

Personalized Skill Development in STEAM Education Using AI tools

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Abstract—This research explores the role of Artificial Intelligence (AI) can enhance personalized skill development within STEAM (Science, Technology, Engineering, Arts, and Mathematics) education. Using a mixed-method approach, it examines both quantitative learning outcomes and qualitative perceptions of educators and students. The study explores awareness, personalization, and the perceived effectiveness of AI-enabled learning. Findings indicate moderate AI literacy and positive perceptions of personalization, with inclusivity and skill development rated highest. However, gaps in AI familiarity, training, and ethical understanding were observed. The study recommends structured AI literacy programs, professional development for educators, and equitable implementation frameworks to maximize the pedagogical impact of AI in STEAM contexts.

Index Terms—Artificial Intelligence, STEAM Education, Personalized Learning, AI Literacy, Skill Development, Inclusivity.

I. INTRODUCTION

Background and Context

The global shift toward a knowledge-driven economy has placed increasing emphasis on developing 21st-century skills such as creativity, collaboration, critical thinking, and problem-solving. These skills can be learned most effectively through STEAM education—an approach that connects different subjects like Science, Technology, and Engineering, Arts, and Mathematics (Yakman & Lee, 2012). STEAM not only fosters analytical thinking but also encourages learners to synthesize knowledge across domains, thereby promoting innovation and creativity. However, one persistent challenge in STEAM education lies in catering to the individual learning needs and skill levels of diverse students. Traditional classroom instruction often adopts uniform teaching methods that overlook personal learning preferences,

pace, and interests (Holmes et al., 2019). In the past few years, Artificial Intelligence (AI) has become a powerful force bringing major changes in education, enabling new types of personalized learning that adapt dynamically to individual learners. AI tools like smart tutoring systems, machine learning methods, and personalized learning platform have demonstrated significant potential in customizing instruction, providing feedback, and predicting learner performance (Chen et al., 2020). Within the STEAM context, AI can analyze students' cognitive and creative patterns, allowing for personalized skill development that matches with both academic and professional competencies. As AI continues to evolve, it is redefining the educational landscape by bridging the gap between learners' unique potential and standardized curricular goals.

Rationale of the Study

While AI-enabled personalization has been widely explored in general education and online learning environments, its application in STEAM education remains underexplored. Most studies have focused on either AI-based assessment systems or isolated learning applications, rather than holistic integration aimed at nurturing a spectrum of STEAM-related skills (Zawacki-Richter et al., 2019). Furthermore, educators often face challenges in implementing AI tools effectively due to limited training, infrastructural barriers, and ethical concerns including concerns like data security and bias (Luckin et al., 2016).

Given that STEAM education inherently values creativity and innovation, integrating AI for personalized skill enhancement could significantly strengthen learning outcomes. Personalized AI tools can adapt instructional content, scaffold complex problem-solving tasks, and provide differentiated learning experiences based on students' real-time

performance data. Such integration supports inclusive education by addressing diverse learners' needs and promoting self-directed learning. Therefore, there is a compelling need to explore how AI tools can be systematically used to develop personalized skills within STEAM frameworks, considering both students' and educators' perceptions.

The study investigates that Artificial Intelligence (AI) tools can enhance personalized skill development within STEAM education. Using a mixed-method approach, it explores both quantitative learning outcomes and qualitative experiences of educators and learners.

Significance of the Study

The current time holds substantial academic, pedagogical, and policy relevance. Academically, it contributes to emerging scholarship on the intersection of AI and STEAM education by emphasizing skill-oriented personalization rather than technology adoption alone. Pedagogically, the findings may assist teachers in designing data-informed, adaptive instructional strategies that recognize each learner's unique cognitive and creative profile. Policymakers and educational leaders can further leverage these insights to inform AI integration strategies that ensure equity, accessibility, and sustainability in digital learning ecosystems (OECD, 2021).

In addition, the research contributes to discussions about how education is evolving in the age of the Fourth Industrial Revolution. (Industry 4.0) era, where automation, creativity, and interdisciplinary knowledge are increasingly valued. By examining both benefits and difficulties in AI supported personalized learning, the research will offer practical and useful insights for curriculum developers, educational technologists, and policymakers.

Theoretical Underpinnings

The study draws upon Constructivist Learning Theory and Connectivism to frame its inquiry. Constructivism (Piaget, 1970; Vygotsky, 1978) states that learners build their understanding by learning from experience, implying that AI systems that adapt to learners' evolving understanding can support meaningful learning. Connectivism (Siemens, 2005) extends this idea into the digital age, emphasizing that knowledge resides within networks of people and technology.

Within this theoretical lens, AI tools serve as cognitive partners, dynamically connecting learners to content, peers, and expert systems in ways that foster skill mastery and innovation.

II. LITERATURE REVIEW

Overview of STEAM Education

STEAM education integrates Science, Technology, Engineering, Arts, and Mathematics into a cohesive learning paradigm that emphasizes creativity, critical thinking, and innovation (Yakman & Lee, 2012). It extends the traditional STEM framework by incorporating the Arts, acknowledging that creativity and design thinking are very important for problem-solving in real-world contexts (Henriksen, 2014). The holistic nature of STEAM aims to reduce the gap between analytical reasoning and creative expression, fostering a balance between technical proficiency and humanistic understanding (Perignat & Katz-Buonincontro, 2019). STEAM education has become popular in schools and institutions to prepare learners for Industry 4.0, where multidisciplinary, having these having skills is important for innovation (Beers, 2011). However, the implementation of STEAM often faces challenges in maintaining interdisciplinarity and matching learning experiences to each individual learners' abilities and interests (Herro et al., 2019). This shortfall underscores the growing relevance of personalized learning models that use technology to adapt instruction according to learner diversity. As the following sections discuss, artificial intelligence (AI) offers a pathway for achieving this personalization effectively.

