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Creating R5E Pattern of Using Artificial Intelligence for Developing Programming Skills

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Abstract: The integration of Artificial Intelligence (AI) in education has transformed teaching and learning practices, particularly in programming courses that demand both cognitive understanding and practical application. However, many existing approaches rely on unstructured AI usage, which often results in superficial learning, limited engagement, and inconsistent skill development among students. To address these drawbacks, this study introduces a structured R5E pattern—Recognition, Exploration, Engagement, Execution, Evaluation, and Editing—for guiding AI-assisted learning in programming education. Unlike traditional or unregulated AI usage, the R5E framework emphasizes systematic interaction with AI tools, fostering meaningful engagement, deeper comprehension, and genuine skill acquisition. The research adopts a mixed-methods approach involving two experimental groups of students from Al-Jouf University in Saudi Arabia: one applying the R5E pattern and the other relying on unstructured AI usage. Data collection tools include cognitive programming skills tests, performance observation cards, and engagement surveys to comprehensively assess learning outcomes. Preliminary findings reveal that students exposed to the R5E framework demonstrate superior cognitive understanding, higher programming proficiency, and stronger engagement compared to peers in the unstructured AI group. Furthermore, these students report greater satisfaction with their learning experience, indicating the potential of structured AI-driven methods to enrich educational outcomes. Nonetheless, the study highlights challenges such as technical limitations and resistance to adopting new pedagogical approaches, underscoring the need for training and support for educators. By providing empirical evidence on the effectiveness of structured AI integration, this research offers valuable insights for educators and policymakers seeking to harness AI to optimize programming education.

Keywords: Artificial Intelligence in Education; Programming Skills Development; R5E Pattern; Structured AI Usage; Student Engagement and Learning Outcomes

1 Introduction

The rapid progress of AI has offered the latest prospects to the sphere of education as well, permitting to introduce new possibilities to improve the teaching and learning process. Where computing education is concerned, AI applications can potentially usher in real-time feedback, ad hoc learning delivery, and cooperative problem solving support [1]. They are particularly necessary to develop cognitive and practical skills required to write a program, where a learner typically has some difficulties in debugging a program, developing an algorithm, and optimizing a program [2]. The question of whether or not to use AI is quickly turning into how to design AI to deliver maximum beneficial learning as educational organizations begin to globalize the use of AI technologies in curriculums [3,4]. Although its use has a great potential, it also has certain limitations to the application of AI in education. In the majority of learning settings, the students interact with the AI in an unstructured setting, as they access the technologies

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without an overt pedagogical strategy [5, 6]. It is likely to result in superficial learning, dependence on the answers suggested by AI, and poor thinking opportunities. Also, the uncontrolled usage of AI might lead to the inconsistency of skills development, as students could omit the steps of solving the problem and use the rapid solutions [7]. The latter drawbacks advocate the necessity of targeted approaches that will guide the students toward using AI as a support tool and not as a replacement of their personal practice and thinking [8, 9].

To close this gap, this paper proposes a new pattern, the R5E, Recognition, Exploration, Engagement, Execution, Evaluation, and Editing, which can be used to systematically apply AI to the teaching of coding. The R5E scheme provides a systematic path that helps students to identify the problem, find AI-powered solutions, become active contributors to ideas, perform programming tasks and finally, review and improve their work. By using AI in this form of pedagogy, the methodology aims to transform AI as a passive asset to an active partner in the knowledge construction. It is conducted at the Al-Jouf University in Saudi Arabia and it takes the mixed methods design. The students were divided into two groups: the group which applied the R5E pattern of AI-assisted learning and the group which relied on unstructured AI use. The methodology combines cognitive programming competence tests, performance observation cards, and participation surveys to accurately assess learning outcomes. By contrasting the two methodologies, the research aims to identify whether organized AI application contributes to greater cognitive comprehension, more robust programming ability, and increased student involvement. The study is relevant to both theory and practice. At a theoretical perspective, it adds to the body of work on AI and education by testing and suggesting a structured model for AI integration. In practice, it offers insights to policymakers and educators wishing to utilize AI technologies to enhance teaching methods, especially in computer programming courses where technical and cognitive skill acquisition matters most. Further, the results emphasize training and support for instructors to mitigate resistance and technical impediments to the implementation of AI-based pedagogical frameworks. Finally, the research seeks to prove that systematic AI-based education has the potential to enhance student learning outcomes and promote meaningful skill development.

