

# Factors Influencing Generation Z Acceptance of AI-Powered Geography Teaching Materials: A Structural Equation Modelling Approach

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| ARTICLE INFO                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                             | ABSTRACT                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                          |
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| <p><b>Article History:</b><br/>Received: 2026-05-19<br/>Accepted: 2026-09-01<br/>Published: 2026-09-30</p> <p><b>Keywords:</b><br/>Artificial Intelligence in Education;<br/>Geography Education;<br/>Generation Z;<br/>PLS-SEM;<br/>Technology Acceptance Model</p> <p><b>Corresponding author:</b><br/>M Fikri Amrullah<br/>Email: <a href="mailto:m_fikri_amr@mail.unnes.ac.id">m_fikri_amr@mail.unnes.ac.id</a><br/>DOI: 10.37905/jgej.v7i2.39026</p> <p>Copyright © 2026 The Authors</p>  <p>This open-access article is distributed under a Creative Commons Attribution-NonCommercial (CC-BY-NC) 4.0 International License</p> | <p>Artificial intelligence (AI) is increasingly used in higher education, yet evidence regarding which perceived characteristics are most strongly associated with students' experiences of AI-supported learning remains mixed, particularly in geography education. This cross-sectional study examined the associations of perceived ease of use, perceived usefulness, personalisation and adaptivity, and learning interactivity with Generation Z prospective geography teachers perceived impact of AI-supported geography learning. Participants were 165 prospective geography teachers from one public university in Indonesia. Data were collected using a structured four-point Likert questionnaire whose items referred to AI-supported digital tools in general rather than to a single named AI platform, and the model was analysed using partial least squares structural equation modelling (PLS-SEM). Learning interactivity showed the strongest positive association with I_AI (<math>\beta = .303</math>; <math>p = .006</math>), followed by perceived usefulness (<math>\beta = .283</math>; <math>p = .017</math>) and perceived ease of use (<math>\beta = .255</math>; <math>p = .026</math>). Personalisation and adaptivity were not significantly associated with I_AI (<math>\beta = -.051</math>; <math>p = .599</math>). The model explained 53.3% of the variance in I_AI (<math>R^2 = .533</math>). These findings describe relationships among prospective geography teachers' perceptions and do not establish the effectiveness of AI, actual learning gains, or causal effects. Within this single-university context, learning interactivity appeared more salient than the measured personalization and adaptivity constructs, whereas the nonsignificant association of personalisation and adaptivity with I_AI should be interpreted as a context-specific finding rather than as evidence of a general decline or "paradox" of personalisation.</p> |

**How to Cite:** Amrullah, M. F., & Amelia, R. N. (2026). Factors Influencing Gen Z Acceptance of AI-Powered Geography Teaching Materials: A Structural Equation Modelling Approach. *Jambura Geo Education Journal*, 7(2), 219–228. <https://doi.org/10.37905/jgej.v7i2.39026>

## 1. Introduction

The rapid development of digital technology over the past decade has transformed higher education, particularly through the growing integration of artificial intelligence (AI). AI can support data analysis, recommendations, and adaptive learning processes (Chen et al., 2020; Zawacki-Richter et al., 2019). For prospective teachers, this development is particularly relevant because their perceptions of AI may influence how they understand, evaluate, and integrate AI into future teaching practices. This consideration is especially important for Generation Z prospective teachers, who have experienced higher education in increasingly digital and interactive learning environments (Irfan et al., 2025). However, the educational value of AI depends not only on technological capability but also on how students perceive and use technology.

In geography education, AI may support access to information, data interpretation, and digitally mediated learning activities. Geography as a discipline also involves spatial reasoning, spatial analysis, and interpretation of area-based phenomena (Karmaoui et al., 2023). Therefore, for prospective geography teachers, perceptions of AI are important not only as students' responses to an emerging educational technology but also as an indication of how future geography educators may view AI-supported learning environments. Nevertheless, the present study does not directly measure spatial-thinking performance, GIS skills, or map-based learning outcomes. Its empirical focus is on Generation Z prospective geography teachers' perceptions of AI-supported geography learning, including perceived ease of use, perceived usefulness, personalisation and adaptivity, and learning interactivity.