Personalized Learning and Skill Development

Personalized learning refers to tailoring instruction to meet the unique needs, preferences, and goals of every learner (Pane et al., 2015). It emphasizes flexible pacing, adaptive content, and continuous feedback. Unlike traditional teacher-centered models, personalized learning shifts focus to the learner, encouraging autonomy and self-directed skill development (Means et al., 2013). Within the context of STEAM education, personalization becomes particularly vital because learners demonstrate different cognitive and creative profiles. For instance, a student excelling in computational logic might struggle with aesthetic design or collaboration.

Personalized learning allows educators to address these gaps through differentiated tasks and adaptive tools (Tomlinson, 2017).

Studies have shown that personalization leads to improved motivation, engagement, and learning outcomes (Walkington, 2013). It also supports metacognitive growth, helping students understand how they learn best. However, implementing personalization manually is complex and resource-intensive, especially in large classrooms. This limitation has accelerated the incorporation of AI-based tools capable of analyzing learning data, predicting progress, and customizing instruction accordingly (Holmes et al., 2019).

Role of Artificial Intelligence in Education

AI in education encompasses a variety of computational techniques—such as machine learning and language processing technologies, and neural networks—used to enhance teaching and learning (Luckin et al., 2016). These technologies can collect and process large amounts of data to understand learners' behaviors, preferences, and performance patterns, forming the foundation of AI-driven personalization. Intelligent Tutoring Systems (ITS) are among the earliest and most effective examples of AI in education. They simulate one-on-one tutoring by diagnosing learners' knowledge states and delivering targeted feedback (VanLehn, 2011). Similarly, adaptive learning platforms such as Smart Sparrow, Knewton, and DreamBox modify content difficulty and presentation style based on real-time learner responses (Baker & Siemens, 2014).

Despite substantial progress in integrating AI into STEAM education, several research gaps persist. There is a requirement for empirical studies that evaluate the long-term effects of AI and Generative AI (GenAI) on learning outcomes, creativity, and skill retention. Current research also lacks evidence on effective methods for improving teachers' professional skills and AI literacy. Moreover, issues of equity and accessibility remain unresolved, as many learners still face barriers due to the digital divide. Future studies should focus on testing proposed implementation frameworks across diverse educational contexts to ensure ethical, equitable, and pedagogically sound integration of AI in STEAM learning

III. OBJECTIVES OF THE STUDY

1. To explore educators' and students' perceptions of AI-enabled personalized learning in STEAM contexts.
2. To recommend strategies for integrating AI-based personalization in STEAM curricula for inclusive and effective learning outcomes.

IV. RESEARCH METHODOLOGY

A survey-based mixed-method design explores AI's role in personalized skill development in STEAM education through quantitative surveys and qualitative interviews. Research Approach Used was Descriptive and exploratory mixed-method (quantitative dominant, qualitative supported). University of Lucknow was taken as Population and further Educators (50) and students (100) from STEAM disciplines selected via purposive sampling. Data Collection Tools used was a Validated questionnaire and brief interviews with structured and open-ended items.

This study employs a survey-based mixed-method design to examine the role of AI tools in enhancing personalized skill development within STEAM education. Quantitative data will be collected through a structured questionnaire targeting 24 educators and 26 students, while qualitative insights will be gathered via open-ended responses and brief interviews. Using purposive sampling, participants with AI-based teaching or learning experience will be selected. The tool will undergo expert validation, pilot testing, and reliability analysis (Cronbach's $\alpha \geq 0.70$). Quantitative information will be studied through descriptive and inferential statistics, whereas qualitative data will be explored using thematic analysis to generate integration models and recommendations.

V. RESULTS AND DISCUSSIONS

Objective 1

Quantitative insights of the data showed that the study included 50 participants (26 students and 24 educators) representing various STEAM disciplines. The mean age was 32.84 years (SD = 8.61), and participants reported an average of 9.64 years of professional or learning experience (SD = 6.16). Gender distribution was relatively balanced 38%

male, 36% female, and 26% other. Among the disciplines, Engineering (24%) and Mathematics (24%) were most represented, followed by science (18%), Technology (18%), and Arts (16%)

and 48% had none. Regarding frequency of AI use, 38% used AI occasionally, 30% never used it, 22% used it daily, and 10% used it weekly. The distribution of years of experience was right-skewed, with the majority having 0–10 years of experience.