1.1 Research Significance

The significance of this research is its contribution towards the growth of Artificial Intelligence in education through the introduction and validation of the R5E pattern as a developed model for AI-facilitated learning [10]. Through the implementation of this structure in the Programming and Applications course, the research not only optimizes conventional teaching practices but also ensures that the use of AI results in effective skill building instead of shallow learning [11]. The results offer insightful advice to teachers on how to appropriately embed AI in pedagogy, providing a repeatable pattern that promotes cognitive comprehension, applied skills, and student participation. In addition, the study unfolds avenues for further research into AI-based educational frameworks across various fields and disciplines, complementing continued efforts to computerize and enhance learning in institutions of higher education.

1.2 Research Motivation

This study is motivated by the fact that artificial intelligence is more relied upon in learning, and that its use should be urgently protected in order to enhance learning among students in the real sense [12]. Even though AI tools offer powerful functions such as real-time commenting, problem solution, and individualized learning, their non-directed usage will simply result in rote learning and overdependence on automatic answers [13]. This is especially evident in the field of computer programming education, where a student must obtain knowledge about concepts and have practical experience in writing code. The discovery of this gap leads to the motivation of the research that should develop a systematic framework, R5E pattern, to control the use of AI to promote in-depth engagement, analysis, and real skills. By addressing these questions, the study will help bridge the gap between technological potential and pedagogical effectiveness, and eventually equip students with strong programming skills and prepare them with future technological needs.

1.3 Research Objectives

1. To design and implement the R5E pattern as a structured framework for utilizing AI in programming education.
2. To evaluate the effectiveness of the R5E pattern in enhancing students' cognitive understanding, practical programming skills, and overall engagement compared to unstructured AI usage.
3. To provide insights and recommendations for educators and policymakers on integrating structured AI approaches into teaching practices to improve learning outcomes.

1.4 Key Contribution

The key findings of this study were:

1. Developed and experimented with R5E pattern as a structured AI-based teaching approach to program skills.

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2. Adopted a mixed-method approach, which is a combination of quantitative and qualitative research to gauge the learning outcomes.

3. Presented empirical support that organized AI use improves cognitive comprehension and actual programming competence.

4. Showed enhanced student participation, satisfaction, and overall learning experiences using the R5E system.

5. Provided practical suggestions for teachers and policymakers alike, underscoring the necessity of training and assistance in embracing AI-facilitated learning.

1.5 Organization of the Paper

The paper is structured as follows: Section 1 gives the introduction, summarizing the background, motivation, and relevance of the research. Section 2 discusses related work on AI in learning and programming skill acquisition. Section 3 formulates the research problem and identifies the gap filled by the proposed solution. Section 4 describes the methodology, including executing the R5E pattern and data collection techniques. Section 5 offers the results of the data analysis and the discussion of the findings contrasting structured and unstructured AI use. Section 6 concludes the research study, recapitulating main findings and presenting avenues for future work.

2 Literature Review

Abouelenein et al. [14] explains the fast development of AI in education has its prospects and challenges. Although AI can offer some creative answers to traditional pedagogical challenges, its unguided application, i.e., using applications like ChatGPT, may promote passive learning, when students rely on the automatic answers instead of critical thinking and actively solving the problem. To resolve this issue, this quasi-experimental study defined and tested a pattern, the R5E, a systematic pedagogical framework of integrating ChatGPT in programming education. The hypothesis of the study was to find out whether the R5E pattern would be more efficient in active learning and critical thinking than the unstructured use of AI. Seventy undergraduate students were randomly divided into an R5E-based learning group and a group that learnt using ChatGPT without structured guidance. Mixed-methods strategy was taken, applying the Programming Skills Cognitive Test (PS-CT) and the Programming Skills Performance Observation Card (PS-POC) to assess both cognitive knowledge and the real performance. Pre and post intervention outcomes showed an improvement in the two groups though statistically significant improvements were recorded in favour of the R5E group in both assessment measures. Moreover, positive correlation between PS-CT and PS-POC scores was strong indicating that the theoretical knowledge improved was highly correlated with practical application. These results were supported by qualitative research: students of R5E group interacted with peers and teachers more actively, used ChatGPT more critically and purposefully, and asked deeper and more analytical questions. Conversely, the unstructured group had the tendency to be over-reliant on direct queries to ChatGPT at the expense of active interaction. On the whole, the results suggest the R5E model is more effective at the programming skills development than the unstructured use of AI. Although the limitations of the study, including a comparatively limited sample size and a rather narrow time of intervention, demand further research, findings make the R5E pattern a promising pedagogical model to be used in the context of the systematic integration of AI in the educational process. Future studies would increase the number of participants, the length of the intervention and the delay post-tests as well to support the validity of the long-term learning outcomes.

