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Article

Vibe Coding AI Agents for an Educational Robot: Teacher Agency in Inclusive Language Education

Seongyong Lee
University College London, United Kingdom

Sooyoun Kim*
Gyeongin National University of Education, Republic of Korea

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Abstract
Generative AI (GenAI) may offer responsive support for slow learners, particularly those who require more time, repetition, and scaffolded participation in language-related tasks. While research often uses the term "borderline intellectual functioning" for this group, in Korean educational and clinical contexts, the label of slow learners frequently overlaps with it. Here, slow learners refer operationally to learners whose slower learning pace requires sustained repetition, simplified sequencing, and closely guided instructional support. Drawing on Universal Design for Learning (UDL), Technological Pedagogical Content Knowledge (TPACK), and teacher agency, this exploratory qualitative study examined an eight-week extracurricular project in which four pre-service elementary teachers developed Gemini-powered prototypes and tested selected task-based agents on a Raspberry Pi 5-based robot for English language teaching on a Raspberry Pi 5-based robot. Data consisted primarily of two rounds of semi-structured interviews, supplemented by project materials. Findings show that teacher agency developed through implementation literacy, pedagogical editing of AI output, UDL-informed design rules, and negotiated engagement with vibe coding and robotic embodiment. Participants moved from consumer-level AI use toward more agentive design practices by revising prompts, hints, pacing, and interaction logic to meet pedagogical goals. Their TPACK development was evident in applying UDL principles to specific accessibility decisions. However, AI-assisted design was constrained by response delay, intention-output mismatch, and unstable behavior, particularly during robotic implementation. The findings suggest that pre-service teacher education should frame AI literacy as a design-and-judgment practice and provide mentoring that supports inclusive AI use.

Keywords
Generative AI, slow learners, teacher agency, Universal Design for Learning, educational robots

*Corresponding author. Email: sooyoun@ginue.ac.kr

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1 Introduction

Elementary language education continues to face the challenge of learner diversity, especially when classrooms include learners who need more time, repetition, and scaffolded interaction to participate successfully (Orío-Aparicio, López-Escribano, et al., 2025; Pulina et al., 2019). Although internationally, adjacent scholarship more often discusses borderline intellectual functioning (BIF) than the label slow learners, this literature consistently points to heterogeneous cognitive and adaptive profiles that make school participation and classroom pacing more difficult for this learner group (Orío-Aparicio, Bel-Fenellós, et al., 2025; Orío-Aparicio, López-Escribano, et al., 2025; Peltopuro et al., 2014; Pulina et al., 2019). In current Korean educational and clinical discussion, however, slow learners may overlap with BIF or borderline intelligence, although the terminology is not fully identical across contexts (Lee & Cheon, 2024). In this article, the term slow learners is therefore used as a context-sensitive operational label for learners who progress more slowly than their peers and who require ongoing instructional support, simplified sequencing, repeated opportunities to consolidate learning, and close instructional guidance, in or near special education settings (Lee & Cheon, 2024; Orío-Aparicio, López-Escribano, et al., 2025; Peltopuro et al., 2014). Recent research on adaptive skills in BIF further underlines why these learners need long-lasting support with pacing, participation, and regular classroom demands (Orío-Aparicio, López-Escribano, et al., 2025). In addition, recent advances in generative AI (GenAI), AI agents, and low-cost robotics have created new pedagogical possibilities for supporting such learners through immediate feedback, multiple representations, and adaptive tutoring (Farhah et al., 2025; Rybakova & Choi, 2025; Zhang et al., 2024). In contrast, unreliable or inappropriately scaffolded AI output may fail to meet learners' instructional needs, making teacher preparation and pedagogical judgment crucial concerns (Gallup et al., 2025; Park & Mohaghegh, 2025).

Teacher education therefore needs to move beyond the basic mastery of technological tools and to help future teachers learn how to design, evaluate, and revise AI-enhanced learning environments in specific subject areas (Heath & Moore, 2024; Jeon & Lee, 2025; S. Lee et al., 2025). This requires attention to enhancing teachers' technological knowledge, pedagogical judgment, inclusive design, and teacher agency, especially when teachers are expected to work on AI tools (Koehler et al., 2013; Mishra & Koehler, 2006; Rao et al., 2023; Shavard, 2022). This challenge becomes more significant when pre-service teachers are not simply selecting existing tools but actively designing how AI systems respond to learners (Aldemir et al., 2025). Recent AI design tools, including vibe coding platforms, lower the technical barrier to building working prototypes, but they also place greater responsibility on teachers to specify pedagogical goals clearly, inspect AI-generated output, and revise the prompts, hints, feedback, and pacing the system provides when those responses do not match learner needs (H. Lee, 2026). When those prototypes are extended to embodied platforms such as educational robots, these pedagogical decisions become more visible in actual teaching because issues such as pace control, personalized feedback, multimodal support, and interaction breakdowns are more readily exposed in classroom use with slow learners (U. Lee et al., 2025; Meske et al., 2025; Song et al., 2026).

Existing studies have examined only one part of this problem at a time: AI-related teacher knowledge and agency in language teacher education (e.g., H. Lee, 2026; S. Lee et al., 2025), UDL-oriented design for learner variability and accessibility (e.g., Lee & Griffin, 2021; Rao et al., 2023; Zhang et al., 2024), or prototype-centered work on robot-supported learning systems (e.g., U. Lee et al., 2025; Song et al., 2026). As a result, less is still known about how pre-service elementary teachers learn to connect these domains when they design AI agents and educational robots, especially for slow learners in language-related tasks. Addressing this gap may help teacher education examine not only whether pre-service teachers can build workable systems, but also how they make pedagogically defensible decisions about student support, pacing, feedback, and accessibility during the design process (Heath & Moore, 2024). To address this gap, the present study explores an eight-week extracurricular project in which four pre-service elementary teachers designed GenAI-powered agents and examined selected task-based agents

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on an educational robot in a South Korean elementary English teacher-education context, focusing on TESOL.

2 Literature Review

2.1 TPACK and AI-integrated teacher knowledge

The TPACK framework has served as a primary model for understanding teachers' knowledge about technology-integrated classrooms (Lee & Jeon, 2024). TPACK posits that effective technology integration requires more than technological knowledge (TK) alone but demands integration with pedagogical knowledge (PK) and content knowledge (CK) to form technological pedagogical content knowledge (Koehler et al., 2013; Mishra & Koehler, 2006). Research on TPACK development in pre-service teacher education demonstrates that blended learning approaches, design-based projects, and ongoing practice opportunities can enhance teachers' technology integration competencies (Alayyar et al., 2012; Lee & Jeon, 2024, 2026).