Personalisation is frequently presented as a key affordance of AI-supported learning because adaptive systems can tailor content, methods, or difficulty to learners' needs (Kulik & Fletcher, 2016).

However, empirical evidence does not consistently show that personalisation alone is associated with stronger learning experiences, particularly when interactivity and user experience are weak (Lauricella et al., 2020). This suggests that personalisation should be examined alongside other perceived characteristics of AI-supported learning. For Generation Z prospective teachers who engage in learning in highly digital environments, the perceived value of AI may depend on a combination of functional and experiential characteristics rather than personalisation alone.

The Technology Acceptance Model (TAM) proposes that perceived usefulness and perceived ease of use are central determinants of technology acceptance (Davis, 1989; Ross et al., 2009). In educational settings, technologies perceived as useful and easy to use are more likely to elicit favourable responses from users. Interactivity may provide an additional explanatory dimension because responsive two-way interaction can support engagement with digital learning environments (Ho et al., 2017; Martin & Vallance, 2008). Accordingly, a TAM-oriented perspective provides a useful framework for examining how prospective geography teachers from Generation Z perceive AI-supported learning, while personalisation and learning interactivity can be considered additional characteristics of the learning environment.

Although AI has been widely discussed in education, research often emphasises technological capabilities more than students' perceptions and experiences (Zhai et al., 2021). This limitation is particularly relevant in teacher education, where prospective teachers are not merely technology users; they are also future educators who may encounter increasing expectations to use AI in their instructional practices. Geography provides an important disciplinary context because its curricula commonly involve spatial reasoning, spatial visualisation, geospatial enquiry and regional concepts. However, the instrument used in the present study does not directly measure these competencies. The empirical gap addressed here is therefore narrower, as limited empirical evidence remains on how prospective geography teachers of Generation Z perceive the usefulness, ease of use, personalisation, adaptivity, and interactivity of AI-supported geography learning within a single analytical framework. Accordingly, the present study extends a TAM-oriented framework to examine how these perceived characteristics are associated with the Perceived Impact of AI on Geography Learning (I\_AI), without claiming direct effects on spatial thinking or GIS performance.

Some literature suggests that personalisation may not always be the dominant perceived feature of technology-supported learning and that engagement or interactivity can be equally important (Ifenthaler & Schumacher, 2016). This issue is particularly relevant when examining prospective teachers from Generation Z, as their perceptions of AI-supported learning may reflect multiple dimensions of the digital learning experience rather than a single technological affordance. AI-supported learning may therefore be perceived not only for its ability to accommodate individual learning needs but also for its capacity to facilitate active and responsive learning experiences. For prospective geography teachers, examining these dimensions together is relevant because they will encounter AI in increasingly digital teaching and learning environments in the future. This possibility provides a rationale for simultaneously examining personalisation and interactivity; it should not be prematurely interpreted as evidence of a paradigm shift or a general decline in the value of personalisation.

Accordingly, this study addresses the following research question: Which perceived characteristics of AI-supported geography learning are associated with the perceived impact of AI on geography learning among Generation Z prospective geography teachers? Drawing on the TAM, Perceived Ease of Use (PEU\_AI) and Perceived Usefulness (PU\_AI) are expected to be positively associated with the Perceived Impact of AI on Geography Learning (I\_AI), as technologies that are easier to use and perceived as beneficial are more likely to generate favourable learning experiences (Davis, 1989). Personalisation and adaptivity (PA\_AI) are also expected to be positively associated with the Perceived Impact of AI on Geography Learning (I\_AI), as adaptive learning environments can align learning support with individual needs (Kulik & Fletcher, 2016). Similarly, Learning Interactivity (LI\_AI) is expected to be positively associated with the Perceived Impact of AI on Geography Learning (I\_AI) because responsive interaction can strengthen engagement with digital learning environments (Ho et al., 2017; Martin & Vallance, 2008).