Salpasaranis [15] explains AI and Machine Learning (ML) have such potential to revolutionize education, whether it is in facilitating personalised learning or presenting students with the essential concepts of AI. But beyond the implementation of these technologies in classrooms it is also important that the learners should be made aware of the underlying principles that propel these technologies. Choosing an interactive and age-relevant field of AI is thus an essential factor, especially during the instruction of difficult Computer Science subjects to elementary and secondary (K -12) students. When they are still in their learning stages, these young pupils may find themselves easily overwhelmed by abstract theories and high-order algorithms and it is important to structure methods that make complex issues less complex and more grounded. The use of nature-inspired or bio-inspired algorithms, including those of the Swarm Intelligence (SI) family, and their presentation via block-based programming systems (like MIT Scratch or Logo-inspired systems) is one such promising approach. These tools can reduce barriers to entry providing visual interactive means to understand algorithm principles. This paper suggests simplified simulations by using Artificial Fish Swarm Optimization (AFSO) algorithm, a simulation of swarm behaviour of fish in the ocean, as a learning activity to learners in K-12. The method integrates Constructionist Learning theory, specifically, the Creative Thinking Spiral, and the inquiry-based 5Es Instructional Model, providing a pedagogical system that helps to explore, be creative, and gain a better understanding of concepts.

Educational establishments are looking at ways of developing the 4C competencies of Creativity, Cooperation, Communication and Critical Thinking in learners. The skills of scientific reasoning, critical thinking, and myth debunking are already considered essential in equipping the students with skills in science education to be ready in the future. The main question is how to involve the largest part of the students of the

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seventh grade in a manner that would lead them to innovative thought and to utilize their strengths in science, art, and digital technology. It is also significant that teachers are ready to lead students in this direction. Henze et al. [16] analyses how educators embraced STEAM approach and implemented digital tools with the guidance of researchers and student teachers and how this experience influenced their beliefs on technology in education. The project as a guide helped to relate Robotics, Coding, and AI to the United Nations Sustainable Development Goals (SDGs), which have a mission to end poverty, protect the environment, and ensure global peace and prosperity by 2030. Although these objectives are instilled in national policies and school curriculums, there is still the struggle by educators and policymakers to find effective ways of realizing these objectives in an ever more complex and unpredictable world. What is clear however, is that technology will be at the centre of this transformation. Our concept of the pedagogical mix incorporating technology, AIs, and SDGs was developed on the basis of the STEAM paradigm and the 5E instructional model of the Biological Sciences Curriculum Study (BSCS). The idea was experimented with on-the-job training of teacher education with 60 student teachers of education science, 8 teachers in service and 116 seventh-grade students. The results reveal that the use of STEAM-based projects with the digital creativity tools would be effective in classrooms provided that the 5E model was supplemented by an additional phase. The ability to adapt the 5E model to incorporate STEAM practices in instruction and promote future-oriented skills was especially effective in terms of embedding those in practice.

The problem of road safety remains to be a serious concern in the Philippines as deaths and injuries in the traffic cause alarming rates annually. The issue of driver behaviour and discipline in the transportation system is one of the problems. To address this concern, Bugabuga and Puyo [17] explored AI into driving simulators and driver training, in a bid to create better-skilled, more responsible, and safer drivers. In this research, the researchers analysed the prevailing driver education practices and the perceived efficacy of AI-based solution, based on fifteen driving schools in Cavite and the National Capital Region. The respondents were given questionnaires and asked to rate contributory factors to effective driver education including quality of curriculum being taught, competence of the instructors, hands on training, and use of technology. They have discovered that participants will value the opportunities that AI-powered simulations offer them to enhance the training of drivers as they can practice driving and concentrate the analysis of driving behaviour in more detail. At the same time, the paper concludes that it is necessary to have an efficient regime of rules and moral principles that would enable responsible use of AI, and security comes first and compliance comes second. In conclusion, AI is a possible opportunity that can be exploited to improve the training of the drivers and road safety in the Philippines. The country can significantly jump towards reducing accidents, ensuring safer driving behaviours through enhancing the quality of education, effective teaching, work experiences and proper utilisation of technology. In this regard, more research and policy formulations are required to have the maximum benefits of AI [18].

