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Do Generation Z Pre-Service ESL Teachers Perceive Artificial Intelligence Negatively? Rasch Analysis

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Abstract
This study investigates the negative attitudes of pre-service English as a Second Language (ESL) teachers toward the integration of Artificial Intelligence (AI) in education. Using a quantitative cross-sectional survey design, data were collected from 363 undergraduate students enrolled in teacher education programs. The participants completed the Negative Attitudes Toward Artificial Intelligence (NATAI) scale which was validated through expert review. Rasch model analysis was employed to examine item fit, reliability, and unidimensionality. The instrument demonstrated high internal consistency (Cronbach's Alpha = 0.84), strong person and item reliability (0.80 and 0.98, respectively), and solid construct validity. The Wright Map revealed a moderate to high concern among students, particularly about AI's emotional and ethical implications. Differential Item Functioning (DIF) analysis based on year of study and gender showed minimal variation across groups, with third-year students expressing slightly stronger ethical concerns. A one-way ANOVA and independent t-test confirmed no significant difference in attitudes based on the year of study, suggesting uniform skepticism across cohorts. These findings imply a need for teacher education curricula to address AI literacy and integrate balanced perspectives to prepare future educators for AI-enhanced classrooms.
Keyword: *Artifical Intelligence, Educational Technology, Generation Z, Pre-servuce ESL Teacher, Rasch Analysis*

INTRODUCTION

The 21st century has witnessed an extraordinary acceleration in the development and implementation of educational technology. Digital tools, online platforms, and data-driven systems are increasingly transforming traditional educational practices, paving the way for more personalized, flexible, and interactive learning environments (Cukurova, 2025; Wang & Huang, 2025). At the forefront of this transformation is Artificial Intelligence (AI), a field of computer science focused on building systems capable of performing tasks that typically require human intelligence. These tasks include language understanding, problem-solving, decision-making, and learning from experience. In education, AI has emerged as a game-changing innovation, offering tools and solutions that support both teaching and learning in unprecedented ways (Leong, Leong, & San Leong, 2024).

The presence of AI in education is no longer futuristic; it is already here and expanding rapidly (Pham & Sampson, 2022; Zhai, et. al., 2021). Intelligent tutoring systems can now adapt to students' learning styles and paces, offering immediate and tailored feedback. Automated essay scoring systems help assess student writing efficiently, while AI-driven chatbots provide real-time assistance for learners outside of class hours. Additionally, AI is embedded in tools that support content creation, grammar checking, lesson planning, and language learning (Guo, Zheng, & Zhai, 2024). These developments mark a significant shift in how knowledge is delivered and acquired, signaling the dawn of an AI-enhanced educational era.

A variety of AI tools have gained popularity among students and teachers alike. Tools such as ChatGPT, Grammarly, QuillBot, Google Bard, and Duolingo are widely used in both formal and informal learning contexts. These platforms assist with generating text, improving language use, paraphrasing content, translating text, and practicing foreign languages. In the context of English as a Second Language (ESL) education, such tools offer unique benefits. For instance, ESL learners can use AI to receive instant grammar corrections, vocabulary suggestions, and pronunciation support. Teachers, on the other hand, may rely on AI for developing teaching materials, generating assessments, and automating repetitive tasks.

Despite the apparent advantages, the use of AI in education remains a controversial topic. Advocates argue that AI enhances efficiency, supports individualized learning, and bridges gaps in accessibility (Kamalov, Santandreu Calonge, & Gurrib, 2023). For instance, AI can provide differentiated instruction that caters to diverse learner needs, a task that is often difficult to achieve in large classrooms. Additionally, it can help reduce teacher workload by automating administrative functions and providing insights through learning analytics (Schiff, 2022; Srinivasa, Kurni, & Saritha, 2022).

However, critics raise important concerns about the implications of AI in education. A growing body of literature and anecdotal evidence suggests that many educators perceive AI as a double-edged sword (Nguyen, Ngo, Hong, Dang, & Nguyen, 2023). Some believe that AI tools may lead to over-reliance among students, reduce human interaction, or compromise the development of higher-order thinking skills (Lee, & Kwon, 2024; Luan, et. al., 2020). Others argue that AI may perpetuate biases, threaten teacher autonomy, or undermine academic integrity by facilitating plagiarism and shortcut learning. These concerns are particularly pronounced among those who view AI as a threat to traditional pedagogical values and the humanistic aspects of teaching (Mhlanga, 2023; Wang, Wang, Zhu, Wang, Tran, & Du, 2024).

