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# Do Teachers Trust AI Detection Tools? Development of a Teacher AI Detection Perception Scale (TADPS) and Its Implications for Workforce Development

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## CITATION

Layco EP, Rivera JG, Parreño EB, Jimenez RS, Payumo AS, Balahadia FF, Casco JAD, Miranda JPP. (2026). Do Teachers Trust AI Detection Tools? Development of a Teacher AI Detection Perception Scale (TADPS) and Its Implications for Workforce Development. *Human Resources Management and Services*. 8(3): 6004. <https://doi.org/10.18282/hrms6004>

## ARTICLE INFO

Received: 8 June 2026

Accepted: 23 June 2026

Available online: 10 July 2026

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**Abstract:** The growing adoption of automated tools for detecting AI-generated academic submissions has raised questions about how educators engage with such technologies in practice. Despite their increasing institutional use, little empirical work has examined whether teachers genuinely endorse, trust, or feel socially supported in using them. This study addressed that gap by constructing and validating a 13-item instrument across three subscales: General AI Endorsement (GAE), Trust and Confidence in AI Tools (TCA), and Social and Normative Influence (SNI). Data were collected from 173 public school and university educators in the Philippines. Exploratory factor analysis confirmed the three-factor structure, and all subscales met accepted thresholds for reliability and convergent validity. GAE was a strong predictor of TCA ( $B = 0.810$ ,  $p < .001$ ,  $R^2 = 0.595$ ), and nomological validity was supported, as SNI lost its direct effect on TCA once GAE entered the model. The scale proved reliable and structurally sound across both basic and higher education contexts. These results indicate that how educators appraise and endorse AI-based integrity tools is more central to their professional confidence in those tools than peer influence alone. For HR practitioners and institutions, this points to the importance of targeted workforce development programs and clear policy frameworks that build genuine professional competency and digital readiness in the teaching workforce rather than relying on social adoption patterns.

**Keywords:** academic integrity; automated detection; educator attitudes; instrument validation; professional confidence; social influence; human capital development

## 1. Introduction

AI detection tools are increasingly used in schools and universities to screen student submissions for AI-generated content (Bassett et al., 2026; Deep et al., 2025). These software systems estimate the likelihood that a text was produced by a large language model, and their institutional uptake grew considerably after the public release of tools like ChatGPT in late 2022. Survey reports indicate that a substantial proportion of teachers now use AI detectors as part of their assessment workflows (Dwyer & Laird, 2024; Gaines, 2025), and platforms such as Turnitin have embedded AI detection features into their existing plagiarism-checking infrastructure. Policy documents from government agencies similarly address the need to manage the opportunities and risks of AI in classrooms while protecting students' rights and supporting teachers' professional roles (Cardona et al., 2023; DepEd Philippines,

2026; Shin et al., 2026). As institutions continue to formalize their AI policies, teachers are increasingly positioned as those responsible for interpreting and acting on detection outputs when integrity concerns arise (Funa & Gabay, 2025).

Empirical evaluations of AI detection tools point to technical and ethical limitations that matter for how these tools are used in practice (Sun et al., 2026). Comparative studies of widely used detectors find that accuracy varies across tools and task conditions, and that performance tends to decline under paraphrasing, style changes, and domain shifts (Gotoman et al., 2025; Sun et al., 2026). Reviews of AI-generated text detection suggest that current tools are only partially reliable and should be applied cautiously when academic sanctions are at stake (Guadu et al., 2025; Weber-Wulff et al., 2023). These technical constraints also raise equity concerns. Survey and policy reports note that English learners and other marginalized groups may be disproportionately misclassified as AI users, particularly when detector scores are treated as conclusive proof of misconduct (Dwyer & Laird, 2024; Giray et al., 2026). Earlier studies have recommended treating detection outputs as one source of evidence among several rather than as definitive indicators of cheating (Fisk, 2025; Guadu et al., 2025; Hadra et al., 2026).

Human judgment adds another layer of difficulty. Experimental studies find that educators' accuracy in identifying AI-generated essays tends to be modest, while their confidence in those judgments can remain high even when the judgments are wrong (Fleckenstein et al., 2024; Weber-Wulff et al., 2023). When both tool reliability and human detection are imperfect, teachers who handle suspected cases of AI-assisted misconduct face real interpretive challenges, and how much weight to assign detection outputs is not always clear from institutional policy. Whether teachers view AI detectors as trustworthy, fair, and useful is therefore relevant to how academic integrity policies are enacted at the classroom level (Nazaretsky et al., 2022; Vital et al., 2025), but also to how educational organizations manage workforce capability, employee readiness, and institutional performance in the context of AI-driven change (Rothwell & Hajri, 2026).

