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Trust-Mediated AI Continuance Intention among Pre-Service Teachers: Integrating UTAUT and the Extended S-O-R-S Framework with AI Brain-Rot Exposure

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Abstract

The rapid use of artificial intelligence (AI) in teacher education raises important concerns about whether pre-service teachers will continue using AI despite emerging risks such as perceived AI brain-rot exposure. Therefore, this study examines how UTAUT-related stimuli, institutional support, and perceived AI brain-rot exposure influence the intention to continue using AI through trust in AI. This study employed a quantitative cross-sectional survey design involving 247 pre-service teachers enrolled in teacher education programmes in Indonesia, all of whom had prior experience using AI for academic or teaching-related purposes. Data were analyzed using Partial Least Squares Structural Equation Modeling. The results showed that performance expectancy and social influence significantly increased trust in AI, whereas effort expectancy and institutional support did not significantly influence trust. Perceived AI brain-rot exposure also significantly influenced trust in AI, but the relationship was positive, suggesting that awareness of AI-related cognitive risks may coexist with selective or calibrated trust. Trust in AI strongly influenced continuance intention and mediated the effects of performance expectancy, social influence, and perceived AI brain-rot exposure on the continuance intention. The model explained 72.1% of the variance in trust in AI, and 62.6% of the variance in continuance intention. This study contributes to the literature by extending the UTAUT and S–O–R with a stressor perspective and by introducing perceived AI brain-rot exposure as an emerging construct in AI-in-education adoption research. These findings suggest that teacher education programmes should prioritize demonstrating AI's concrete pedagogical benefits and fostering reflective AI literacy to build trust, rather than relying solely on institutional policy or ease-of-use considerations.

Keywords: AI brain-rot exposure; Continuance intention; Pre-service teachers; S-O-R-S model; Trust in AI.

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1. Introduction

The rapid proliferation of generative artificial intelligence (AI) tools in higher education has fundamentally reshaped the learning landscape, with pre-service teachers emerging as one of the most consequential user groups (Panday-Shukla, 2025). As future educators, pre-service teachers' adoption and sustained use of AI will directly shape pedagogical practices and digital literacy outcomes in future classrooms (Liu et al., 2025; Zheng et al., 2025). However, alongside the educational affordances of AI, an emerging and underexamined concern is the phenomenon of "brain rot" sustained exposure to shallow, repetitive, and cognitively unchallenging AI-mediated content (Heaton, 2024), which was designated as the Word of the Year, noting a 230% surge in usage frequency between 2023 and 2024. Empirical evidence suggests that intensive AI tool use is associated with increased cognitive offloading, reduced critical thinking engagement, and diminished capacity for independent evaluation (Gerlich, 2025; Yousef et al., 2025a). Consequently, while pre-service teachers stand to benefit substantially from AI-assisted learning, their perceived exposure to brain-rot-inducing AI content may simultaneously erode the epistemic trust and deep-processing competencies that underpin effective and sustained AI use.

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Prior research examining AI adoption in educational settings has predominantly drawn upon TAM and UTAUT, identifying performance expectancy, effort expectancy, social influence, and facilitating conditions as robust predictors of behavioral intention (Foroughi et al., 2024; Strzelecki, 2024; Venkatesh et al., 2003). Institutional support and trust in AI have been established as significant determinants of teachers' and students' intention to adopt and continue using AI tools in educational contexts (Viberg et al., 2025). However, the preponderance of these studies conceptualizes AI adoption as a unidirectional, benefit-driven process, largely neglecting the role of negative AI-related experiences as stressors that may suppress continued use (Duong, 2024). Critically, no study to date has examined how perceived AI brain-rot exposure operates as a stressor capable of undermining trust in AI and, consequently, attenuating the continuance intention among pre-service teachers specifically. This theoretical gap is significant, as the brain-rot phenomenon remains under-theorized within AI-in-education research, and its implications for trust and sustained AI engagement have yet to be empirically examined.

To address this gap, the present study adopts an extended Stimulus–Organism–Response (S–O–R) framework, originally grounded in environmental psychology (Mehrabian & Russell, 1974), which posits that external environmental stimuli activate internal psychological states in the organism, which in turn generate observable behavioral responses. The stressor extension of the S–O–R model established in the technostress and social media overload literature (Duong et al., 2024; Fu et al., 2020) was incorporated to accommodate the disruptive and cognitively demanding nature of perceived AI brain-rot exposure as a negative stimulus operating alongside positive adoption drivers. UTAUT constructs performance expectancy, effort expectancy, and social influence serve as positive stimuli reflecting the functional and social motivations for AI use, while institutional support captures the enabling or constraining conditions of the pre-service teachers' educational environment ((Strzelecki, 2024). Trust in AI is positioned as the organism, representing pre-service teachers' internal psychological evaluation of AI reliability, functional utility, and pedagogical appropriateness, an internal state that positive stimuli are expected to strengthen and perceived brain-rot exposure to undermine (Choung et al., 2023).

