Creation: active co-construction and passive acceptance; Evaluative Competency Development	Conceptual background: studies on co-creativity (Lubart, 2005; Rezwana & Maher, 2025) and on assessment literacy (DeLuca et al., 2016; Popham, 2009)	11 and 15 (all newly developed)

Items were rated from 1 (Strongly disagree) to 7 (Strongly agree); use behaviour was derived from the self-reported frequency of use and number of sessions, on a scale from 1 to 5. Before the analyses, the 113 questionnaires were screened for response quality (Meade & Craig, 2012). Twelve respondents gave the same response to all 60 items rated from 1 to 7, including the reverse-worded ones, and thus stated at the same time, for example, that they had accepted the rubric without changes and that they had critically reviewed it. One further trainee reported never having used the assistant. These 13 cases were excluded; all analyses were also repeated on the full set of 113 questionnaires. Scale scores were computed as the mean of their items. Co-creation was described by two scores, active co-construction (8 items) and passive acceptance (3 items), which were not correlated in the data ($\varrho = -.120$). Two reverse-worded items, one on effort expectancy and one on trust, were excluded because of their poor consistency with the other items of their scale (Table 2).

[1] The questionnaire is available at https://forms.cloud.microsoft/e/DWkSRxhGKy

Table 2. Constructs of the questionnaire.

Construct	Description	No. of items
AI Literacy (AI_LIT)	Self-reported knowledge and skills relating to AI.	6 items
Performance expectancy (PE)	Perceived usefulness of the assistant for improving the quality and efficiency of assessment design.	5 items
Effort expectancy (EE)	Perceived ease of learning and using the assistant and of writing prompts.	3 items (+1 excluded)
Social influence (SI)	Perceived support for using the assistant from teachers, tutors, colleagues and key figures at school.	4 items
Facilitating conditions (FC)	Availability of tools, instructions and support for using the assistant.	4 items
Hedonic motivation (HM)	Enjoyment, engagement and intellectual stimulation during the interaction with the assistant.	3 items
Trust in AI (TRUST)	Trust in the quality, reliability and relevance of the assistant's proposals.	4 items (+1 excluded)
Behavioural intention (BI)	Intention to continue using the assistant in future professional practice.	3 items
Use behaviour (UB)	Self-reported use of the assistant during the pathway, measured through frequency of use and number of sessions.	2 indicators (1–5 scale)
Active co-construction (ATT)	Critical and progressive reworking of AI outputs, integrated with one's own professional competencies.	8 items
Passive acceptance (PA)	Acceptance of AI outputs without substantial reworking.	3 items
Evaluative Competency Development (ECD)	Perception of having developed or consolidated one's own competencies in assessing learning.	15 items

The analyses, carried out with jamovi and its Rj module, which runs R code (The jamovi project, 2026), included descriptive statistics, scale reliability (Cronbach's α), Spearman correlations (ϱ) and five multiple regressions, which estimate the association of each factor with the outcome while holding the others constant. In the regressions, the direction and size of each association were expressed by the standardised coefficient β; *p* values were computed using HC3 robust standard errors. A regression with an interaction term tested whether the association between active co-construction and perceived competencies varied with the level of AI Literacy. Indirect effects were estimated in single-mediator models without covariates, with 95% percentile bootstrap confidence intervals (CIs) based on 5,000 resamples and with the standardised coefficients recomputed in each resample (Hayes, 2022); group comparisons used the Mann–Whitney test. Given the exploratory nature of the study, no correction for multiple comparisons was applied. Testing the factor structure of the new scales is deferred to a larger, independent sample. With 100 cases, the stability of a factor solution is not guaranteed; moreover, defining the structure of the scales and estimating their associations on the same sample would require a subsequent independent validation.

3. Results

Means were high: for almost all scales they lay between 5 and 5.6 out of 7, with negative skewness (Table 3); correlations were therefore computed with Spearman's ϱ, which does not assume a normal distribution. The exception was passive acceptance, whose mean lay below the scale midpoint (3.55) and whose variability was the widest. Reliability was adequate for all scales, ranging from α = .731 for AI Literacy to α = .965 for perceived competencies.