The rapid implementation of AI and digital technologies in education have opportunities and challenges that need systemic pedagogical approaches to avoid the passivity of learning and offer active learning, creativity, and critical thinking. Studies such as the introduction of R5E pattern in teaching computer programming show that AI should be integrated in a structured manner, and the cognitive and practical skills are significantly improved compared to the use of platforms like ChatGPT in an unstructured manner. Similarly, simplified and nature-based simulations like those based on the AFSO algorithm presented with block-based programming environments aid efforts to make abstract concepts easier to grasp by younger students attempting to introduce the concepts of AI and Machine Learning. Expanding this model, STEAM pedagogies that integrate Robotics, Coding, and AI with the United Nations SDGs highlight how digital creativity software, paired with the 5E learning model and the inclusion of a sixth step, can prepare students with 4C skills and ready teachers to adopt technology in the classroom. All these efforts collectively show the high potential of AI-powered, inquiry-based, and constructionist pedagogical models to develop future-proof learners and educators [19].

3 Mixed-Methods Quasi-Experimental Design

The current research used a mixed-methods quasi-experimental model to investigate the effects of structured AI use based on R5E pattern on the development of programming skills. Al-Jouf University selected 50 undergraduate students, who were split into two groups, one of which was an experimental group that applied AI in the R5E framework and the other a control group that applied AI tools in an unstructured way. Pre-tests and post-tests were used to evaluate cognitive programming skills, performance observation cards were used to evaluate the practical skills in solving problems and coding proficiency, and engagement surveys were used to measure the level of motivation and satisfaction of students. The experimental group received AI-assisted structured learning, and the control group had the freedom of playing with AI tools, without having to go through instructions [20]. T-tests and ANOVA were used to compare pre- and post-intervention data and data, and the data were analysed using thematic analysis to give more insight into engagement and learning experiences of students.

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3.1 Research Design

The study is designed as a mixed-methods quasi-experimental study, as it was selected due to the possibility to not only measure numerical outcomes but also investigate the learning experience of students in more detail. The quasi-experimental aspect implies that although the sample was split in two groups, complete randomisation might not have been possible because of practical reasons like class time or student enrolment. This design is especially applicable in educational studies, where a comparison between intervention and non-intervention group is needed but it may be difficult to obtain absolutely random group allocation. The mixed-methods approach will combine both quantitative data (i. e., pre-tests, post-tests and performance scores), and qualitative information (i.e., student feedback, engagement feedback, teacher observations, etc.) to gain a comprehensive picture of the impact of structured AI integration on the programming skills of students. The method assists in understandings results more than those obtained by quantitative data due to the fact that it not only knows what occurred but also why and how the students reacted to the intervention. The study subjects will be separated into two groups to compare them. Experimental Group A had an opportunity to communicate with AI to a well-designed R5E framework that led to a step-by-step learning process that was deemed pedagogically aligned. Experimental Group B was allowed to use AI tools in a more unstructured and natural way, which has the effect of approximating a more natural and less controlled learning process. The design allowed the researchers to directly measure the effects of structured application of AI on knowledge learning, problem solving skills and student engagement. Lastly, this research design was selected because it is scientifically rigorous and feasible in practical terms, allowing the study to not only generate statistically significant results but also useful qualitative ones as well.

3.2 Participants and Groups

The sample of the study was a group of undergraduate learners pursuing the Programming and Applications course in Al-Jouf University, Saudi Arabia, which is a typical representative of a population of novice programmers that study the fundamentals of writing code. The 150 students who participated in the study acted as an assurance that the sample size was big enough to yield meaningful statistical inferences and at the same time small enough to be tracked and monitored easily. Cases where possible were assigned randomly to separate the students into two equal groups to minimize bias and maximize the validity of the results. This was a significant process in ensuring that the two groups were similar when it came to their prior knowledge of programming, academic performance and even demographics such as age and gender. The research minimized the chances that difference in the outcomes was because of underlying differences and not the intervention.