This study therefore aims to examine how UTAUT-related stimuli, institutional support, and perceived AI brain-rot exposure influence pre-service teachers' continuance intention to use AI, with trust in AI as the mediating organism. Theoretically, this study contributes to the literature by integrating UTAUT, the S–O–R model, and a stressor perspective into a unified explanatory framework and is one of the first studies to formally operationalize AI brain-rot exposure as a measurable stressor construct within the technology acceptance domain. Empirically, this study extends prior SOR-based AI continuance research (Duong, 2024; Duong et al., 2024) to pre-service teachers, whose AI use behaviors carry amplified longitudinal significance given their future instructional roles. Practically, the findings are intended to inform teacher education programmes in designing AI literacy curricula, institutional AI use policies, and responsible AI training frameworks that simultaneously cultivate AI competence and protect against the cognitive and epistemic risks of low-quality AI content exposure.

2. Literature Review

2.1. Stimulus–Organism–Response Model with Stressor Extension (SORS)

The Stimulus–Organism–Response (SOR) model explains how external stimuli influence an individual's internal psychological state, which then shapes behavioral responses (Mehrabian & Russell, 1974). In AI-use research, this model is useful because pre-service teachers do not respond to AI tools based only on technical features but also through internal evaluations such as trust, confidence, and perceived risk. Recent GenAI continuance studies have also used the S–O–R model to explain how users' internal states shape their continuance intention (Yousef et al., 2025b; Zhou & Ma, 2025).This study extends the S–O–R model by adding a stressor component, where performance expectancy, effort expectancy, social influence, and institutional support are positioned as stimuli, perceived AI brain-rot exposure as the stressor, trust in AI as the organism, and the intention to continue using AI as the response.

2.2. UTAUT

UTAUT provides a relevant theoretical basis for explaining technology acceptance because it emphasizes performance expectancy, effort expectancy, and social influence as key factors that shape users' acceptance of technology (Venkatesh et al., 2003). The original UTAUT model identifies these factors as central determinants of technology-related intention and use, while recent studies have applied UTAUT to examine pre-service teachers' intentions to adopt AI in educational contexts (Weis et al., 2026). In this study, pre-service teachers were expected to develop stronger trust in AI when they perceived AI as useful for teaching-related tasks, easy to use, and supported by important people around them. Therefore, the following hypotheses are proposed:

H1: Performance Expectancy positively influences Trust in AI;
H2: Effort Expectancy positively influences Trust in AI;
H3: Social Influence positively influences Trust in AI.

2.3. Institutional Support and Trust in AI

Institutional support represents the extent to which universities or teacher-education institutions provide policies, guidance, infrastructure, and encouragement for responsible AI use (Ceallaigh et al., 2025). In the context of teacher education, institutional support is important because pre-service teachers' AI use is not only an individual decision but is also shaped by academic norms, ethical expectations, and institutional readiness. UNESCO reported that many higher education institutions have already developed or are developing guidance for AI use, indicating the growing importance of institutional direction in the adoption of educational AI (UNESCO, 2025). Thus, clear institutional support may strengthen pre-service teachers' confidence that AI can be used responsibly and pedagogically.

H4: Institutional Support positively influences Trust in AI.

2.4. Perceived AI Brain-Rot Exposure and Trust in AI

Perceived AI Brain-Rot Exposure refers to pre-service teachers' perception that AI-related use or AI-mediated content may encourage shallow thinking, cognitive passivity, reduced independent reasoning, or overdependence on AI (Heaton, 2024). From a stressor perspective, such exposure may weaken trust because pre-service teachers may question whether AI supports meaningful learning or instead promotes passive and uncritical dependence. However, the direction of this relationship may not be entirely negative, because awareness of AI-related cognitive risks can also reflect a more critical and selective engagement with AI.(Schiavo & Andrao, 2026). In this sense, pre-service teachers who recognize the risks of AI brain-rot exposure may still develop calibrated trust when they believe AI remains useful if applied carefully and responsibly. Therefore, the following exploratory hypothesis is proposed:

H5: Perceived AI Brain-Rot Exposure significantly influences Trust in AI.

2.5. Trust in AI as Organism and Mediator

Trust in AI is positioned as the organism variable because it reflects pre-service teachers' internal evaluation of AI reliability, usefulness, integrity, and pedagogical acceptability. Trust is particularly important in AI-supported education because users must believe that AI outputs are sufficiently reliable and appropriate before they continue using them for teaching-related purposes (Afroogh et al., 2024). Recent studies on Gen AI continuance intention also emphasize trust as an important internal mechanism explaining users' willingness to continue using AI tools (Abdelazim et al., 2025). Accordingly, the following hypotheses are proposed:

H6: Trust in AI positively influences Continuance Intention to Use AI;
H7: Trust in AI mediates the relationship between Performance Expectancy and Continuance Intention to Use AI;
H8: Trust in AI mediates the relationship between Effort Expectancy and Continuance Intention to Use AI;
H9: Trust in AI mediates the relationship between Social Influence and Continuance Intention to Use AI;
H10: Trust in AI mediates the relationship between Institutional Support and Continuance Intention to Use AI;
H11: Trust in AI mediates the relationship between Perceived AI Brain-Rot Exposure and Continuance Intention to Use AI.