Table 3. Reliability and descriptive statistics of the scales (N = 100).

Scale	Items	α	M	SD	Skew.	Kurt.
AI Literacy	6	.731	5.44	0.80	−0.74	0.32
Performance expectancy	5	.943	5.33	1.21	−0.95	0.39
Effort expectancy	3	.837	5.52	1.07	−0.89	0.58
Social influence	4	.806	5.35	0.90	−0.93	1.17
Facilitating conditions	4	.865	5.49	1.05	−0.95	1.07
Hedonic motivation	3	.893	5.32	1.11	−0.85	0.78
Trust in AI	4	.930	5.04	1.11	−0.63	0.11
Behavioural intention	3	.932	5.33	1.06	−0.82	0.65
Use behaviour (1–5)	2	—	3.04	0.75	0.10	−0.76
Active co-construction	8	.871	5.33	0.93	−0.75	0.88
Passive acceptance	3	.921	3.55	1.52	0.40	−0.71
Evaluative Competency Development	15	.965	5.58	0.80	−0.93	0.65

Note. Scales range from 1 to 7, except use behaviour (1 to 5). Skew. = skewness; Kurt. = kurtosis. The Shapiro–Wilk test rejects normality for all scores ($p \leq .002$). Passive acceptance: higher values indicate greater acceptance of the outputs without reworking.

For behavioural intention, the five factors considered were all highly correlated with it (ϱs = .557–.711; Figure 1). When they were considered jointly, only two remained associated with intention: trust (β = .325) and performance expectancy (β = .301). Effort expectancy, social influence and hedonic motivation made little unique contribution, because their association with intention was largely shared with the other factors. The model explained 62% of the variance (Figure 2). Intention was in turn associated with use behaviour (β = .427), whereas facilitating conditions made little unique contribution once intention was taken into account. The data are consistent with part of the association between social influence and intention running through trust (standardised indirect effect = .231, 95% CI [.119, .370]).

Figure 1. Spearman correlations (ϱ) among the constructs (N = 100; estimates computed in jamovi).