Given this tension, understanding teachers' attitudes toward AI is crucial. Teachers play a pivotal role in determining the success or failure of educational innovations (Galindo-Domínguez, Delgado, Campo, & Losada, 2024). If educators hold negative perceptions of AI, they may resist its use, limit its integration, or discourage students from engaging with AI tools—regardless of the tools' actual educational value. Thus, the success of AI in educational settings partly depends on how current and future teachers perceive and interact with it (Yue, Jong, & Ng, 2024).

In this context, examining the perceptions of Generation Z (Gen Z) pre-service ESL teachers becomes particularly relevant. Gen Z, typically defined as individuals born between 1995 and 2012, represents the first generation to grow up with smartphones, social media, and high-speed internet (Erişen, & Bavlı, 2024). As digital natives, members of Gen Z are often assumed to be tech-savvy, comfortable with innovation, and open to using new technologies in both personal and professional contexts. Given their familiarity with digital tools, one might expect them to embrace AI as a natural extension of their technological ecosystem (Chan, & Lee, 2023). However, emerging evidence suggests that digital nativeness does not automatically translate to positive attitudes toward all forms of technology—especially those that are complex, ethically ambiguous, or potentially disruptive, such as AI. In fact, Gen Z pre-service teachers may also harbor concerns about AI's role in education, especially in shaping the cognitive, emotional, and social development of students. These concerns might be shaped by personal values, educational philosophies, previous experiences with technology, or exposure to public discourse about AI's risks.

Therefore, it is essential to investigate the extent to which Gen Z pre-service ESL teachers view AI negatively. Their attitudes are not only indicative of the broader generational response to AI in education but are also likely to influence how they implement (or avoid) AI in their future teaching practices. As future educators, their perceptions will shape classroom technology adoption and, consequently, the learning experiences of their students.

Despite the growing interest in AI integration within educational research, there remains a significant research gap concerning negative attitudes toward AI (NATAI) among Gen Z pre-service teachers, particularly in the field of ESL education. Most existing studies tend to focus on general teacher readiness, AI acceptance models, or ethical debates surrounding AI use. Few have employed rigorous psychometric approaches—such as Rasch analysis—to measure latent constructs like negative attitudes in a reliable and valid manner. Additionally, demographic variables such as gender and year of study, which may influence attitudes toward AI, are often overlooked or analyzed in a superficial manner. To address this gap, the present study seeks to explore how Gen Z pre-service ESL teachers perceive AI, with a specific focus on negative attitudes toward AI (NATAI). Utilizing Rasch modeling, this research aims to provide a robust measurement of NATAI levels and to examine whether these attitudes vary according to gender and academic standing.

METHODS

Research Design

This study employed a quantitative research approach using a cross-sectional survey design. A cross-sectional survey involves collecting data from a population or a representative subset at a single point in time (Qudratuddarsi, Meivawati, & Saputra, 2024). This design is commonly used in social science and educational research to examine the current status of attitudes, behaviors, opinions, or characteristics across a sample (Bloomfield, & Fisher, 2019; Goertzen, 2017). This design is suitable for this study purposes to gain a better understanding of a group of students related to AI.

Research Subject

Participants were recruited through convenience sampling, with the consideration that research could be carried out effectively and efficiently as they were students enrolled in courses taught by the researchers (Etikan, Musa, & Alkassim, 2016; Golzar, Noor, & Tajik, 2022). Table 1 presents the distribution of the study sample based on gender and year of study. The total number of participants is 363. In terms of gender, the majority of respondents are female, accounting for 314 individuals or 86.50% of the total sample, while male participants represent only 49 individuals or 13.50%. Regarding the year of study, the largest proportion of participants are second-year students, comprising 203 individuals or 55.92%. This is followed by third-year students with 121 participants (33.33%), and first-year students with 39 participants (10.74%). Overall, the sample is predominantly composed of female and second-year students.

