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Coached by My Future Self: A Syllabus-Driven AI Mentor to Build Grit, Agency, and Learning Performance through a Mantle-of-the-Expert Journey

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Abstract: Learning is a transformative journey from not knowing to mastery, guided by syllabi that outline weekly topics, learning objectives, tasks, and assessment rubrics. While these documents scaffold academic content, they rarely engage students as developing professionals or motivate them through long-term identity growth. Many learners struggle to stay on track—grappling with procrastination, low persistence, and a diminished sense of ownership over one's learning—especially when weekly tasks feel disconnected from their future goals. This paper introduces a new approach to AI-enhanced learning: a "Future Self Coach" that transforms a standard course syllabus into a personalized mentor. Rather than functioning as a virtual assistant, this large language model (LLM)-powered agent embodies the student's envisioned expert self at the end of the course. The system leverages existing course syllabi—specifically their objectives and rubrics, framed as identity-progress dashboards—as inputs to generate personalized guidance aligned with weekly expectations, without requiring teachers to author complex content. Through this interaction, students are not only supported in completing tasks, but also gradually adopt the mindset promoted by the Mantle-of-the-Expert approach, where learning is framed as stepping into expert roles. A quasi-experimental study with 97 vocational students in hospitality training compared three conditions: (1) a learning management system (LMS) with the Future Self Coach, (2) an LMS with a general-purpose AI assistant, and (3) a standard LMS. Results showed that students supported by the Future Self Coach significantly outperformed the other groups across all measures—demonstrating higher learning performance, greater grit, stronger sense of agency, and engaged more frequently. This study presents a scalable, psychologically grounded framework for integrating AI into existing courses without burdening instructors. By leveraging the syllabus as both a roadmap and motivational scaffold, the system bridges the gap between short-term tasks and long-term identity, helping learners stay focused, resilient, and committed to their professional growth.

Keywords: *Future Self, LLM, Grit, Sense of Agency, Personalized Learning*

1. Introduction

Learning is a cumulative journey toward expertise, structured not only by the content students consume but also by how they engage with it over time. Many students know *what* to do in a course, but struggle to stay motivated about *why* it matters (Reeve, 2024). Weekly tasks often feel like isolated checkboxes, disconnected from personal growth or professional identity. This disconnect leads to familiar struggles: procrastination, declining persistence, and a diminished sense of ownership over one's learning (Kirschner & Hendrick, 2024). These internal struggles—often invisible to instructors—can critically affect learning outcomes. While syllabi offer week-by-week structure—laying out topics, tasks, and assessments—they rarely help students see themselves as future professionals in the making (Harrington & Thomas, 2023). The gap between present effort and future identity is rarely made visible or actionable within the learning process.

This paper reimagines the syllabus not just as a roadmap for content, but as a bridge to the student's future self—the envisioned expert identity they hope to achieve (Hershfield, 2011; Pataranutaporn et al., 2024). We introduce the *Future Self Coach*, an AI-powered mentor built on large language models (LLMs) that uses course syllabi and rubrics to guide students on their journey toward becoming competent or "expert" by the end of a course. Unlike conventional virtual assistants or helpdesk-style chatbots, the pop-up coach speaks as the learner's future professional self—helping them stay focused, track progress, and receive motivational feedback. Our approach is grounded in the *Mantle-of-the-Expert* (*MoE*) pedagogy, which positions learners as professionals-in-training by having them adopt the roles and responsibilities of real-world experts (Heathcote & Bolton, 1994; Taylor, 2025). Rather than inventing new curricula, we turn existing course artifacts—especially the syllabus and its rubrics—into what we call an *identity-progress dashboard* (Novice → Apprentice → Expert) to make identity progress visible. This enables students to track their growth not only through grades, but through gradual mastery of expert habits and mindsets.