2.6. Trust in AI and Continuance Intention to Use AI as Response

Continuance intention to use AI was positioned as the response variable because this study focused on pre-service teachers who already had prior experience using AI for academic or teaching-related purposes (AL-Hawamleh, 2024). In this context, trust in AI is expected to play a central role because pre-service teachers are more likely to continue using AI when they perceive it as reliable, useful, and appropriate for supporting learning and teaching preparation. A higher level of trust may strengthen their willingness to use AI consistently in future lesson planning, instructional material development, and pedagogical activities. Therefore, this study proposes that trust in AI positively influences pre-service teachers' continuance intention to use AI. The full conceptual model is presented in Figure 1.

3. Research Method and Materials

3.1. Research Design

This study used a quantitative approach with a cross-sectional survey design (Cresswell, 2017). This design was suitable because the study aimed to test the relationships among the proposed variables and statistically examine the hypotheses. Data were collected at one point in time from pre-service teachers to capture their perceptions of AI use, trust in AI, perceived AI brain-rot exposure, and continuance intention to use AI. Therefore, this approach was appropriate for explaining the factors that influence pre-service teachers' continuance intention to use artificial intelligence.

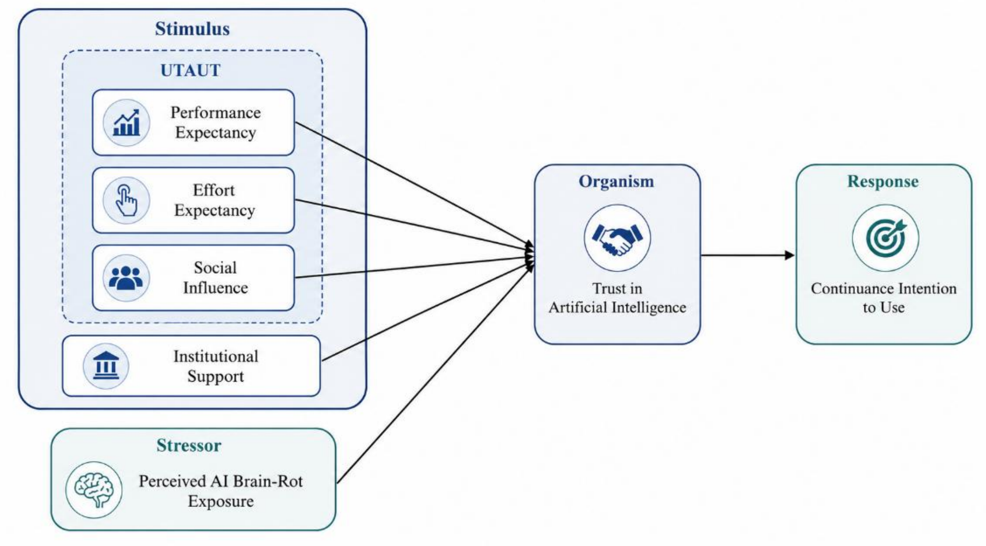

Figure 1. Conceptual Framework

3.2. Participants and Sampling Technique

The participants in this study were pre-service teachers who had experience using artificial intelligence for teaching-related purposes. Participants were recruited from teacher education programs at universities in Indonesia, particularly from programs related to educational sciences and teacher preparation. A purposive sampling technique was used because the study required respondents who met specific criteria relevant to the research objectives (Zickar & Keith, 2023). The main inclusion criterion was that the participants had previously used AI tools for teaching preparation, such as lesson planning, instructional material development, assessment design, or other academic and pedagogical activities. This criterion ensured that respondents were able to provide relevant perceptions regarding AI use, trust in AI, perceived AI brain-rot exposure, and continuance intention to use AI.

The minimum required sample size was determined using G*Power 3.1 (Faul et al., 2007). The analysis used an F-test for linear multiple regression with a fixed model and R^2 deviation from zero, a medium effect size of $f^2 = 0.15$, a significance level of $\alpha = 0.05$, a statistical power of 0.95, and five predictors, representing the maximum number of variables directed toward one endogenous construct in the proposed model. The analysis indicated that the minimum required sample size was approximately 138 respondents. Therefore, the study targeted a sample size above the minimum requirement to ensure adequate statistical power for the PLS-SEM analysis.

3.3. Research Instrument

The research instrument was developed in the form of a structured questionnaire. The questionnaire consisted of two main parts. The first part collected respondents' demographic information, including gender, age, and frequency of AI use. This section was included to describe the respondents' basic profile and to ensure that participants had relevant experience using AI for academic or teaching-related activities.

The second part measured the main constructs in the proposed research model, namely performance expectancy, effort expectancy, social influence, institutional support, perceived AI brain-rot exposure, trust in artificial intelligence, and continuance intention to use artificial intelligence. The items for performance expectancy, effort expectancy, and social influence were adapted from the UTAUT/UTAUT2 measurement tradition developed by Venkatesh et al. (2003), while the items for trust in AI were adapted from prior work on trust in AI and AI technology acceptance, particularly Choung et al. (2023), who conceptualized trust as users' belief in the reliability and functionality of AI technologies.