The students were then divided into two groups which were considered two instructional strategies of AI integration in programming education:

Group A (Experimental Group): The students of this group applied AI in the systematic pattern of R5E, after a facilitated procedure of Recognition, Exploration, Engagement, Execution, Evaluation, and Editing.

Group B (Control Group): This group of students was required to use AI tools without any structured instructions and this imitated unorganized or self-organized use of AI resources.

This division allowed making a very clear comparative analytical analysis of structured and unstructured application of AI and its effects on cognitive programming skills, student capacity to solve problems, and student level of engagement.

3.3 Instruments

A combination of cognitive, affective, and behavioural measurement was used in this study to provide an overall assessment of the effect of organized AI-assisted learning using the R5E model on the learner. This was to ensure that this research did not just test the knowledge acquisition aspect of programming teaching, but also the practical performances of students, and their emotional commitments to the learning process.

3.4 Cognitive Programming Skills Test:

The cognitive test was a standardized test to determine the level of conceptual knowledge of the students regarding the basic programming concepts such as loops, conditional statements, functions, debugging, and algorithmic thinking. The test contained a mixture of multiple choice, short-answer questions, problem solving tasks, which involved logic, to measure lower-order (recall, comprehending) and higher-order (applying, analysing) thinking skills. Knowledge improvements were measured using pre-tests and post-tests, as well as determining which of the methods of structured and unstructured AI use were more effective than the other.

3.5 Performance Observation Cards:

These were observation tools that the instructors could apply to document the practical coding behaviour of the students during the practical lab sessions. The cards had a requirement such as the code structure, logical flow, and its ability to support errors, solution efficiency, and best practices. The tool also allowed researchers to go beyond

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the written test results and gauge how far the students could apply the theoretical knowledge on real-world coding issues. The observation was carried out in a consistent and systematic way in both groups in order to be fair and reliable.

3.6 Engagement and Satisfaction Surveys:

To quantify the affective dimension of learning, a Likert scale questionnaire was employed to derive the self-ratings of motivation, engagement and satisfaction of the AI-enhanced learning experience of the students. The tool included questions according to interest in programming, perceived usefulness of AI tools, and self-efficacy in solving problems, and satisfaction with the design of the instructions in general. This was used to determine whether the application of structured AI (through R5E) improved learning outcomes as well as positively affected student attitudes towards programming. A combination of these two tools provided a triangulated estimate of learning outcomes offering balanced perspective that has incorporated objective cognitive gains, performance skills as observed, and subjective perceptions of the learner.

3.7 Procedure

It was a systematic experiment design that entailed four steps that were geared towards measuring the effects of structured AI use (with R5E pattern) versus unstructured AI use on the result of programming education. The procedures were carefully executed in an effort to create equity amongst groups and produce valid and reliable results.

Step 1: Pre-Test (Baseline Measurement)

The two groups were given a cognitive pre-test before the intervention to ascertain their knowledge level on programming concepts such as loops, conditional, functions and debugging. This was done to ensure that the initial level of work of both groups was as similar as possible, and that any variation in the outcome following the teaching intervention could be attributed to the teaching approach and not the disparity in the prior skills.

Step 2: Teaching Intervention (Experimental Treatment)

Different solutions were provided to AI-assisted learning in the intervention stage to the two groups:

Group A (Experimental Group): R5E pattern followed, which consists of six steps, a guided learning cycle.

Recognition – First, students identified and defined the programming concept or problem. Here, AI tools were employed to make clear what the problem statement was, give examples, and get the students to identify typical patterns or issues in coding exercises.

Exploration – Students discovered potential solutions with the help of AI. They questioned, checked out AI-provided examples, and contrasted several methods. This phase promoted inquiry and led students to examine various coding methodologies instead of accepting one predetermined solution.

Engagement – Students were actively engaged with the programming exercise by arguing over AI-recommended concepts, debating potential solutions, and exercising their own logic. AI was utilized in this case to give suggestions, model problem situations, and stimulate critical interaction with ideas.