Our design rationale activates two essential psychological drivers: **grit**—the ability to sustain effort toward long-term goals (Derakhshan et al., 2025; Duckworth et al., 2007)—and **sense of agency**, or the belief that one's actions can shape meaningful outcomes (Haggard, 2017; McGivney, 2025). Both are essential to learning, but often neglected in digital learning systems, which mostly focus on content delivery and reactive help (Labadze et al., 2023). Such systems lack mechanisms to support long-term motivation or translate course milestones into emotionally resonant, identity-centered guidance. To address this gap, we introduce the Future Self Coach and investigate its effects on student learning performance. A quasi-experimental study was conducted in a university-level foreign language hospitality course, comparing three learning conditions: (1) a standard LMS, (2) an LMS with a general-purpose AI assistant, and (3) an LMS enhanced with the Future Self Coach. The study is guided by the following research questions:

1. **RQ1**: How does the Future Self Coach affect students' learning achievement?
2. **RQ2**: How does it influence students' grit?
3. **RQ3**: How does it impact students' sense of agency?
4. **RQ4**: How does it affect students' engagement frequency over time?

Together, our contribution lies in presenting a zero-authoring, syllabus-driven AI coach that transforms standard course artifacts into a personalized mentoring system—without adding any workload for teachers. The remainder of this paper outlines the theoretical framework, system design and implementation, research methods, results, and implications.

2. Theoretical Framework

2.1 Future Self

The concept of the future self refers to an individual's mental image of who they aspire to become (Hershfield, 2011). This psychological construct has been widely studied in fields such as human-computer interaction (Pataranutaporn et al., 2024), health behavior (Zhao et al., 2022), and behavioral economics (Taylor & Carlson, 2025). A consistent finding across these domains is that when individuals feel a stronger connection to their future selves—a state known as future self-continuity—they are more likely to delay gratification, make responsible decisions, and persist through short-term discomfort in pursuit of long-term goals.

Despite its motivational promise, the future self remains rarely applied in educational settings, and even less so as an embedded element of daily coursework (Feng & Papi, 2020). Most implementations take the form of one-off journaling or career reflections (Beauvais, 2025), disconnected from the flow of instructional content. Our approach fills this gap by treating the future self not as a passive vision, but as an active mentor. The Future Self Coach simulates a student's professional identity at the course's end, guiding their weekly learning while reinforcing alignment with long-term goals. This identity framing lays the foundation for our integration of role-based pedagogies such as Mantle-of-the-Expert.

2.2 Mantle-of-the-Expert (MoE) Pedagogy

Mantle-of-the-Expert (MoE) is a role-based pedagogy that invites students to learn by stepping into professional identities within realistic scenarios (Heathcote & Bolton, 1994). Rather than passively absorbing content, they take on expert roles—such as managers or service staff—to solve problems and build both skills and identity through structured narratives. MoE fosters agency and responsibility by framing learners as competent actors from the outset.

Prior research has shown MoE's value in project-based and interdisciplinary learning, especially in drama education and humanities (Taylor, 2025; Kosma, 2021). However, it remains largely absent from digital or AI-enhanced platforms, which often focus on content rather than professional identity. Our system adapts MoE for the digital space by mapping syllabus goals to role-based progression. Weekly tasks are framed as real-world challenges, supported by an AI coach that reinforces students' expert identity throughout the course.

2.3 LMS-Integrated AI Mentorship

AI has advanced rapidly in education, particularly in adaptive feedback, automated grading, and tutoring systems (Mittal et al., 2024). Recent developments in large language models (LLMs) have enabled richer dialogue-based interactions, with growing interest in conversational agents for learning (McTear, 2022). However, most implementations remain task-centric rather than long-term motivation or identity development.

Several studies have explored AI assistants or virtual agents in LMS environments (Gubareva & Lopes, 2020; Sougleridi et al., 2023), but these typically focus on reactive help—not on representing who the learner could become. To our knowledge, no existing system meaningfully integrates teacher-authored documents—such as syllabi or rubrics—into identity-aware guidance. Our system is best described as an LLM-powered conversational agent, accessible through a chat-like interface embedded in the LMS. It delivers weekly check-ins through messages that link course tasks to future professional roles, encourage self-reflection, and offer motivational support when students encounter challenges. This design shifts the role of the AI assistant from a content responder to an identity-centered mentor.

