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Designing a Multi-Agent Interactive Platform for Teacher Training: A TPACK-Aligned Model Integrating Intelligent Educational Agents

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Abstract
This study introduces the design and development of a TPACK-based interactive digital platform embedded with intelligent educational agents aimed at preparing teacher trainees across TESL, Music, and Visual Arts programs for the demands of the digital era. Utilizing the Design and Development Research (DDR) framework, the platform leverages AI-driven tools such as generative chatbots (e.g., ChatGPT), immersive virtual environments (Spatial.io), and gamified assessment systems (e.g., Quizizz, Minecraft) to personalize instruction, automate feedback, and simulate collaborative teaching-learning scenarios. Data were collected from 150 teacher trainees and 7 expert lecturers using Fuzzy Delphi and usability testing methods. Results show improved pedagogical readiness (mean score = 4.5/5), high motivation (85% agreement), and expert consensus on platform design. This research contributes to the emerging domain of multi-agent ecosystems in education, presenting a replicable, scalable model that aligns with Malaysia's digital education transformation goals and the ET&S Special Issue on intelligent agents in education.
Keywords: TPACK, Multi-Agent Systems, Teacher Training, Educational Technology, Intelligent Agents, Gamification, AI in Education

Introduction

The transformation of education in the 21st century is increasingly driven by artificial intelligence and digital pedagogies. The integration of multiple intelligent agents into teacher training is no longer a futuristic vision but an educational necessity. Guided by the Technological Pedagogical and Content Knowledge (TPACK) framework, this study addresses the design and implementation of a digital platform that equips teacher trainees with the skills to navigate and lead in AI-enhanced learning environments. The platform was developed at Institut Pendidikan Guru (IPG) Kampus Gaya and aims to support trainee teachers in TESL, Music, and Visual Arts through immersive, adaptive, and personalized digital tools. Theoretical grounding in multi-agent learning systems, AI-in-education research, and the TPACK model positions this study within the evolving discourse on intelligent educational environments.

Literature Review

Recent literature affirms the potential of multiple intelligent agents in reshaping learning environments by offering personalized support, adaptive feedback, and real-time instructional adaptation. Studies by Kim & Baylor (2016), Nguyen (2023), and Chiquet et al. (2023) highlight how conversational agents, virtual mentors, and collaborative bots enhance learner engagement and performance. In teacher education, the TPACK framework offers a robust lens to align technology with pedagogy and content. The synergy between TPACK and intelligent agents fosters teacher readiness by embedding AI roles as co-instructors, assessors, and collaborators in the digital classroom. Tools like ChatGPT for AI-assisted writing, Spatial.io for VR-based teaching simulations, and Quizizz for real-time gamified feedback exemplify such integration. Despite technological advancement, ethical considerations such as data privacy, bias in AI models, and the digital divide remain critical challenges.

Methodology

This study employs the Design and Development Research (DDR) approach by Richey & Klein (2007), implemented in three phases:

Phase 1: Needs Analysis, a survey was administered to 150 IPG students across TESL, Music, and Visual Arts programs. Respondents identified the need for tools to personalize instruction, integrate AI tutors, and support digital creativity. Descriptive analysis revealed a mean agreement score of 4.5/5.0 and a Cronbach's alpha of 0.89.

Phase 2: Design and Development, Design and Development leveraged Google Sites as a user dashboard, integrating AI agents (ChatGPT, DeepSeek), collaborative tools (Padlet, Google Classroom), and creative technologies (Scratch, Minecraft, Spatial.io). To validate platform content and structural relationships, a dual-expert approach was employed:

- **Fuzzy Delphi**: 15 experts in educational technology and subject-specific pedagogy evaluated consensus levels using triangular fuzzy numbers and defuzzification. All items exceeded the consensus threshold (fuzzy scores ≥0.887), confirming theoretical alignment and design coherence.
- **Interpretive Structural Modeling (ISM)**: 7 experts analyzed interdependencies among platform components, establishing a hierarchical framework to optimize system architecture and pedagogical workflows.