The items for perceived AI brain-rot exposure were newly developed for this study because there are still limited established measurements for this construct in AI-in-education adoption research. The development of these items was conceptually guided by the recent literature on brain rot, cognitive offloading, technostress, and digital overload, which highlights concerns about low-quality digital content, passive cognitive processing, reduced critical thinking, and technology-related strain (Yousef et al., 2025b). All items were adjusted to fit the context of pre-service teachers' use of AI for academic and teaching-related activities. All construct items were measured using a six-point Likert scale, ranging from 1 = strongly disagree to 6 = strongly agree. A six-point scale was used to reduce neutral responses and encourage respondents to express a clearer level of agreement or disagreement with the statements.

3.4. Data Collection Procedure

Data were collected through an online questionnaire distributed to pre-service teachers who met the inclusion criteria. Before completing the questionnaire, the respondents were informed about the purpose of the study, the voluntary nature of participation, and the confidentiality of their responses. Respondents were also asked to confirm whether they had previously used AI tools for teaching-related or academic purposes. Only the responses from participants who met this criterion were included in the analysis.

3.5. Data Analysis

The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). PLS-SEM was selected because this study aimed to examine the predictive relationships among latent variables and test the proposed research model. The analysis was conducted in two main stages: assessment of the measurement model and assessment of the structural model (Bentler & Huang, 2014; Henseler et al., 2014).

The measurement model was evaluated using indicator reliability, internal consistency reliability, convergent validity, and discriminant validity using the SmartPLS version 4.1.0.3. Indicator reliability was assessed through outer loading values, with loadings of 0.70 or higher considered acceptable (Hair, 2017). Internal consistency reliability was examined using Cronbach's alpha and composite reliability, with values above 0.70 indicating adequate reliability (Hair, 2017). Convergent validity was assessed using the average variance extracted (AVE), with values of 0.50 or higher indicating that the construct explained more than half of the variance of its indicators (Hair et al., 2019). Discriminant validity was primarily assessed using the heterotrait–monotrait ratio (HTMT). HTMT values below 0.85 were considered evidence of strict discriminant validity, while values below 0.90 were considered acceptable for conceptually related constructs (Henseler et al., 2015). In addition, the HTMT confidence interval should not include 1.00, indicating that the constructs are empirically distinct from one another.

Before assessing the structural model, common method bias (CMB) was examined because the data were collected using a self-reported questionnaire at a single point in time (Kock, 2015). CMB was assessed using the full collinearity VIF approach, with VIF values below 5.00 indicating that common method bias was unlikely to threaten the validity of the results (Sarstedt et al., 2014). This procedure was conducted to ensure that the relationships among the constructs were not substantially inflated by common method variance. After the CMB assessment, the structural model The explanatory power of the endogenous constructs was assessed using R^2, with values of 0.25, 0.50, and 0.75 interpreted as weak, moderate, and substantial, respectively (Henseler et al., 2009). The effect size was examined using f^2, with values of 0.02, 0.15, and 0.35 indicating small, medium, and large effects (Cohen, 2013). Predictive relevance was assessed using Q^2, where values greater than 0 indicate that the model has predictive relevance for the endogenous constructs (Hair et al., 2021).

Lastly, the hypothesized relationships were tested using a bootstrapping procedure with 5,000 subsamples and a two-tailed test at a 5% significance level. The path coefficients were evaluated based on their beta values, t-statistics, p-values, and confidence intervals. A hypothesis was considered supported when the path coefficient was statistically significant, with t-values greater than 1.96 and p-values below 0.05 in the two-tailed test (Hair et al., 2021; Patricia Aguilera-Hermida, 2020).

3.6. Ethical Considerations

This study followed basic ethical principles in survey-based research. Participation was voluntary, and respondents were informed that they could withdraw from the study at any time. The questionnaire did not collect personally identifying information, and all responses were treated confidentially. The collected data were used only for research purposes and reported in aggregate form.

4. Results and Discussion

4.1. Respondent Characteristics

A total of 247 valid responses were obtained, exceeding the minimum sample size of 138 required based on the G*Power analysis. The demographic profile of the respondents, including gender, age, and frequency of AI use in learning contexts, is presented in Table 1.

Table 1. Demographic Respondent Results

Variable	Category	Frequency N=247	Percentage
Gender	Female	165	66.8%
	Male	82	33.2%
Age	17–19 years	37	15.0%
	20–22 years	174	70.4%
	23–25 years	24	9.7%
	26–30 years	12	4.9%
Frequency of AI Use in Learning Context	Every day	76	30.8%
	3–5 times per week	64	25.9%
	1–2 times per week	52	21.1%
	Rarely	55	22.3%

Note. N is total respondent

The respondent characteristics indicate that the sample is dominated by female pre-service teachers, with most respondents aged 20–22 years, which reflects the typical age profile of undergraduate students in teacher education programs. This demographic pattern is relevant because respondents in this age range are generally active in academic learning, teaching preparation, microteaching, and practicum-related activities, making them suitable for examining AI use in educational contexts. The frequency of AI use also shows that many respondents had meaningful exposure to AI, as more than half reported using AI either every day or three to five times per week. This supports the relevance of using continuance intention as the outcome variable, since the respondents were not merely potential users but had already interacted with AI in learning-related activities. At the same time, the presence of respondents with lower AI-use frequency provides useful variation for understanding differences in trust in AI, perceived AI brain-rot exposure, and willingness to continue using AI in future teaching-related practices.