2.4 Grit and Sense of Agency

Academic success requires more than subject knowledge—it hinges on a combination of non-cognitive skills that enable students to stay motivated, manage time, and cope with frustration. Among these, grit—the capacity to sustain passion and effort over long periods—is a strong predictor of persistence and goal completion (Derakhshan et al., 2025; Duckworth et al., 2007). Equally important is a sense of agency, or the belief that one's actions meaningfully influence outcomes (Haggard, 2017; McGivney, 2025). Students who perceive high agency are more likely to take initiative, persevere, and remain engaged over time.

Some studies have explored grit interventions (e.g., goal setting, mindset prompts), but few tie them to curriculum structure or identity growth (Chen et al., 2024; Ghafouri, 2024). Our system operationalizes these traits by embedding them into the weekly learning process. Students interact with a future-self coach that affirms long-term goals, while the syllabus-aligned rubric is visualized as an identity-progress dashboard. Badge levels (Novice →

Apprentice → Expert) help learners track not just task completion, but the development of mindset, responsibility, and professional habits over time.

3. System Design and Implementation

The Future Self Coach is designed to deliver scalable, identity-based mentorship aligned with the Mantle-of-the-Expert (MoE) principles. In MoE, students are positioned as professionals-in-training from the outset—learning not as passive recipients, but as emerging experts responsible for real-world tasks. The system enables students to interact with an AI agent that guides them through weekly challenges, framed in the voice of their envisioned future self. Rather than viewing assignments as isolated tasks, learners are coached to see each activity as a meaningful step in their journey toward expertise.

Technically, the system operates as a conversational agent powered by a large language model (LLM), embedded into the Learning Management System (LMS) via a pop-up chat interface. OpenAI's GPT-3.5-turbo model was used via API integration. The Future Self Coach uses a role-conditioning technique based on prompt initialization (Al Hakim et al., 2024), which primes the LLM to consistently respond as the student's future professional self. Students engage with the coach weekly to receive personalized feedback, encouragement, and guidance—generated by comparing two structured data streams: (1) the syllabus and its rubric, which serve as a static map of expectations, and (2) real-time student activity data, including task completion and rubric-aligned scores. The first defines *where* students are expected to go; the second reveals *where* they currently are. The system architecture—including all core components and teacher-student roles—is shown in Figure 1.

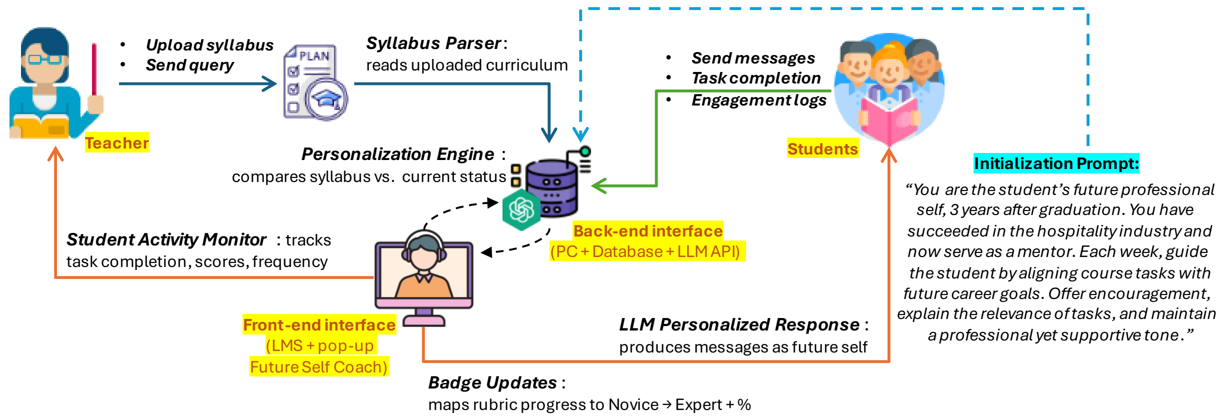


Figure 1. System architecture of the Future Self Coach.