However, since traditional TPACK frameworks were developed before the widespread use of GenAI tools, they may not fully capture teacher knowledge necessary for AI-integrated subject teaching. In this situation, recent studies for intelligent-TPACK are suggested by Aldemir et al. (2025), emphasizing additional competencies such as evaluating AI outputs, understanding algorithmic bias, maintaining human oversight, and designing prompts that align with pedagogical goals. Related work on critical TPACK (Jeon & Lee, 2025) further argues that AI-era teacher knowledge should include explicit judgment about the value-driven nature of GenAI outputs, not only the mechanical mastery of AI usage. These competencies extend beyond using AI tools to actively shaping how AI responds in educational interaction.

In language education, the majority of the evidence on TPACK comes from English language teaching (ELT) and other language teacher education contexts (H. Lee, 2026; S. Lee et al., 2025; Shin et al., 2026). Research suggests that AI-integrated TPACK requires understanding how GenAI models can support language learning goals while handling constraints such as over-reliance on automated AI feedback or failure to provide appropriate scaffolding (Cheon et al., 2025; Lee & Jeon, 2026). Studies further emphasize that pre-service teachers need to learn how to design prompts that help generate responses suitable for the lesson goal, task, and learner level, evaluate AI-generated language for accuracy and appropriateness, and integrate AI support into classroom activities (Cheon et al., 2025). Recent research in language teacher education also suggests that GenAI competence develops meaningfully when pre-service teachers engage in reflective and collaborative lesson design with GenAI rather than simply using it as a ready-made tool (Gao et al., 2026; H. Lee, 2026; S. Lee et al., 2025). Specifically, they need to learn not only how to operate GenAI tools, but also how to judge when AI-generated explanations, feedback, prompts, or scaffolded practice are appropriate for a particular lesson goal, learner group, and classroom context (Heath & Moore, 2024; Jeon & Lee, 2025).

2.2 Universal design for learning and AI-enhanced language teaching

UDL is an instructional design framework that encourages teachers to plan for learner variability as a normal condition of teaching rather than as an exception (Rao et al., 2023). UDL asks teachers to anticipate learner differences in planning instruction, rather than waiting until difficulties appear and then adding support afterward (Rao et al., 2023). In language education, this may mean deciding in advance how learners will receive input, participate in tasks, and show understanding when they differ in processing speed, confidence, or language proficiency (Lee & Griffin, 2021; Rao et al., 2023). UDL emphasizes three principles: providing multiple means of engagement, representation, and action and expression (Rao et al., 2023). In elementary language education, UDL-aligned class design might include

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offering text and audio input options, adjusting task complexity based on learner performance, and providing diverse feedback modalities (Lee & Griffin, 2021; Rao et al., 2023).

Research on UDL implementation emphasizes that successful integration depends on teachers' capabilities to turn broad principles such as access, flexibility, and learner participation into concrete instructional decisions (Lee & Griffin, 2021; Rao et al., 2023; Zhang et al., 2022). When AI tools are involved, such instructional decision-making becomes a design task; that is, teachers must decide how much help the system should provide, how difficult tasks should be, when the learner should receive hints, whether repetition is available, and how learners can respond or move to the next step (Lee & Griffin, 2021; Yan et al., 2024; Zhang et al., 2022). GenAI can support this work by generating multiple explanations, examples, representations, and scaffolded practice on demand (Farhah et al., 2025; Kalaigian et al., 2024).

At the same time, previous studies caution that AI support may become too narrow or directive if the AI system pushes learners along a fixed sequence or provides the same level of help regardless of their need (Sutherland et al., 2023; Zhang et al., 2024). In language learning tasks, UDL-oriented AI design also means making room for different entry points and support levels, rather than assuming that all learners should proceed through the same prompts, pace, or type of support (Lee & Griffin, 2021; Yan et al., 2024; Zhang et al., 2024). For example, learners may need to choose text or audio input, request repetition, receive shorter or more explicit hints, and move through tasks at a manageable pace, while the teacher remains responsible for judging whether those options are appropriate for the learner and lesson goal (Lee & Griffin, 2021; Yan et al., 2024; Zhang et al., 2024). Thus, pre-service teachers need opportunities to practice making these design decisions with feedback and mentoring rather than learning UDL only as a set of abstract principles (Lee & Griffin, 2021; Rao et al., 2023).

2.3 Embodied AI and robots in language education

Embodied AI agents and robots can provide unique affordances for language learning through their physical presence, multimodal interaction capabilities, and capacity for social functions (Rybakova & Choi, 2025). Previous studies indicate that robots can support turn-taking, collective attention, and conversational practice for diverse learners, including those with special needs (Belpaeme et al., 2018; Hughes-Roberts et al., 2019). In particular, the physical embodiment of robots appears to enhance engagement and social presence compared to screen-based agents, particularly for young learners (Yin et al., 2024). For elementary language education, educational robots can provide human interaction partners for language practice without the social anxiety that may accompany human-human interaction (Rybakova & Choi, 2025; Yin et al., 2024). Robots can deliver repetitive practice opportunities, maintain predictable interaction routines, and provide immediate feedback on oral or written language use (Hughes-Roberts et al., 2019; Rybakova & Choi, 2025). This is particularly useful for slow learners who may require extended practice time and repeated exposure to language patterns.

However, research emphasizes that the effectiveness of adopting robots depends on pedagogical integration rather than technical capabilities alone (U. Lee et al., 2025). Robots that attract learners' attention but are not tied to clear learning goals may increase momentary engagement without leading to lasting language learning (Hong et al., 2016). That is, the key to effective robot integration lies in designing robot-mediated tasks that align with language learning objectives, provide meaningful communicative purposes, and integrate with broader instructional sequences (Hong et al., 2016; Rybakova & Choi, 2025). In addition, teacher perceptions play a critical role in determining whether robots are appropriately adopted in classrooms. Specifically, research indicates that teachers value robots for reducing repetitive instructional burdens but also express concerns about losing professional control, ethical implications of assigning relational and emotional support roles to robots, and practical challenges of utilizing robots (Galvez Trigo et al., 2019; Starks & Reich, 2023). Therefore, teacher education programs should address both the potential and limitations of educational robotics, preparing

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teachers to make informed decisions about when and how to deploy robotic support (Galvez Trigo et al., 2019; Starks & Reich, 2023).

Recent development in low-cost computer hardware and AI-assisted coding tools has made robot prototyping more practical and accessible to teachers without professional engineering backgrounds (Lim, 2026; U. Lee et al., 2025). For example, U. Lee et al. (2025) showed that an LLM-based robot for autistic students could be built on a Raspberry Pi platform, offering customizability, age-appropriate interaction, and practical implementation in educational settings. At the same time, recent studies of embodied and robot-supported learning environments suggest that embodiment can broaden the design space for interaction, but only when pedagogical orchestration remains explicit and technically manageable (Rybakova & Choi, 2025; Song et al., 2026). However, limited research examines how pre-service language teachers may experience this development process and what support they require to succeed.