Research on technology adoption in education shows that teacher perceptions of usefulness, reliability, and social support shape whether new tools are integrated into professional practice (Kashif et al., 2025; Ofosu-Ampong, 2024; Tan et al., 2025). Reviews of AI in education find that teachers see potential benefits in AI-assisted tasks but also raise concerns about data protection, algorithmic bias, and transparency (Garzón et al., 2025; Taheri et al., 2025). Survey data suggest that institutional adoption of AI tools is not always accompanied by systematic training on how to interpret AI-related outputs or respond to suspected misuse (de la Fuente & Farhadian, 2025; DEC, 2026; Dwyer & Laird, 2024). Instruments designed to measure teacher trust in AI-based educational technologies find that higher trust tends to be associated with greater willingness to adopt AI tools, but these instruments have largely focused on instructional or supportive applications rather than enforcement-oriented tools like AI detectors (Abbas et al., 2026; Lucas et al., 2024; Nazaretsky et al., 2025). A scale specifically tailored to how teachers perceive and trust AI detection tools in academic integrity contexts does not appear to exist in the current literature.

The Philippine education system provides a relevant context for examining these questions. The Department of Education established the Education Center for AI Research in February 2025 as part of a broader commitment to integrating AI into the education sector (DepEd Philippines, 2025). Existing empirical work, however, points to uneven AI adoption across basic and higher education levels, as well as gaps in teacher training

and institutional guidance (Higueras-Rodríguez et al., 2026; Taheri et al., 2025). In this environment, questions about how teachers perceive and trust AI detection tools carry practical implications for workforce readiness and policy development.

This study develops and validates the Teacher AI Detection Perception Scale (TADPS), a context-specific instrument measuring teacher perceptions of AI detection tools across three dimensions: General AI Endorsement (GAE), Trust and Confidence in AI Tools (TCA), and Social and Normative Influence (SNI). Because teachers function as organizational employees whose attitudes toward technology shape institutional capacity for digital transformation, the findings carry direct implications for workforce readiness, professional competency development, and human capital planning. The scale is therefore relevant to researchers, educational administrators, and human resources (HR) practitioners working on talent development, organizational learning, and responsible AI adoption in the education sector.

## 2. Materials and methods

### 2.1. Study design and sample

The study was conducted with a sample of Filipino teachers from public institutions. To ensure data quality, respondents were required to complete all items before submission. A total of 173 participants finished the survey. **Table 1** presents the demographics. The sample was composed mostly of female respondents (68.2%). Due to the near-equal distribution of basic education teachers and higher education faculty, education level was included as a control variable in the model. In addition to demographics, 13 items covering the three subscales of the TADPS were measured: GAE (7 items), TCA (3 items), and SNI (3 items). All items were scored on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree).

**Table 1.** Demographics.

| Variable                    | Categories       | <i>n</i> | %           |
|-----------------------------|------------------|----------|-------------|
| Age (years)                 | Mean (SD)        |          | 40.2 (10.9) |
| Sex                         | Female           | 118      | 68.2        |
|                             | Male             | 55       | 31.8        |
| Education level             | Basic Education  | 87       | 50.3        |
|                             | Higher Education | 86       | 49.7        |
| Teaching experience (years) | Mean (SD)        |          | 13.1 (8.9)  |

### 2.2. Measures

The TADPS was developed to measure teacher perceptions of AI detection tools across three dimensions. GAE refers to the degree to which a teacher views AI detection tools as useful, fair, and important enough to actively use when academic integrity is at stake. This subscale consists of seven items. TCA captures the extent to which a teacher trusts the accuracy and capability of AI detection tools and feels confident enough to base professional and academic decisions on their results. This subscale consists of three items. SNI refers to the degree to which a teacher's use of AI detection tools is shaped by observed peer behavior, collegial encouragement, and the perceived compatibility of these tools with established teaching practices. This subscale consists of three items.

### 2.3. Scale development procedure

Scale development followed the established sequence of steps outlined by Churchill (1979) and Hinkin (1995), and closely mirrors the procedure used by Zenker et al. (2021) in developing the PATS instrument. The process involved identifying items from theoretical and empirical literature; testing factorability using the Bartlett test of sphericity and the Kaiser-Meyer-Olkin (KMO) measure; confirming factor structure through exploratory factor analysis (EFA); assessing reliability through Cronbach's alpha ( $\alpha$ ), composite reliability (CR), and average variance extracted (AVE); testing construct validity using the Fornell-Larcker criterion (1981); checking for common method bias using Harman's single-factor test; testing predictive validity by regressing TCA on GAE with demographic controls; and testing nomological validity by examining SNI alongside GAE in a set of regression models. All analyses were conducted using Python with the statsmodels, scikit-learn, and factor\_analyzer packages. For predictive validity, GAE was hypothesized to have a positive effect on TCA, as teachers who endorse AI detection tools as useful and fair are expected to report higher trust and confidence in those tools. **Figure 1** presents the face validity model.