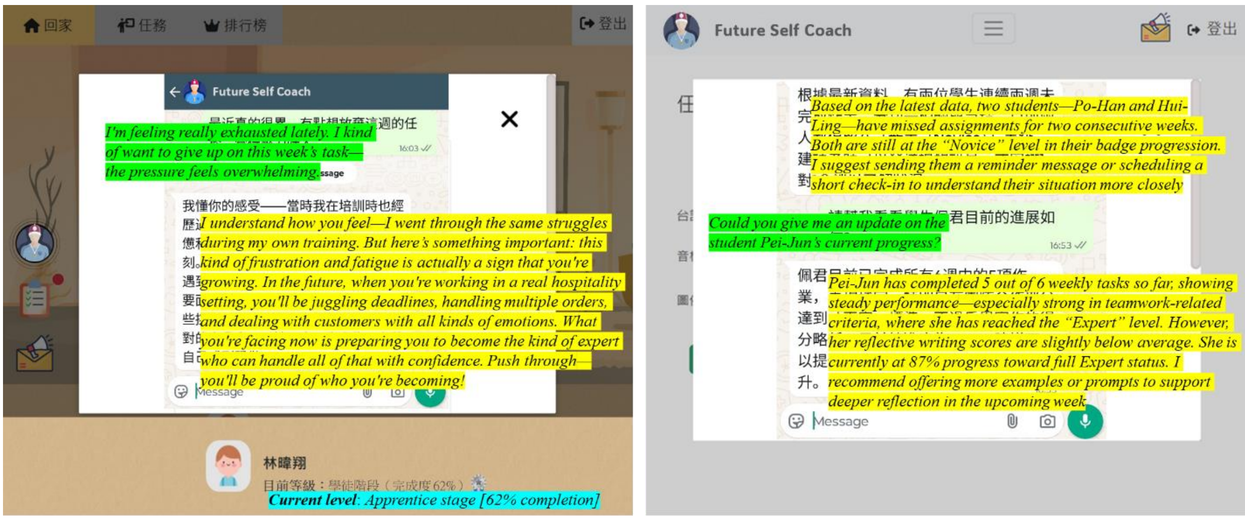


Figure 2. Example interactions with the Future Self Coach.

The system supports the development of grit and sense of agency by reinforcing key behaviors such as time management, tolerance for frustration, growth mindset, and the willingness to take on challenges. Through weekly AI interactions, students receive messages that help them reframe setbacks as growth opportunities and connect momentary difficulty to long-term identity development (see Figure 2, left). This future-facing narrative helps normalize frustration as part of the expert development process. Besides, Student progress is visualized through a badge-based identity dashboard. Learners begin as *Novice*, advance to *Apprentice*, and ultimately reach *Expert* level. Each badge maps directly to rubric dimensions, with progression tracked as a percentage of rubric mastery. This mechanism not only motivates continued effort but also gives students agency to set micro-goals and monitor their development in real time. Teachers play a foundational yet low-effort role in the system. They upload syllabi and its rubrics in structured formats and can monitor student progress via a dashboard. The AI assistant can also respond to teacher queries—for example, summarizing badge progress (see Figure 2, right). These dual-use capabilities allow the system to act as both a mentor for the student and a consultant for the teacher.

System implementation follows a modular and replicable architecture. The backend is built in Python and connects to LLM services via OpenAI API endpoints. The frontend chat interface is implemented in JavaScript and embedded into the LMS via iframe or plugin. Student progress data is securely stored in a cloud-based database, and badge updates are computed by a rubric-aligned scoring engine. The system supports containerized deployment using Docker, with optional Kubernetes orchestration for institutional scalability. Authentication follows OAuth 2.0 standards to ensure secure and role-based access.