In terms of AI exposure, 52% had formal AI training,

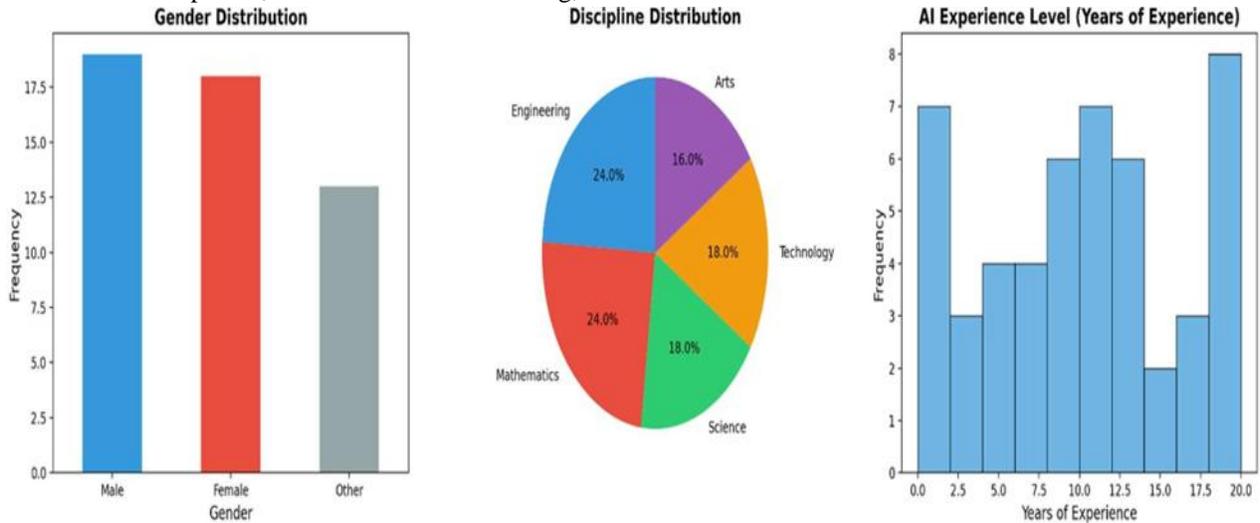


FIGURE-1

The demographic data indicate a diverse and balanced representation of genders and disciplines, suggesting that both educators and students bring varied backgrounds to AI-integrated STEAM learning. The moderate exposure to AI tools (with only half trained) reflects a developing stage of AI adoption, which may influence perceptions and readiness for AI-enabled personalized learning. Findings of Descriptive Statistics are shown here-

Descriptive Statistics of Key Variables

Variable	count	mean	std	min	25%	50%	75%	max
Age	50	32.84	8.61	18	27	32	36.75	50
Years_of_Exp	50	9.64	6.16	0	5	10	13.75	20
ai_awareness	50	2.95	0.42	2.1	2.6	2.95	3.2	3.9
ai_personaliz	50	3.15	0.41	2.4	2.9	3.1	3.4	4.3

TABLE- 1

Age and Experience

Participants in the study had an average age of 32.84 years (SD = 8.61), with the youngest being 18 and the oldest 50. The average years of experience was 9.64 (SD = 6.16), ranging from newcomers (0 years) to

highly experienced professionals (20 years). The age and experience distribution suggests that the sample includes a mix of early-career educators and learners along with experienced professionals. This variation provides a comprehensive understanding of how AI-

enabled learning is perceived across different stages of professional maturity. The broad age range strengthens the generalizability of perceptions across age groups within STEAM education.

AI Awareness

The mean score for AI awareness was 2.95 (SD = 0.42) on a likely 5-point scale. This suggests that participants, on average, possess a moderate level of understanding about AI tools and their applications in education. A low standard deviation suggests little variation in the data, consistency in awareness levels among respondents. While participants are somewhat aware of AI, the mean below the midpoint of 3.0 implies that AI literacy remains developing rather than advanced. This highlights the importance of structured AI training and exposure programs to enhance comprehension and confidence in using AI-driven tools for personalized skill development.

AI Personalization

The mean score for AI personalization was 3.15 (SD = 0.41), slightly higher than AI awareness. This shows that respondents believe AI tools as having moderate potential to personalize learning experiences. The interquartile range (2.9–3.4) suggests most

respondents share similar views. This finding shows positive but cautious optimism toward AI’s ability to adapt learning experiences to individual needs. Participants recognize its potential but may still encounter barriers such as limited implementation experience or technical knowledge. The close proximity of AI awareness and AI personalization means understanding AI’s functions directly influences perceived personalization benefits.

Comparative Insight

Although AI personalization (M = 3.15) is slightly higher than AI awareness (M = 2.95), the difference is modest, suggesting that gains in awareness may directly enhance perceptions of personalization. This connection suggests that increasing AI literacy and hands-on practice could strengthen belief in AI’s role in customizing learning processes. Shapiro–Wilk normality test was applied for every continuous variable researcher tested the null hypothesis.

A p-value < 0.05 means we reject normality. Only Years of Experience shows a significant departure from normality. All other variables have p > 0.05 → we do not reject the Normal assumption for those distributions.

Shapiro-Wilk Normality Test Results for Continuous Variables

Variable	W statistic	p-value
Age	0.9555	0.0574
Years_of_Experience	0.946	0.0235
ai_awareness_usage	0.9799	0.5493
ai_personalized_learning	0.9644	0.1359

TABLE-2

Distribution diagnostics: Histograms with normal curve + QQ plots

For each composite, left panel is a histogram overlaid with the fitted normal curve; right panel is the QQ plot against normal. The composites look reasonably symmetric with mild deviations from perfect normality. Overall Perception shows more discreteness.