4.2. Measurement Models

Table 3 presents the assessment of construct loadings, internal consistency reliability, and convergent validity. The measurement model was evaluated using outer loadings, Cronbach's alpha, composite reliability rho_A, composite reliability rho_C, and average variance extracted (AVE). These criteria were used to determine whether the indicators adequately measured their respective latent constructs.

As shown in Table 2, all indicator loadings ranged from 0.799 to 0.916, exceeding the recommended threshold of 0.70. This indicates that all items had sufficient indicator reliability and could be retained in the measurement model. The reliability results also showed strong internal consistency, with Cronbach's alpha values ranging from 0.915 to 0.930, composite reliability rho_A values ranging from 0.916 to 0.933, and composite reliability rho_C values ranging from 0.936 to 0.947. These values were above the recommended threshold of 0.70, confirming that all constructs demonstrated adequate reliability. In addition, the AVE values ranged from 0.747 to 0.782, exceeding the minimum threshold of 0.50, which confirms the convergent validity of all constructs. Overall, the results indicate that the measurement model met the required criteria for indicator reliability, internal consistency reliability, and convergent validity. Therefore, the constructs used in this study were considered reliable and valid for further analysis of the structural model.

As shown in Table 3, all HTMT values were below 0.90, indicating that discriminant validity was achieved. The highest HTMT value was found between performance expectancy and effort expectancy at 0.875, followed by performance expectancy and trust in AI at 0.868, and continuance intention to use AI and trust in AI at 0.859. Although these values are above the stricter 0.85 criterion, they remain acceptable because the constructs are closely connected in the proposed UTAUT–S–O–R–Stressor framework. For example, pre-service teachers who perceive AI as useful and easy to use may naturally report stronger trust in AI and a stronger intention to continue using it. Overall, the HTMT results confirm that the constructs in the model are empirically distinct, while still being theoretically related.

As shown in Table 4, all VIF values were below the recommended threshold of 5.00. The highest VIF value was found in the path PE → TAI with a value of 3.661, followed by EE → TAI with a value of 3.453. Although these two values are higher than the other paths, they remain within the acceptable range, indicating that performance expectancy and effort expectancy are related but do not create serious multicollinearity problems in the model.

Table 2. Assessment of Construct Loadings, Reliability, and Convergent Validity

Construct	Items	Outer Loading	Cronbach Alpha	rho_a	rho_c	AVE
Performance Expectancy (PE)	PE1	0.883	0.928	0.930	0.946	0.777
	PE2	0.891				
	PE3	0.867				
	PE4	0.886				
	PE5	0.881				
Effort Expectancy (EE)	EE1	0.879	0.930	0.933	0.947	0.782
	EE2	0.903				
	EE3	0.916				
	EE4	0.852				
	EE5	0.870				
Social Influence (SI1)	SI1	0.867	0.923	0.924	0.942	0.765
	SI2	0.897				
	SI3	0.862				
	SI4	0.879				
	SI5	0.867				
Institutional Support (IS)	IS1	0.799	0.916	0.917	0.938	0.751
	IS2	0.874				
	IS3	0.873				
	IS4	0.904				
	IS5	0.878				
Perceived AI Brain-Rot Exposure (AIBR)	AIBR1	0.851	0.915	0.916	0.936	0.747
	AIBR2	0.880				
	AIBR3	0.896				
	AIBR4	0.855				
	AIBR5	0.838				
Trust in AI	TAI1	0.869	0.920	0.920	0.940	0.758
	TAI2	0.850				
	TAI3	0.877				
	TAI4	0.890				
	TAI5	0.867				
Continuance Intention to Use AI	CTU1	0.871	0.923	0.923	0.942	0.764
	CTU2	0.875				
	CTU3	0.880				
	CTU4	0.894				
	CTU5	0.848				

The R-squared results indicate that the model has a strong explanatory power for the endogenous constructs. The R^2 value for Trust in AI was 0.721, meaning that performance expectancy, effort expectancy, social influence, institutional support, and perceived AI brain-rot exposure explained 72.1% of the variance in trust in AI. This value indicates a high level of explanatory power, approaching the substantial category. The R^2 value for the Continuance Intention to Use AI was 0.626, showing that trust in AI explained 62.6% of the variance in the continuance intention. This suggests that trust in AI is an important mechanism for explaining pre-service teachers' willingness to continue using AI.

The f-square results show the relative contribution of each predictor in the structural model. The effect of Trust in AI on Continuance Intention was very large, with an f^2 value of 1.677, indicating that trust in AI is the dominant predictor of continuance intention. Among the predictors of trust in AI, Performance Expectancy had the strongest effect, with an f^2 value of 0.192, which falls into the medium effect category. Social Influence showed a small effect with an f^2 value of 0.076, while Institutional Support and Perceived AI Brain-Rot Exposure also showed small effects with f^2 values of

0.029 and 0.032, respectively. In contrast, Effort Expectancy had a negligible effect on trust in AI, with an f^2 value of 0.007.