4. Experimental Design

4.1 Participants, Ethics, and Learning Content

A quasi-experimental study was conducted in Taiwan with 97 undergraduate students majoring in Hospitality Management, all of whom were preparing for roles in Japanese restaurant service. To ensure group comparability, students were stratified based on their most recent course grades, then randomly assigned to one of three independent groups. Experimental Group A (LMS with the Future Self Coach) included 34 students (20 female, 14 male); Experimental Group B (LMS with a general-purpose AI assistant using API access to ChatGPT) included 32 students (19 female, 13 male); and the Control Group (standard LMS) included 31 students (17 female, 14 male). Unlike Group A, the assistant in Group B did not initiate role-based coaching. Its replies were primarily task-oriented—providing factual answers or clarifications without future-oriented framing or emotional scaffolding. This contrast allowed the study to isolate the effects of identity-based mentorship featured in Group A.

All participants had similar academic backgrounds, were around 21 years old, and were taught by the same instructors to control for instructional variability. Group assignments were completely independent, and no cross-group interaction occurred during the study. The research was approved by the university's institutional review board [IRB No.: NCUEREC-110-011], and all participants provided informed consent. They were informed of their right to withdraw at any point without penalty, and all privacy protocols were strictly followed.

The learning content was designed by the course instructor in the form of structured service scripts, aligning closely with both the course objectives and students' prior training. Scenarios simulated professional roles in Japanese restaurant settings—such as service staff, cashiers, and floor managers—emphasizing not only technical procedures but also customer interaction, emotional adaptability, and real-time problem solving. For example, one script tasked students with handling an emotionally upset customer while role-playing as a cashier who had made a billing error, requiring both empathy and accountability. These scenarios were designed to reflect authentic workplace challenges, supporting both skill development and professional identity formation in line with the MoE approach.

4.2 Instruments and Data Analysis

To evaluate learning achievement (**RQ1**), students completed a pre-test and post-test aligned with the course objectives. The two versions included variations in question phrasing and order to reduce memorization effects. The test consisted of 13 items, scored from 0 to 100, and demonstrated high internal reliability (Cronbach's α = .863). Learning gains across groups were compared using ANCOVA, with pre-test scores as covariates to control for baseline differences.

Grit (**RQ2**) was measured using a 10-item, five-point Likert scale adapted from Duckworth et al. (2007), showing strong internal consistency (Cronbach's α = .88). A sample item includes: "*I finish whatever I begin*." This reflects the sustained passion and perseverance component central to the grit construct. Sense of agency (**RQ3**) was assessed using a 13-item, five-point Likert scale adapted from Tapal et al. (2017), with reliability at Cronbach's α = .78. A representative item is: "*I am in full control of what I do*." This captures the individual's belief in their capacity to influence outcomes through their own actions. One-way ANOVAs were performed separately to compare group differences in both grit and agency scores.

To assess study frequency (**RQ4**), system log data were extracted from the LMS to capture the number of active learning sessions per student per day. Daily averages were calculated for each group, and engagement trends were visualized over time to identify behavioral differences.

In addition, semi-structured interview questions (Al Hakim et al., 2025) were conducted to explore student perceptions and motivational factors influencing their willingness to engage with the learning system.

4.3 Procedure

The experiment was conducted over an eight-week period and fully embedded within students' regular classroom training. The system was designed to complement conventional instruction, allowing seamless integration into scheduled topics without disrupting the existing curriculum. While this study focused on an eight-week implementation, the system itself is scalable and can be extended to support full-semester use, including repeated cycles of learning outcome demonstrations.