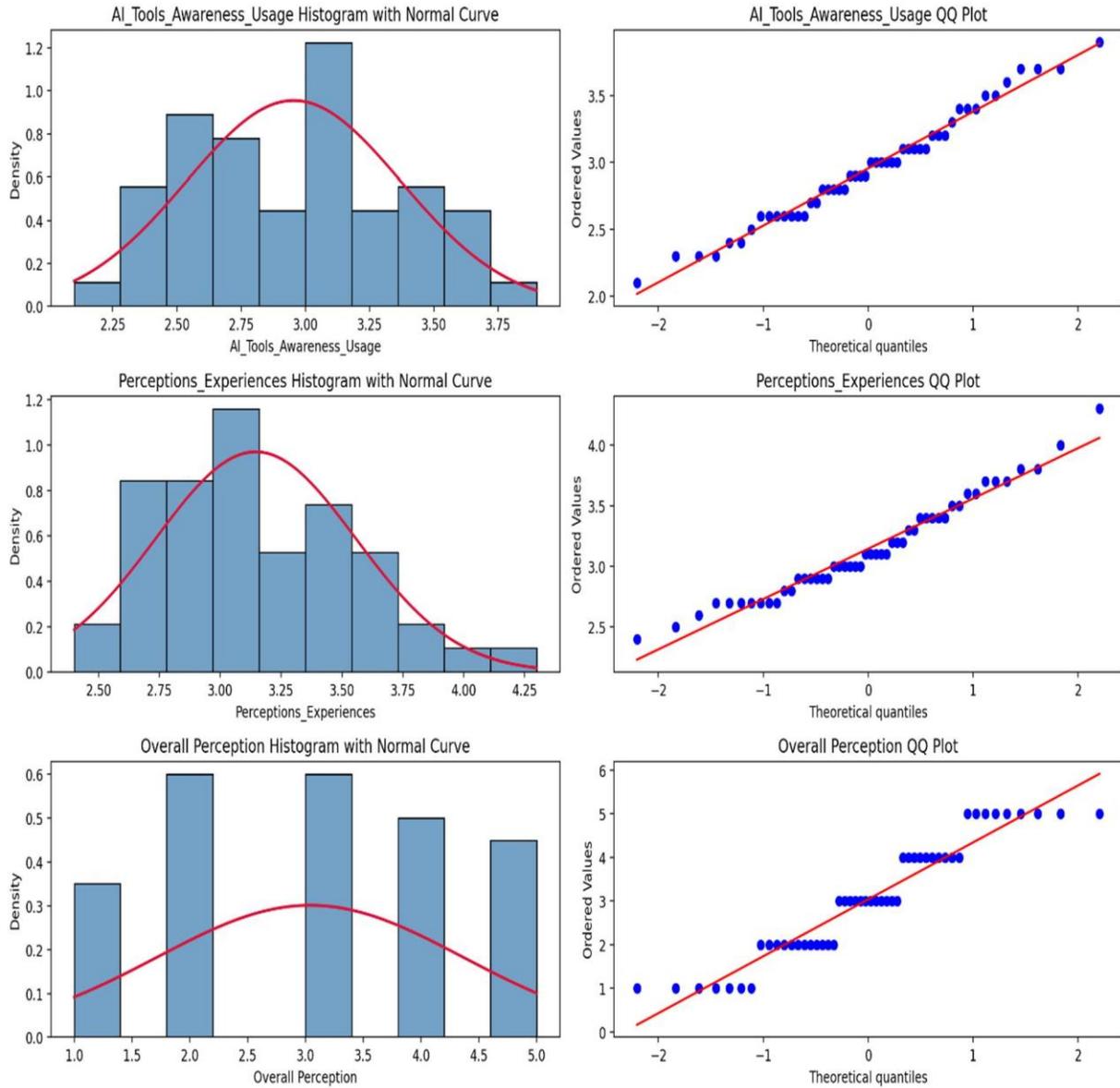


FIGURE-2

Descriptive Analysis of Perceptions Toward AI-Enabled Personalized Learning Responses on the 10-item perception the scale items were organized into four categories; Effectiveness (Items 1–3), Engagement (Items 4–6), Skill Development (Items 7–8) Inclusivity (Items 9–10). The radar chart illustrates the comparative mean scores.

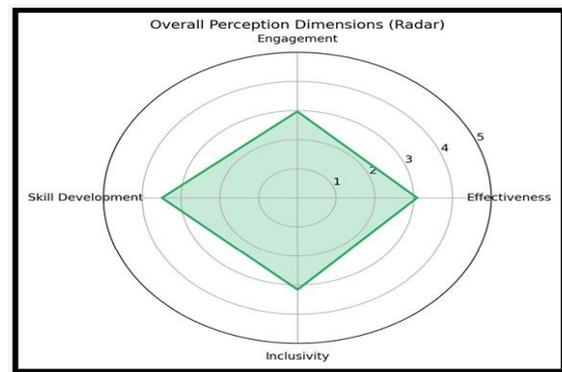


FIGURE-3

Skill Development and Inclusivity showed a small increase in mean scores relative to Effectiveness and Engagement. Standard deviations ranged from 1.3 to 1.5, suggesting moderate variability and diverse perspectives among respondents. Participants generally viewed AI tools as moderately effective and engaging, but perceived greater benefits in skill development and inclusivity. This aligns with AI's capacity to support adaptive learning and address diverse learner needs. The moderate variability highlights that individual

experience with AI likely shapes perceptions, indicating a need for consistent exposure and guided integration across STEAM domains.