Table 1. Distribution of sample

Sample	N	Percentage
Gender		
Male	49	13.50%
Female	314	86.50%
Year of study		
First year	39	10.74%
Second year	203	55.92%
Third year	121	33.33%
Total	363	100 %

Instrument

The instrument used in this study was adapted from the work of Schepman and Rodway (2020), who developed a scale to measure general attitudes toward Artificial Intelligence (AI). To better align with the specific context of this research, several of the original statements were modified to reflect a focus on positive attitudes toward AI in the educational setting. These adapted items were reviewed and validated by three subject matter experts in the fields of educational technology and psychometrics. Their feedback was used to refine the wording, clarity, and contextual relevance of the statements, thereby enhancing the instrument's content validity.

Reliability and Separation

Table 2 presents the reliability and separation indices for the NATAI scale, which measures pre-service ESL teachers' negative attitudes toward artificial intelligence in education. The results indicate strong psychometric qualities of the scale. The person reliability value is 0.80, which suggests a high level of internal consistency in the responses among the participants. This means that the scale can reliably distinguish individuals based on their levels of negative attitudes toward AI (Qudratuddarsi, Hidayat, Nasir, Imami, & bin Mat Nor, 2022). Even more impressively, the item reliability is 0.98, indicating that the sample was sufficiently large and diverse to provide stable and replicable estimates of item difficulties. The Cronbach's Alpha coefficient of 0.84 further supports the internal consistency of the instrument, reflecting that the items collectively measure a cohesive underlying construct—negative attitudes toward AI.

In terms of separation indices, the person separation value of 2.02 indicates that the scale can distinguish between approximately two distinct levels of negative attitude among respondents. This means the instrument is capable of grouping individuals into low and high negative attitude categories with reasonable accuracy. The item separation index of 7.62 is exceptionally strong, implying that the items vary widely in their difficulty levels and can be reliably ranked along the continuum of negativity toward AI. This wide spread of item difficulties enhances the scale's usefulness in differentiating between various intensities of negative perception. Finally, the significant chi-square value ($\chi^2 = 5777.65$, df = 2510, $p < .01$) indicates that the differences in item difficulty are statistically significant, further validating the measurement precision of the instrument.

Table 2. Reliability and Separation of NATAI

Indicator	Value
Person Reliability	0.80
Item Reliability	0.98
Cronbach Alpha	0.84
Person Separation	2.02
Item Separation	7.62
Chi-square	5777.65^{**} (d.f. 2510)

Item Fit Statistics

Table 3 presents the item fit statistics for the NATAI scale, including Infit and Outfit Mean Square (MNSQ) values and the Point-Measure Correlation (Pt Mea Corr) for each item. In Rasch measurement, acceptable MNSQ values typically range from 0.6 to 1.5, indicating that items are functioning in line with model expectations. All items in the NATAI scale fall within this acceptable range, suggesting that each item contributes meaningfully to the measurement of negative attitudes toward AI among pre-service ESL teachers. Specifically, Items NATAI1, NATAI2, NATAI3, and NATAI7 exhibit MNSQ values below 1.0, indicating that respondents' responses to these items are slightly more predictable than expected, which often reflects strong item functioning. Items NATAI4, NATAI5, NATAI6 and NATAI8 fall close to 1.0, indicating ideal fit.

The Point-Measure Correlations (Pt Mea Corr) for all items are positive and relatively high, ranging from 0.56 to 0.77, indicating strong and consistent alignment between each item and the overall measure of negative attitude toward AI. Item NATAI3 shows the highest correlation (0.77), suggesting it is one of the most central items in reflecting the core construct. Although Items NATAI5 and NATAI6 have the lowest Pt Mea Corr values (0.56 and 0.61, respectively), they still fall within an acceptable range and provide meaningful contributions to the scale, particularly in capturing more affective or speculative dimensions of negative perception.