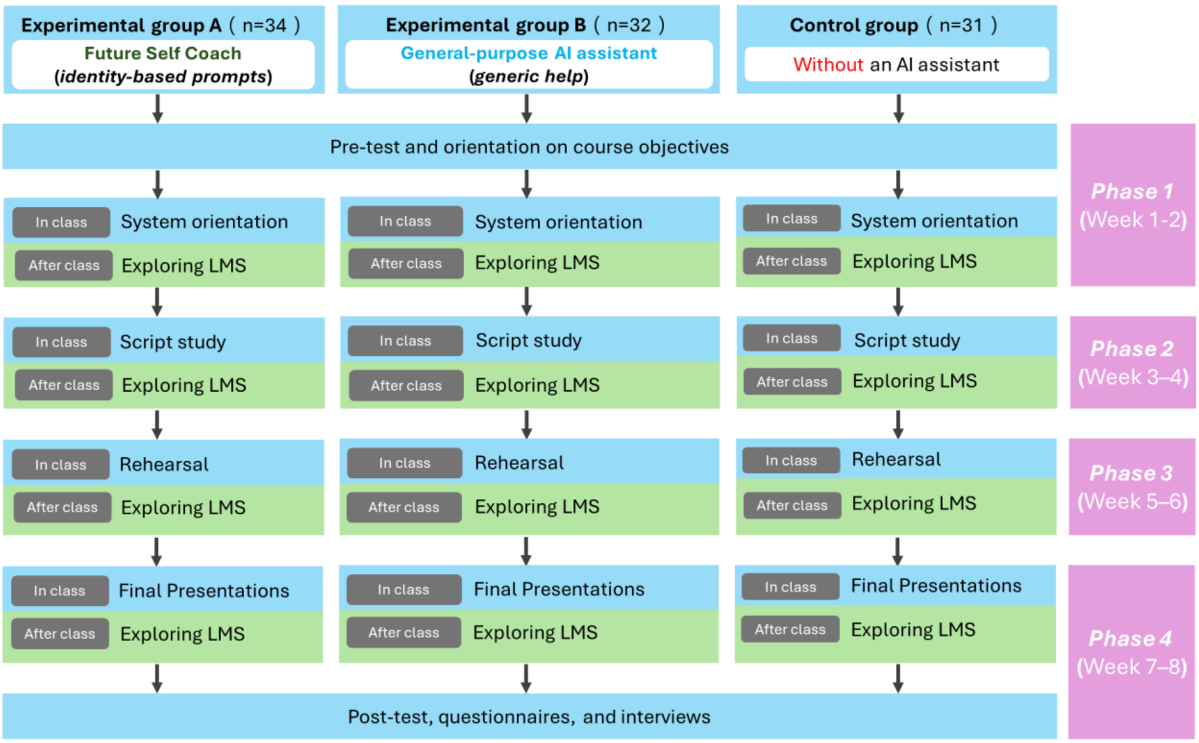


Figure 3. Experimental procedure.

The intervention was structured into four sequential phases, each lasting two weeks. Sessions were held once a week for 100 minutes, in accordance with institutional guidelines. Each phase introduced new tasks aligned with the syllabus, allowing students to gradually build their skills while maintaining a consistent instructional rhythm.

As shown in Figure 3, the experimental procedure included both in-class and out-of-class components. Students progressed through phases involving LMS onboarding, scenario-based script study, rehearsal sessions, and final role-play presentations—mirroring authentic professional development cycles in the hospitality industry.

The nature of system interaction varied by group. Students in the Future Self Coach group received identity-framed guidance, responding in the voice of their future professional self. For example, when a student typed, "*I got confused during the team role-play—I didn't know how to respond in Japanese*," the system replied, "*As your future self managing an international service team, I remember moments like this too. Staying calm and asking teammates for backup helped me handle language gaps professionally. You've just experienced a real challenge experts often face*." In contrast, students in the conventional AI assistant group received generic replies such as: "*That sounds difficult. Try reviewing your script or asking your teacher*." These differences reflect the distinction between identity-based mentorship and standard task-level support.

5. Results and Discussion

5.1 Learning Performance

An ANCOVA was conducted on students' post-test scores, with pre-test scores as the covariate and group intervention as the independent variable. An initial ANOVA showed no significant difference in pre-test scores among the groups (F = 0.417, p > 0.05), indicating baseline equivalence. The assumption of homogeneity of regression slopes was met (F = 1.268, p > 0.05), justifying the use of ANCOVA.