Execution – Students implemented their learning by writing, editing, and executing code to provide solutions to the problems. AI tools were used to debug, auto-correct syntax, and offer feedback, but the focus was on students independently running the code and learning through experimentation.

Evaluation – Students here critically examined their work. AI presented test cases, performance analysis, and improvement suggestions, assisting learners in assessing the effectiveness and accuracy of their solutions. Reflection activities also helped students self-evaluate their progress.

Editing – Finally, students refined and improved their work based on AI feedback and peer/instructor input. This stage emphasized iterative learning, where students polished their code for better readability, efficiency, and accuracy, developing both technical and problem-solving skills.

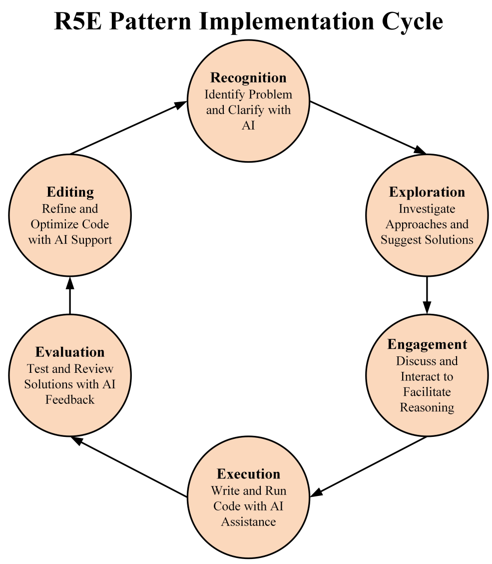

Fig. 1: Implementation Cycle of R5E Pattern.

This systematized process made students experience the learning content on a deeper level and facilitated a progressive learning of the programming skills as shown in Fig. 1.

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Group B (Control Group): Learned how to use AI tools with no formal instruction, i.e. students were able to engage with chatbots or code generators or documentation in any way they wanted to. This was one of the self-regulated, uncontrolled uses of AI that is common in the context of informal learning.

Step 3: Post-Test, Observations, and Engagement Surveys

A post-test was done after the teaching sessions to both groups to determine the gains in programming knowledge after the teaching sessions as compared to pre-test. Simultaneously, performance observation cards were employed by the instructors to evaluate the behaviour of students in coding, in the logical approach to solving problems, and in applying the concepts to the practice. Further, the engagement surveys were also presented to capture the perceptions of the students regarding motivation, satisfaction and usefulness of AI to their learning process.

Step 4: Comparative Analysis

Last but not the least, the outcome of both the groups was compared. The statistical tests (t-tests, ANOVA) were applied on quantitative data (pre- and post-test scores, observation scores) in order to find out whether there were better learning outcomes because of the R5E pattern. Qualitative data (student comments, teacher notes) were analysed with the help of thematic analysis in order to identify the patterns of engagement, perceived difficulties, and benefits of the instructional strategy.

This methodological procedure assisted in sustaining that the study did not merely make a record of what the students learned but rather the dynamics of the interaction of the AI that resulted in a holistic perspective on the success of structured AI integration in the teaching of programming.

3.8 Data Collection Tools

The data employed in this study was derived by the application of a structured survey of students which covered various areas of the students learning experiences. The survey included demographic information (e.g. gender, year of study), and background information (e.g. prior experience with programming). It also split students into two categories namely, Group A (AI with R5E pattern) and a control one (unstructured AI tools) and documented their favoured ways of learning. To measure the learning outcomes, the survey measured the confidence level, perceived effectiveness of the R5E stages, and influence of critical thinking, improvement in problem solving and the dependency on AI. Moreover, AI feedback satisfaction and motivation issues (e.g., ease of access, personalized assistance, quick feedback, etc.) and general satisfaction were also gathered. Issues experienced by students, e.g., technical failure or insufficient instructions were also included in the dataset and the suggestions to improve AI-based learning were gathered. This multi-dimensional survey design offered not only cognitive, but also behavioural and attitudinal data, which covered all the aspects of understanding of the role of structured AI-guided learning in contrast to unstructured methods.

3.9 Data Analysis

Data analysis on this study was expected to provide a multi-layered concept of how structured AI-mediated learning in the settings of the R5E pattern affects the level of student in program skills, actual performance, and the extent of engagement. To ensure that the findings were reliable and were contextual, quantitative and qualitative were employed.