Table 3. Item Fit Statistics of NATAI

Item	MNSQ		Pt Mea Corr
	Infit	Outfit	
NATAI1	0.82	0.82	0.73
NATAI2	0.82	0.82	0.72
NATAI3	0.76	0.76	0.77
NATAI4	1.14	1.15	0.72
NATAI5	1.43	1.42	0.56
NATAI6	1.23	1.24	0.61
NATAI7	0.81	0.80	0.68
NATAI8	0.93	0.92	0.67

Unidimensionality

Table 4 presents the unidimensionality analysis of the NATAI scale based on Rasch model output. Unidimensionality is a crucial assumption in Rasch measurement, indicating that the set of items primarily measures a single underlying construct—in this case, pre-service ESL teachers' negative attitudes toward artificial intelligence (Von Davier, 2016). The analysis shows that 27.8% of the raw variance is explained by the persons, and 22.0% is explained by the items, while the total variance explained by the measures is 49.8%. This indicates that nearly half of the variability in responses is accounted for by the Rasch model, which is a strong indicator that the scale is functioning as intended. To assess whether a secondary dimension might be present, the unexplained variance in the first contrast of the residuals is examined. The eigenvalue of 2.4 for the first contrast and its corresponding percentage of 14.8% suggest that while there is some residual variance not captured by the primary measurement dimension, it does not exceed the critical threshold that would suggest a serious threat to unidimensionality. In Rasch analysis, a first contrast eigenvalue below 3.0 and unexplained variance below 15% are generally considered acceptable, indicating that no major secondary dimension is undermining the scale's measurement validity.

Table 4. Unidimensionality of PATAI

	Value
Raw variance explained by persons	27.8%
Raw variance explained by items	22.0%
Raw variance explained by measures	49.8%
Unexplained variance in 1st contrast (eigenvalue)	2.4
Unexplained variance in 1st contrast (percentage)	14.8%

Data Collection

To collect the data, the researcher met participants directly through a door-to-door approach. This method ensured that participants clearly understood the purpose of the questionnaire and provided an opportunity to ask questions if they found any items confusing. Before completing the questionnaire, the researcher explained its purpose and emphasized that participation was entirely voluntary and would not affect the participants' grades (Hammer, 2017; Suhonen, Stolt, Katajisto & Leino-Kilpi, 2015). The questionnaire was administered using Google Forms to promote environmental sustainability by reducing paper usage compared to traditional paper-based surveys. Additionally, this method allowed for easier data management and analysis, as digital responses could be automatically recorded and organized. It also ensured better accuracy in data entry and minimized the risk of losing responses (Aktar, et. Al., 2020).

Data Analysis

The collected data were compiled into an Excel (.xls) file format to facilitate further analysis. The data were then processed using WINSTEPS, a software program designed for Rasch model measurement analysis. WINSTEPS allows for detailed and reliable examination of item and person performance based on Rasch principles. In this study, several key outputs from WINSTEPS were considered. First, the Wright Map was used to visualize the distribution of person abilities and item difficulties on the same scale, offering insight into the instrument's effectiveness. Second, a Differential Item Functioning (DIF) analysis was conducted based on participants' year of study, followed by a one-way ANOVA to determine whether there were statistically significant differences across groups. Third, a separate DIF analysis was carried out based on gender, and this was followed by an independent samples t-test to examine differences between male and female pre-serice ESL teachers (Rahayu, Meiliyanti & Rabbani, 2024).

RESULTS AND DISCUSSION

Wright Map

The analysis of perceptions regarding negative attitude toward artificial intelligence (NATAI) in education, conducted through the Rasch model approach, is presented in the form of a Wright Map (Item–Person Map)(Figure 1). This map displays the distribution of both items and respondents on a single logit continuum, allowing for an assessment of how well item difficulty aligns with the respondents' tendencies to agree with specific statements. At the top of the map (higher logits), items such as NATAI3 ("AI in teaching and learning is dangerous"), NATAI2 ("The use of AI in schools/campuses is unethical"), and NATAI4 ("AI is used for cheating") are located. Their position at the high end of the logit scale indicates that these statements were more difficult for respondents to endorse, meaning only those with strong negative perceptions of AI agreed with them. This suggests that extreme concerns or moral objections toward AI are not widely held among the participants.