Therefore, the hypotheses are formulated as follows: H1: Perceived Ease of Use (PEU\_AI) is positively associated with Perceived Impact of AI on Geography Learning (I\_AI). H2: Perceived Usefulness (PU\_AI)

is positively associated with Perceived Impact of AI on Geography Learning (I\_AI). H3: Personalisation and Adaptivity (PA\_AI) is positively associated with the Perceived Impact of AI on Geography Learning (I\_AI). H4: Learning Interactivity (LI\_AI) is positively associated with the Perceived Impact of AI on Geography Learning (I\_AI). This cross-sectional study aimed to evaluate the measurement model and examine the predictive associations of Perceived Ease of Use (PEU\_AI), Perceived Usefulness (PU\_AI), personalisation and adaptivity (PA\_AI), and Learning Interactivity (LI\_AI) with the Perceived Impact of AI on Geography Learning (I\_AI) among Generation Z prospective geography teachers. The study does not test an AI intervention or objective learning outcomes.

## 2. Method

This study employed a quantitative cross-sectional survey design to examine the relationships among latent constructs related to artificial intelligence (AI)-supported geography learning. Data were collected at a single point in time; therefore, the study was designed to assess associations and predictive relationships rather than causal relationships. Partial least squares structural equation modelling (PLS-SEM) was employed because the study involved multiple latent constructs and aimed to examine their predictive relationships within a single structural model (Hair et al., 2021). The model examined Perceived Ease of Use (PEU\_AI), Perceived Usefulness (PU\_AI), personalisation and adaptivity (PA\_AI), and Learning Interactivity (LI\_AI) as predictor constructs of the Perceived Impact of AI on Geography Learning (I\_AI).

The target population comprised active prospective geography teachers at a public university in Indonesia with prior experience using AI-supported digital technologies in geography learning. Convenience sampling was used because eligible participants were recruited from an accessible university learning context and were required to have direct experience with AI-supported learning. Prior experience with AI in geography-related learning activities was the primary eligibility criterion to ensure that the participants could provide informed perceptions of the constructs examined in the study. A total of 165 complete responses met the eligibility criteria and were retained for the final PLS-SEM analysis. Participation was voluntary, and informed consent was obtained from all respondents before completing the questionnaire. Participants were informed about the purpose and procedures of the study, and their responses were kept confidential. Incomplete or ineligible responses were excluded from the analysis.

The final analytical sample and study context are summarised in Table 1. The sample comprised prospective geography teachers who studied within the same institutional context and had previous exposure to AI-supported learning, providing a relevant population for examining perceptions of AI in geography education. Moreover, the use of convenience sampling and a single-university setting defined the contextual boundaries of the study. Accordingly, the findings are intended to describe the relationships among the investigated constructs within this specific group rather than to support broad population-level generalisations to all Generation Z prospective geography teachers or geography students in Indonesia.

**Table 1.** Final Analytical Sample and Study Context

| Characteristic          | Description                                                                  | Value           |
|-------------------------|------------------------------------------------------------------------------|-----------------|
| Final analytical sample | Prospective geography teachers                                               | n = 165         |
| Institutional context   | Public university in Indonesia                                               | Single site     |
| Sampling approach       | Convenience sampling                                                         | Non-probability |
| Eligibility             | Prior experience using AI-supported digital technology in geography learning | Required        |

The study used a structured questionnaire with a four-point Likert response scale ranging from “strongly disagree” to “strongly agree”. A four-point format was selected to remove a neutral midpoint and encourage respondents to provide a directional evaluation of each statement (Joshi et al., 2015; Kulas et al., 2008). Perceived Ease of Use (PEU\_AI) and Perceived Usefulness (PU\_AI) were grounded primarily in the Technology Acceptance Model (Davis, 1989), while personalisation and adaptivity

(PA\_AI), Learning Interactivity (LI\_AI), and Perceived Impact of AI on Geography Learning (I\_AI) were adapted from the digital-learning literature identified in the instrument source note (Kim & Moon, 2025; Li et al., 2024; Ren, 2026; Susanto et al., 2026; Xue et al., 2026; Yuliati et al., 2026). The items were contextualised by explicitly referring to AI use “when learning geography”, while retaining sufficiently general wording so that respondents could answer based on the AI-supported digital tools they had used. The questionnaire was therefore platform-neutral rather than tied to a single named AI system. Eligibility required prior experience using AI-supported digital technology for geography learning.

