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Artificial Intelligence–Powered Adaptive Learning Systems in Technical and Vocational Education: Effects on Skill Mastery, Self-Regulated Learning, And Learner Autonomy

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Abstract- The use of Artificial Intelligence (AI) in education has brought about adaptive learning systems that can tailor instruction to fit the performance and engagement levels of students. While there has been some research into how AI is applied in general education, there has been less focus on its effects in Technical and Vocational Education and Training (TVET), where developing competencies and hands-on skills is key. This study looked into how an AI-driven adaptive learning system influenced technical skill mastery, self-regulated learning, and learner autonomy among the TVET students. We used a quasi-experimental pretest-posttest control group design with 180 second year technical college students. The experimental group (n=90) engaged with an AI-adaptive learning platform for eight weeks, while the control group (n=90) followed a traditional learning management system. We gathered data using a technical skill performance rubric, the Self-Regulated Learning Scale and the Learner Autonomy Questionnaire. The results from ANCOVA showed that students who used the AI-adaptive system achieved significantly higher skill mastery (F (1177) = 18.64, p <0.001), better self-regulated learning (F (1177) = 21.47, p<0,001|), and increased learner autonomy (F(1177) = 16.32, p<0.001) compared to those in the control group. Additionally, structural equation modeling indicated that self-regulated learning and learner autonomy played a partial mediating role in the connection between AI-adaptive learning and skill mastery. These findings suggest that AI-powered adaptive systems can significantly enhance competency-based technical training by promoting independent learning habits and improving practical performance outcomes.

Index Terms- Artificial Intelligence, Adaptive Learning Systems, TVET, Skill Mastery, Self-Regulated Learning, Learner Autonomy.

I. INTRODUCTION

Artificial Intelligence (AI) is shaking things up in the world of education, paving the way for personalized learning experiences, predictive analytics, and automated feedback systems (Holmes et al., 2019). One of the standout applications is AI-powered adaptive learning systems, which are crafted to tailor instructional content, pacing, and assessments in real-time based on how students interact and perform (Pane et al., 2017). These systems are becoming more common in higher education and online learning spaces. However, we still have a limited amount of solid evidence regarding their effectiveness in Technical and Vocational Education and Training (TVET).

TVET stands apart from traditional academic education because it focuses on competency-based instruction and the development of practical skills (UNESCO, 2020). Students need to grasp theoretical concepts and also show they can apply them in real-world scenarios. Unfortunately, traditional Learning Management Systems (LMS) often provide the same content to everyone, ignoring individual skill gaps. This one-size-fits-all approach can slow down progress, especially for students who learn at different paces.

Self-regulated learning (SRL) is crucial in technical education. Students are expected to plan their tasks, keep track of their performance, and tweak their strategies during hands-on activities (Zimmerman, 2020). Likewise, learner autonomy the ability to take charge of one's own learning plays a key role in developing long-term professional skills (Little, 2015). AI-adaptive systems could enhance these qualities by providing real-time analytics, focused feedback, and a pathway to mastery. Even though there is a growing buzz around AI in education, we still lack enough empirical research that looks into its direct and indirect effects on skill mastery in TVET settings. This study aims to fill that gap.

II. LITERATURE REVIEW

Artificial Intelligence and Adaptive Learning in Education

Artificial Intelligence (AI) has evolved from a concept that seemed far-off into a practical tool that is reshaping modern education. AI-driven adaptive learning systems utilize machine learning algorithms, learner analytics, and predictive modeling to customize educational materials to fit each student's unique needs (Holmes et al., 2019). Unlike traditional Learning Management Systems (LMS) that offer a one-size-fits-all approach, adaptive platforms can adjust the difficulty of tasks, suggest additional activities for those who need extra help, and provide immediate feedback based on how students are performing.

Research in general education shows that these adaptive learning systems can boost academic success and help close learning gaps (Pane et al., 2017). Hariyanto (2025) found that intelligent tutoring systems often lead to moderate to significant improvements in learning compared to standard teaching methods. However, most of the research has concentrated on subjects like Mathematics, Science, and language arts. There is still a big question mark over how these systems impact competency-based and skill-focused learning environments, such as Technical and Vocational Education and Training (TVET).