Items around the middle of the scale (approximately logit 0), such as NATAI1 ("The use of AI is dangerous"), NATAI6 ("AI will control teachers and students"), and NATAI7 ("AI makes many mistakes"), indicate that respondents were more divided in their opinions. These items reflect moderate concerns that are still open to discussion and may be influenced by context, individual experiences, or varying levels of AI literacy. Conversely, items like NATAI5 ("I feel afraid...") and NATAI8 ("I would suffer as a teacher...") are located at the lower end of the logit scale, making them easier to endorse. Their position suggests that many respondents found these emotionally framed items relatable, revealing that personal and emotional concerns about AI's impact on future teaching roles are more prevalent. These concerns may stem from uncertainty, lack of control, or fear of being replaced or devalued by technology.

The distribution of persons on the right side of the map is relatively well spread across the logit continuum, though a noticeable concentration appears between 0 and +2 logits. This indicates that most respondents had moderate to somewhat high levels of concern about the negative use of AI in education. Very few respondents appeared at the extremes, suggesting that perceptions of AI among this group were not highly polarized but generally cautious or concerned.

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       Item - MAP - Person
         <rare>|<more>
    6          +  00111  01921  05122
               |  06312
    5          +
    4          +
               |  00711  16212
    3          +  02912  04012
               |  09512
               |T
               |  04212  05812  11113  18012
               |  01811  02412  02822  03621  03711  05512  05622  10112  12022 34813
                  20613  22113  22813  23013  23313  26313  29613  29923  31712 32012
    2          +
               |  00521  12212  19712  26413  26723  33111  34723
               |  18812  22913  24913  28112  33311
               |  11213  16112  21513  21613  23413  24913  27712  33423  35222
              T|S
    1          +  00311  04612  05212  06512  07311  11612  19213  23713  25413
                  26113  30812  34213
       NATAI3  |  01111  03912  04912  07412  08112  11512  13422  14412  17312
                  19312  21413  27212  29412  31612  32123  32613  33212
NATAI2 NATAI4 S|  03112  05712  07111  09012  09612  10212  10712  13312  13912 34123
                  15812  17412  17612  19612  24213  28812  32213  32513  33823
       NATAI1  |  02011  02111  06811  06911  07512  09312  09412  09812  11913
                  12312  12712  16712  16812  17212  17912  18113  20212  20412
                  22423  24113  24513  24823  25013  28412  28712  29012  29312
                  29512  31822  34321  34513  35323  35813  36012
    0  NATAI6 M+  00411  00911  01621  02212  02612  03211  03411  03511  04112
                  04712  04822  05312  05912  06012  07812  08012  08212  08312
                  08412  08512  08712  08812  08912  09212  10012  10412  10612
                  11712  12512  12612  12912  13812  14912  15112  15312  15612
                  15712  15913  16412  16512  18413  18523  18622  18722  20513
                  20723  20823  21323  22213  23913  24613  25113  27112  27312
                  27412  28012  28612  30012  30112  30212  30322  30412  30512
                  31012  31212  31412  31512  32313  33613  33913  34413  34613
                  34913  35013  35113  35413  35623
        NATAI7 |M
        NATAI8 |  01511  02322  02512  04312  09112  14012  14713  15212  15412
                  16312  19112  24313  25213  25313  25513  26513  27612  28312
                  29212  30612
              S|  01211  05422  06712  07211  09712  10813  11313  11412  11812
                  12112  13612  14112  14312  16612  18213  19012  19912  20312
                  21113  23113  23613  25613  27812  28212  33713  35723  36111
               |  00611  01321  06612  10512  11013  12412  13022  13212  14212 33013
                  16912  17512  20112  21713  23813  24713  25813  28912  31923 35913
   -1          +
       NATAI5 T|  03311  07612  09912  10312  13112  13512  14613  15512  16012
                  19412  19912  20012  21013  22613  23513  24413  29112  34013
               |S 06212  07912  17712  17812  18313  19512  25923  26813  26923
                  27022  27912  31312  33523
               |  03012  03811  04412  07011  14512  18912  21813  22013  22313
                  22513  28512  29713  30912  32723
               |  00211  07712  23213  24023  26023  29813
   -2          +
               |  00811  01411  01721  05012  06113  08612  15012  21913  30712
                  32913  36313
               |  04512  13712  32822  35513
               |T 14813  17012  17112  21213  25713  31112  32421  36213
   -3          +  01011  12812  19822  22713  26213  26613  27512
               |  02722
               |  06412
   -4          +
        <frequ>|<less>
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Figure 1. Wright Map