Table 3. HTMT Result

	CTU	EE	IS	AIBR	PE	SI	TAI
CTU							
EE	0.773						
IS	0.631	0.731					
AIBR	0.489	0.473	0.351				
PE	0.804	0.875	0.707	0.470			
SI	0.760	0.699	0.707	0.480	0.762		
TAI	0.859	0.787	0.721	0.522	0.868	0.789	

Table 4. Inner VIF Result

Construct	VIF
EE -> TAI	3.453
IS -> TAI	2.190
AIBR -> TAI	1.316
PE -> TAI	3.661
SI -> TAI	2.412
TAI -> CTU	1.000

The Q^2predict results indicate that the model has a strong predictive relevance. The Q^2predict value for Trust in AI was 0.686, whereas the value for Continuance Intention to Use AI was 0.599. As both values are greater than zero and exceed the 0.50 benchmark, the model demonstrates strong predictive relevance for both endogenous constructs. Overall, these results suggest that the model has adequate explanatory strength and meaningful predictive capability, with a particularly strong role for trust in AI in shaping pre-service teachers' continuance intention to use artificial intelligence.

4.3. Structural Model Result

On Table 5, among the three UTAUT-derived stimulus variables, Performance Expectancy (PE) was the strongest predictor of Trust in AI ($\beta = 0.442$, $t = 4.393$, $p < 0.001$), indicating that pre-service teachers are more likely to trust AI when they perceive it as useful for academic work and teaching preparation. This suggests that trust in AI is not formed automatically but is strongly shaped by the perceived functional value of AI. Social Influence (SI) also had a significant positive effect on Trust in AI ($\beta = 0.226$, $t = 2.195$, $p = 0.028$), showing that encouragement from peers, lecturers, or academic communities contributes to pre-service teachers' trust formation. In contrast, Effort Expectancy (EE) did not significantly influence Trust in AI ($\beta = 0.083$, $t = 1.039$, $p = 0.299$), suggesting that ease of use may no longer be a decisive factor because generative AI tools are generally intuitive and familiar to digitally experienced users.

Table 5. Direct Effect Result

Hypothesis	Original sample (O)	T statistics (|O/STDEV|)	97.5% Confidence interval	P values	Decision
EE -> TAI	0.083	1.039	0.251	0.299	Rejected
IS -> TAI	0.133	1.580	0.290	0.114	Rejected
AIBR -> TAI	0.108	2.321	0.207	0.020	Accepted
PE -> TAI	0.442	4.393	0.631	0.000	Accepted
SI -> TAI	0.226	2.195	0.441	0.028	Accepted
TAI -> CTU	0.791	21.610	0.856	0.000	Accepted

The effect of Institutional Support (IS) on Trust in AI was also not statistically significant ($\beta = 0.133$, $t = 1.580$, $p = 0.114$). Although the relationship was positive, the results suggest that institutional policies or support may not yet be strong enough to directly shape pre-service teachers' trust in AI. This may indicate that their trust is formed more through personal experience and social influence than through formal institutional endorsements. Therefore, institutional support must be clearer, more consistent, and more closely connected to students' actual AI-use experiences before it can meaningfully influence trust.

A central contribution of this study is the inclusion of Perceived AI Brain-Rot Exposure (AIBR) as a stressor in the extended S–O–R framework. The results showed that AIBR had a significant effect on Trust in AI (β = 0.108, t = 2.321, p = 0.020), supporting H5. As H5 was formulated as a non-directional hypothesis, the positive coefficient does not contradict the hypothesis but indicates that perceived AI brain-rot exposure is significantly associated with trust in AI. This direction requires careful interpretation because a higher awareness of AI-related cognitive risks may coexist with a more selective or calibrated form of trust rather than simply reducing trust. Another possible explanation is that respondents who use AI more frequently are more exposed to brain rot-related concerns while also developing trust through repeated use. However, because this study used a cross-sectional design, the causal direction could not be confirmed. Overall, the findings show that AIBR is a relevant psychological construct for explaining trust in AI.

The effect of Trust in AI (TAI) on Continuance Intention to Use AI (CTU) was strongly supported and produced the largest path coefficient in the model (β = 0.791, t = 21.610, p < 0.001). This finding confirms that trust is the primary psychological mechanism linking AI-related stimuli and stressor perceptions to continued AI use. Within the S–O–R framework, trust functions as an organism variable that converts external inputs into behavioral intentions. The strong coefficient indicates that pre-service teachers are more likely to continue using AI when they perceive it to be reliable, useful, and appropriate for educational purposes. Therefore, efforts to increase sustained AI use among pre-service teachers should prioritize building trust in AI rather than focusing only on usability or institutional encouragement.