Skill Mastery in Technical and Vocational Education

Technical and Vocational Education and Training (TVET) is all about mastering specific competencies. Unlike theoretical subjects where the focus is mainly on cognitive understanding, TVET prioritizes the demonstration of practical and psychomotor skills (UNESCO, 2020). Achieving mastery in this field requires lots of practice, constructive feedback, and timely corrections.

One ongoing challenge in TVET is the differences in students' prior knowledge, motor skills, and problem-solving capabilities. When instruction is delivered in a uniform manner, those who learn at a slower pace may find it hard to reach competency levels, while quicker learners might lose interest. Adaptive learning systems have the potential to tackle this challenge by allowing learners to progress at their own pace moving forward only after they have shown they truly understand the material. This concept ties back to Hariyanto,(2025) mastery learning theory, which highlights the importance of corrective feedback and personalized pacing. However, despite these theoretical connections, there is a noticeable lack of empirical research that looks into whether AI-driven adaptive systems actually lead to significant improvements in measurable technical skills within workshop-based learning environments.

Self-Regulated Learning in Technology-Enhanced Environments

Self-regulated learning (SRL) is all about how learners can plan, monitor, and assess their own learning journeys (Zimmerman, 2020). It encompasses goal-setting, strategic planning, self-monitoring, and reflection. These skills are especially vital in technical education, where learners often find themselves troubleshooting, correcting errors, and practicing iteratively.

Digital learning environments can really boost SRL by providing performance dashboards, progress indicators, and instant feedback (Broadbent & Poon, 2015). AI-adaptive systems take this a step further by pinpointing performance gaps and recommending tailored learning paths. When learners get immediate, data-driven feedback, they are more inclined to tweak their strategies and push through challenges. That said, the development of SRL is not just about how the system is designed; it also hinges on how engaged learners are with the system. Therefore, it is crucial to validate these findings in TVET settings.

Learner Autonomy and Technology Integration

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Learner autonomy is all about taking charge of one's own learning decisions, including how fast to go, which strategies to use, and how to evaluate performance (Little, 2015). In technical professions, this autonomy is key since workers need to be able to solve practical problems on their own. Technology-enhanced environments often support this autonomy by allowing for self-paced learning and flexible access to resources (Holmes et al., 2019). Adaptive systems can really empower learners by giving them the reins to steer their own learning paths while still providing some helpful structure along the way. However, some experts caution that if students become too dependent on these technological supports, it might stifle their ability to think independently. So, it is crucial to explore whether AI systems truly foster autonomy in the realm of technical education.

Research Gap

Although there is a wealth of research highlighting the advantages of AI in broader academic settings, there is still a noticeable lack of empirical studies that focus specifically on:

- Mastery of psychomotor skills
- Competency-based technical education
- The mediating effects of self-regulated learning (SRL) and autonomy

This study aims to fill that gap by looking into both the direct and indirect relationships between AI-adaptive learning and performance in technical skills.

III. METHODOLOGY

Research Design

In this study, we went with a quasi-experimental pretest–posttest control group design. While true randomization was not possible due to scheduling issues at the institution, we made sure to randomly assign intact classes to either the experimental or control group to keep selection bias to a minimum.

Participants

We had 180 second-year students from a technical college that offers courses in Electrical Installation and Maintenance. These students were between 18 and 24 years old. We split them evenly, with ninety students in the experimental group and ninety in the control group.

A power analysis using G*Power showed that we needed at least 150 participants to detect medium effect sizes ($f = 0.25$) at $\alpha = 0.05$ and power = 0.80. With our final sample of 180, we comfortably exceeded that requirement.

Intervention

The experimental group utilized an AI-powered adaptive learning platform for eight weeks. This system featured:

- Personalized content sequencing
- Real-time corrective feedback
- Skill diagnostic quizzes
- Performance dashboards
- Automated remediation recommendations

On the other hand, the control group received instruction through a traditional LMS that had the same instructional content but lacked those adaptive features. Both groups had the same amount of instructional time (3 hours per week) and were taught by the same instructor to ensure consistency in teaching effects.