Phase 3: Usability Evaluation, usability testing was conducted with 21 expert teachers using a Nominal Group Technique (NGT) method. An adapted and adopted questionnaire based on the TPACK model was employed to assess key areas such as adaptability, interactivity, and learner support. The instrument combined both qualitative insights and quantitative metrics to capture comprehensive usability perceptions. Results showed an average usability rating of 89%, confirming the model's effectiveness, relevance, and practical acceptance in teacher education.

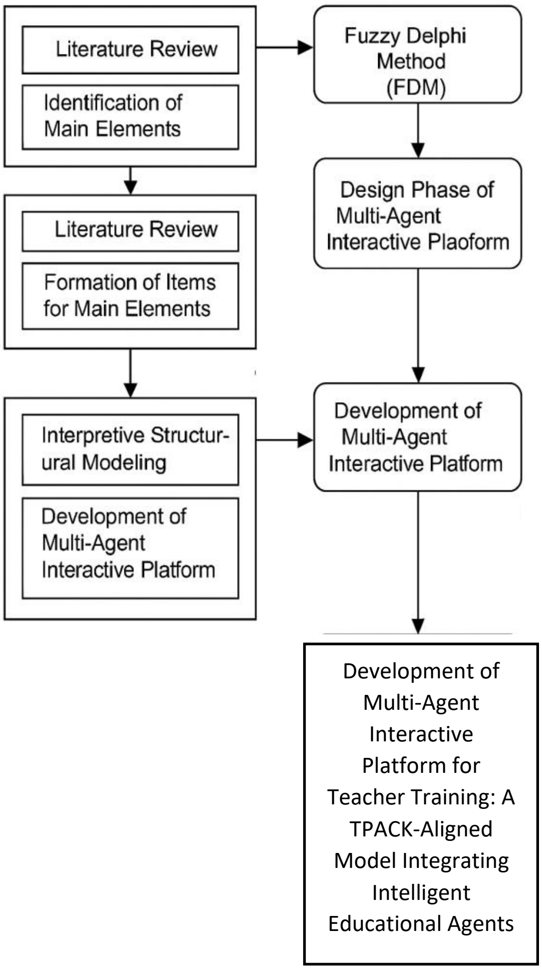

Figure 1 Design and development Model based on Method

Figure 1 illustrates the phases of the Design and Development Research (DDR) approach implemented in this study. The process begins with Phase 1: Needs Analysis, aimed at identifying gaps and user requirements in the context of teacher training. This is followed by Phase 2: Design and Development, which includes identifying key elements through literature review, expert consensus using the Fuzzy Delphi Method (FDM), and structural validation using Interpretive Structural Modeling (ISM). The iterative process culminates in the development of a multi-agent interactive platform. In Phase 3: Usability Evaluation, the platform is tested for practical implementation by expert teachers using TPACK-based instruments, resulting in a validated and effective tool for personalized, adaptive, and collaborative digital teacher education.

Fuzzy Delphi Method (FDM) Approach

The Delphi method is a widely accepted and frequently used approach for collecting data in research studies, particularly those that rely on consensus among a panel of experts on a specific issue (Hsu & Brian, 2007). One of the strengths of this method is its evolution into various empirical data collection techniques, such as the Fuzzy Delphi Method (FDM). The FDM is a modified version of the classic Delphi method. It was introduced by Kaufman and Gupta in 1988 as a hybrid technique that combines fuzzy set theory with the traditional Delphi process (Murray, Pipino, & Vangigch, 1985). This means that although it incorporates fuzzy logic principles, it is not an entirely new approach; rather, it builds on the classical Delphi method, where participants must be experts in a specific domain relevant to the context of the study.