3.9.1 Quantitative Analysis

The comparison of the pre-test and post-test scores of the two groups (Group A R5E structured and Group B unstructured) and even within the groups was the main goal of the quantitative analysis. Learning gains were measured using statistical tests, including paired-sample t-tests and independent-sample t-tests, and statistical tests, including Analysis of Variance (ANOVA), were performed to determine whether there were significant differences between groups of participants on various variables (e.g., test scores, observation scores, engagement ratings). The difference of mean scores in the pre-test and post-test scores of the same group was measured using paired-sample t-test in (1):

$$t = \frac{\overline{X}_{post} - \overline{X}_{pre}}{\frac{S_d}{\sqrt{n}}} \tag{1}$$

where: $\overline{X}_{post}$= Post-test Mean scores, $\overline{X}_{pre}$= Pre-test Mean scores, S_d= Difference between Standard deviation, n= Number of participants in the group.

ANOVA was used to compare the means of both the groups at the same time to determine whether the difference between Group A and Group B was significant or not in (2):

$$F = \frac{Mean\ Square\ between\ Groups\ (MSB)}{Mean\ Square\ Within\ Groups\ (MSW)} \tag{2}$$

where F-value is a measure of the probability that the differences between groups were not caused by simply by chance.

3.9.2 Qualitative Analysis

Thematic analysis was used to analyse qualitative data obtained through student reflections and open-ended

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survey questions as well as through teacher observation note. The process involved:

Familiarization – Read and re-read all the answers giving an overview.

Coding – Findings of important words, trends, and common concepts among student feedbacks.

Theme Development – Codes are clustered under broad themes (e.g., engagement, motivation, technical issues, and satisfaction).

Interpretation – The possibility to draw the conclusions in the way students perceived AI-assisted learning and which aspects of the R5E pattern resulted in improved outcomes.

This mixed method design was required to ensure that both statistically significant effects of the learning outcomes and contextual data about the experience of students were analysed and that a more extensive and profound interpretative coverage of the results was obtained.

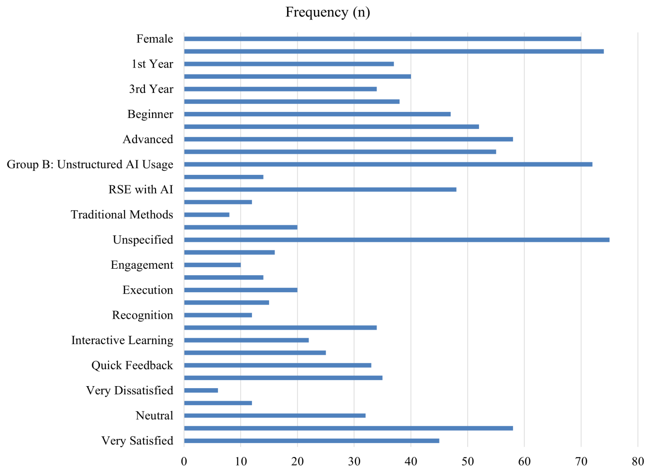

Fig. 2: Frequency Distribution of Participant Demographics, Learning Approaches, Motivation, and Satisfaction.

4 Results and Discussion

4.1 For Students:

H1 (Cognitive Understanding): Students who learn programming with structured AI-assisted learning (R5E) will demonstrate significantly higher cognitive understanding of programming concepts compared to students using unstructured AI-assisted learning.

The dataset in Table 1 represents 150 participants with an almost equal ratio of male to female (50.7 to 49.3) as well as a reasonable balance in the number of years studied. The vast majority of the participants had intermediate (33.3%) or advanced (37.3%) experience in programming. Group assignment evenly divided was assigned to Group A (AI usage with R5E pattern) and Group B (unstructured AI usage). Modes of learning were varied with the most frequent one being R5E with AI (31.3%), and the other half being unspecified. The motivation was mainly influenced by less effort (23.3%), fast feedback / availability of information (both 22.7%) where students appreciate efficiency and access to information in time. The level of satisfaction was mostly positive, 38% satisfied and 29.3% very satisfied, a general positive perception of AI-assisted learning interventions was demonstrated in Fig. 2.