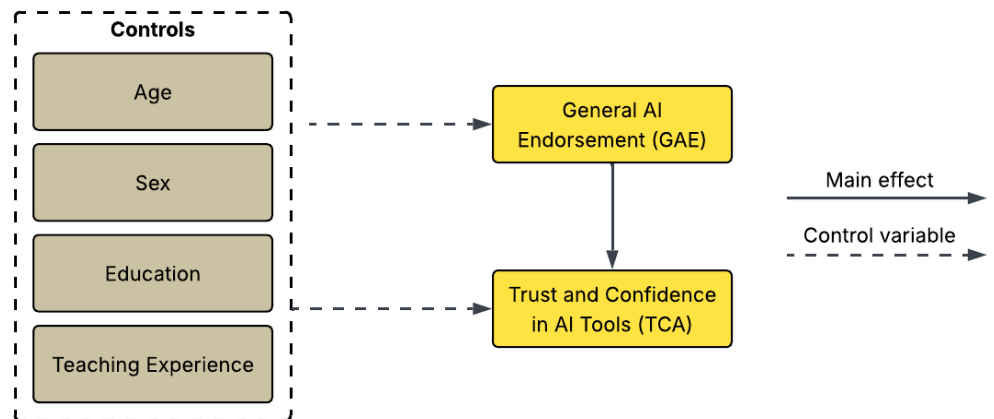


**Figure 1.** Face validity (GAE → TCA with demographic controls).

For nomological validity, SNI was hypothesized to predict GAE, and both SNI and GAE were tested simultaneously as predictors of TCA. **Figure 2** presents the full nomological validity model.

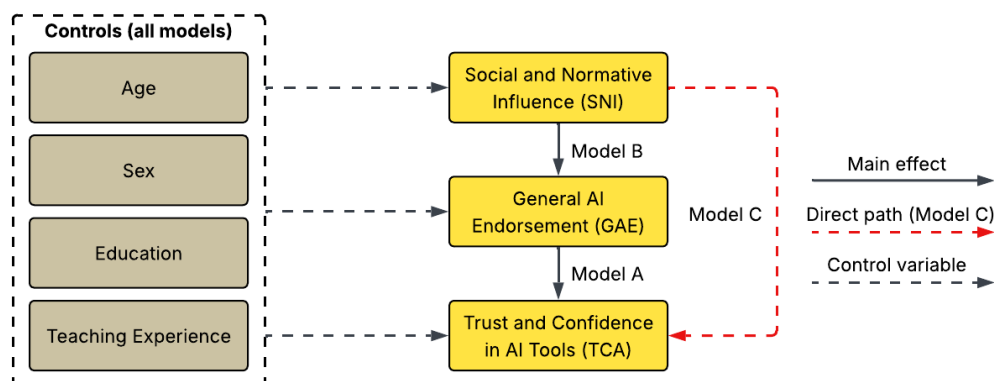


**Figure 2.** Nomological validity with Models A, B, and C.

## 3. Results and discussion

### 3.1. Exploratory factor analysis for scale development

The data were first submitted to an EFA using all 13 items. Both the Bartlett

test of sphericity ( $\chi^2(78) = 1,013.47, p = .000$ ) and the Kaiser-Meyer-Olkin Measure of Sampling Adequacy ( $KMO = 0.859$ ) reported satisfactory statistics. The varimax rotation and parallel analysis indicated three factors with eigenvalues larger than one, corresponding to the three subscales of TADPS.