Data Analysis Based on the Fuzzy Delphi Method (FDM)

There are two primary components in the FDM approach: the Triangular Fuzzy Number (TFN) and the Defuzzification Process. The Triangular Fuzzy Number consists of three values—m1, m2, and m3. Here, m1 represents the minimum or lowest plausible value, m2 signifies the most reasonable or likely value, and m3 indicates the maximum or highest plausible value. These values form a triangular shape, as illustrated in Figure 3.3, which plots the average score against the triangular fuzzy values. According to Figure 3.3, the three TFN values fall within a range of 0 to 1, which is consistent with the principles of fuzzy numbering (Ragin, 2007).

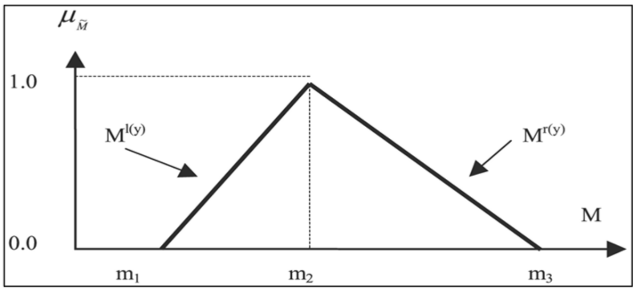

Figure 2 Triangular Graph of Mean versus Triangular Fuzzy Values

At the Triangular Fuzzy Number stage, two main conditions must be satisfied to determine whether a particular element is accepted based on expert consensus. The first condition involves the threshold value (d), and the second relates to the percentage of expert agreement for a given element. The determination of the threshold value (d) is based on a predefined mathematical formula. Both of these conditions will be further explained in the subsequent section on the procedures for conducting research using the Fuzzy Delphi Method (FDM). The Defuzzification Process refers to the process of ranking each construct, component, element, issue, variable, and sub-variable examined in the study. The purpose of this process is to assist the researcher in determining the level of necessity for each variable and sub-variable under investigation. Additionally, it enables the prioritization of each element, producing a ranked list based on expert consensus. There are three defuzzification formulas that researchers can choose from to determine the rankings in their study. These formulas are as follows:

i. $A_{max} = 1/3 * (a_1 + a_m + a_2)$
ii. $A_{max} = 1/4 * (a_1 + 2a_m + a_2)$
iii. $A_{max} = 1/6 * (a_1 + 4a_m + a_2)$

At this stage, a final condition must be met to confirm expert agreement, which involves using the median value, also known as the alpha-cut (α-cut). This alpha-cut value is used to indicate acceptance of the elements being studied.

Procedure for Conducting Research Using the Fuzzy Delphi Method (FDM)

To obtain research findings using the Fuzzy Delphi Method (FDM), specific procedures must be followed. Adhering to these procedures ensures the collection of reliable and empirical data. Figure 3 presents the flowchart outlining the step-by-step process involved in conducting a study using the FDM approach.