2.4 Teacher agency in AI co-design

Teacher agency refers to educators' capacity to make intentional choices, take purposeful action, and influence their professional contexts in relation to both pedagogical opportunities and obstacles (Heath & Moore, 2024; Lai et al., 2026). Research emphasizes that teacher agency is not an individual teacher's fixed trait but is emergent and dynamic through relationships, resources, and institutional conditions that enable or constrain their professional action (S. Lee et al., 2025; Shavard, 2022). Ecological and distributed perspectives of agency are especially relevant in GenAI contexts, where human judgment, GenAI outputs, institutional norms, and material conditions together influence teachers' instructional decisions in practice (Godwin-Jones, 2024). In technology integration contexts, agency manifests when teachers adapt tools to their specific situations, resist inappropriate mandates, and advocate for pedagogically suitable practices (Bower, 2019; Heath & Moore, 2024).

When teachers engage in co-designing educational materials with AI tools rather than simply adopting them as final solutions, they exercise agency by defining how the AI will respond, encoding pedagogical values into instructions for AI, and maintaining control over AI's automated actions (Doherty et al., 2025; Lim, 2026). This design-oriented agency is especially important in inclusive education because teachers need to decide how AI will pace tasks, respond to errors, and offer different ways for learners to participate rather than pushing everyone through the same sequence of support (Gallup et al., 2025; Starks & Reich, 2023). In teacher education, this means learning not only to use AI tools but also to inspect their output, revise their support, and justify those revisions in relation to learner variability (Jeon & Lee, 2025; Lai et al., 2026). Recent studies of pre-service language teachers likewise suggest that agency in GenAI contexts includes orchestration, responsible validation, and self-directed learning beyond formal instruction (S. Lee et al., 2025).

Vibe coding environments, where AI assistants help generate and debug code through natural language prompts, offer new opportunities for teachers without programming backgrounds to engage in technology design (H. Lee, 2026; Shin et al., 2026). Meske et al. (2025) describe vibe coding as a reconfiguration of intent mediation in software development, one that lowers technical barriers while redistributing cognitive and evaluative work between humans and AI systems. Related ELT work on no-code approaches similarly suggests that GenAI may support teachers' design access even when they do not possess programming knowledge (Shin et al., 2026). However, these environments also introduce tensions between accessibility and control, as teachers may struggle to understand or modify AI-generated code when problems such as coding errors or intention-output mismatches occur (Yan et al., 2024; Zhang et al., 2024). Therefore, additional research is necessary on how vibe coding can shape teacher agency and design capacity in authentic educational development contexts.

Lim (2026) describes how building a semi-agentic co-researcher system redistributed work between an educator and an AI system. The literature is relevant here because it shows how AI-

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assisted construction can involve technical trial and error, identity reconstruction, and a shift from direct execution toward planning and orchestration. H. Lee (2026) provides a related teacher-education example. In a semester-long service-learning project, 39 pre-service English teachers used vibe coding to develop multilingual materials for international students. These studies suggest that AI-assisted design can widen participation in educational technology development, as well as increasing the need for teachers to evaluate, revise, and pedagogically justify AI-generated outputs. The present study examines this issue in the narrower context of an extracurricular elementary teacher-education project.

Mentoring and collaborative design experiences therefore play important roles in supporting pre-service teacher agency when implementing technology development projects (H. Lee, 2026; Lim, 2026). When mentors model design thinking, provide just-in-time support, and validate teacher decisions, pre-service teachers are more likely to tackle challenges and develop confidence in their design capabilities (Briscoe, 2019; S. Lee et al., 2025). For technically and pedagogically complex projects, no single mentor necessarily holds all the relevant knowledge; instead, mentoring support may draw on different forms of expertise, including a teacher educator's conceptual and technical scaffolding and an in-service teacher's classroom-grounded knowledge of learners, routines, and feasible support (Briscoe, 2019; Zhang et al., 2022). Collaborative design structures may additionally distribute cognitive load, bring multiple perspectives to design problems, and create shared responsibility without removing participants' individual design authority (Zhang et al., 2022).

Despite growing work in these related areas, we still know relatively little about how generalist pre-service elementary teachers learn to design AI-supported and embodied tools for slow learners. Specifically, what is still unclear is how novice pre-service elementary teachers, supported by university faculty and a practising teacher, learn to judge GenAI output, revise AI prompts and tasks, and transform UDL principles into workable AI behavior, which refers to AI interaction with humans, for slow learners. Thus, this study aims to examine how pre-service elementary teachers developed teacher agency, AI-integrated TPACK, and UDL-oriented pedagogy while designing and revising AI agents for slow learners, with particular attention to their language arts work in an eight-week extracurricular project. It asks the following research questions.

RQ1. How do pre-service elementary teachers develop teacher agency and AI-integrated TPACK while designing and revising AI agents for slow learners in language-related tasks?

RQ2. How do pre-service teachers use UDL principles to guide AI design for slow learners, and what tensions arise between personalized support and limiting learners' options for participation and progress?

RQ3. What affordances and constraints do pre-service teachers experience when working with vibe coding, mentoring, and Raspberry Pi-based robot embodiment in educational agent development?

3 Methods

This study adopted an exploratory qualitative design to examine how pre-service teachers developed teacher agency, TPACK, and UDL-oriented design while building AI agents and extending them to an educational robot. Using interviews (Braun & Clarke, 2022; Nowell et al., 2017), the study focused on how participants interpreted learner needs, turned pedagogical intentions into prompts, interaction sequences, and practical design rules, and reflected on their own decision-making across the project.

3.1 Participants and context

The participants in this study were four pre-service elementary teachers enrolled in a department of elementary education at a national university of education in South Korea. As generalist elementary

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teachers in preparation, they had been trained to teach across the primary curriculum rather than specializing in a single school subject. All four participants volunteered for the project after recruitment in September 2025 through departmental announcements and project flyers. The participant selection was based on potential interest in AI-supported teaching and inclusive education rather than prior coding experience. Table 1 offers the profile information of the participants.

Table 1

Profile Information of Participants and Mentor Teacher

Participant	Pseudonym	Gender	Age	Prior AI experience	Reported background
Student 1	Wooju	Male	21	Had used AI before and was the most experienced AI user in the group	Reported strong interest in computing and technology
Student 2	Bumho	Male	21	Had used AI to a limited extent before the project	No additional subject-specific interest was clearly reported in the interview profile
Student 3	Juhee	Female	25	No prior AI use reported	Reported interest in Korean language and English education
Student 4	Sanghee	Female	22	No prior AI use reported	No additional background detail was clearly reported in the interview profile
Mentor Teacher	MT	Male	29	About two years of AI use for teaching; no prior AI-coding or vibe-coding experience	Five years of teaching experience; mainly inclusive classrooms with special education support

Note. MT is the in-service mentor teacher and is not counted among the four pre-service teacher participants.

One in-service mentor teacher with classroom experience in inclusive and special education participated as a pedagogical advisor and interviewee. Two university professors served as faculty mentors and program facilitators but did not participate in the interviews. The faculty mentors mainly supported conceptual framing and technical implementation, including AI-tool use, vibe coding, software-to-robot transfer, UDL, and reasoning about learner characteristics in inclusive and special education contexts. The in-service teacher complemented this support by sharing classroom-grounded examples of prompts, teacher language, learning routines, and feasible forms of learner support. In this sense, the project relied on mentoring support in which different forms of expertise were distributed across mentors (Briscoe, 2019; Zhang et al., 2022).