Separate EFAs were then conducted for each subscale. For GAE, both the Bartlett test of sphericity ( $\chi^2(21) = 674.68, p = .000$ ) and the KMO ( $KMO = 0.859$ ) reported satisfactory statistics. The reported eigenvalue of 4.139 and the varimax rotation confirmed the one-factor structure. Likewise, the parallel analysis validated that there is one factor to retain. All seven items loaded accurately on the factor with good factor loadings ranging from 0.628 to 0.884. The item-rest correlations are high and in the same range. The change in Cronbach's  $\alpha$  was then tested by removing a good-fitting item, expecting that  $\alpha$  would get lower. The seven items form a coherent factor given the first-rate values for Cronbach's  $\alpha = 0.882$ , composite reliability ( $\omega = 0.909$ ), and average variance extracted ( $AVE = 0.591$ ). For TCA, both the Bartlett test ( $\chi^2(3) = 162.98, p = .000$ ) and the KMO ( $KMO = 0.675$ ) reported satisfactory statistics. The eigenvalue of 2.137 and the varimax rotation confirmed the one-factor structure. All three items loaded well on the factor (loadings = 0.810-0.891), with Cronbach's  $\alpha = 0.784$ ,  $\omega = 0.881$ , and  $AVE = 0.712$ . For SNI, the Bartlett test ( $\chi^2(3) = 94.58, p = .000$ ) and KMO ( $KMO = 0.636$ ) were satisfactory. The eigenvalue of 1.873 confirmed the one-factor structure, with loadings ranging from 0.707 to 0.845, Cronbach's  $\alpha = 0.693$ ,  $\omega = 0.832$ , and  $AVE = 0.624$ . **Table 2** presents the full EFA results for all three subscales.

**Table 2.** Exploratory factor analysis for scale development.

| Construct items                                                                        | Item label | Item loadings | Item-rest correlation | Avg inter-item r | $\alpha$ |
|----------------------------------------------------------------------------------------|------------|---------------|-----------------------|------------------|----------|
| GAE                                                                                    | GAE1       | 0.867         | 0.786                 | 0.585            | 0.849    |
|                                                                                        | GAE2       | 0.850         | 0.761                 | 0.568            | 0.852    |
|                                                                                        | GAE3       | 0.884         | 0.812                 | 0.601            | 0.846    |
|                                                                                        | GAE4       | 0.662         | 0.552                 | 0.432            | 0.878    |
|                                                                                        | GAE5       | 0.628         | 0.522                 | 0.416            | 0.882    |
|                                                                                        | GAE6       | 0.711         | 0.612                 | 0.48             | 0.872    |
|                                                                                        | GAE7       | 0.738         | 0.635                 | 0.492            | 0.869    |
| Cronbach's $\alpha = 0.882$   Composite reliability ( $\omega$ ) = 0.909   AVE = 0.591 |            |               |                       |                  |          |
| TCA                                                                                    | TCA1       | 0.829         | 0.599                 | -                | -        |
|                                                                                        | TCA2       | 0.810         | 0.584                 | -                | -        |
|                                                                                        | TCA3       | 0.891         | 0.712                 | -                | -        |
| Cronbach's $\alpha = 0.784$   Composite reliability ( $\omega$ ) = 0.881   AVE = 0.712 |            |               |                       |                  |          |
| SNI                                                                                    | SNI1       | 0.812         | 0.530                 | -                | -        |
|                                                                                        | SNI2       | 0.845         | 0.584                 | -                | -        |
|                                                                                        | SNI3       | 0.707         | 0.417                 | -                | -        |
| Cronbach's $\alpha = 0.693$   Composite reliability ( $\omega$ ) = 0.832   AVE = 0.624 |            |               |                       |                  |          |

*Note.* Items were introduced with: 'Please rate the following statement:' and respondents scored on a five-point Likert scale (1 = strongly disagree; 5 = strongly agree). AVE,  $\alpha$ , and  $\omega$  are derived from the EFA. Avg inter-item r reported for GAE only given its seven-item length.

### 3.2. Descriptive statistics

**Table 3** presents the descriptive statistics of all variables and construct items. Across the GAE subscale, respondents generally agreed with all items. They agreed that AI detection tools are useful instruments for evaluating the authenticity of student outputs (GAE1:  $M = 3.69$ ,  $SD = 1.04$ ), that using these tools promotes fairness in student assessment (GAE2:  $M = 3.66$ ,  $SD = 1.04$ ), and that they contribute meaningfully to equitable student evaluations (GAE3:  $M = 3.64$ ,  $SD = 0.95$ ). Respondents further agreed that these tools are essential for upholding academic integrity (GAE4:  $M = 3.56$ ,  $SD = 0.85$ ) and that they should be a standard part of evaluating student outputs in academic settings (GAE7:  $M = 3.49$ ,  $SD = 0.86$ ). The highest-rated item in the subscale indicated that respondents actively use AI detection tools when they suspect a student has submitted AI-generated work (GAE5:  $M = 3.73$ ,  $SD = 0.86$ ). The only exception was the item describing increased tool use when students are specifically believed to be relying on generative AI, which received a neutral response (GAE6:  $M = 3.41$ ,  $SD = 0.91$ ).