Table 6. Indirect Effect Result

Hypothesis	Original sample (O)	T statistics (|O/STDEV|)	97.5% Confidence interval	P values	Decision
EE -> TAI -> CTU	0.066	1.023	0.203	0.306	Rejected
IS -> TAI -> CTU	0.106	1.580	0.230	0.114	Rejected
AIBR -> TAI -> CTU	0.085	2.308	0.165	0.021	Accepted
PE -> TAI-> CTU	0.350	4.398	0.502	0.000	Accepted
SI -> TAI -> CTU	0.179	2.156	0.353	0.031	Accepted

The indirect effect results reported in Table 6 show that Trust in AI served as a mediating mechanism in the relationships between Performance Expectancy (PE), Social Influence (SI), and Perceived AI Brain-Rot Exposure (AIBR) with Continuance Intention to Use AI (CTU). Performance Expectancy had the strongest indirect effect on continuance intention (β = 0.350, t = 4.398, p < 0.001), followed by Social Influence (β = 0.179, t = 2.156, p = 0.031), and AIBR (β = 0.085, t = 2.308, p = 0.021). These results indicate that pre-service teachers' continuance intention is shaped by trust when AI is perceived as useful, socially supported, and associated with awareness of AI brain-rot exposure. In contrast, the indirect effects of Effort Expectancy (β = 0.066, p = 0.306) and Institutional Support (β = 0.106, p = 0.114) were not significant, consistent with their non-significant effects on Trust in AI. Overall, the findings confirm the central role of Trust in AI as the psychological pathway linking the supported antecedents to continuance intention.

Collectively, these findings advance the extended UTAUT–S–O–R–Stressor framework in three analytically distinct ways. First, they confirm that the positive adoption stimuli theorized by UTAUT, particularly performance expectancy, retain their explanatory relevance even when reframed through the organism-mediation logic of S–O–R rather than the direct intention logic of standard acceptance models. Second, they demonstrated that a cognitive stressor perceived AI brain-rot exposure is not theoretically extraneous to the adoption process but is an active co-determinant of the psychological state of trust. Third, and most broadly, they reveal that pre-service teachers' decisions to continue using AI are not driven primarily by usability or institutional endorsement, but by a deeply trust-mediated appraisal process in which the perceived functional value of AI and the normative context of its use are far more influential than structural facilitation or perceived ease.

4.4. Discussions

The present findings largely corroborate the established role of Performance Expectancy (PE) as a dominant antecedent of technology-related psychological states in educational AI contexts. The strong effect of PE on Trust in AI (β = 0.442) reinforces the position that when pre-service teachers perceive AI as genuinely useful for their academic and teaching preparation needs, their confidence in the technology is substantially strengthened. This finding aligns with (Zheng et al., 2025), who similarly identified performance-related perceptions as the most consequential predictor of continuance intention among pre-service teachers using generative AI, and with (Duong, 2024) whose SOR-UTAUT model confirmed that performance expectancy was a stronger driver than effort expectancy in a large Vietnamese higher education sample. The significant effect of Social Influence (SI) on Trust in AI (β = 0.226) is equally consistent with the broader literature: (Cao et al., 2025) found that normative cues from peers and institutional networks positively influenced teachers' AI adoption through both direct and mediated pathways, while (Acosta-Enriquez et al., 2025a) confirmed social influence as a robust contextual predictor of AI acceptance across educational settings.

The non-significant effects of Effort Expectancy (EE) and Institutional Support (IS) represent important differences from parts of the existing literature. Previous UTAUT-based studies in educational AI adoption have often reported significant effort-related effects; for example, (Bhat et al., 2024) found effort expectancy to be a key predictor of educators' chatbot acceptance, while (Acosta-Enriquez et al., 2025b) reported a significant effect of EE in their UTAUT2-based study of Spanish university professors. In contrast, the present findings suggest that ease of use may be less decisive for pre-service teachers, possibly because generative AI tools are increasingly intuitive and already familiar to digitally experienced users. For institutional support, the non-significant result differs from (Ceallaigh et al., 2025), who found that institutional support influenced teachers' AI intention, but it is more consistent with (Jiang et al., 2025), who noted that institutional AI policies in higher education are often ambiguous or inconsistently communicated. This suggests that institutional support may not influence trust unless it is clearly communicated, practically experienced, and connected to students' actual AI use practices.

The significant positive effect of Perceived AI Brain-Rot Exposure (AIBR) on Trust in AI represents a novel finding because previous AI adoption studies have not yet clearly operationalized or empirically tested this construct. Therefore, the main theoretical contribution of this study lies in integrating AIBR as a stressor within the S–O–R framework alongside conventional UTAUT stimuli. Unlike prior AI adoption studies, including, including (Strzelecki, 2024) and (Foroughi et al., 2024), which mainly constructed benefit-driven models where predictors are expected to support adoption, this study recognizes that AI use may involve both positive affordances and cognitively concerning experiences. The unexpected positive direction can be interpreted through cognitive appraisal theory (Lazarus & Folkman, 1984), which explains that individuals do not respond to stressors automatically but first evaluate whether the stressor is threatening, manageable, or useful for adaptive coping. In this study, pre-service teachers who are aware of the risks of AI brain-rot may not necessarily avoid AI; instead, they may develop more selective and reflective trust by recognizing both the benefits and limitations of AI. This interpretation is also consistent with dual-process theory (Gawronski et al., 2014), which states that awareness of cognitive risks may activate more deliberate and analytical processing rather than automatic acceptance, leading to a more cautious but stable form of trust.

Moreover, while studies such as (Paltsoglou & Zafiropoulos, 2025) commonly model UTAUT variables as direct predictors of intention, this study positions them as stimuli that influence continuance intention indirectly through trust. This structure provides a more psychologically grounded explanation of how pre-service teachers form sustained intention to use AI, especially because they are both current learners and future educators whose AI-use patterns may later shape classroom practice.