This research project was an extracurricular activity rather than a part of a course. Thus, the project served as a voluntary design-based experience intended to help pre-service teachers explore how AI agents and low-cost robotics might support slow learners across elementary curriculum areas. Before participation, the research team provided information about the study and obtained informed consent in accordance with National Research Foundation of Korea research ethics guidelines. Accordingly, the entire research process was shared with participants, and all interview excerpts reported in this paper were anonymized.

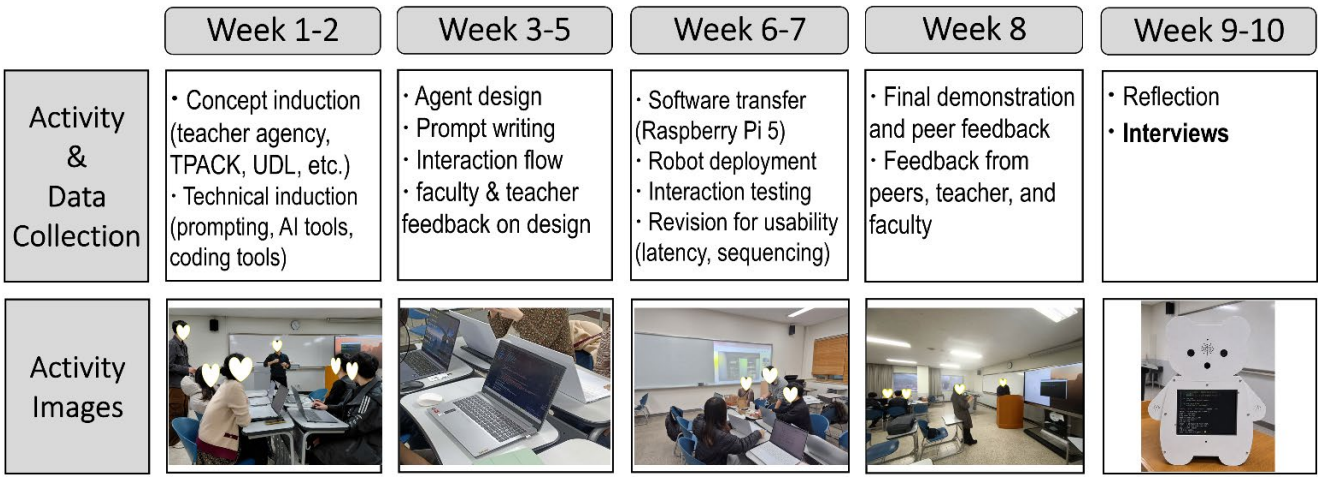
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3.2 Research procedure

The project was operated for eight weekly sessions of approximately three hours each. Although the participants learned how to engage in the project together, the design work itself was individual: each pre-service teacher created and tried several subject-specific agent prototypes before selecting and refining an agent for final demonstration on the shared robot platform. Figure 1 provides a visual overview of the research procedure, including project activities, activity images, and interview process.

Figure 1

Research Procedure: AI Agent Design Flow



Weeks 1-2 focused on conceptual and technical foundations. The faculty mentors introduced teacher agency, TPACK, and UDL as design lenses and guided participants through prompt engineering, Gemini 2.5, AI studio, basic Python execution, API calling, and conversational-flow logic. The in-service mentor teacher then helped participants connect these frameworks and tools to classroom practice by shaping their instructional intentions for slow learners into concrete design criteria, such as gentle feedback, short turns, repeated practice, and multimodal response options (Briscoe, 2019; Lee & Griffin, 2021; Rao et al., 2023).

Weeks 3–5 focused on agent design and iterative prototyping. Participants explored learning purposes across English, Korean language arts, social studies, and mathematics and produced multiple prototypes for elementary education. The project itself was primarily situated in English teacher education, but complete task-level records were not preserved for every prototype; therefore, the remaining examples are treated as broader project context rather than as evidence for specific English-language learning outcomes. Participants then developed prompts, interaction sequences, and practical if–then rules to align AI responses with learner needs. To support implementation, they used Gemini 2.5, AI Studio, Cursor, and other AI-assisted development practices. The faculty mentors provided conceptual and technical feedback, while the in-service teacher commented on whether prompts, tone, pacing, and task routines seemed realistic for actual learners and classrooms. The project did not systematically collect or retain participant-level final-agent records, prompt histories, or before/after prompt versions as research data. We therefore report participants' retrospective accounts of their design work rather than reconstructing participant-specific prompt revisions or presenting an artifact table that cannot be verified.

Weeks 6-7 focused on robotic embodiment and testing. A Raspberry Pi 5-based robot served as the shared deployment platform. The robot used Raspberry Pi OS and was housed in a portable 3D-printed bear-shaped enclosure. The device included two cameras, two microphones, two speakers, and a 7-inch front screen. In structuring this stage, the research team was attentive to prior LLM-based social robot work emphasizing customizability, age-appropriate interaction, and practical implementation in special

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education contexts (U. Lee et al., 2025). Participants therefore transferred their software to the device, tested text and voice interaction, and revised their agents in response to latency, sequencing, usability, and appropriateness issues. The participants took turns deploying their agents and observed one another's demonstrations.

Week 8 focused on presentation, peer review, and reflection. Each participant demonstrated their agent on the robot and received feedback from the other three pre-service teachers, the mentor teacher, and the professors. After the project was completed, the four participants took part in two rounds of individual semi-structured interviews designed to elicit retrospective reflection on the overall design process and its educational meaning.

3.3 Data collection

The main corpus for analysis comprised eight individual semi-structured interviews with the four pre-service teachers: the first post-project interview and one follow-up interview per participant. Each interview lasted around 30 minutes, for a total interview time of 4 hours 12 minutes. The mentor-teacher interview was used as contextual material and was not included in the analytic corpus. No formal member checking was conducted. The coding unit and a complete worked codebook example were not preserved in the available research records, so the analysis is reported as a thematic interpretation of the English-language interview material rather than as a reproducible coding audit. Both interviews, including the initial interview and the follow-up interview, were conducted after the project had been completed. They elicited retrospective descriptions of the participants' experiences, pedagogical goals, views of AI-assisted development, evaluations of the final prototypes, perceived TPACK development, and future teaching trajectories. The study did not include baseline interviews, in-process interview data, or a systematic analysis of prompt-revision histories; therefore, claims about change are presented as participants' reported perceptions rather than as independently observed developmental trajectories. The interviews were conducted in Korean. The first author translated the interview material into English, and the second author reviewed theme-centered passages in the English material. Coding was conducted on the English translations. No formal back-translation was conducted. Because the analysis concerns participants' descriptions of tone and supportive interaction, the translation process is treated as a methodological limitation, and the English quotations are not presented as linguistically neutral substitutes for the Korean interviews. A supplementary interview with the mentor teacher focused on his observations of participants' prototypes, classroom suitability for slow learners, practical constraints on implementation, and the mentoring role. We used this interview as contextual material rather than as part of the main analytic corpus. Relevant MT quotations are kept only when explicitly labelled as contextual interview evidence and are not presented as evidence of the pre-service teachers' own accounts or as material that constituted the participant themes.