Table I shows the ANCOVA results, revealed a significant effect of group assignment on post-test scores (F = 13.42, p < 0.001), with a large effect size (partial η^2 = 0.21). Pairwise comparisons showed that students in the Future Self Coach group significantly outperformed those in the AI assistant group and the control group. The AI assistant group also performed significantly better than the control.

Table 1. *ANCOVA results for students' learning performance*

Group	***N***	**Mean**	**SD**	**Adj. Mean**	**F-value**	**Pairwise Comparisons**	**Effect Sizes (η_p^2)**
Exp. A	34	83.1	5.1	84.6	13.42*	A > B	0.21
Exp. B	32	77.8	6.2	78.3		A > C	
Control	31	73.1	4.9	72.8		B > C	

*p < 0.05

These results suggest that the personalized, identity-based feedback provided by the Future Self Coach enhanced students' conceptual understanding and application. The causal mechanism may involve a sequence of motivational and cognitive processes: identity-framing increased perceived relevance, which enhanced focus and effort, leading to deeper processing and improved learning outcomes (Burnette et al., 2020). By aligning weekly tasks with future professional goals, the coach helped students sustain attention and make connections across lessons. These patterns can be interpreted through the lens of identity-based motivation theory, which emphasizes the role of long-term goal alignment in driving learning persistence (Oyserman, 2024). One student remarked, "*It felt like I was being guided by my future self. That made the lessons more serious and made me want to do better*." Another noted, "*The coach reminded me what kind of expert I want to become, and that helped me push through even when I didn't feel like studying*."

5.2 Grit

A one-way ANOVA was performed to compare grit scores among the three groups (see Table 2 below). The analysis revealed significant differences (F = 7.45, p < 0.05), with a moderate effect size (partial η^2 = 0.11). Pairwise tests showed that the Future Self Coach group reported significantly higher grit than both the AI assistant group and the control group, while the difference between Group B and the control was not statistically significant.

Table 2. *ANOVA results for students' grit and sense of agency*

Measure	Group	*N*	Mean	SD	F-value	Pairwise Comparisons	Effect Sizes (η_p^2)
Grit	Exp. A	34	83.1	5.1	7.45*	A > B	0.11
	Exp. B	32	77.8	6.2		A > C	
	Control	31	73.1	4.9			
Sense of Agency	Exp. A	34	83.1	5.1	6.97*	A > B	0.12
	Exp. B	32	77.8	6.2		A > C	
	Control	31	73.1	4.9			

*p < 0.05

The increased grit observed in Group A likely stems from the system's ability to contextualize challenges within a long-term identity narrative. When weekly obstacles were framed as necessary steps toward becoming an expert, students were more likely to persist through setbacks (Derakhshan et al., 2025). This approach resonates with Duckworth et al. (2007), who emphasize that purpose and meaning are central to sustained effort. In contrast, Group B's generic AI lacked future-oriented framing, and students in the control group had no additional support. Interview responses reflected this pattern. One student shared, "*When I felt stuck, the coach reminded me why I was doing this. It helped me not give up*." Another said, "*It felt like someone believed in my future version, so I kept pushing*."