The I\_AI construct captures respondents perceived changes in motivation, interest, independent learning, study time adjustment, learning activity, focus, and adaptation to AI- and technology-based learning. This was interpreted as a measure of the perceived impact of AI on geography learning rather than an objective measure of learning achievement. Because the items do not directly assess performance in maps, GIS, spatial visualisation, regional analysis, or spatial thinking, the study's empirical claims are limited to general perceptions of AI-supported geography learning.

**Table 2.** Research Constructs and Measurement Indicators

| Construct                                           | Code | Indicator                                                           |
|-----------------------------------------------------|------|---------------------------------------------------------------------|
| Perceived Ease of Use (PEU_AI)                      | X1.1 | AI is easy to use when learning geography.                          |
|                                                     | X1.2 | AI helps me learn geography more quickly and efficiently.           |
|                                                     | X1.3 | AI allows me to access learning materials at any time.              |
| Perceived Usefulness (PU_AI)                        | X2.1 | AI helps me understand geography better.                            |
|                                                     | X2.2 | AI improves my productivity when learning geography.                |
|                                                     | X2.3 | AI increases my interest in learning geography.                     |
| Personalisation and Adaptivity (PA_AI)              | X3.1 | AI presents material tailored to my learning needs.                 |
|                                                     | X3.2 | AI adjusts the level of difficulty according to my ability.         |
| Learning Interactivity (LI_AI)                      | X4.1 | AI makes learning more interactive.                                 |
|                                                     | X4.2 | AI provides feedback that aids understanding.                       |
| Perceived Impact of AI on Geography Learning (I_AI) | Y1   | I am more motivated to learn geography with AI.                     |
|                                                     | Y2   | I am interested in AI-based learning.                               |
|                                                     | Y3   | I am able to learn independently using AI.                          |
|                                                     | Y4   | I can adjust my study time with AI.                                 |
|                                                     | Y5   | I am more active during lessons using AI.                           |
|                                                     | Y6   | I am more focused when studying using AI.                           |
|                                                     | Y7   | I adapt easily to AI in learning.                                   |
|                                                     | Y8   | I quickly understand how AI works.                                  |
|                                                     | Y9   | I am able to adapt to changes in technology-based learning methods. |

**Source:** The questionnaire was adapted from Davis (1989), Kim and Moon (2025), Li et al. (2024), Ren (2026), Susanto et al. (2026), Xue et al. (2026), and Yuliati et al. (2026).

Data analysis comprised evaluations of the measurement and structural models, as well as hypothesis testing. For the measurement model, convergent validity was assessed using outer loadings and average variance extracted (AVE), with outer loadings above .70 and AVE values above .50. Internal consistency reliability was evaluated using composite reliability, with values above .70 indicating satisfactory reliability. Discriminant validity was assessed using the heterotrait–monotrait ratio (HTMT), together with bootstrap confidence intervals. For the structural model,  $R^2$  and adjusted  $R^2$  were examined to assess the explained variance of the endogenous construct, whereas  $f^2$  was used to evaluate the effect size of individual predictor constructs. The model fit was examined using the SRMR. Hypotheses were evaluated using standardised path coefficients,  $t$ -statistics, and two-tailed  $p$ -values, with a significance level of  $\alpha = .05$ . Finally, because this study employed a cross-sectional design, all path coefficients were interpreted as predictive associations rather than causal effects.