The interview protocol was developed around three main theoretical lenses: teacher agency, TPACK, and UDL in teacher education contexts (Heath & Moore, 2024; Lee & Jeon, 2024, 2026; Mishra & Koehler, 2006; Rao et al., 2023; Shavard, 2022). Specifically, the first domain concerned participants' prior experiences with AI, coding, and technology-related experimentation, together with their reflective interpretations of their role as future teachers. The second one focused on participants' technological and pedagogical reasoning while using tools such as Gemini and Cursor, including how they evaluated prototypes, reflected on mentoring, and interpreted their own TPACK development. The third one addressed pedagogical goals for slow learners and how those goals shaped design choices, particularly when participants tried to specify pacing, repetition, multimodal support, and emotionally safe interaction in UDL-oriented ways. These domains were also informed by recent work on pre-service teacher agency in GenAI-supported teacher education and UDL-oriented design in teacher preparation (Lee & Jeon, 2024; Rao et al., 2023; S. Lee et al., 2025). Sample interview questions are presented in Appendix 1.

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3.4 Data analysis

The interview data were analyzed using thematic analysis following Braun and Clarke's (2022) six-step procedure: (1) two rounds of interview recordings were transcribed and anonymized; (2) the authors repeatedly read the transcripts and wrote analysis memos; (3) meaning units were coded line by line; (4) emerging categories that were relevant to research focuses were grouped into specific patterns; (5) these patterns were reviewed against the full interview datasets while looking at supplementary project materials, such as participants' coding and AI agent output for further clarification; and (6) the final themes were refined and named with attention to conceptual coherence.

The authors read the full interview datasets to keep the context of participants' design experiences across the initial post-project interview and the follow-up interview. The primary analysis data consisted of interview passages concerning English language arts. Cross-curricular episodes were included only when participants explicitly linked a design principle first encountered in another subject, such as mathematics, to the later design or revision of a language-oriented agent. In other words, passages were included because they fell within this language-arts focus, not because one participant's prototype seemed stronger or more polished than another's. For this analysis, evidence of agency was identified when participants' reflections connected an intentional pedagogical purpose with an evaluative judgment about an AI response, design alternative, or implementation constraint, followed by a consequential design action. Their output revision alone was not interpreted as the exercise of agency. By contrast, simple acceptance of AI output or changes described without an articulated pedagogical rationale were not interpreted as sufficient evidence of agency. They also identified emergent codes that captured recurring issues in participants' descriptions, such as learning to diagnose and revise AI-generated code, shaping the tone of feedback for learners, adjusting the size and sequence of hints, treating response delay as a pedagogical barrier, using the robot as a low-stakes space for practice, and managing cases in which AI output did not match instructional intent. The authors compared and reorganized the codes until they finalized the themes addressed in this study. No formal member checking was conducted. This absence, together with the unavailable coding unit and detailed codebook, is acknowledged as a limitation on the auditability and confirmability of the thematic interpretation.

4 Findings

Table 2

Summary of the Findings

Theme	RQs	Findings	Supporting theory
1. From AI use to implementation literacy	RQ1	Participants learned key technical concepts, diagnosed errors, and revised agent behavior for pedagogical purposes.	TPACK; teacher agency
2. Teacher agency as pedagogical editing	RQ1	Agency appeared in revising prompts, tone, hints, interaction length, and pace for slow learners.	Teacher agency; TPACK
3. Shaping UDL-based design rules for slow learners	RQ2	Participants built multimodal participation, smaller task units, repetition, and slower pacing into agent design.	UDL
4. Robot-supported practice and the double-edged nature of vibe coding	RQ3	Participants viewed the robot as a practice medium and experienced vibe coding as both enabling and fragile.	Teacher agency; TPACK; UDL

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Analysis of the interview data regarding participants' reflections on English-oriented design presented four core themes: (1) learning to make pedagogy work technically, (2) revising prompts, hints, and interaction in relation to learner needs, (3) applying UDL principles to design rules for slow learners, and (4) experiencing robot-supported practice and vibe coding as enabling and constraining conditions. The first two themes relate directly to RQ1 on teacher agency and AI-integrated TPACK development, the third theme addresses RQ2 on UDL-guided design and its tensions, and the fourth theme addresses RQ3 on the affordances and constraints of vibe coding, mentoring, and robot embodiment. Table 2 summarizes four themes in the findings.

4.1 From AI use to implementation literacy: Learning to make pedagogy work technically

Participants described beginning the project with little coding experience, although some had already used AI as everyday users. In their retrospective reflections they described learning to adjust and troubleshoot AI agents in ways they understood as serving their pedagogical goals. We interpret these reflections as evidence of reported implementation literacy and perceived TPACK- and agency-related learning, not as direct evidence of change measured across the project. Also, in their post-project accounts, they described the important shift not simply as encountering new tools, but as coming to understand how they could adjust and troubleshoot AI agents in ways they believed served their pedagogical goals.

One important part of this shift was learning the language of technical control over AI and coding. Some core terms such as API key, prompt, model response, and retrieval augmented generation (RAG) formed a lexical foundation for understanding where a problem might lie and for making deliberate changes to AI agents rather than simply reacting to unexpected output, as two participants described below:

> I had used AI before, but I did not really know how it worked. In this project I learned things like the API key and how the model changes depending on how I command it. (Wooju)
>
> Before this, using AI felt like asking for help. During this project, it became more like telling the system what kind of teaching support I wanted it to provide. (Bumho)

Debugging also became an important part of learning. Participants described errors not as proof of failure, but as moments when the workings of the technology became easier to understand. They repeatedly mentioned tracking down small formatting problems, logic errors, or mismatches between prompt and output, and then rerunning the system until the response came closer to what they had intended, as illustrated below:

> There was a time when one small spacing problem stopped everything. I spotted the error and checked it step by step with Gemini. After that, technology did not feel impossible anymore. (Juhee)
>
> Even if it did not work at first, I learned that it was something I could fix by checking the message and changing the code little by little with AI. (Sanghee)

4.2 Teacher agency as pedagogical editing: Prompts, hints, and interaction design

Through interview data, participants did not describe agency in terms of dramatic ownership or complete technical skills. Instead, they showed teacher agency through small scales of repeated design choices, such as revising prompts, shortening hints, slowing interaction, or restructuring tasks when AI output did not fit learner needs. Read together with the previous theme, these decisions show that TPACK growth and agency development were closely intertwined in the revision process. In this study, participants'

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interviews were interpreted as relevant to agency when they connected an evaluation of an AI response or design constraint to a stated pedagogical purpose and described a consequential revision, rejection, or redirection. Their revision alone was not treated as evidence of agency.