DIF analysis based on year of study

The Person DIF plot based on the Rasch model was analyzed to examine differences in negative attitudes toward AI among first-year (Group 1), second-year (Group 2), and third-year (Group 3) pre-service ESL teachers. The analysis was conducted across eight negatively worded items (NATAI1–NATAI8) related to perceptions of AI in the teaching and learning process. Overall, the DIF values for most items remained relatively consistent across the three groups, suggesting that year of study had minimal influence on how the items were interpreted. However, several notable patterns emerged.

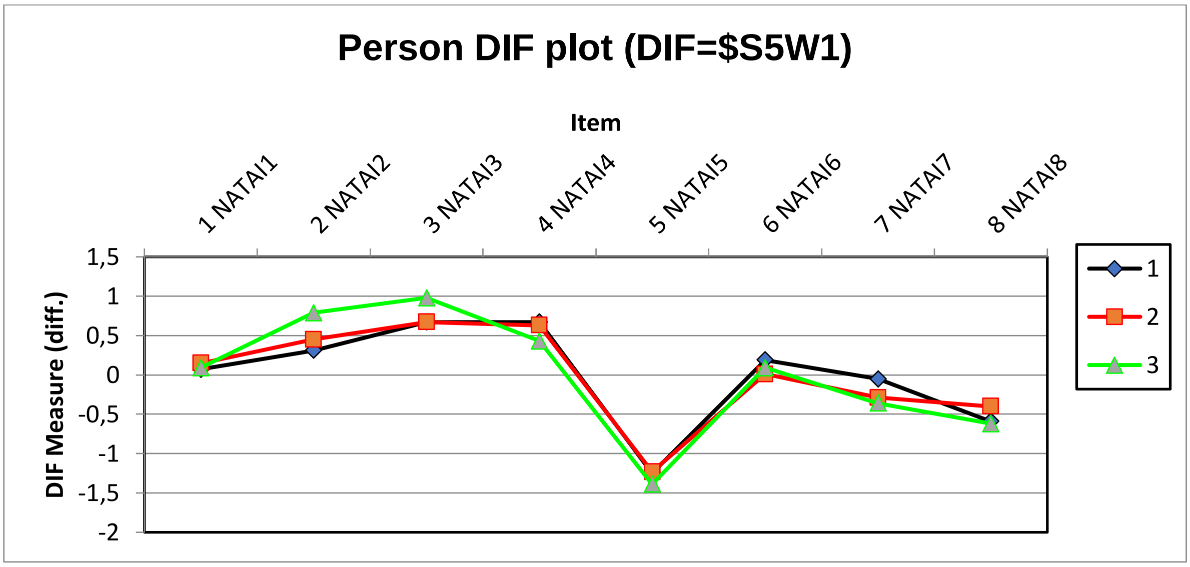

Figure 2. DIF analysis based on year of study

For Item 1 ("The use of AI in teaching and learning is dangerous"), all three groups showed similar responses, with only slight variations, indicating a shared perception of AI's potential risk. A clearer separation emerged in Item 2 ("The use of AI in schools/universities is unethical") and Item 3 ("The use of AI in teaching and learning is evil"), where third-year students (Group 3) reported noticeably more negative responses than the first- and second-year students. This may suggest that students in more advanced stages of their training have developed stronger ethical concerns or critical reflections about AI integration in education, possibly due to increased exposure to classroom environments and pedagogical discussions. Item 4 ("AI is used to cheat in the teaching and learning process") displayed minimal DIF across all groups, implying that perceptions about AI-facilitated cheating are consistent regardless of academic level. In contrast, Item 5 ("I feel afraid when imagining the negative impact of AI on the future of education") revealed the largest DIF, with third-year students showing the strongest fear response. This could indicate heightened anxiety among more experienced pre-service teachers about their future roles, job security, or the transformative influence of AI on the teaching profession. Meanwhile, first- and second-year students appeared less apprehensive, possibly due to their limited immersion in real teaching scenarios.