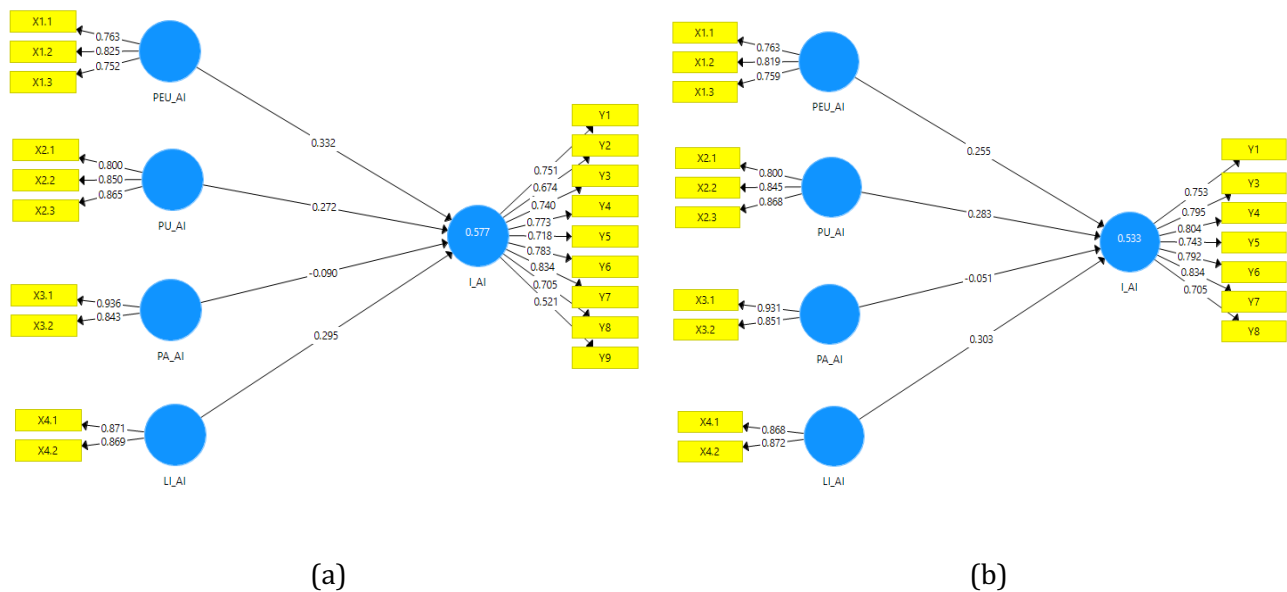
### 3. Results and Discussion

The empirical results are presented and interpreted in relation to students' perceptions of AI-supported geography learning. The analysis proceeds from measurement-model evaluation to structural-model evaluation and hypothesis testing. Because the data are cross-sectional and self-

reported, the path coefficients are interpreted as predictive associations among perceptions, not as evidence that AI caused changes in learning outcomes.

### 3.1 Measurement Model Evaluation (Outer Model)

A measurement model evaluation was conducted to ensure that each construct in the study met the validity and reliability criteria prior to structural equation modelling. Convergent validity was assessed using factor loadings. The results for the original model (see Figure 1a) showed that two indicators did not meet the criteria for convergent validity: indicator Y2 ( $\lambda_2 = .674$ ) and indicator Y9 ( $\lambda_9 = .521$ ), both below the threshold of .70. Methodologically, indicators with loading values below .70 may not adequately represent the latent construct and should therefore be eliminated to improve the quality of the measurement model (Hair et al., 2014). Consequently, the model was modified by removing indicators that did not meet these criteria, yielding a more stable and representative measurement model.