Group Differences in Perceptions (Educators vs. Students)

An independent samples t-test compared perceptions of AI-enabled personalized learning between educators and students. This bar chart shows group means with SD error bars.

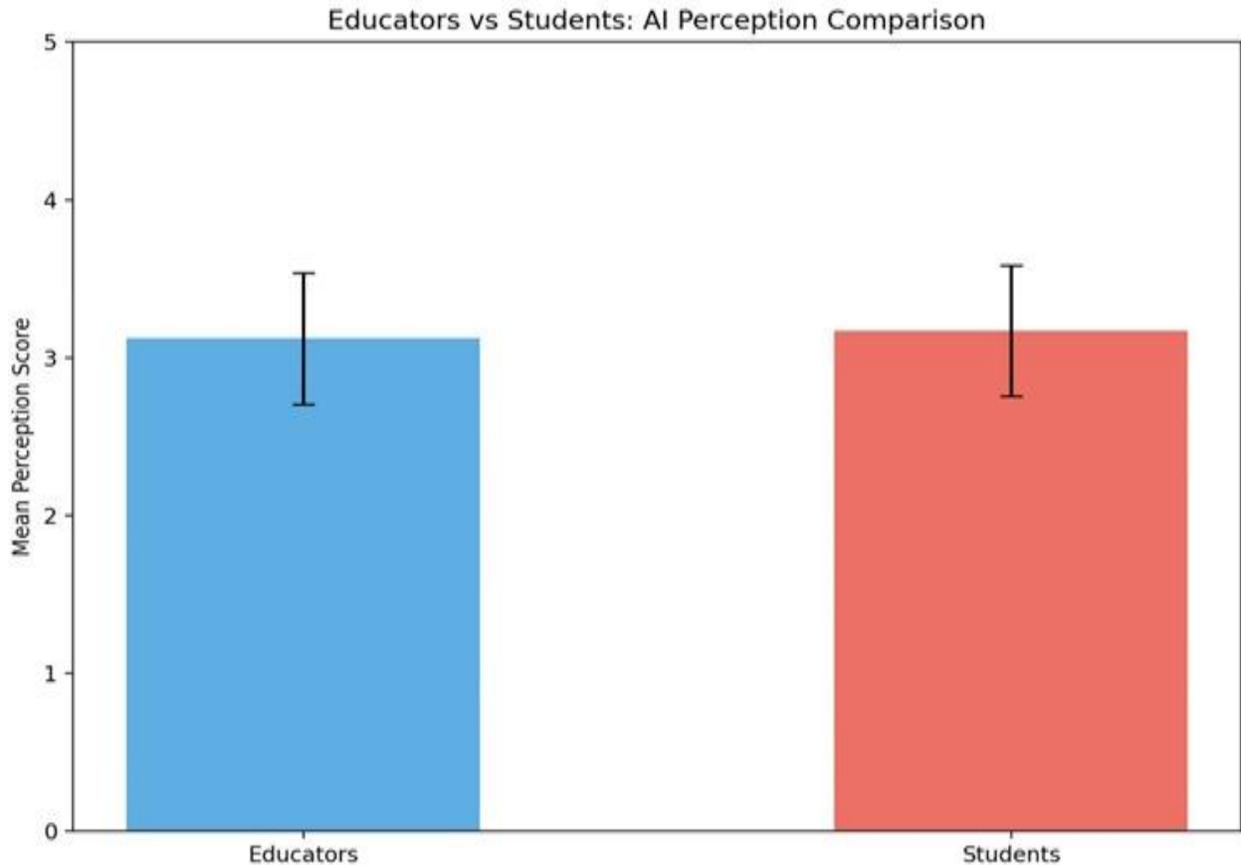


FIGURE-4

Educators ($M = 3.12, SD = 0.42$) and students ($M = 3.17, SD = 0.41$) showed no significant difference, $t(48) = -0.41, p = .68, \text{Mean Difference} = -0.048$

Both educators and students shared comparable perceptions of AI-enabled learning, suggesting a shared understanding and openness toward AI integration. The absence of significant difference indicates that perceived usefulness and

engagement are not strongly influenced by participant role, reinforcing the notion that AI's impact is experienced similarly by both groups when applied in a STEAM context.

Disciplinary Variations in Perceptions

A boxplot visualization revealed discipline-based variation, with Engineering and Mathematics participants expressing slightly higher overall perception scores than Arts and Technology.

However, these differences were not meaningful in statistical terms., implying that AI's perceived benefits are broadly consistent across STEAM domains.
 Boxplot (distribution by discipline)