INSTRUMENTS

Technical Skill Performance Rubric

Students completed a practical wiring installation task, which we assessed using a standardized competency rubric. This rubric evaluated:

- Accuracy
- Procedural adherence
- Safety compliance
- Troubleshooting ability

The inter-rater reliability coefficient was 0.89

Self-Regulated Learning Scale

We adapted this from validated SRL instruments (Zimmerman, 2000), and it had a Cronbach's alpha of 0.91

Learner Autonomy Questionnaire

This measured students' responsibility for their learning, their ability to solve problems

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independently, and their decision-making skills, with a Cronbach's alpha of 0.86

IV. DATA ANALYSIS

- Descriptive statistics (Mean, SD)
- ANCOVA to account for pretest differences
- Effect size calculation (η^2)
- Structural Equation Modeling (AMOS 24)
- Bootstrapping for mediation analysis

We made sure to test and confirm the assumptions of normality, homogeneity of variance, and linearity.

V. RESULTS

Descriptive Statistics

Table 1: Posttest Means and Standard Deviations for Study Variables

Variable	Group	N	Mean	Standard Deviation (SD)
Skill Mastery	Experimental	90	82.45	6.12
	Control	90	74.33	7.01
Self-Regulated Learning	Experimental	90	4.12	0.52
	Control	90	3.54	0.60
Learner Autonomy	Experimental	90	4.05	0.49
	Control	90	3.61	0.55

Table 2: Pretest Means and Standard Deviations

Variable	Group	N	Mean	Standard Deviation (SD)
Skill Mastery	Experimental	90	65.12	6.45
	Control	90	64.87	6.38
Self-Regulated Learning	Experimental	90	3.48	0.55
	Control	90	3.50	0.58
Learner Autonomy	Experimental	90	3.52	0.51
	Control	90	3.55	0.53

Table 1: Pretest and Posttest Means

Variable	Group	Pretest Mean	Posttest Mean
Skill Mastery	Experimental	65.12	82.45
Skill Mastery	Control	64.87	74.33
SRL	Experimental	3.48	4.12
SRL	Control	3.50	3.54
Autonomy	Experimental	3.52	4.05
Autonomy	Control	3.55	3.61

Pretest differences were not statistically significant ($p > 0.05$).
ANCOVA Results
After controlling for pretest scores:
Skill Mastery: $F (1177) = 18.64$, $p < 0.001$, $\eta^2 = 0.095$
SRL: $F (1177) = 21.47$, $p < 0.001$, $\eta^2 = 0.108$
Autonomy: $F (1177) = 16.32$, $p < 0.001$, $\eta^2 = 0.084$
These results indicate moderate effect sizes.

Structural Equation Modeling
The SEM model demonstrated acceptable fit:

- $\chi^2/df = 2.11$
- CFI = 0.94
- TLI = 0.92
- RMSEA = 0.06

Path coefficients:
AI → SRL ($\beta = 0.48$, $p < 0.001$)
SRL → Autonomy ($\beta = 0.44$, $p < 0.001$)
Autonomy → Skill Mastery ($\beta = 0.39$, $p < 0.01$)
Bootstrapping confirmed partial mediation (indirect effect $\beta = 0.21$, $p < 0.01$).

The results demonstrate that AI-powered adaptive learning systems not only directly improve technical skill performance but also indirectly enhance outcomes by strengthening learners' self-regulation and autonomy.

V. DISCUSSION

This study aimed to explore a practical yet significant idea: when TVET learners receive AI-driven adaptive support like personalized sequencing, immediate feedback and targeted remediation, their technical performance gets a boost. This improvement is partly linked to enhanced self-regulated learning (SRL) and greater learner autonomy. The results back up this idea, aligning with how adaptive learning platforms are designed to function. They act like an always-on instructional support system that constantly identifies skill gaps and provides tailored practice and feedback. Recent reviews of AI-enabled adaptive learning platforms highlight this personalization-feedback loop as the key mechanism through which learning gains are typically achieved.