The first form of agency is relevant to what might be called the teacher voice of the agent. Participants described applying the supplied UDL-oriented guidance about positive, encouraging feedback to interactions in which learners made mistakes, hesitated, or needed repeated attempts (see Appendix 2). This evidence demonstrates contextual enactment of the reference; without a documented departure or extension, it does not by itself demonstrate that participants independently originated the teacher-voice principle.

> I tried to make it speak more gently. I did not want it to say something like 'wrong.' I wanted it to respond in a way that would help a child try again. (Wooju)
>
> The mentor teacher's prompt examples helped me notice that the tone matters. It was not just about getting an answer. It was about how the answer is delivered to the learner. (Bumho)

A second form of agency was related to revising the structure of hints for potential students. The participants noticed that AI-generated hints were often too abstract, too wordy, or too large a leap for slow learners. In response, they broke the support into smaller steps and designed hints to return learners to an earlier point they could manage, rather than pushing them further ahead, as shown below.

> I realized that if the student could not solve the current task, the hint should not make the next step harder. It should reconnect them with something they can already do. (Sanghee)

A third form of agency involved limiting the length and pace of interaction. Participants repeatedly described long responses, multi-part questions, and dense explanations as obstacles to slow learners' comprehension and participation, as the excerpts below indicate.

> When the chatbot asked too many things at once, it became confusing. So I changed it to one sentence or one question at a time. (Sanghee)
>
> I kept cutting the response down because being detailed was not always being helpful. (Wooju)

The manifestation of agency in these decisions was supported by mentoring rather than by AI interaction alone. The faculty mentors helped participants understand relevant theoretical principles and work through the technical implications of their ideas. During workshops and final demonstrations, their feedback connected prototypes to notable issues such as processing load, functional skills, generalization of learning, and the fit between AI responses and pedagogical purpose. Within this context, the in-service mentor teacher played a complementary role; that is, the participants addressed the teacher's prompt examples and comments as concrete traces of classroom experience and used them to make their own instructions more specific, as the following comments illustrate.

> When I looked at the mentor teacher's prompt, I could see what he must have noticed while teaching students. Even small details, such as what tone the agent should use, gave me something I could apply when I become a teacher. (Wooju)
>
> When I tried to decide the UDL criteria by talking only with AI, they still felt abstract. The teacher's example helped me specify the categories and think about what should go into each one. (Sanghee)

Participants also described the in-service teacher as a relational bridge between themselves and the faculty mentors. The point was not that the professors were unavailable; rather, the practising teacher reduced the perceived distance of the university setting and made it easier to voice uncertainty, as the excerpt below suggests.

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I feel the mentor teacher was always there to help us with our learning. Even a short comment made me feel more comfortable and supported. (Bumho)

4.3 Shaping UDL-based design rules for slow learners

The third theme concerns how participants described contextualizing a supplied UDL-oriented prompt reference into concrete system rules. Their reflections referred to choices such as offering text and voice options, reducing task load, building in repetition, and slowing the pace of interaction. These priorities overlapped with the reference used in the project, which emphasized simplified vocabulary, short responses, repetition, encouragement, and response options. Therefore, the available evidence supports a claim about contextual enactment and adaptation within a provided design frame, not about independent creation of these principles or departure from the reference.

The first UDL-related pattern was multimodality, which provides multiple modes for slow learners to take part in the task. Participants did not frame text and voice options as technological novelty; instead, they regarded them as necessary entry points for learners with different strengths, as shown in the excerpts below.

> I wanted both text and voice because some students may be more comfortable typing, while others may need to respond by speaking. (Wooju)
>
> The important point was not adding many features. It was making sure there was more than one way for a student to participate. (Bumho)

The second pattern was on sequencing and repetition. Specifically, the participants intentionally reduced the number of tasks presented at once, repeated difficult items, and imagined agents that could notice where learners tended to struggle and respond with another chance to practice, as the following excerpt indicates.

> For slow learners, small success matters. I wanted the program to return to the basics again instead of pushing the learner forward too quickly. (Sanghee)

The third pattern concerned the speed and rhythm of interaction. Participants repeatedly described slow learners as needing reduced information load, slower response timing, and a more predictable conversational flow, as illustrated below.

> If the response comes too fast, or if the robot asks the next question immediately, the student may give up before participating. (Sanghee)
>
> Pacing became part of accessibility for me. I had to think not only about what the agent says, but when and how quickly it says it. (Wooju)

The mentor teacher additionally observed, “The multiplication quiz itself was a good choice, but when it was delivered only through audio, it became harder than when a teacher could quickly draw or show it visually” (MT, contextual interview).

4.4 Robot-supported practice and the double-edged nature of vibe coding

Theme 4 identified from the data is regarding how the pre-service teachers understood the educational role of the robot and how they experienced AI-assisted coding as enabling affordances and unstable constraints. These two issues were closely linked because once the agent was placed in an embodied interaction setting, technical limitations became more visible and difficult to ignore.

The participants did not view or design the robot as a substitute teacher; instead, they described it as a teaching agent that can provide repetitive, low-stakes, and patient practice for slow learners when

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classroom time is limited. They also saw it as a learning agent that had to be customized for a specific learner profile and specific pedagogical purposes, rather than as a general-purpose AI device, as shown in the excerpts below.

> A teacher needs patience, but there are limits. AI can keep practicing with a learner over and over. I don't think that replaces the teacher, but it can support what the teacher cannot always repeat endlessly. (Juhee)
>
> I wanted these students to rehearse social situations, like meeting someone for the first time or apologizing after conflict. With the chatbot, they can practice without damaging a real relationship. (Bumho)
>
> Individualized education is becoming more important, but teachers do not have enough time. If teachers can code a chatbot a little differently for each child, this could be genuinely effective. (MT)

At the same time, participants emphasized that the robot was only meaningful when tied to a worthwhile task, as the following comments indicate.

> If the conversation feels forced or the task is boring, the robot will just become another unnecessary, uninteresting assignment. It has to be part of something meaningful. (Sanghee)
>
> The robot itself should not be the goal. What matters is whether it helps the learner practice something they really need. (MT)

Regarding the potential of vibe coding, they described it in similarly double-edged terms. On the one hand, AI-assisted development tools lowered the threshold for participation in coding and made it easier for non-programmers to imagine themselves building a working agent, as the excerpts below show.

> I never thought I could make something like this. Even someone without strong coding knowledge can build a prototype if they can explain what they want. (Bumho)
>
> Even people who know little about coding can now participate, but the quality still depends a lot on how well they can ask and direct the system. (MT)

On the other hand, the participants also described repeated mismatches between their coding intention and AI agent output, unstable behavior, and response delay as constraints, as illustrated below.