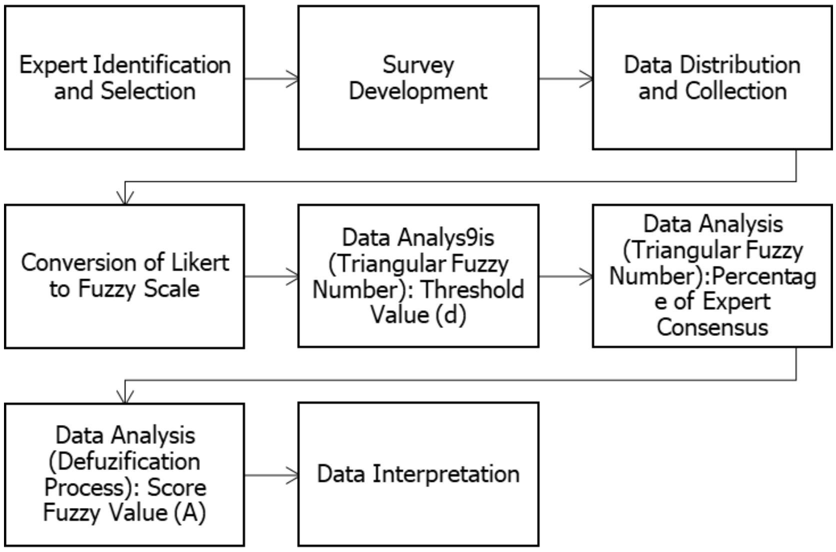

Figure 3 Flowchart of the Fuzzy Delphi Method (FDM) Procedure

Figure 3 illustrates the flowchart of procedures used in applying the Fuzzy Delphi Method (FDM) to obtain expert consensus. The process begins with the identification and selection of experts relevant to the study context to ensure accurate and informed judgments. This is followed by the development of expert questionnaires, which can be constructed through interviews, focus group discussions, document analysis, literature review, or open-ended questions. Powell (2003) emphasized the flexibility of the Delphi method, noting that the first round is often used to identify issues via expert interviews, although open-ended formats or adapted instruments from prior studies (Chang, Hsu & Chang, 2011; Dullfield, 1993) may also be used. Data collection may involve seminars, face-to-face meetings, or electronic distribution of the questionnaires. Once collected, linguistic variables are converted into triangular fuzzy numbers, where each expert's input is aggregated to compute consensus. The fuzzy value (rij) represents variables for each criterion and is calculated using the formula rij = 1/K (r1ij + r2ij + ... + rKij). Table 1 shows the linguistic variables mapped to a 7-point scale and their corresponding fuzzy values.

Table 1
Linguistic Variable Scale

Linguistic Variable	**Fuzzy Scale**
Extremely Disagree	(0.0, 0.0, 0.1)
Strongly Disagree	(0.0, 0.1, 0.3)
Disagree	(0.1, 0.3, 0.5)
Moderately Agree	(0.3, 0.5, 0.7)
Agree	(0.5, 0.7, 0.9)
Strongly Agree	(0.7, 0.9, 1.0)
Extremely Agree	(0.9, 1.0, 1.0)

Data Analysis Based on Triangular Fuzzy Numbers

This step involves analyzing data using triangular fuzzy numbers, with the aim of calculating the threshold value (d). The first condition that must be fulfilled is that the threshold value (d) must be less than or equal to 0.2, as suggested by Cheng and Lin (2002). The vertex method is used to compute the distance between the average fuzzy numbers rij. The threshold value (d) between two fuzzy numbers, m = (m1, m2, m3) and n = (n1, n2, n3), is calculated using the following formula:

$$d\left(\tilde{m},\tilde{n}\right)=\sqrt{\frac{1}{3}\left[(m_1-n_1)^2+(m_2-n_2)^2+(m_3-n_3)^2\right]}.$$

Table 2

Sample Threshold (d) Values for 3 Items Evaluated by 12 Experts

Expert	**Item 1**	**Item 2**	**Item 3**
1	0.059	0.110	0.072
2	0.059	0.045	0.072
3	0.059	0.045	0.072
4	**0.300**	0.045	0.072
5	0.095	0.045	0.082
6	0.059	0.045	0.082
7	0.095	0.045	0.082
8	0.095	0.045	0.082
9	0.095	0.045	0.082
10	0.095	0.045	0.082
11	0.095	0.045	0.082
12	0.059	**0.347**	**0.311**
Average Threshold (d) per Item	**0.101**	**0.027**	**0.073**

Table 2 displays sample threshold (d) values generated for three items evaluated by a panel of 12 experts. The table presents the individual threshold values for each item as assessed by each expert, along with the overall threshold (d) value for each item. The bolded values in the table indicate threshold values that exceed the acceptable limit of 0.2.