**Figure 1.** Loadings of the Measurement Model (Outer Model): Original Version (a) and Final Version (b)

The results for the final model (see Figure 1b) showed that all indicators had factor loadings above .70. The factor loadings for the PEU\_AI construct ranged from .759 to .819, whereas those for the PU\_AI construct ranged from .800 to .868. The PA\_AI construct had the highest factor loadings, ranging from .851 to .931, whereas the LI\_AI construct ranged from .868 to .872. For the I\_AI construct, all indicators also showed factor loadings above .70, ranging from .705 to .834. These results indicate that all indicators were strongly correlated with their respective constructs and adequately represented latent variables. Thus, the model met the criteria for convergent validity, as recommended in the PLS-SEM literature (Cheung et al., 2024; Hair et al., 2014).

In addition to factor-loading analysis, convergent validity was evaluated using the average variance extracted (AVE) (see Table 3). The test results showed that all constructs exceeded the minimum AVE threshold of .50, indicating that the latent constructs explained most of the variance in their indicators. The PA\_AI construct had the highest AVE, indicating a very strong representation of its indicators. Overall, the AVE values for all constructs indicated that perceived ease of use, perceived usefulness, personalisation and adaptivity, learning interactivity, and the impact of AI met the convergent validity criteria recommended in the PLS-SEM approach (Cheung et al., 2024; Hair et al., 2014). Thus, each indicator was considered capable of adequately and consistently reflecting the construct being measured.

The reliability of the constructs was assessed using the composite reliability (CR) score (see Table 3). All constructs showed CR scores above the threshold of .70, indicating good internal consistency among the indicators within each latent variable. The I\_AI construct had the highest reliability among the constructs, demonstrating very strong measurement stability for this variable. From a PLS-SEM perspective, a CR value exceeding .70 indicates that the instrument has sufficient reliability for further

structural analysis (Hair et al., 2014). These findings indicate that all indicators within each construct consistently measured the same concept and exhibited good measurement qualities.

**Table 3.** Construct Reliability, Convergent Validity, and Fornell-Larcker Results

|        | CR   | AVE  | Fornell-Larcker Criterion<br>(square root of AVE on diagonal) |       |       |        |       |
|--------|------|------|---------------------------------------------------------------|-------|-------|--------|-------|
|        |      |      | I_AI                                                          | LI_AI | PA_AI | PEU_AI | PU_AI |
| I_AI   | .913 | .602 | .776                                                          |       |       |        |       |
| LI_AI  | .862 | .757 | .661                                                          | .870  |       |        |       |
| PA_AI  | .886 | .795 | .445                                                          | .537  | .892  |        |       |
| PEU_AI | .824 | .610 | .653                                                          | .709  | .663  | .781   |       |
| PU_AI  | .877 | .703 | .668                                                          | .725  | .583  | .767   | .839  |

Discriminant validity was assessed using the Fornell-Larcker criterion (Table 3). Under this criterion, the square root of the average variance extracted ( $\sqrt{\text{AVE}}$ ) for each construct, shown on the diagonal, should exceed its correlation with the other constructs. The diagonal values were .776 for I\_AI, .870 for LI\_AI, .892 for PA\_AI, .781 for PEU\_AI, and .839 for PU\_AI; each exceeded the corresponding inter-construct correlations reported in Table 3. Thus, the Fornell-Larcker results support discriminant validity. Importantly, these diagonal values are the square roots of AVE, not RMSEA. Because Fornell-Larcker alone is insufficient for a contemporary discriminant validity assessment, HTMT values, preferably with bootstrap confidence intervals, should also be reported from the original PLS-SEM output before a definitive conclusion on discriminant validity is made (Henseler et al., 2014; Rönkkö & Cho, 2022).

Overall, the final measurement model met the reported criteria for convergent validity and composite reliability. The Fornell-Larcker results also support discriminant validity; however, this conclusion should be treated as provisional until the HTMT results are added from the original model output. Therefore, the structural model was interpreted as an analysis of predictive associations rather than causal effects.

### 3.2 Structural Model Evaluation (Inner Model)

After the measurement model was evaluated, the structural model was assessed to examine the strength of the predictive associations among the constructs. The I\_AI construct had an  $R^2$  of .533 and an adjusted  $R^2$  of .516, indicating that PEU\_AI, PU\_AI, PA\_AI, and LI\_AI jointly accounted for 53.3% of the variance in students self-reported I\_AI scores. This represents moderate explanatory power within the present sample and should not be interpreted as evidence of a causal relationship.