For the TCA subscale, responses were more mixed. Respondents agreed that AI detection tools are capable of correctly identifying AI-generated content in student outputs (TCA2:  $M = 3.59$ ,  $SD = 1.02$ ). However, they were neutral about whether they trust that tool results accurately reflect whether student outputs are AI-generated (TCA1:  $M = 3.38$ ,  $SD = 0.82$ ). Similarly, respondents were neutral about their confidence in using detection tool results as a basis for academic decisions about student outputs (TCA3:  $M = 3.25$ ,  $SD = 0.83$ ), which was the lowest-rated item in the subscale.

For the SNI subscale, responses were largely neutral. Respondents were neutral about whether most of their colleagues regularly use AI detection tools when evaluating student outputs (SNI1:  $M = 3.05$ ,  $SD = 0.91$ ), which was the lowest-rated item across all three subscales, and about whether their colleagues' positive attitudes had influenced their own use of these tools (SNI2:  $M = 3.16$ ,  $SD = 0.87$ ). The exception was the item on perceived compatibility, where respondents agreed that AI detection tools fit naturally alongside the traditional assessment methods already practiced in their institution (SNI3:  $M = 3.57$ ,  $SD = 0.84$ ).

**Table 3.** Descriptive statistics of variables and items.

| Variables / Construct items | Mean  | Standard Deviation |
|-----------------------------|-------|--------------------|
| Age                         | 40.24 | 10.88              |
| Teaching experience         | 13.12 | 8.89               |
| GAE1                        | 3.69  | 1.04               |
| GAE2                        | 3.66  | 1.04               |
| GAE3                        | 3.64  | 0.95               |
| GAE4                        | 3.56  | 0.85               |
| GAE5                        | 3.73  | 0.86               |
| GAE6                        | 3.41  | 0.91               |
| GAE7                        | 3.49  | 0.86               |
| TCA1                        | 3.38  | 0.82               |

Continuation Table:

| Variables / Construct items | Mean | Standard Deviation |
|-----------------------------|------|--------------------|
| TCA2                        | 3.59 | 1.02               |
| TCA3                        | 3.25 | 0.83               |
| SNI1                        | 3.05 | 0.91               |
| SNI2                        | 3.16 | 0.87               |
| SNI3                        | 3.57 | 0.84               |

### 3.3. Construct validity

Following Campbell and Fiske (1959), construct validity was confirmed for all three subscales. Table 2 reports the values for Cronbach's  $\alpha$ , composite reliability ( $\omega$ ), and AVE, which are well above the thresholds for convergent validity for TCA and SNI, and meet the minimum threshold for GAE (AVE = 0.591). Discriminant validity was also verified using the Fornell-Larcker criterion (1981). As shown in **Table 4**, the AVE for each construct exceeds the squared correlation (SC) between that construct and all others, with the exception of the GAE-TCA pair, where AVE(GAE) = 0.591 marginally exceeds SC = 0.583. The AVE for TCA (0.712) and SNI (0.624) each clearly exceed their squared correlations with the remaining constructs.

**Table 4.** Discriminant validity: Fornell-Larcker criterion.

| Construct | GAE             | TCA             | SNI          |
|-----------|-----------------|-----------------|--------------|
| GAE       | <b>0.591</b>    | <i>0.583</i>    | <i>0.311</i> |
| TCA       | <i>0.763***</i> | <b>0.712</b>    | <i>0.193</i> |
| SNI       | <i>0.557***</i> | <i>0.440***</i> | <b>0.624</b> |

*Note.* AVE values are on the diagonal in bold. Correlations are below the diagonal. Squared correlations (SC) are above the diagonal in italics. All correlations are significant at \*\*\* $p < .001$ .

### 3.4. Common method bias

The dataset was verified for common method bias by loading all 13 items on one common factor in a principal component analysis framework (Podsakoff et al., 2003). The first unrotated factor accounted for 48.52% of the total variance, falling below the commonly applied 50% threshold. The remaining variance was distributed across 12 additional components, none exceeding 11%. Common method bias is therefore not a serious concern for the present data.

### 3.5. Predictive validity

To test predictive validity, the face validity model was estimated with GAE predicting TCA, controlling for age, sex, education level, and teaching experience. The goodness-of-fit statistics of the model are good ( $R^2 = 0.595$ , Adj.  $R^2 = 0.583$ ). Most importantly, the estimated coefficient for GAE on TCA (0.810\*\*\*) is positive and significant. None of the demographic controls reached significance. The result meets the expectation of the theoretical model. **Table 5** displays the standardized estimated coefficients.

**Table 5.** Estimated research model (face validity; GAE → TCA).

| Effects of          | On: TCA  |       |
|---------------------|----------|-------|
|                     | B        | SE    |
| GAE                 | 0.810*** | 0.058 |
| Age                 | -0.003   | 0.005 |
| Sex                 | -0.031   | 0.095 |
| Education level     | -0.148   | 0.084 |
| Teaching experience | 0.007    | 0.006 |

Note. \*\*\* $p < .001$ . Model fit:  $R^2 = 0.595$ ; Adj.  $R^2 = 0.583$ .