> Sometimes the code looked right, but it did something different from what I wanted. That was sometimes frustrating because I still had to decide whether it matched my goal. (Juhee)

In response to these difficulties, mentoring from the in-service teacher was considered especially important. The faculty mentors helped diagnose implementation problems and reconnect technical choices to UDL and pedagogical goals, while the in-service teacher brought classroom concerns into the design process and reassured participants that revision was part of responsible design work, as the following excerpts show.

> When I talked only with the AI, my ideas stayed abstract. When the mentor teacher gave concrete examples, I could turn them into actual prompts and rules. (Bumho)
>
> Knowing that someone could help us think through the problem made it easier to continue. Without that, I might have stopped in the middle. (Wooju)
>
> My role was not to give them the answer, but to help them ask whether the output really matched the learner and the classroom situation. (MT)

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5 Discussion

Recent work on AI-integrated TPACK and teacher agency has argued that pre-service teachers need opportunities not only to use AI tools but also to examine outputs, revise prompts, and judge whether AI support is appropriate for a particular lesson and learner group (Heath & Moore, 2024; Jeon & Lee, 2025; Lee & Jeon, 2024, 2026). The present study makes this argument more concrete by showing how participants described learning to make agents usable for slow learners in language-related tasks. They did not develop AI-related pedagogical knowledge simply by spending more time with GenAI. They developed the knowledge by adjusting the agent's system prompt, hint sequence, response length, and interaction pace for learners who needed more processing time. These revisions were both technical and pedagogical: participants had to make the agent run reliably and tune its responses to fit slow learners' instructional and processing needs. This finding may advance current research on TPACK and teacher agency by showing that, in AI-agent design for slow learners, these two forms of professional learning can develop together through repeated decisions about how the agent should behave (Alayyar et al., 2012; H. Lee, 2026; Lee & Jeon, 2024, 2026).

The findings also support ecological and distributed views of teacher agency, which address agency as what is shaped through relationships, resources, and professional judgment rather than as an individual property alone (Godwin-Jones, 2024; Semon et al., 2020; Shavard, 2022). In this project, participants became more agentive when they revised their work in a setting where coding problems, classroom plausibility, and learner needs could be discussed together. The two faculty mentors mainly helped participants interpret implementation problems and connect them to TPACK and UDL, whereas the in-service mentor teacher helped them judge whether prompts, hints, tone, and routines would be appropriate and workable for actual slow learners. While earlier studies have shown how experienced educators or pre-service language teachers can take on co-designer roles in AI-supported projects (H. Lee, 2026; Lim, 2026), the present study suggests how such a role can develop when the participants are still teacher candidates with limited technical confidence and classroom experience. This development depended on a mentoring structure that combined faculty expertise, practicing-teacher knowledge, peer exchange, and AI-assisted experimentation (Briscoe, 2019; Gao et al., 2026; H. Lee, 2026; Lai et al., 2026).

Research on UDL has emphasized teachers' capacity to design how content is presented, how learners participate in tasks, and how they respond or show understanding (Lee & Griffin, 2021; Rao et al., 2023; Zhang et al., 2024). The present study advances this work by showing how pre-service teachers enacted this capacity in language-related agent design for slow learners. Participants in this study had to decide the response mode, the return point of hints, the number of questions in each turn, and the waiting time before the next prompt. These decisions show that UDL-oriented AI design for slow learners was not simply a matter of adding more functions to the agent. It required teachers to set limits on the AI agent's language use, timing, and hint structure so that its support remained adjustable to students' needs rather than becoming a fixed path through the task. In this regard, the study adds empirical detail to warnings that AI assistance can constrain participation when agents move learners through predetermined sequences or provide support that is not adjusted to learner need (Sutherland et al., 2023; Yan et al., 2024; Zhang et al., 2024).

This issue is particularly important because research has rarely examined AI-supported language education within the context of special education for slow learners. Studies in language education have shown that AI agents can support participation and engagement when teachers manage vocabulary, task structure, feedback timing, and response mode rather than leaving those features to generic AI output (Cheon et al., 2025; Jeon & Lee, 2025; Mohamad & Pozzi, 2023). Studies on slow learners and AI-supported disability education, in turn, emphasize the need for short instructions, repeated practice, manageable response demands, and emotionally safe feedback (Farhah et al., 2025; Pulina et al.,

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2019; Zhang et al., 2024). The present study brings these two concerns into the same design setting. Specifically, it shows how pre-service elementary teachers tried to make language tasks usable for slow learners by limiting turn length, slowing the pace of interaction, staging hints, softening corrective feedback, and allowing text, voice, or repeated responses. These agentic actions by pre-service teachers were not simply attempts to make the agents easier to use, but efforts to keep the language task open enough for slow learners to understand the prompt, respond without pressure, and re-enter the task after encountering learning difficulties (Cheon et al., 2025; Lee & Griffin, 2021; Mohamad & Pozzi, 2023; Pulina et al., 2019).

The role of vibe coding and robot embodiment also needs to be discussed together in teacher training on the development of AI agents for language education. Recent studies have indicated that prompt-based or no-code AI development can lower technical barriers for teachers, leaving them responsible for checking outputs, correcting problems, and maintaining pedagogical oversight (H. Lee, 2026; Meske et al., 2025; Shin et al., 2026). While supporting this claim, the present study shows more specifically that moving an AI agent onto a physical robot made pedagogical weaknesses immediately visible by revealing whether its timing, turn-taking, multimodal coordination, and response clarity remained workable for slow learners. The participants described vibe coding as a convenient technique that made agent development possible for non-programmers, but they also pointed out technological issues, such as latency, intention-output mismatch, unstable code, and turn-taking problems. Once the chatbot agents were embedded into the Raspberry Pi robot, those weaknesses became harder to ignore because timing, usability, and multimodal coordination immediately affected whether the interaction still made sense for a slow learner. In this respect, the current study extends U. Lee et al.'s (2025) work on LLM-based social robots by showing that embodiment did not simply add realism to the prototype. Instead, it exposed the educational consequences of design choices that might have remained less visible in screen-based testing alone, especially choices about pacing, clarity, and the learner's ability to stay engaged in the task (Meske et al., 2025; Song et al., 2026).

This discussion supports a more integrated model of teacher education for AI-supported inclusive practice. In inclusive classrooms, differentiation is not an optional add-on but a routine pedagogical responsibility because teachers must plan for learner variability in advance rather than respond to it only after difficulties appear (Rao et al., 2023; Zhang et al., 2022). For some students in formal special education, this work may be shared with special educators through collaborative support structures, but many slow learners in regular classrooms are still supported mainly by the classroom teacher even when they need similar adjustments in pacing, repetition, response mode, and emotional support (Pulina et al., 2019; Semon et al., 2020; Starks & Reich, 2023). Seen in this light, the value of GenAI in teacher education is not that it reduces the need for teacher judgment; rather, it can become a teacher-directed partner that helps future generalist teachers carry out differentiation in more feasible and responsive ways, provided they retain responsibility for judging task fit, timing, tone, and the amount of support given (Godwin-Jones, 2024; Heath & Moore, 2024). Therefore, teacher education programs should not address AI literacy as a matter of basic technique of using tools, and they should not separate technical training from pedagogical judgment, UDL-oriented design, and mentoring (Briscoe, 2019; Gallup et al., 2025; Heath & Moore, 2024; Rao et al., 2023; Zhang et al., 2022).