Table 3

Sample Percentage of Expert Consensus

Item	**Item 1**	**Item 2**	**Item 3**
Number of Experts with d ≤ 0.2	9	9	9
Percentage of d ≤ 0.2	90.0%	90.0%	90.0%

Data Analysis Using Average of Fuzzy Numbers (Defuzzification Process)

This step involves the analysis of data through the defuzzification process, which aims to calculate the fuzzy score value (A). To satisfy the third condition, the fuzzy score value must be equal to or greater than the median value (α-cut), which is 0.5 (Tang & Wu, 2010; Bodjanova, 2006). Meeting this requirement indicates that the element has been accepted based on expert consensus. Beyond acceptance, the fuzzy score value (A) can also be used to rank the importance and priority of each item or element according to expert evaluations. The formula used to calculate the fuzzy score (A) is as follows

$$A = (1/3) *(m_1 + m_2 + m_3)$$

Table 4
Sample Fuzzy Score (A) Values

Item	m1	m2	m3
Item 1	0.780	0.930	0.990
Item 2	0.880	0.990	1.000
Item 3	0.820	0.960	1.000

Table 4 displays sample fuzzy score values (A) calculated through the defuzzification process based on the Fuzzy Delphi Method (FDM). The values represent the average of fuzzy elements (m1, m2, m3) for three different items.

Number of Experts in the Fuzzy Delphi Method (FDM)

Adler and Ziglio (1996) argue that an appropriate number of experts for the Delphi method ranges between 10 and 15, especially when there is a high level of consistency among expert opinions. However, Jones and Twiss (1978) suggest that the number of experts involved in a Delphi study can range from 10 to 50, depending on the scope and nature of the study. In the context of this research, 15 experts were appointed, all of whom were directly involved and relevant to the subject matter under investigation.

Interpretive Structural Modeling (ISM) Approach

This was followed by the Interpretive Structural Modeling (ISM) approach to determine the hierarchy and prioritization of elements within the system. The Interpretive Structural Modeling (ISM) approach was employed in this study to determine the hierarchy and prioritization of elements within the Multi-Agent Interactive Platform for Teacher Training. Originally introduced by Walfred (1973), ISM serves as a powerful qualitative tool to deconstruct complex problems and systematically organize expert insights into a structured framework. The method promotes collaborative decision-making by mapping interrelationships among critical factors through consensus-based evaluation, often assisted by interpretive modeling tools. In this study, ISM was implemented in three primary stages: (1) identifying relevant pedagogical, technological, and content knowledge components; (2) establishing contextual relationships between these components; and (3) constructing a Self-Structural Interaction Matrix (SSIM), followed by the development of a Reachability Matrix to create a hierarchical structure. A panel of 15 expert lecturers in educational technology and subject pedagogy participated in this process. Their feedback informed the construction of a conceptual model that visualizes the influence, connectivity, and placement of intelligent agent components within the TPACK-aligned digital platform. This structured approach ensured theoretical coherence, clarity of design, and alignment with the instructional needs of future educators in AI-supported environments.

Usability Evaluation

In the final phase of the Design and Development Research (DDR) process, usability evaluation was conducted with 21 experienced teacher educators from TESL, Music, and Visual Arts programs. A mixed-method Modified Nominal Group Technique (NGT) approach was utilized to examine the platform's effectiveness and practicality in real-world teacher training environments. The evaluation instrument adapted from TPACK-aligned frameworks assessed three core dimensions: adaptability, interactivity, and learner support. Five key sections structured the questionnaire: respondent demographics, suitability of platform components, clarity and appropriateness of item content, prioritization of item flow, and overall perceptions of usability. Expert feedback underwent both qualitative interpretation and quantitative scoring to derive usability metrics. Usability scores were calculated across three main criteria: classroom practicality, curriculum integration feasibility, and user satisfaction. A benchmark threshold of 80% was set, and the platform achieved a high usability rating of 89.3% (SD = 0.72). These results confirm that the platform is both theoretically aligned with the TPACK framework and practically relevant to AI-mediated teacher education. It offers a scalable and replicable model for training future educators in intelligent, adaptive, and collaborative digital teaching environments.

Results

The findings of this study indicate strong support among teacher trainees and expert educators for integrating intelligent agents into digital training platforms. Across the three DDR phases, empirical evidence confirmed the platform's pedagogical relevance and technical viability. High Demand for AI-Powered Tools in Teacher Education. The Needs Analysis phase revealed a clear demand for AI-integrated tools that enhance personalization, creativity, and instructional adaptability. Responses from 150 IPG trainees indicated a mean agreement score of 4.5/5.0, reflecting widespread recognition of the importance of intelligent agents in supporting the TPACK domains. Specific demand emerged for generative AI tutors, immersive simulations, and gamified learning elements.