Why skill mastery improved in the AI-adaptive group
One of the standout contributions of this study is that it focuses on skill mastery rather than just test scores, which is crucial for competency-based TVET. In hands-on learning environments, students often struggle not due to a lack of motivation, but because they practice the wrong sub-skills, repeat mistakes without receiving corrective feedback, or move on before mastering foundational steps. AI-adaptive systems help minimize these pitfalls by (a) pinpointing where students are having trouble, (b) offering targeted remediation, and (c) ensuring mastery before advancing. This aligns with findings from intelligent tutoring and adaptive instruction research, which show that personalized feedback and guided practice are among the most effective ways to enhance learning outcomes.
Crucially, the TVET context may amplify the advantages of adaptivity since many technical tasks have clear criteria for procedural correctness (like accuracy, safety compliance, and troubleshooting steps). When performance standards are clear, adaptive systems can provide feedback that is timely and actionable precisely what students need to fix errors before they turn into bad habits.

Why self-regulated learning has gained traction and why it is crucial in TVET
The rise in self-regulated learning (SRL) is not just a nice bonus; it is arguably one of the most significant achievements in technical education. SRL empowers learners to plan tasks, keep track of their progress, understand mistakes, and adjust their strategies skills that are essential for troubleshooting in the workplace and for ongoing technical education. This aligns with findings from learning analytics and dashboard studies, which indicate that progress indicators, performance summaries, and reflection prompts can enhance the appraisal and reflection stages of SRL especially when learners have clear frameworks to make sense of their data. In your intervention, the feedback and diagnostics from the AI platform likely acted as an external metacognitive mirror, helping learners recognize their gaps and become more strategic in addressing them.

However, effective interpretation requires a careful approach: dashboards and analytics do not automatically lead to SRL. If the data is too complicated or if learners do not have guidance on the next steps, it can be overwhelming. The stronger SRL outcomes observed in this study suggest that the platform's feedback was easy to understand and actionable an important takeaway for implementing TVET programs.

Learner autonomy as a developmental outcome not just a perception variable
Learner autonomy improved alongside SRL, and the mediation pathway indicates that autonomy is not just a self-reported feeling, but a developmental outcome tied to actual performance. This aligns with broader evidence that AI-driven educational interventions can promote self-directed learning and autonomy, particularly when systems facilitate goal-setting, monitoring, and adaptive guidance.

In the context of TVET, autonomy is closely linked to professional competence: technicians need to work independently, make safe decisions, and troubleshoot under pressure. This suggests that AI-adaptive learning can help cultivate work-ready habits not just by improving skills but also by fostering a mindset geared towards independence and problem-solving.

The mediation findings: how the technology effect transforms into a learning effect.
The mediation results stand out as one of the most significant theoretical contributions of this study. Instead of viewing AI as a magical tool that simply boosts scores, the model offers a more grounded perspective:

- AI adaptivity delivers tailored, structured feedback and sequencing (instructional affordance).

- In response, learners start to plan more effectively, keep track of their progress, and tweak their strategies (self-regulated learning).
- As time goes on, they cultivate greater independence in decision-making and a sense of ownership (autonomy).
- These steps lead to improved practice and performance (skill mastery).

This aligns with recent research on adaptive support for self-regulated learning in digital environments, highlighting that AI shines brightest when it acts as adaptive scaffolding that enhances learners' regulatory skills rather than taking over.

Practical implications for TVET institutions and policy
From a high-impact perspective, it is crucial to turn these findings into practical actions:

- Instructional design: TVET programs should focus on platforms that integrate (i) mastery progression, (ii) instant corrective feedback, and (iii) user-friendly analytics dashboards that learners can easily understand.
- Teacher role: AI does not eliminate the instructor; it reshapes their role. Teachers evolve into coaches who (a) analyze data, (b) apply human judgment to complex errors, and (c) guard against over-dependence. Mixed results in intelligent tutoring research highlight that context and implementation quality are key.
- Equity and ethics: TVET learners come from varied backgrounds in terms of tech exposure. Institutions need to ensure access to devices, reliable connectivity, and proper training and they should treat privacy and algorithmic bias as essential components of implementation, not just afterthoughts. Recent analyses of AI trends in vocational education consistently point out that ethics and governance are critical issues.