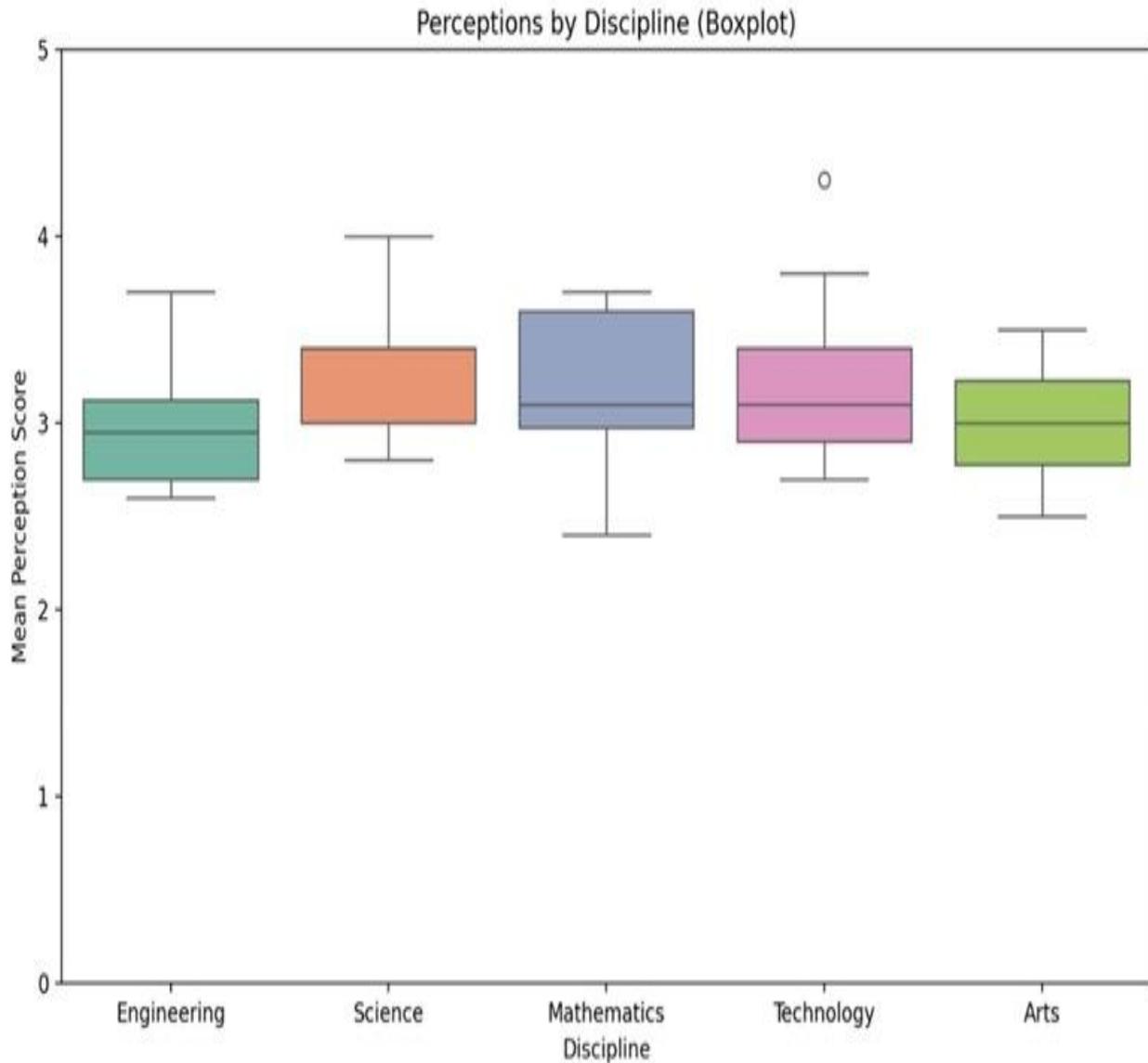


FIGURE-5

While technical disciplines may feel more comfortable using AI, the results suggest that AI personalization frameworks are applicable across all STEAM fields. The finding underscores the potential for cross-disciplinary AI integration with appropriate contextualization.

Correlation Analysis among Key Constructs

A correlation heatmap and pairwise correlation tests revealed mostly weak or near-zero relationships among constructs. The heatmap shows how strong the relationship is and whether it is positive or negative the level and type of relationship between the four key constructs.

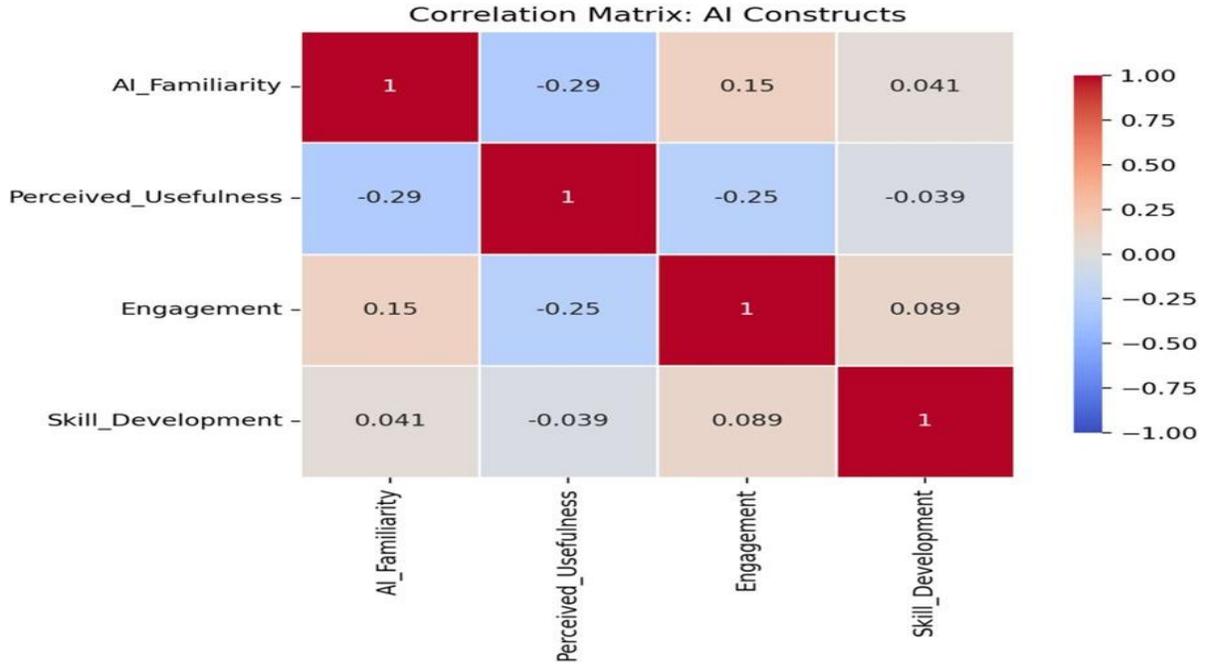


FIGURE-6

Scatterplot for Significant Correlation:

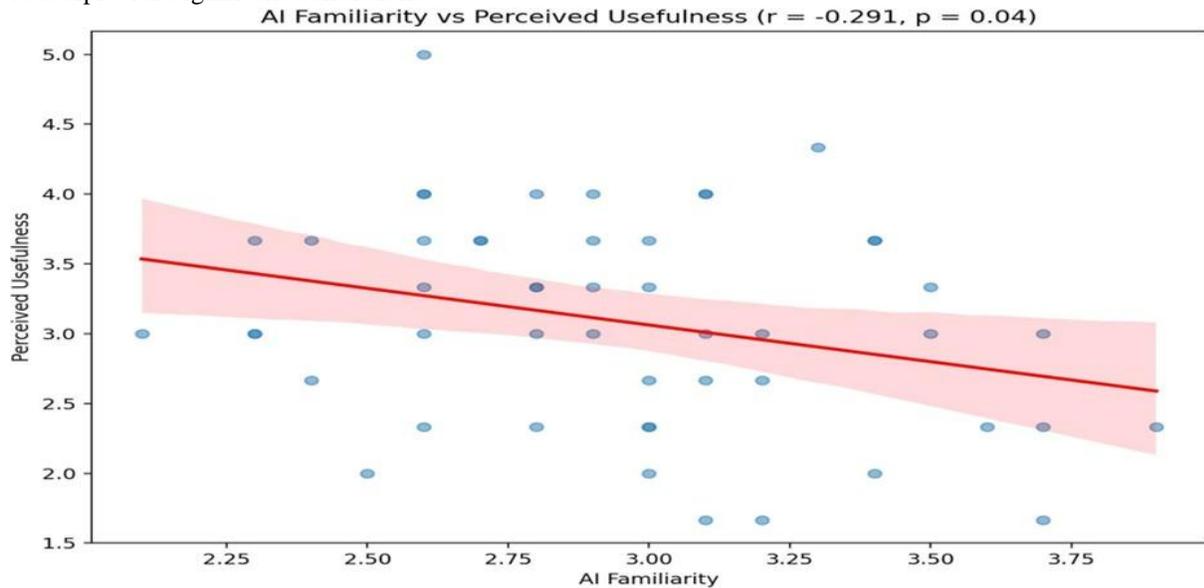


FIGURE-7 (Scatterplot for Significant Correlation)

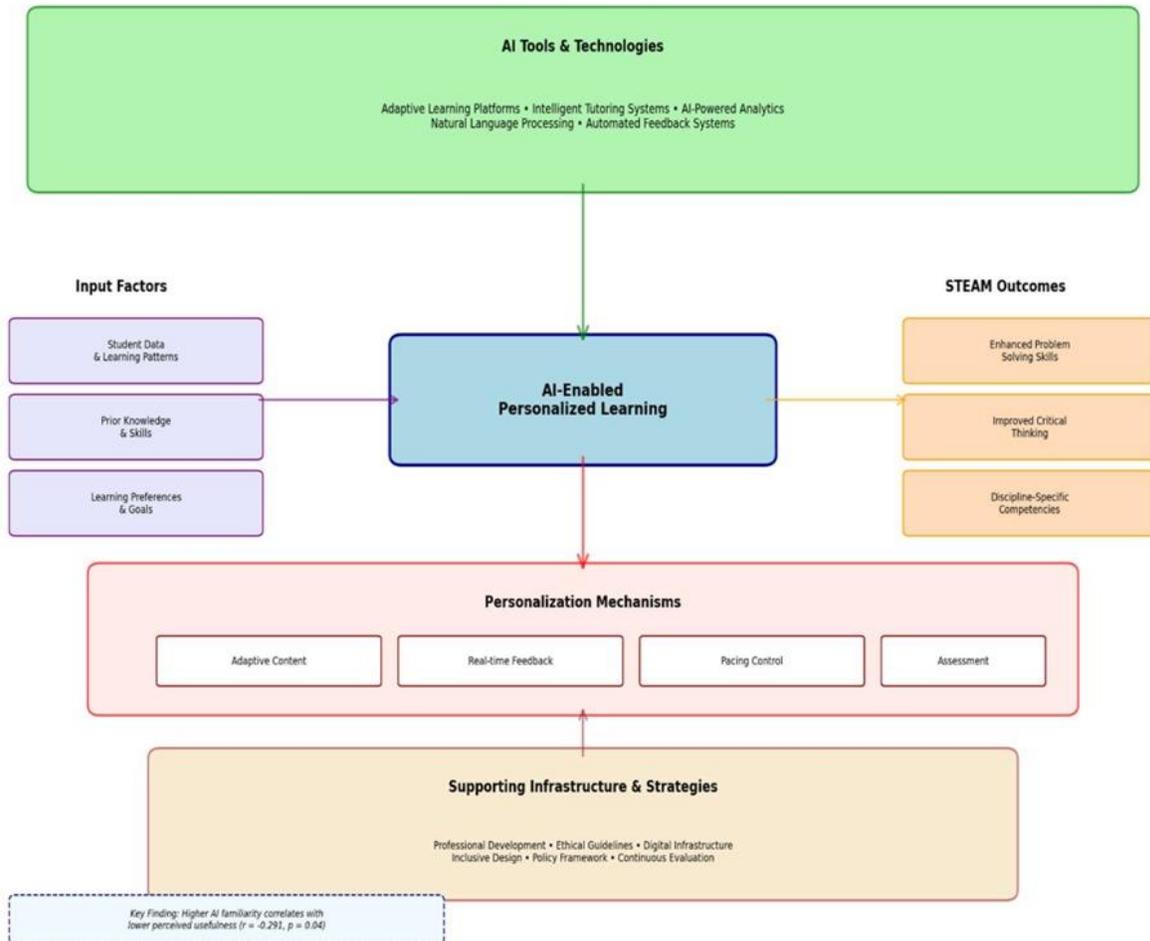
A strong negative relationship was observed between AI Familiarity and Perceived Usefulness ($r = -0.291$, $p = 0.04$). This unexpected result shows that people who know more about AI tools may find them less useful, potentially due to awareness of limitations, ethical concerns, or overexposure effects. Other correlations (e.g., between engagement and skill development) were non-significant, implying that perceptions of