Finally, the present findings may lead to three practical implications. First, pre-service teachers need design experiences in which they should judge and revise AI output rather than simply adopt it. Second, they need mentoring arrangements that help them retain their capacity through debugging, uncertainty, and revision instead of concluding that AI design belongs only to technical experts. Third, they need opportunities for repeated practice in specifying how inclusive principles, such as multimodal participation, manageable pacing, and staged support, should appear in the actual behavior of an educational agent.

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6 Conclusion

This study argues that the educational value of AI agents for slow learners does not lie mainly in automation or simply in novelty. Instead, it depends on whether pre-service teachers can design those agents in ways that are pedagogically usable, emotionally appropriate, and instructionally manageable. In the present project, this crafting work involved learning enough about prompts, timing, hint structure, multimodal participation, and robot-based interaction to make the agents serve a specific learner and task. Therefore, the study may contribute to current discussions of teacher agency by showing how participants' retrospective accounts located agency in repeated acts of pedagogical revision rather than in simple tool adoption.

This study has several limitations. First, in terms of methodology, the participant group was small, the project lasted eight weeks, and the analysis focused on retrospective interview data rather than long-term classroom implementation. Future studies should therefore examine similar design work with larger participant groups, longer project periods, and classroom-based data that may show how such AI agents are used over time. Second, although the broader project addressed several elementary curriculum areas, the present article reported only the language-arts-related topics. Future studies need to explore whether the design patterns identified here appear in similar ways across other subjects and learner profiles. A further limitation is that this was a voluntary extracurricular design project rather than a class or classroom intervention. No learners or classroom teachers participated as co-designers, testers, or outcome evaluators. Thus, the findings describe the four pre-service teachers' retrospective reflections of design possibilities rather than learners' experiences, classroom feasibility, or learning outcomes. Future research should use participatory and co-design approaches that involve slow learners and their teachers in defining goals, evaluating interaction routines, and revising the agents across classroom use. Finally, because the interviews were conducted in Korean and reported in English, interpretations of tone, register, and emotionally supportive language may be affected by translation. Although the second author reviewed theme-centered passages, no formal back-translation was conducted. Thus, we treat the translated quotations as representations of participants' accounts and avoid making stronger claims about fine-grained interactional meaning than the translation procedure permits.

As AI becomes more common in language education, the key question is not whether to use it, but how to make sure it serves pedagogical goals and accommodates learner diversity. For slow learners in inclusive classrooms, this question is closely associated with how teachers can sustain meaningful differentiation in everyday teaching. The present study suggests that when teachers learn to design prompts, pacing, feedback, and participation options for particular learners, GenAI can serve not as a replacement for teacher expertise but as an important partner in extending teacher agency for more responsible and inclusive language education.

Declaration of Generative AI Usage

The authors declare that they used ChatGPT for preparing this manuscript to enhance its linguistic aspects, such as clarity, coherence, and readability but they do not use it to generate any content. The authors take full responsibility for the content of this work.

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Appendix

Appendix 1. Semi-Structured Interview Questions

1. Teacher agency trajectory

1) Before joining this project, what kinds of experience did you have with AI tools, coding, or other forms of technology-related experimentation?

2) During the design process, when did you feel that you were making important decisions yourself rather than simply following AI-generated suggestions?

3) Across the project, how did your role change as a future teacher who might use, adapt, or design AI-supported learning tools?

4) How has this experience shaped your longer-term vision of teaching with AI or educational robots?

2. Pedagogical goals and UDL-oriented design

1) At different stages of the project, what pedagogical goals did you set for slow learners, and how did those goals influence your design choices?

2) How did you try to reflect UDL principles such as multiple means of representation, engagement, or action and expression in the agent's design?

3) What kinds of support did you think slow learners would need most, such as pacing, repetition, simplified language, multimodal input, or emotionally safe feedback?

4) What difficulties did you encounter when turning those ideas into actual prompts, interaction flows, or supporting materials?

3. Vibe coding, mentoring, and design constraints

1) What possibilities did you experience while using vibe coding tools such as Gemini, Claude Code, and Cursor?

2) What constraints or frustrations did you encounter when working with AI-generated code, prompts, or agent responses?

3) When the output did not match your educational intentions, how did you decide what to revise?

4) How did feedback from the mentor teacher and the two faculty mentors influence your decisions during the design process?

4. Final evaluation and TPACK development

1) How would you evaluate the final agent or robot-based demonstration that you created?

2) In what ways did the final result match, or fail to match, your original pedagogical intentions?

3) What do you think your prototype could realistically contribute to supporting slow learners in school settings?

4) In what ways, if any, did your technological knowledge, pedagogical reasoning, or integrated TPACK develop through this project?

5) Looking back on the whole process, what was the most important thing you learned as a pre-service teacher designing AI-supported instruction?

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Appendix 2. Excerpt from the UDL-Oriented System-Prompt Reference

1. Use very simple, familiar vocabulary, maintain a positive tone, and explain difficult terms through everyday examples.
2. Keep responses short, usually one to three sentences, and break difficult content into smaller steps.
3. Emphasize key ideas, encourage repetition, and summarize complex content briefly when needed.
4. Support learner autonomy by offering follow-up activities at appropriate points and by linking tasks to everyday life.
5. Provide encouraging feedback, praise effort, and guide learners back to relevant parts rather than simply marking answers as wrong.
6. In voice interaction, repeat utterances on request, slow down when asked, and confirm spoken input before moving on.
7. Open the interaction by introducing the agent, asking the learner's name, and inviting the learner to choose a topic.

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Seongyong Lee is Lecturer (Assistant Professor) at UCL Institute of Education. His research focuses on AI in L2 education, teacher education, and Global Englishes. He has published numerous articles in leading journals such as *TESOL Quarterly*, *Computers & Education*, *Applied Linguistics*, *Computer Assisted Language Learning*, *Language Learning & Technology, Education & Information Technologies*, *Interactive Learning Environments*, *ELT Journal*, and *System*, among others. He is serving as the editor of Multimedia Assisted Language Learning and as an editorial board member of *British Educational Research Journal*, *European Journal of Teacher Education*, and *Asia Pacific Education Review*.

ORCID: 0000-0002-9436-4272

Sooyoun Kim is a Professor in the Department of Special (Inclusive) Education at Gyeongin National University of Education. Her scholarly interests encompass inclusive education, building caring communities, positive behavior support, and teacher education. She has an extensive record of publications in peer-reviewed special education journals and has led numerous government-funded research projects as principal investigator.

ORCID: 0009-0007-2857-6318

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