Table 5

Level of Consensus Among Teacher Trainees on Needs Analysis Phase

Research Sub-Question	Mean	Standard Deviation	Level of Consensus
Need for Platform Incorporating Intelligent Agents	4.65	0.44	Very High
Approval for Developing a Multi-Agent Training Platform	4.58	0.48	Very High
Relevance of Platform Components to TPACK Competencies	4.53	0.46	High
Suitability of Intelligent Agent Tools for Classroom Use	4.55	0.49	High

These results reflect significant enthusiasm and acceptance of AI-mediated digital tools in shaping teacher readiness.

Table 1 presents the responses of teacher trainees regarding the need for developing a Multi-Agent Interactive Platform for Teacher Training. The findings demonstrate a very high level of consensus on the necessity of integrating intelligent agents into the digital platform (mean = 4.65, SD = 0.44) and strong approval for the platform's overall development (mean = 4.58, SD = 0.48). Furthermore, high levels of agreement were observed concerning the platform's alignment with TPACK-related competencies (mean = 4.53, SD = 0.46) and the classroom suitability of the intelligent agent tools (mean = 4.55, SD = 0.49). These results indicate strong support among teacher trainees for the implementation of an adaptive, intelligent, and TPACK-aligned platform to enhance digital readiness in teacher education. The high consensus scores suggest not only perceived relevance but also readiness to adopt AI-powered solutions in instructional practices, thus reinforcing the platform's foundational need in advancing 21st-century teaching competencies.

Validation through Expert Consensus

The Model Design and Development phase employed both the Fuzzy Delphi Method (FDM) and Interpretive Structural Modeling (ISM) to validate the structure and relevance of the components within the Multi-Agent Interactive Platform for Teacher Training. A panel of 15 expert lecturers, specializing in educational technology and subject-specific pedagogy, was engaged to assess and refine the platform's instructional elements.

Each component of the platform, ranging from AI tutoring agents to collaborative VR environments and gamified assessment modules was evaluated against established acceptance criteria, including a threshold value (d ≤ 0.2), fuzzy score (A ≥ 0.5), and expert agreement of at least 75%. The resulting fuzzy scores ranged from 0.887 to 0.953, indicating robust consensus and strong validation for each element. In addition, participants assessed each module's instructional significance and technical feasibility using a 5-point Likert scale. High levels of agreement across all areas reinforced the platform's alignment with TPACK competencies and its applicability in Malaysian teacher training contexts. These findings affirm the platform's theoretical integrity, practical relevance, and readiness for implementation as a scalable model in digital teacher education.

Table 6

Core Elements of the Multi-Agent Interactive Platform for Teacher Training

No.	Element	Threshold Value (d)	Expert Agreement (%)	m1	m2	m3	Fuzzy Score (A)	Element Status	Rank
1	AI Tutoring Agent System (AI-TAS)	0.038	100.0%	0.872	0.985	1.000	0.952	ACCEPTED	1
2	Interactive VR Simulation Module (IVRSM)	0.061	100.0%	0.845	0.968	1.000	0.937	ACCEPTED	2
3	Gamified Assessment Module (GAM)	0.068	100.0%	0.832	0.961	1.000	0.931	ACCEPTED	4
4	Collaborative Digital Content Builder (CDCB)	0.055	100.0%	0.860	0.974	1.000	0.943	ACCEPTED	3