AI's usefulness operate independently across dimensions.

Objective 2

Qualitative Insights from Thematic Analysis indicates that Thematic analysis of open-ended responses and the interviews revealed four main themes.

AI Tools Supporting Personalized Skill Development in STEAM



(FIGURE 8: THEMATIC DIAGRAM)

1. Adaptive and Personalized Learning: AI tools were seen as enablers of individualized learning paths, adaptive assessments, and differentiated instruction.
2. Enhanced Skill Development: Participants highlighted improved critical thinking, creativity, and interdisciplinary problem-solving.
3. Barriers to Effective Implementation: Themes included lack of AI literacy, limited access, and ethical apprehensions about data privacy.
4. Need for Educator Training and Ethical Frameworks: Respondents emphasized structured

professional development and policy support for sustainable AI integration.

Qualitative findings reinforce quantitative trends by revealing that AI tools are appreciated for their adaptability and inclusivity but hindered by training and accessibility gaps. This confirms the importance of teacher capacity building and ethical implementation guidelines for equitable AI-driven STEAM education.

VI. FINDINGS AND CONCLUSION

Integrated Findings

Objective	Quantitative Findings	Qualitative Themes	Interpretation
Identify AI tools for personalized skill development	Moderate to high perception scores on skill development and inclusivity	AI supports adaptive feedback, real-time assessment, and skill enhancement	AI tools effectively enhance personalized learning outcomes
Explore perceptions Of educators and students	No significant group difference (p = .68)	Shared optimism toward AI-assisted learning	Both groups view AI as beneficial for personalization
Recommend integration strategies	Weak correlations and Negative link between familiarity & usefulness	Need for training, policy, and ethical literacy	Structured AI literacy programs can improve utility perceptions

VII. SUMMARY OF FINDINGS

Overall, the results reveal that AI tools hold strong potential for enhancing personalized skill development within STEAM education, particularly in promoting inclusivity and adaptability. However, familiarity without guided training may reduce perceived usefulness, highlighting the importance of teacher training and ethical guidelines and context-specific AI integration strategies to achieve sustainable and equitable outcomes.

VIII. CONCLUSION

Findings from the current study is consistent with previous research. demonstrating AI’s potential for adaptive, inclusive, and personalized learning. The lack of significant differences between educators’ and students’ perceptions reinforces the universality of AI’s perceived benefits across roles. However, moderate AI awareness levels reveal an ongoing need for literacy and training. The negative correlation between AI familiarity and perceived usefulness echoes the caution raised in earlier studies (e.g., Papers A and D), where overexposure led to critical awareness of AI’s ethical and pedagogical limitations. Qualitative themes—adaptive learning, skill enhancement, and implementation barriers—mirror global findings emphasizing teacher capacity building, ethical considerations, and equitable access.

IX. RECOMMENDATIONS

1. AI Literacy Programs: Incorporate structured training for both educators and students.
2. Professional Development: Facilitate workshops on pedagogically sound AI use.
3. Ethical Frameworks: Implement institutional policies for responsible AI deployment.
4. Cross-disciplinary Integration: Embed AI projects across STEAM curricula.
5. Equity Initiatives: Invest in resources to bridge the digital divide and ensure universal access.

Implications of the Study

1. For Educators: Encourages AI-informed pedagogy and learner-centric innovation.
2. For Policymakers: Supports AI literacy inclusion in teacher education.
3. For Researchers: Establishes groundwork for empirical testing of AI frameworks.

X. LIMITATIONS AND FUTURE SCOPE

This study’s sample is limited to a specific academic context, which restricts generalization. Future research should test the proposed integration strategies across diverse populations and educational levels. Longitudinal and experimental studies are needed to evaluate AI’s sustained impact on learning and creativity.

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