VI. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

When it comes to meeting high-impact standards, it is crucial to clarify what the study does not claim:

- Quasi-experimental design: Since full randomization is not possible, we cannot completely eliminate selection effects, even with ANCOVA controls in place. Future research could benefit from using randomized controlled trials or more robust matching designs.
- Short intervention window: While an eight-week period can show some improvement, TVET programs need to provide evidence on retention, how skills transfer to workplace tasks, and long-term autonomy.
- Measurement balance: Self-reports on self-regulated learning (SRL) and autonomy are important, but future studies should also incorporate trace or log data like time spent on tasks, revision cycles, and help-seeking behaviors. This approach is increasingly recommended by learning analytics research to validate SRL.
- Implementation variability: Different trades, such as electrical installation, machining, and welding, might respond differently based on how easily their tasks can be digitized and assessed.

CONCLUSION

This study shows that AI-powered adaptive learning systems can significantly enhance outcomes in Technical and Vocational Education and Training (TVET). They not only help learners' master technical skills but also foster essential learning behaviors like self-regulated learning and learner autonomy. The research supports a model where AI adaptivity acts as a structured support system, steering learners towards effective practices, facilitating reflection through feedback and analytics, and gradually handing over control to the learners themselves. This perspective aligns with current studies that view AI as a tool that boosts regulation and autonomy when it is designed to provide adaptive support rather than replace human learning processes.

For TVET institutions, this has practical and strategic implications: investing in AI-adaptive learning is not just about upgrading technology; it is a way to enhance competency-based training by smoothing out uneven progress, providing immediate feedback, and encouraging learners to take charge of their own mastery journey. However, successful implementation requires careful design choices (like user-friendly dashboards, mastery assessments, and meaningful feedback), building instructor capacity and ensuring ethical governance around data privacy and fairness, issues that are central to the current discussions in vocational education AI research.

Looking ahead, future studies should explore longer interventions, involve multiple trades and institutions, and combine learning analytics with performance rubrics to better understand how adaptive systems influence self-regulated learning and autonomy over time. By taking these steps, the field can transition from a general optimism about AI in education to providing evidence-based guidance for creating adaptive systems that truly enhance technical skill development and foster independent professional learning.

VII. RECOMMENDATIONS

Based on the findings of this study and the current state of research on AI-powered adaptive learning systems in vocational and technical education, the following recommendations are proposed for educators, policymakers, and future researchers:

1. For Educators and TVET Institutions
a. Invest in high-quality adaptive platforms: Prioritize learning systems that offer real-time diagnostics, personalized content sequencing, and feedback mechanisms to support individualized learning pathways for students. This aligns with broader evidence showing that adaptive systems can enhance learner engagement and outcomes when pedagogically sound and well-implemented.
b. Train instructors as facilitators of learning: Teachers should be empowered not just as content deliverers but as coaches and data interpreters who can guide students in interpreting their progress analytics and making productive learning decisions. This dual role enhances the benefit of adaptive systems.
c. Blend technology with hands-on practice: Adaptive systems should complement but not replace practical, hands-on TVET experiences. Tools like AI-powered platforms can prepare learners for workshop tasks and real-world practice, but physical performance evaluation remains essential.

2. For Policy and Decision Makers
a. Develop AI readiness strategies: Ensure that policies support infrastructure, device access, electricity reliability, and teacher readiness so that adaptive learning systems are not constrained by infrastructural barriers. Without addressing systemic issues, AI tools may benefit only a subset of learners.
b. Emphasize ethical and equitable implementation: Establish standards for privacy, transparency, and fairness in AI model design to prevent algorithmic bias and protect learner data especially in diverse TVET settings.

For Future Research
a. Expand scope and context: Conduct large-scale longitudinal studies across multiple TVET disciplines and institutions to verify the long-term effects of AI-adaptive learning on skill retention and workforce preparedness.
b. Use blended data sources: Future studies should integrate learning analytics trace data (e.g., interaction logs, time-on-task, error rates) with traditional performance measures to deepen understanding of how adaptive feedback influences learning behaviour.
c. Explore hybrid AI models: Investigate how emerging techniques, such as generative AI and reinforcement learning, can further improve adaptive instruction, especially for complex vocational tasks that require creative problem solving.

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