5.3 Sense of Agency

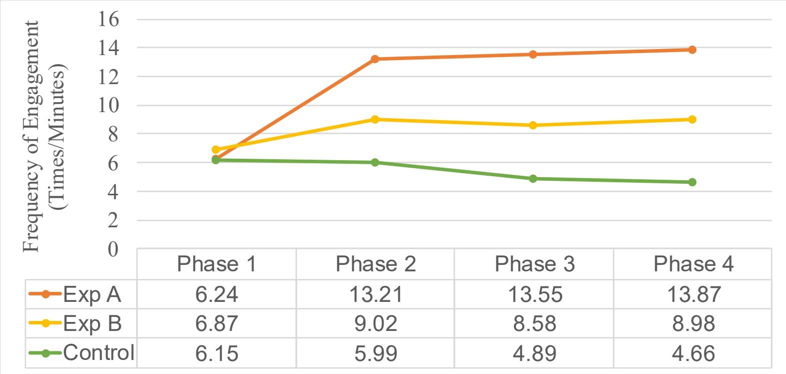
Sense of agency was also assessed via one-way ANOVA (see Table 2 above), revealing significant group differences (F = 6.97, p < 0.05), with a moderate effect size (partial η^2 = 0.12). Pairwise analysis indicated that Group A scored significantly higher than both Group B and the control group, while the difference between Group B and the control was not significant.

The enhanced sense of agency in the Future Self Coach group can be attributed to the badge-based identity dashboard. By translating rubric criteria into visual badge progress (Novice → Apprentice → Expert), students could track and influence their trajectory in real time. This feedback loop promoted autonomy, as students set micro-goals and monitored their own growth (Al Hakim et al. 2025). The design aligns with Self-Determination Theory, where perceived control over outcomes supports intrinsic motivation (Deci & Ryan, 2020). One participant explained, "*Seeing my badge level change made me feel like I had control. I knew what I needed to work on*." Another noted, "*The AI helped me connect my actions to progress*."

5.4 Engagement Frequency

Analysis of LMS activity logs revealed significant differences in engagement frequency across groups. Students in the Future Self Coach group engaged in more consistent out-of-class activity, averaging 11.72 weekly sessions, compared to 8.36 in the AI assistant group and 5.42 in the control group. Fig. 4 illustrates that Group A's engagement remained stable and slightly increased over time, peaking during rehearsal and presentation phases. In contrast, Groups B and C showed more variable activity, with noticeable drops after the script study phase.

This consistent engagement in Group A stemmed from the Future Self Coach's identity-framed prompts, which framed each week as a step toward real-world expertise. These emotionally resonant messages offered motivational nudges beyond formal instruction, helping embed learning into daily routines. As one student shared, “*The coach kept checking in and reminding me why the task mattered in the real world. That kept me going even when I was tired*.”



	Phase 1	Phase 2	Phase 3	Phase 4
Exp A	6.24	13.21	13.55	13.87
Exp B	6.87	9.02	8.58	8.98
Control	6.15	5.99	4.89	4.66

Figure 4. Observed study frequency among groups.

6. Conclusion, Limitations, and Future Works

This study introduces a new direction for using LLM-powered AI in education through a scalable and psychologically grounded framework that embeds identity-based mentorship into existing course structures. By transforming standard syllabi and rubrics into interactive, future-self-aligned coaching dialogues, the system not only improved learning performance, but also significantly enhanced students' grit, sense of agency, and study frequency. The Future Self Coach repositions AI from a reactive content assistant to a proactive identity guide, showing how syllabus-driven personalization can shift learners’ mindsets and behaviors over time. These results mark an important step toward rethinking AI in education—not just as a tutor, but as a partner in professional identity development. The integration of Mantle-of-the-Expert pedagogy into LMS environments demonstrates how expert-role framing can support both hard and soft skill acquisition while maintaining instructional scalability. By embedding motivation into weekly check-ins, the system promotes emotional engagement and professional self-concept—without adding to teacher workload.

While promising, this study has limitations. It was conducted in a single discipline within a specific cultural and institutional context (hospitality training in Taiwan), and over a short-term deployment. Moreover, although the rubric-aligned badge system and conversational coaching provided robust support, the system did not yet adapt task difficulty or pacing in real time. Future work should explore longer-term use, cross-disciplinary replication, and integration with motivational scaffolds like peer coaching, social comparison, or gamified goal-tracking. Enhancements such as behavioral analytics, emotional state recognition, and embodied AI agents may unlock richer, more adaptive interactions. Ultimately, this work lays the foundation for AI mentors that are not only intelligent but personally meaningful—capable of evolving with learners and sustaining expert identity over time.

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