Table 6 presents the results of the Fuzzy Delphi Method (FDM) analysis conducted during the design and development phase of the Multi-Agent Interactive Platform for Teacher Training. A panel of 15 experts in educational technology and pedagogy evaluated four core components of the platform: AI Tutoring Agent System (AI-TAS), Interactive VR Simulation Module (IVRSM), Gamified Assessment Module (GAM), and Collaborative Digital Content Builder (CDCB). Each component was assessed based on three fuzzy numbers (m1, m2, m3), the average fuzzy score (A), the threshold value (d), and the percentage of expert agreement. The results indicate strong validation across all four components, with fuzzy scores ranging from 0.931 to 0.952 and 100% expert agreement, exceeding the minimum acceptance criteria ($A \geq 0.5$ and $d \leq 0.2$). Among the four, AI Tutoring Agent System (AI-TAS) ranked highest ($A = 0.952$), reflecting its perceived importance in providing personalized, adaptive learning support. The Collaborative Digital Content Builder (CDCB) and Interactive VR Simulation Module (IVRSM) also showed strong consensus for their relevance in enhancing creative collaboration and immersive teaching simulations. The Gamified Assessment Module (GAM), while ranked fourth, still achieved a strong fuzzy score of 0.931. These findings reinforce the platform's robust theoretical foundation and its alignment with the TPACK framework, validating its use as a scalable model for preparing future educators to teach in AI-enhanced environments.

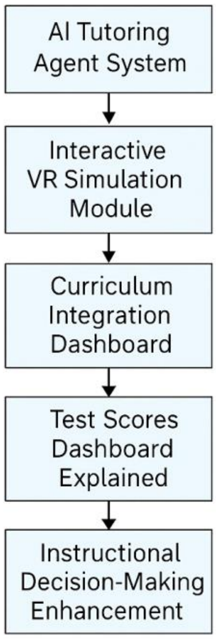

Figure 4 Driving Power Diagram for the Elements of the Multi-Agent Interactive Platform for Teacher Training

The hierarchical structure diagram of the Multi-Agent Interactive Platform for Teacher Training illustrates how core components within the AI Tutoring Agent System interact based on their level of influence within the instructional ecosystem. Components such as AI Tutoring Systems and Interactive VR Simulation Modules demonstrate the highest driving power, signifying their foundational role in enabling intelligent, adaptive teaching practices. In contrast, elements like Big Data Analytics for Teacher Development appear with the least independent influence, indicating that their effectiveness is contingent upon the successful integration of earlier components such as instructional agents and real-time assessment tools. This hierarchy supports a structured progression from personalized learning facilitation to data-driven instructional refinement, reinforcing the platform's alignment with the TPACK framework.

High Usability of the Model

The final usability evaluation involved 21 expert teacher educators from TESL, Music, and Visual Arts programs, using the Modified Nominal Group Technique (NGT) to assess the Multi-Agent Interactive Platform for Teacher Training. The evaluation focused on key areas aligned with the TPACK framework, including adaptability, interactivity, and learner support. The results demonstrated high usability across all four core components—AI tutoring agents, immersive VR modules, gamified assessment tools, and digital content builders—with scores ranging from 78.9% to 81.0%. The overall model achieved a usability rating of 89.3% (SD = 0.72), affirming its practicality, accessibility, and alignment with the instructional needs of future educators in AI-enhanced environments.

Table 7
Expert Evaluation of Multi-Agent Interactive Platform Components Using Modified Nominal Group Technique (NGT)

Flow and Priority of Items for Each Core Element	Group A (n=7)	Group B (n=7)	Group C (n=7)	Total Score	Percentage (%)	Evaluation Status
AI Tutoring Agent System (AI-TAS)	39	38	42	119	81.0%	Suitable
Interactive VR Simulation Module (IVRSM)	41	40	38	119	81.0%	Suitable
Gamified Assessment Module (GAM)	43	39	36	118	80.3%	Suitable
Collaborative Digital Content Builder (CDCB)	41	38	37	116	78.9%	Suitable