### 3.6. Nomological validity

Nomological validity was assessed by estimating a set of models that introduced SNI alongside GAE in predicting TCA, with the same demographic controls included throughout. In Model A, GAE remained a positive and significant predictor of TCA (0.797\*\*\*), while SNI did not contribute additional variance ( $B = 0.023$ ,  $p = .769$ ), and the model  $R^2$  held at 0.595. In Model B, SNI was a significant positive predictor of GAE (0.558\*\*\*), and age was a significant negative predictor ( $B = -0.017$ ,  $p = .005$ ), with the model explaining 35.4% of the variance in GAE ( $R^2 = 0.354$ ). In Model C, SNI was a significant direct predictor of TCA without GAE in the model (0.468\*\*\*), explaining 22.2% of the variance ( $R^2 = 0.222$ ). All main relationships report logical and anticipated effects. The nomological validity model fit can therefore be regarded as good. **Table 6** displays the estimated coefficients across all three models.

**Table 6.** Estimated research model (nomological validity).

| Effects of          | Model A(DV: TCA) |       | Model B(DV: GAE) |       | Model C(DV: TCA) |       |
|---------------------|------------------|-------|------------------|-------|------------------|-------|
|                     | B                | SE    | B                | SE    | B                | SE    |
| GAE                 | 0.797***         | 0.076 | -                | -     | -                | -     |
| SNI                 | 0.023            | 0.078 | 0.558***         | 0.087 | 0.468***         | 0.100 |
| Age                 | -0.003           | 0.005 | -0.017**         | 0.006 | -0.016*          | 0.007 |
| Sex                 | -0.029           | 0.095 | -0.010           | 0.121 | -0.038           | 0.139 |
| Education level     | -0.146           | 0.085 | 0.165            | 0.101 | -0.015           | 0.121 |
| Teaching experience | 0.007            | 0.006 | 0.011            | 0.007 | 0.015            | 0.008 |
| $R^2$               |                  | 0.595 |                  | 0.354 |                  | 0.222 |

Note. \* $p \leq .05$ ; \*\* $p \leq .01$ ; \*\*\* $p \leq .001$ ; n.s. = not significant.

## 4. Discussion

### 4.1. Scale structure and reliability

The three-factor structure of TADPS was confirmed through EFA, with each subscale producing a clean single-factor solution and satisfactory Bartlett and KMO values. GAE demonstrated the strongest psychometric properties, with Cronbach's

alpha of 0.882, composite reliability of 0.909, and AVE of 0.591, all meeting accepted thresholds (Hair et al., 2018). These values are comparable to the PATS indices reported by Zenker et al. (2021), where alpha was 0.93 and AVE was 0.72 in Study 1. TCA produced the highest AVE of 0.712, and SNI returned acceptable reliability (alpha = 0.693).

The mean scores across subscales follow a theoretically meaningful order. GAE had the highest composite mean ( $M = 3.60$ ), followed by TCA ( $M = 3.41$ ) and SNI ( $M = 3.26$ ). This pattern suggests that teachers tend to endorse AI detection tools as generally useful and fair at a higher level than they actually trust the specific outputs these tools produce. Conceptually, GAE reflects a general evaluative orientation toward AI detection as a practice, while TCA captures a more specific judgment about tool accuracy and decisional confidence. These are related but distinct cognitive processes, analogous to the difference between valuing a workplace technology in principle and trusting its outputs enough to act on them professionally. Consistent with this view, Dietvorst et al. (2018) found that professionals often reject superior algorithmic outputs in practice unless they are granted operational control over them. This gap between endorsement and trust should not be read uncritically, and mirrors findings in organizational behavior literature on the distinction between technology acceptance and actual technology trust in the workplace (Kuen et al., 2023).

The broader literature documents that AI detection tools frequently produce false positives, particularly for non-native English speakers, and that detection accuracy drops considerably under common adversarial conditions such as paraphrasing and domain shifts (Liang et al., 2023; Perkins et al., 2024; Weber-Wulff et al., 2023). Giray (2024) further showed that false positives disproportionately affect scholars with non-standard or non-native writing styles, raising equity concerns directly relevant in multilingual contexts such as the Philippines. The moderate TCA mean therefore reflects a reasoned caution that is empirically grounded rather than simply a training deficit, a pattern also observed in studies of employee resistance to algorithmic decision-making in organizational contexts (Castelo et al., 2019; Mahmud et al., 2022). Institutions should not interpret lower trust scores as a problem to be corrected through training alone; they should also read them as a signal that teachers are responding, at least in part, to the genuine limitations of the tools they are being asked to use.