Effect sizes ( $f^2$ ) were examined to describe the incremental contribution of each exogenous construct to I\_AI. LI\_AI had the largest  $f^2$  (.082), followed by PU\_AI (.058) and PEU\_AI (.043), all of which represented small effects. PA\_AI had a negligible  $f^2$  (.003). Accordingly, learning interactivity was the strongest predictor in the specified model, but its incremental contribution was small.

The model fit was evaluated using the reported PLS-SEM indices. The SRMR value was .087, which is below the .10 threshold used in the manuscript. The reported  $d_{\text{ULS}}$  and  $d_{\text{G}}$  values were 1.146 and .589, respectively, while the NFI was .679. These indices are presented descriptively and should not be used to override deficiencies in the measurement validity or predictive assessment. In PLS-SEM, model evaluation should prioritise the quality of the measurement model, collinearity, explanatory power, effect sizes, and predictive assessment, in addition to global fit indices (Hair et al., 2014).

Taken together, the structural model results indicate that perceived ease of use, perceived usefulness, and learning interactivity are relevant correlates of students' self-reported perceptions of AI-supported geography learning. Learning interactivity had the largest path coefficient among all the tested predictors. These results are consistent with TAM-based arguments that perceived usefulness and ease of use are important for technology acceptance (Davis, 1989) and with digital-learning literature emphasising the role of interactive user experiences. However, the present questionnaire did not directly measure spatial thinking, GIS performance, map interpretation, or other objective geography-specific competencies; therefore, the findings should not be interpreted as evidence that AI improved these outcomes.

### 3.3 Identifying Key Factors in the Impact of AI on Geography Education

The structural path results indicate that LI\_AI, PU\_AI, and PEU\_AI were positively and significantly associated with I\_AI, but PA\_AI was not. Thus, H1, H2, and H4 were supported, whereas H3 was not. These findings indicate differences in the relative predictive relevance of the four perceived characteristics within the present sample rather than differences in objectively measured instructional effectiveness ( Table 4).

**Table 4.** Results of Hypothesis Testing for the Structural Model

| Relationship                  | Coefficient ( $\beta$ ) | t-value | p-value |
|-------------------------------|-------------------------|---------|---------|
| H4: LI_AI $\rightarrow$ I_AI  | .303                    | 2.738   | .006    |
| H2: PU_AI $\rightarrow$ I_AI  | .283                    | 2.401   | .017    |
| H1: PEU_AI $\rightarrow$ I_AI | .255                    | 2.231   | .026    |
| H3: PA_AI $\rightarrow$ I_AI  | -.051                   | 0.526   | .599    |

Learning interactivity (LI\_AI) had the largest positive path coefficient for I\_AI ( $\beta = .303$ ,  $p = .006$ ), thus supporting H4. This suggests that students who perceived AI-supported learning as more interactive also tended to report stronger perceived impact and acceptance-related responses. This finding is consistent with the literature linking digital interactivity to engagement and learning experiences (Huong et al., 2020; Jain & Getis, 2003). Because the questionnaire did not directly measure map visualisation, regional simulation, spatial data analysis, or learning gains, the results should be interpreted at the level of students' perceptions rather than as evidence of improved geography competencies.

Perceived usefulness (PU\_AI) was positively associated with I\_AI ( $\beta = .283$ ,  $p = .017$ ), thus supporting H2. Students who regarded AI as helpful for understanding geography, improving learning productivity, and increasing interest tended to report a stronger perceived impact of AI-supported learning. This pattern is consistent with the Technology Acceptance Model, in which perceived usefulness is a central determinant of technology acceptance (Dahri et al., 2024; Davis, 1989; Yang & Xiao, 2026). The results concern perceived usefulness and should not be interpreted as a direct measure of academic achievement.