The findings have three layers of importance. First, they confirm that trust is not merely one predictor among many, but is effectively the singular psychological gateway to sustained AI use in this population, the organism variable through which all external stimuli, positive and negative, must pass before producing behavioral outcomes. The magnitude of the TAI → CTU path ($\beta = 0.791$) establishes this architecturally; influencing continuance without influencing trust is, within this model, structurally impossible. This finding reinforces and extends the work of Al-Emran and Griffy-Brown (2025), whose systematic review of trust in Gen AI within higher education consistently identified trust as the most proximal determinant of educators' continued engagement with AI tools. Second, the non-significance of Effort Expectancy challenges a design assumption carried forward uncritically from early TAM studies into the generative AI era. This finding is consistent with the observations (Al-Amri & Al-Abdullatif, 2024), who noted that effort expectancy failed to reach significance among adolescent and pre-service teacher populations, attributing this to the increasingly intuitive and user-friendly design of contemporary generative AI tools that effectively eliminate perceived complexity as a differentiating factor. Third, the non-significance of Institutional Support raises a critical question about the translation gap between policy provision and individual psychological states gap with practical urgency given the finding by (Jiang et al., 2025) that fewer than one-third of top global universities had implemented clear GenAI policies as of 2022, and that those that had often communicated them in ambiguous or incomplete terms that failed to reach students and teachers at the cognitive-evaluative level.

Scientifically, this study advances the literature by positioning Trust in AI as the central organism variable linking supported stimuli and stressor perceptions to pre-service teachers' continuance intention. The positive relationship between Perceived AI Brain-Rot Exposure and trust raises an important theoretical question: awareness of AI-related cognitive risks may encourage calibrated trust, but it may also reflect frequent AI use and accumulated trust. Because the study is cross-sectional, this mechanism should be interpreted cautiously and examined further through longitudinal research. Practically, the primacy of Performance Expectancy signals that teacher education programs and AI developers should prioritize demonstrating clear, pedagogically specific performance benefits to pre-service teachers not as promotional communication, but as an evidence-based trust-building strategy, consistent with the recommendation of (Viberg et al., 2025) that AI tools used in teacher education be accompanied by transparent performance evidence and pedagogical rationale. The non-significance of Institutional Support does not render it irrelevant from a practice standpoint; rather, it follows the argument of (Amir et al., 2025) that institutions must invest not only in providing structural support but in communicating that support in personally meaningful ways that reach the individual psychological layer where trust is actually formed. The positive AIBR finding further suggests that AI literacy programs embedded in teacher education should channel awareness of AI's cognitive risks including brain-rot exposure toward reflective, evaluative engagement rather than avoidance, as also recommended by (Yousef et al., 2025b) in their review of brain rot in the digital era.

The proposed extended UTAUT–S–O–R–Stressor framework was empirically tested, and the hypothesized mediation role of Trust in AI in connecting stimuli and stressor to continuance intention was substantiated for three of five antecedent paths. The goal of formally operationalizing Perceived AI Brain-Rot Exposure as a stressor construct was achieved, with the construct demonstrating statistically significant co-variation with trust, thereby validating its theoretical inclusion in the model. The research goal of identifying which UTAUT stimuli most consequentially shape trust formation was met with empirical clarity: performance expectancy and social influence are effective trust-building stimuli in this population, whereas effort expectancy is not. Where the model fell short of its hypothesized effects the non-significant paths of EE and IS these outcomes are themselves analytically productive, revealing context-specific boundary conditions of established theoretical propositions and generating more refined questions for future research. In this regard, the study's contribution is not diminished by these null findings; rather, as (Venkatesh et al., 2003) themselves cautioned, the explanatory power of UTAUT constructs is inherently moderated by context, and identifying where those boundary conditions operate is as theoretically meaningful as confirming where they do not.

5. Conclusion

This study concludes that pre-service teachers’ continuance intention to use artificial intelligence is strongly shaped by trust in AI, which serves as the central psychological mechanism linking AI-related stimuli and stressor perceptions to sustained use. Performance expectancy was the strongest predictor of trust, followed by social influence, indicating that pre-service teachers are more likely to trust AI when they perceive it as useful for teaching-related tasks and when its use is reinforced by their social environment. Effort expectancy and institutional support did not significantly influence trust, suggesting that ease of use and institutional encouragement may be less decisive when pre-service teachers already have practical experience with AI tools. Perceived AI brain-rot exposure significantly influenced trust in AI in a positive direction; however, this direction was unexpected and should not be treated as straightforward confirmation of the original theoretical assumption, but rather as a basis for revising and refining how AI-related cognitive risks are conceptualized in future studies. Practically, teacher education curriculum designers should integrate AI literacy programs that encourage reflective discussion of AI’s cognitive risks, including overdependence, passive thinking, and shallow engagement, as part of trust-building rather than fear-based avoidance. University administrators should also ensure that AI-use policies are communicated in personally meaningful and practically experienced ways, supported by clear guidance, examples, and training rather than abstract policy documents alone. This study is limited by its cross-sectional design, self-reported data, and focus on pre-service teachers in a specific research context; therefore, future studies should use longitudinal designs, broader samples, and further validation of the perceived AI brain-rot exposure construct.

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