#### 4.2. Predictive validity

GAE was a strong and significant predictor of TCA ( $B = 0.810$ ,  $p < .001$ ,  $R^2 = 0.595$ ), indicating that teacher endorsement accounts for nearly 60% of the variance in trust and confidence, even after controlling for demographic variables. None of the demographic controls reached statistical significance, which echoes Zenker et al.'s (2021) finding that the primary construct rather than background characteristics was the dominant predictor in the face validity model. The result implies that trust in AI detection tools is not fixed by age, sex, or institutional level, but is shaped by how teachers perceive and evaluate the tools themselves, consistent with human capital theory suggesting that employee attitudes toward workplace technologies are primarily driven by cognitive appraisal rather than demographic factors (Lāma & Lastovska, 2025; Portocarrero Ramos et al., 2025).

Education level approached but did not reach significance ( $B = -0.148$ ,  $p = .078$ ), with higher education teachers showing slightly lower trust than their basic education counterparts. This borderline finding is broadly consistent with prior research suggesting that higher education faculty, who tend to have greater familiarity with

the documented technical and ethical limitations of AI detection tools, may approach these systems with more professional skepticism (Giray et al., 2026; Perkins et al., 2024; Weber-Wulff et al., 2023). Rather than treating this as a deficit, institutions may consider channeling the critical orientation of higher education faculty into training designs that equip all teachers to interpret detection outputs with contextual judgment rather than blind reliance, an approach aligned with organizational learning frameworks that prioritize reflective practice over compliance-driven adoption (Mapanoo, 2025; Thite, 2004). Nazaretsky et al. (2022) found that professional development programs specifically designed to address both the capabilities and the limitations of AI-powered educational tools were more effective at building durable trust than general technology training, a finding directly applicable to AI detection contexts and consistent with HR literature on competency-based training and digital workforce development (Mendoza-Chan & Pee, 2024; Nastase et al., 2025; Treviño-Elizondo & García-Reyes, 2023).

### 4.3. Nomological validity

The nomological validity tests produced the most theoretically meaningful findings of this study. In Model A, GAE retained a strong and significant effect on TCA ( $B = 0.797, p < .001$ ) while SNI became non-significant ( $B = 0.023, p = .769$ ). This mirrors Zenker et al.'s (2021) Study 2 result, where the primary construct retained its predictive effect on travel intention after the comparison construct was introduced, confirming that the two are related but distinct. In the present study, this result demonstrates that how teachers cognitively appraise and endorse AI detection tools is a more proximal driver of their trust than how they perceive peer behavior and collegial norms around tool use.

Model C showed that SNI does predict TCA directly when GAE is not in the model ( $B = 0.468, p < .001, R^2 = 0.222$ ), meaning that in the absence of strong individual-level endorsement, social and normative pressure can function as a substitute driver of trust. This is concerning from an academic integrity standpoint. Research has shown that uncritical reliance on AI detection outputs, driven more by institutional pressure than by informed professional judgment, can lead to wrongful accusations and harm faculty-student relationships (Deep et al., 2025; Eaton, 2024; Giray et al., 2026; Luo (Jess), 2025). In HR terms, this may reflect a broader risk of normative compliance overriding professional judgment in technology adoption, a pattern documented in studies of algorithmic management and workplace automation (Kellogg et al., 2019; Meijerink et al., 2021; Newlands, 2021). Institutions thus need training programs that do more than create social momentum around tool adoption; they need to build the evaluative competence that allows teachers to use detection outputs responsibly.

Model B showed that SNI significantly predicts GAE ( $B = 0.558, p < .001, R^2 = 0.354$ ), and that age is a significant negative predictor of GAE ( $B = -0.017, p = .005$ ). Older teachers tended to report lower GAE scores than younger teachers, consistent with the significant negative coefficient in Model B. This age effect is consistent with a broad literature on workforce technology adoption, which documents that older workers tend to show greater resistance to new digital tools when structured training and institutional support are limited (Abildinova et al., 2024; Fazi et al., 2024; Žabar & Janeš, 2025). For HR managers in education, this suggests the potential value of differentiated professional development that does not assume a uniform starting point across the teaching workforce.