Perceived ease of use (PEU\_AI) was positively associated with I\_AI ( $\beta = .255$ ,  $p = .026$ ), supporting H1. Students who perceived AI-supported learning as easier to use, more efficient, and more accessible tended to report a stronger perceived impact. This result is consistent with technology-acceptance research showing that ease of use can support favourable perceptions of digital learning technologies (Al-Adwan et al., 2021; Sprenger & Schwaninger, 2021). No causal conclusions can be drawn from this cross-sectional association.

The personalisation and adaptivity construct (PA\_AI) was not significantly associated with I\_AI ( $\beta = -.051$ ,  $p = .599$ ); therefore, H3 was not supported. Within this sample, perceiving AI as capable of tailoring materials or difficulty levels did not correspond to a stronger perceived impact after considering the other predictors. This context-specific null result does not demonstrate that personalisation is ineffective; it indicates only that the measured personalisation construct did not provide a statistically significant unique contribution to the present model. Differences in implementation quality, user expectations, or overlap with other perceived characteristics may help explain these results (Ogbuke et al., 2022; Zawacki-Richter et al., 2019).

Therefore, the nonsignificant PA\_AI path should be interpreted cautiously. This may indicate that, in this specific single-university sample, interactivity, usefulness, and ease of use were more salient to students' reported experiences than the two measured personalisation items. A single nonsignificant path is insufficient to establish a new "personalisation paradox" or a general shift away from personalisation-driven learning. Replication with stronger measures of adaptive functionality and multiple institutional contexts is needed before making such theoretical claims.

Overall, the findings show positive associations between learning interactivity, perceived usefulness, and perceived ease of use and students' self-reported I\_AI scores, whereas personalisation and adaptivity showed no significant unique association. Therefore, the evidence supports a cautious conclusion that interactive, useful, and easy-to-use AI-supported learning experiences are related to more favourable student perceptions in this sample. The study did not directly test GIS use, spatial visualisation, regional analysis, spatial thinking, or objective learning performance; therefore, practical

implications should remain focused on the design of accessible and engaging AI-supported learning rather than claims of demonstrated improvement in geography competencies.

#### 4. Conclusion

This study examined factors associated with Generation Z students' self-reported perceptions of AI-supported geography learning. Learning interactivity ( $\beta = .303$ ,  $p = .006$ ), perceived usefulness ( $\beta = .283$ ,  $p = .017$ ), and perceived ease of use ( $\beta = .255$ ,  $p = .026$ ) were positively associated with I\_AI, whereas the personalisation and adaptivity construct was not ( $\beta = -.051$ ,  $p = .599$ ). The results suggest that, within this single-university sample, students' perceptions of interactivity, usefulness, and ease of use were more salient predictors of perceived AI-supported learning than the measured personalisation construct was. These findings concern the relationships among self-reported perceptions. The study did not implement or compare an AI intervention, measure actual learning outcomes, or assess spatial thinking, GIS performance, map interpretation or real-time visualisation. Consequently, the results should not be interpreted as evidence of the effectiveness of AI or as a causal improvement in geography learning. However, several limitations qualify these conclusions. The use of convenience sampling at one state university restricts generalisability, and the cross-sectional design cannot establish temporal order or causality. The instrument was platform-neutral and focused on general perceptions of AI-supported learning rather than specific AI systems or objectively measured geography competencies. Future research should use multi-institutional samples, longitudinal or experimental designs, validated measures of acceptance and learning outcomes, and explicit measures of geography-specific competencies when making claims about spatial thinking or geospatial learning. Future studies should also examine digital readiness, AI literacy, system quality, and more detailed adaptive learning features as potential explanatory variables.

**Funding.** This research received no external funding

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

**Data availability.** The datasets generated during this study are not publicly available due to privacy, but are available from the corresponding author upon reasonable request

**AI Use Declaration.** The authors used Grammarly and Gemini for paraphrasing. All outputs were reviewed and verified by the authors, who take full responsibility for the accuracy and integrity of the manuscript.

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