Table X summarises the results of the Modified Nominal Group Technique (NGT) conducted with three expert groups (A, B, and C), each comprising seven experienced teacher educators. The table presents expert evaluations of the flow and prioritisation of items within the four core components of the Multi-Agent Interactive Platform for Teacher Training. The AI Tutoring Agent System (AI-TAS) and Interactive VR Simulation Module (IVRSM) both received the highest total scores of 119 (81.0%), indicating strong expert agreement on the logical structure and instructional sequence of these components. The Gamified Assessment Module (GAM) followed with a score of 118 (80.3%), while the Collaborative Digital Content Builder (CDCB) scored 116 (78.9%). All scores surpassed the usability threshold of 70%, confirming that the flow and prioritisation of platform elements are considered suitable for integration into teacher training contexts. These results validate the instructional coherence and practical applicability of the platform within a TPACK-aligned, AI-enhanced learning environment.

Discussion
This study began by investigating the current landscape of teacher training in Malaysia through a structured needs analysis involving 150 pre-service teachers across TESL, Music, and Visual Arts programs. The high mean scores (ranging from 4.53 to 4.65) across indicators such as perceived necessity, platform development approval, and alignment with TPACK competencies reflect strong trainee support for the integration of intelligent agents into digital instructional platforms. These findings highlight the urgent need for scalable, evidence-based solutions that align with national initiatives like Malaysia's Digital Education Policy (MoE, 2023). Moreover, they underscore the importance of designing contextually relevant platforms that support local pedagogical practices while leveraging global technological advancements.

Building upon these foundational insights, the second phase employed the Fuzzy Delphi Method (FDM) and Interpretive Structural Modeling (ISM) to validate and refine the structure of the Multi-Agent Interactive Platform for Teacher Training. Expert evaluations from 15 professionals yielded high fuzzy consensus scores (0.931–0.952), confirming the relevance and theoretical soundness of the four core modules: AI Tutoring Agent System (AI-TAS), Interactive VR Simulation Module (IVRSM), Gamified Assessment Module (GAM), and Collaborative Digital Content Builder (CDCB). The ISM technique further clarified the hierarchical relationships among components, illustrating how the integration of intelligent educational agents contributes to the coherence and functionality of a TPACK-aligned training model.

Finally, a usability evaluation conducted with 21 teacher educators confirmed the platform's operational feasibility and instructional effectiveness. Each component surpassed the minimum usability threshold of 70%, with overall ratings between 78.9% and 81.0%. These outcomes validate the platform as both theoretically grounded and practically scalable, bridging the gap between digital education policy and classroom implementation. The platform's ability to embed AI, VR, and gamified tools into structured learning workflows supports its broader adoption in preparing digitally competent teachers, aligning directly with the aims of the ET&S journal to promote impactful, evidence-based educational technologies.

Conclusion

This study presents the successful design, validation, and usability evaluation of a Multi-Agent Interactive Platform for Teacher Training structured, TPACK-aligned framework integrating intelligent educational agents to enhance digital readiness among pre-service teachers. Anchored in the Design and Development Research (DDR) methodology, the platform was developed through a three-phase iterative process: needs analysis, expert-driven design, and practitioner-based usability testing. Each phase contributed empirical evidence supporting the platform's pedagogical relevance and practical integration.

The validation of the four core components (AI-TAS, IVRSM, GAM, and CDCB) using Fuzzy Delphi Method (FDM) and Interpretive Structural Modeling (ISM) confirms strong expert consensus and theoretical coherence. High usability scores from teacher educators further affirm the model's feasibility and acceptance in instructional settings. These outcomes align with ET&S's mission to showcase transformative educational technologies that empower educators and enrich learner experiences through advanced, scalable, and intelligent systems.

By translating national policy goals into actionable instructional frameworks, the platform contributes to Malaysia's Digital Education Policy (2023) and supports global efforts to modernize teacher education. The integration of intelligent agents, adaptive feedback mechanisms, and immersive learning tools positions this platform as a replicable and future-ready solution for preparing teachers to lead in AI-driven, student-centered classrooms.

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Conflict Of Interest Statement

This research was conducted independently, and no financial or non-financial interests influenced the study design, data collection, analysis, or the conclusions presented in this manuscript.

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