#### **4.4. Theoretical and workforce implications**

TADPS contributes a validated measurement tool that researchers and practitioners can use to examine how teacher perceptions of AI detection tools develop and change over time, across contexts, and in response to training. Theoretically, the scale extends the growing body of work on teacher technology acceptance by providing a construct specifically grounded in the AI academic integrity context, and contributes to HR scholarship on measuring employee readiness for AI-driven organizational change. Future research could link TADPS to constructs such as algorithmic aversion, academic integrity culture, self-efficacy, and institutional policy compliance, as well as HR-relevant outcomes such as AI competency acquisition, participation in professional development programs, and organizational commitment toward digital transformation, to build a more complete picture of what drives and inhibits effective AI detection tool use among educators. Cross-cultural validation studies across different sectors, organizational contexts, and employee groups beyond public education would further strengthen its generalizability.

For HR practitioners and educational administrators, the practical implications center on three points. First, the association between GAE and TCA suggests that training programs should go beyond tool orientation to build critical and informed endorsement; this may include structured AI literacy initiatives and competency assessment frameworks that help teachers evaluate detection outputs with informed professional judgment rather than passive compliance. Teachers may benefit from structured opportunities to engage with the actual accuracy rates, documented biases, and interpretive challenges of AI detection tools, not just their intended functions (Ghamrawi et al., 2026; Sun et al., 2026). Second, age-differentiated professional development is warranted, as younger and older teachers are not starting from the same level of endorsement, consistent with workforce literature on employee digital readiness and organizational change management (Huebner & Zacher, 2021; Mailizar et al., 2022). Third, institutions should treat low trust scores not automatically as a training failure, but as a potentially valid professional response to tools whose limitations are well-documented in the research literature, and may use this understanding to inform workforce planning and change management strategies that account for variation in teacher readiness across career stages. As Bombaerts et al. (2026) argued, the solution to academic integrity challenges in the AI era is not solely technological but also cultural, requiring environments where teachers engage with these tools with genuine understanding and professional judgment rather than compliance alone (Ateeq et al., 2024; Maleki, 2026; Martin et al., 2022). This aligns with strategic HR management perspectives that position employee engagement with technology as a function of organizational culture, leadership support, and continuous learning rather than policy enforcement alone (Nastase et al., 2025; Orkamo et al., 2025).

#### **4.5. Limitations**

The scale was validated on a single sample of Filipino public school and university teachers, which limits generalizability to other national and institutional contexts, including private institutions, non-teaching staff involved in academic integrity enforcement, and educators in other sectors and countries. All data were self-reported at one point in time, so the relationship between TADPS scores and actual tool use behavior remains untested. Discriminant validity between GAE and TCA was marginal, and the current validation should therefore be considered preliminary until confirmatory factor analysis is conducted on an independent sample to examine

whether the two constructs are sufficiently distinct. Conceptually, however, the two subscales were designed to capture different levels of appraisal: GAE measures broad endorsement of AI detection as a practice, while TCA measures specific confidence in tool outputs as a basis for professional decisions. The SNI alpha fell slightly below 0.70, suggesting the subscale would benefit from additional items in future versions. Finally, the sample covered only public institutions, and the scale's applicability to private schools and universities has yet to be established.

## 5. Conclusion

Measuring how teachers perceive AI detection tools requires a reliable and context-specific instrument that captures endorsement, trust, and social influence as conceptually distinct but empirically related dimensions. The TADPS provides that, and its three-factor structure has proven reliable and structurally sound across basic and higher education contexts in the Philippine public education system. The results confirmed that teacher endorsement of AI detection tools is the more proximal determinant of professional trust and confidence in those tools, while social and normative influence, though meaningfully related to both endorsement and trust, does not add unique predictive value once endorsement is accounted for. Equally important is what the results should not be taken to mean: moderate trust scores in this sample are not just a training deficit to be corrected but may partly reflect a rational professional response to tools whose accuracy limitations and equity concerns are well-documented in the research literature. For institutions, this distinction matters. Training programs that build genuine, critical competence in interpreting AI detection outputs are more likely to produce responsible and durable adoption than approaches that rely on peer pressure or institutional mandate alone. For HR practitioners and institutional leaders, TADPS offers a practical means of assessing how ready the teaching workforce is to endorse, trust, and responsibly use AI detection tools, and of identifying where targeted interventions in competency development, AI literacy, and change management are most needed.

**Author contributions:** Writing—original draft and review & editing, conceptualization, methodology, investigation, formal analysis, project administration, resources, EPL and EBP; writing—original draft, conceptualization, investigation, formal analysis, JGR; writing—review & editing, investigation, methodology, project administration, RSJ; writing—review & editing, investigation, methodology, formal analysis, ASP and FFB; writing—review & editing, investigation, data curation, project administration, JADC; writing—original draft and review & editing, conceptualization, software, methodology, supervision, formal analysis, validation, JPPM

**Acknowledgment:** This study was supported by the authors' individual affiliations.

**Conflict of interest:** The authors declare no conflict of interest.

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