Item 6 ("AI will control teachers and students in the teaching and learning process") revealed moderate alignment across all groups, with only slight differences, suggesting a general shared concern about AI and autonomy. Items 7 ("AI often makes mistakes when used in the teaching and learning process") and 8 ("I would suffer as a teacher if AI continues to be used") showed very minimal DIF among the three groups. This consistency implies that regardless of their academic progression, pre-service teachers tend to hold a similar level of skepticism about AI's reliability and emotional impact on their future roles.

To confirm the findings, A one-way ANOVA was conducted to examine whether students' responses on positive attitude toward AI differed significantly based on their year of study (first year, second year, third year). The results of the one-way ANOVA, $F(2, 360) = 1.076$, $p = .342$, indicate no statistically significant difference in positive attitudes toward AI among pre-service ESL teachers based on their year of study. This suggests that negative perceptions of AI are consistent across all academic levels. One possible explanation is that Generation Z students, regardless of whether they are in their first, second, or third year, share common experiences as digital natives. Growing up in a technology-rich environment, they are familiar with AI but may still harbor skepticism toward its role in education, particularly in language teaching, where human interaction is central. Furthermore, many pre-service ESL programs may not offer differentiated or in-depth exposure to AI tools across different years, resulting in a uniform knowledge base and set of attitudes. If the curriculum lacks progressive integration of AI concepts, students in all years are likely to form similar impressions—often shaped more by societal narratives about AI, such as concerns over job displacement or ethical issues, than by academic learning. Additionally, the limited incorporation of AI in pedagogical training means students may not fully grasp its educational potential, leading to cautious or negative views that do not shift significantly as they advance through their studies.

Table 5. One Way ANOVA result

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.846	2	.423	1.076	.342
Within Groups	141.547	360	.393		
Total	142.393	362			

DIF analysis based on Gender

The Person DIF plot based on the Rasch model was analyzed to identify whether there were differences in how female (Group 1) and male (Group 2) pre-service ESL teachers responded to eight negatively worded items related to attitudes toward AI in education as shown in Figure 3.