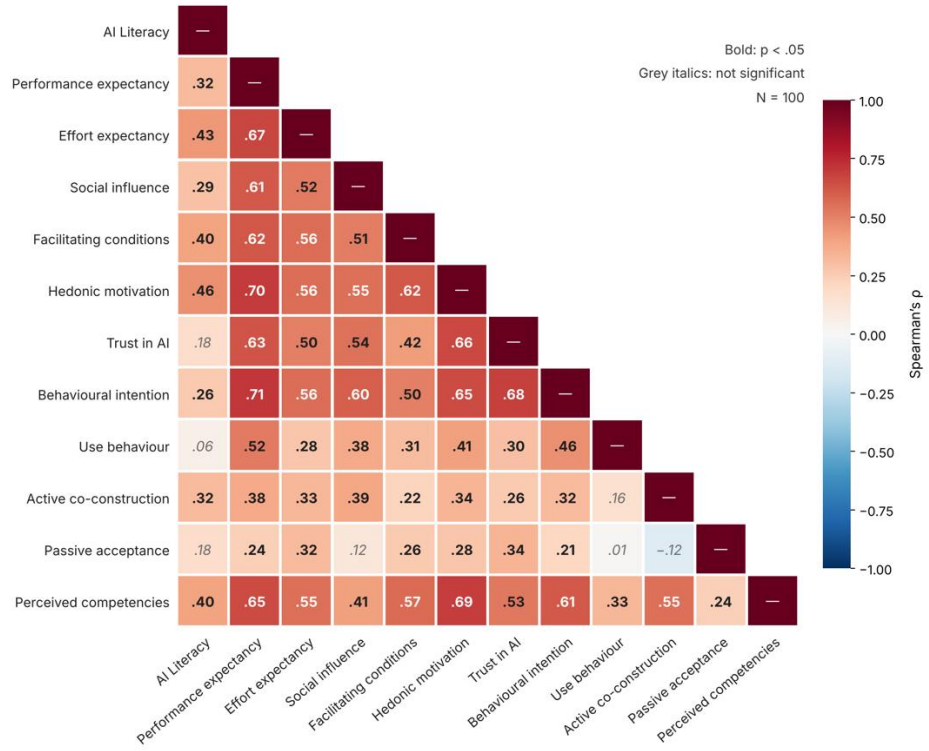
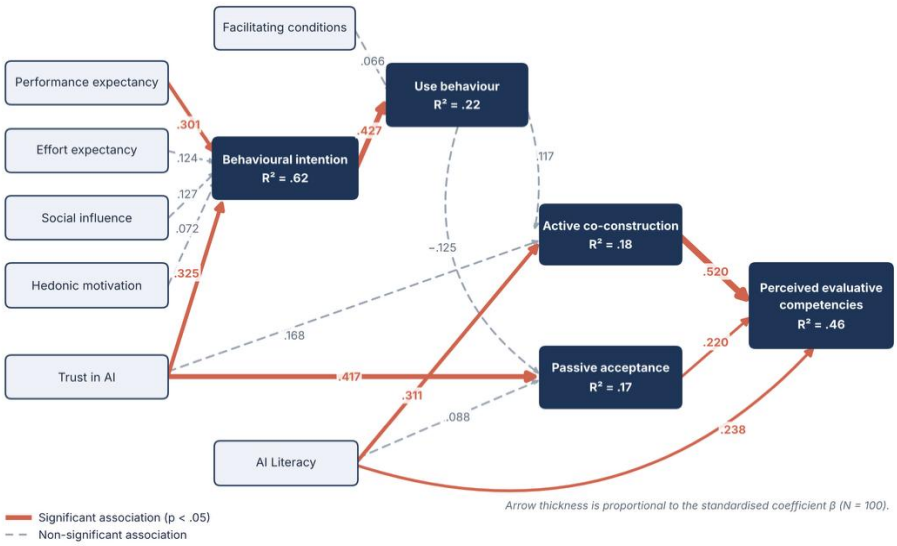


Figure 2. Standardised β coefficients of the five regression models (N = 100; estimates computed in jamovi).



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The two ways of working with the assistant were associated with different factors. Active co-construction was associated only with AI Literacy (β = .311); once AI Literacy was controlled for, trust and use behaviour were not significantly associated with it. Passive acceptance was associated only with trust (β = .417), with a positive sign, whereas a negative one had been expected: those who trusted the assistant more were also more willing to accept its proposals without reworking them. Among the components of active co-construction, trust was associated with the integration of professional knowledge (ϱ = .292) and not with critical review (ϱ = .124). Both models explained about 17% of the variance.

For perceived competencies, active co-construction was the most strongly associated variable (β = .520), followed by AI Literacy (β = .238); the model explained 46% of the variance. Among the components of active co-construction, the most strongly associated was the integration of professional knowledge (ϱ = .551), followed by iterative interaction (ϱ = .494) and critical review (ϱ = .338). Two results ran contrary to expectations. Passive acceptance was also positively associated with perceived competencies (β = .220): with active co-construction and AI Literacy held constant, those who reworked the outputs less reported having learned more. Furthermore, the association between active co-construction and perceived competencies weakened as AI Literacy increased, while remaining positive (interaction β = −.169, p = .018). The simple slope of active co-construction was .697 at low AI Literacy (−1 SD), .528 at the mean and .359 at high AI Literacy (+1 SD). The data are consistent with an indirect effect of AI Literacy on perceived competencies via active co-construction (standardised indirect effect = .170, 95% CI [.051, .300]); for use behaviour, the 95% CI of the indirect effect included zero.

In group comparisons, contrary to the expectation of higher values in the 60-credit pathway, trainees in the two pathways reported similar levels of active co-construction, passive acceptance and perceived competencies. Women reported higher scores than men on almost all scales and lower passive acceptance, with small to medium differences; trust did not differ. In the sensitivity analyses, the conclusions did not change when the two excluded items were reinstated or when the analyses were repeated on the 113 questionnaires. In the latter case, the associations were generally stronger, in line with the hypothesis that uniform responses inflate them, and the link between trust and active co-construction and the indirect effect of use behaviour also became significant.