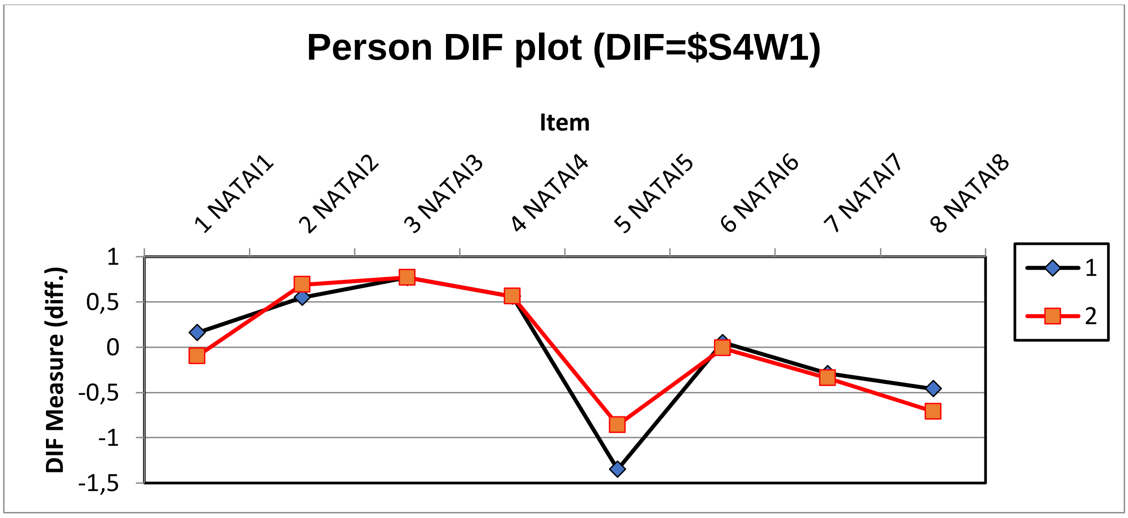

Figure 3. DIF analysis based on Gender

Overall, the results show that most items do not exhibit substantial Differential Item Functioning (DIF), indicating that male and female respondents generally interpreted and responded to the items similarly. However, some items showed minor variations worth noting. For Item 1 ("The use of AI in teaching and learning is dangerous") and Item 2 ("The use of AI in schools/universities is unethical"), female participants reported slightly more negative attitudes than males, suggesting they may perceive AI as more ethically problematic or potentially harmful in educational contexts. A similar pattern was seen in Item 3 ("The use of AI in teaching and learning is evil"), where females again showed slightly stronger agreement, although the difference was not large. No significant difference was observed in Item 4 ("AI is used to cheat in the teaching and learning process"), indicating that both genders shared a similar perception of the risk of cheating associated with AI. Notably, Item 5 ("I feel afraid when imagining the negative impact of AI on the future of education") showed the largest DIF, with male participants demonstrating a significantly stronger fear response than females.

This suggests that males may be more anxious about the long-term implications of AI in education, such as job security or professional relevance. In Item 6 ("AI will control teachers and students in the teaching and learning process"), females showed slightly more concern, potentially reflecting sensitivity to issues of autonomy and control. For Items 7 ("AI often makes mistakes when used in the teaching and learning process") and 8 ("I would suffer as a teacher if AI continues to be used"), both groups reported similar levels of agreement, with only minimal differences observed. These results suggest that while male and female pre-service ESL teachers generally share similar negative perceptions of AI, some gender-based nuances exist. Females appear more attuned to ethical and control-related concerns, whereas males express deeper fears about the long-term impact of AI. Nonetheless, the magnitude of these differences is relatively small, indicating that the items function fairly across gender and that the scale is generally free of significant bias.

An independent samples t-test was conducted to examine whether there was a significant difference between male and female pre-service ESL teachers in terms of their negative attitudes toward artificial intelligence (AI). Before interpreting the results of the t-test, Levene's Test for Equality of Variances was performed to assess whether the assumption of equal variances could be met. The test yielded a significance value of 0.046, which is below the conventional alpha level of 0.05. This indicates a statistically significant difference in variances between the two groups, suggesting that the assumption of equal variances was violated. As a result, the t-test results under the "equal variances not assumed" condition were considered more appropriate for interpretation.

Table 6. t-test result

		t-test for Equality of Means						
							95% Confidence Interval	
		T	df	Sig.	Mean Difference	Std. Error Difference	Lower	Upper
score	Equal variances assumed	-.813	361	.417	-.07831	.09638	-.26785	.11123
	Equal variances not assumed	-.678	57.436	.501	-.07831	.11555	-.30965	.15303

The results of this test showed a t-value of -0.678 with 57.436 degrees of freedom and a p-value of 0.501. Since the p-value is substantially higher than 0.05, it can be concluded that there is no statistically significant difference between male and female pre-service ESL teachers in their negative attitudes toward AI. Although the mean difference was -0.07831, indicating that male respondents scored slightly lower on negative attitude than their female counterparts, the difference is minimal and not statistically meaningful. Furthermore, the 95% confidence interval for the mean difference ranged from -0.30965 to 0.15303, which includes zero, further confirming that the observed difference could have occurred by chance. These results suggest that gender does not significantly influence how pre-service ESL teachers perceive AI negatively, and that both male and female respondents, despite minor individual variation, tend to hold similarly cautious or critical views toward AI integration in language teaching contexts.

CONCLUSION

This study offers a comprehensive look at how pre-service ESL teachers perceive the use of Artificial Intelligence in educational settings, specifically focusing on negative attitudes. The findings, supported by robust Rasch model analysis, demonstrate that while most respondents exhibited moderate concerns about AI, especially regarding its emotional and ethical impact, their attitudes were not significantly influenced by gender or year of study. Items related to fear of future displacement and ethical misuse of AI garnered higher agreement, suggesting an underlying anxiety about the evolving role of educators in an AI-integrated classroom.

The consistency in attitudes across all academic levels implies that current teacher education programs may not be providing differentiated or progressive exposure to AI-related pedagogical content. This uniformity could stem from a shared generational experience with technology but also signals a gap in formal training related to AI tools and their educational applications. Furthermore, while third-year students exhibited slightly stronger ethical concerns, this did not translate into statistically significant differences, reinforcing the need for curriculum enhancements across all levels of teacher training.

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