4. Discussion

The results distinguish two aspects of the relationship between pre-service teachers and AI assistants: the willingness to use the tool and the way it is used. Willingness, the focus of the first research question, is associated with trust and performance expectancy, as in the study by Lai et al. (2024) and in the review by Kelly et al. (2023). Contrary to the review of AI in higher education (Acosta-Enriquez et al., 2024), hedonic motivation makes little unique contribution once the other factors are held constant. It is plausible that, in a professional task such as building a rubric, judgements about the assistant depend more on how useful and reliable it is than on the pleasure of using it.

The way the assistant is used, the focus of the second research question, shows a different pattern. Trust is associated with passive acceptance of the outputs and not with their critical review, whereas active work on the outputs is associated with

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AI Literacy. This pattern is consistent with the risk of overreliance pointed out by Glikson and Woolley (2020) and with the concern, voiced in a qualitative study of pre-service teachers' use of generative AI in instructional design (Wu et al., 2025), that overreliance may weaken design skills. For teacher education, the results suggest examining whether activities that strengthen the ability to understand and critically evaluate AI foster the quality of the work more than activities aimed at increasing familiarity with the tool or trust in it.

Regarding the third research question, active co-construction is the aspect most strongly associated with perceived competencies. Among its components, the most strongly associated is the integration of professional knowledge, through which trainees adapt the generated content to their own subject and class; critical review, which was expected to be among the most strongly associated, is instead the least associated. It is possible that, for trainees with little assessment experience, adapting a proposal to their own context is more accessible than questioning its overall design, and that critical review requires evaluative criteria that are still being developed. If so, teacher education should support critical review explicitly, for example by asking trainees to justify in writing the changes they make to the rubric. Moreover, the association between active co-construction and perceived competencies is stronger for those with lower AI Literacy. One possible interpretation is compensatory: for those who know less about AI, reworking the assistant's proposals would be the main opportunity to reason about criteria and levels.

The most unexpected result concerns passive acceptance, which is also associated with higher perceived competencies. The questionnaire measures what trainees believe they have learned: those who delegate more to the assistant still obtain a complete rubric and may credit themselves with progress that their own work has not necessarily produced. This result would be consistent with poor *metacognitive calibration*, that is, with a gap between the competence one attributes to oneself and one's actual competence. In two studies on logical reasoning problems, participants working with the help of AI obtained higher scores but overestimated their scores by about 4 answers out of 20; overestimation also occurred among those working without AI (Fernandes et al., 2026). Another explanation concerns the instrument: the passive acceptance items are the only reverse-worded items left in the questionnaire, and responses may be affected by this wording. Distinguishing between the two explanations requires an external evaluation of the rubrics and the analysis, already planned, of the open-ended responses.

This study has several limitations. The cross-sectional design does not allow causal inferences. Moreover, use behaviour refers to the period of the pathway and intention to the following period, whereas the UTAUT model assumes the reverse order. All data come from the same self-administered questionnaire, a condition that tends to inflate the associations between scales. The sample is a small convenience sample, unbalanced across pathways; the authors taught in the pathways, and some socially desirable responding is possible despite anonymity. The new scales still await a test of their structure. Finally, the exclusion of questionnaires and items was decided after examining the data. The next phase will involve an independent sample of at least 200 participants, in which the structure of the new scales will be tested.

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5. Conclusions

The central finding of the study concerns the way people work with AI. Trust and performance expectancy are associated with the intention to continue using the assistant. Active co-construction, by contrast, is associated with AI Literacy, and not with use behaviour, and is the aspect most strongly associated with perceived competencies. For initial teacher education, this suggests fostering, alongside access to the tools, the ability to question and rework what AI produces. This implication should be interpreted with caution, because the competencies measured are perceived ones and those who accept the outputs more also report having learned more. The next phase of the research, on a new sample, will therefore compare the trainees' perceptions with the actual quality of their rubrics.

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