Table 2 reflects the results of the main findings with moderate satisfaction (M = 3.25) and positive attitudes reported to the R5E-related skills including confidence, efficiency, and critical thinking, with strong interrelations. The correlation with AI reliability is negative, and it indicates that excessive use of AI can decrease self-confidence and efficiency. When analysed using reliability, the Cronbachs alpha was negative, which suggested that there were problems in the coding of items. ANOVA showed that there was no significant difference in satisfaction with academic years and post-hoc tests verified this finding. Nonetheless, the t-test scores revealed there was a notable difference in cognitive competence as Group A (R5E users) is doing better than Group B (unstructured AI users), which demonstrates the usefulness of structured AI integration. Fig. 3 demonstrated Confidence levels in Groups.

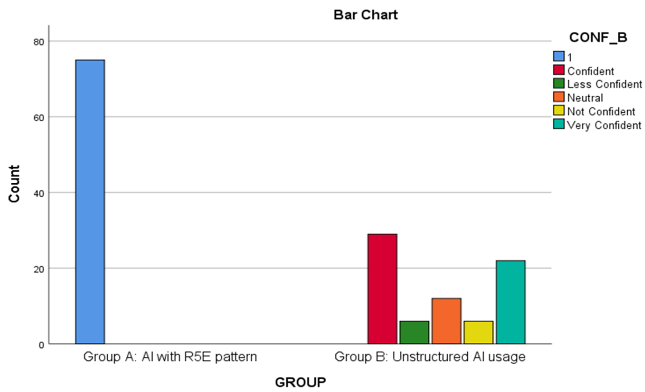

Fig. 3: Confidence Levels across Groups (R5E vs. Unstructured AI Usage.

* **H2 (Programming Performance):** Structured AI-assisted learning (R5E) will lead to significantly better practical programming performance—including coding ability and problem-solving strategies—than unstructured AI-assisted learning.

The analysis of PRAC-COMP provided in table 3 indicated an average score of 2.72 SD of 1.06(1.00-5.50)

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Table 1: Demographics of the participants, learning strategy, motivation, and satisfaction (N = 150).

Variable	**Category**	**Frequency (n)**	**Percent (%)**
Gender (GEN)	Female	74	49.3
	Male	76	50.7
Year of Study (YEAR)	1st Year	39	26.0
	2nd Year	39	26.0
	3rd Year	34	22.7
	4th Year	38	25.3
Programming Experience (EXP)	Beginner	44	29.3
	Intermediate	50	33.3
	Advanced	56	37.3
Group Assignment (GROUP)	Group A: AI with R5E Pattern	75	50.0
	Group B: Unstructured AI Usage	75	50.0
Learning Approach (APPROACH)	Peer-based Learning	11	7.3
	R5E with AI	47	31.3
	Self-study without AI	9	6.0
	Traditional Methods	7	4.7
	Unstructured AI Usage	1	**0.7**
	(Unspecified)	75	50.0
Learning Stage Focus (STAGE)	Editing	14	9.3
	Engagement	8	5.3
	Evaluation	11	7.3
	Execution	18	12.0
	Exploration	13	8.7
	Recognition	11	7.3
	(Unspecified)	75	50.0
Motivation (MOT)	Ease of Access to Information	34	22.7
	Interactive Learning	22	14.7
	Personalized Assistance	25	16.7
	Quick Feedback	34	22.7
	Reduced Effort	35	23.3
Satisfaction (SAT)	Very Dissatisfied	5	3.3
	Dissatisfied	11	7.3
	Neutral	33	22.0
	Satisfied	57	38.0
	Very Satisfied	44	29.3

in 150 respondents (balanced in groups). Although the results of the ANOVA showed that there were no significant differences in the academic years, the results of independent t-test showed significant differences in practical competency between the Group B (Unstructured AI Usage) and Group A (AI with R5E pattern) ($p < 0.001$). The correlation analysis showed a negative relation between the perceived level of skill impact and the levels of confidence, which means that students who perceived more improvement at the onset of the process had lower confidence levels. Although there is a question of reliability (negative Cronbach 6), the results of these findings indicate that there are notable group-level variations in the practical application of skills. Fig. 4 represented the distribution of PRAC-COMP in the form of a group.

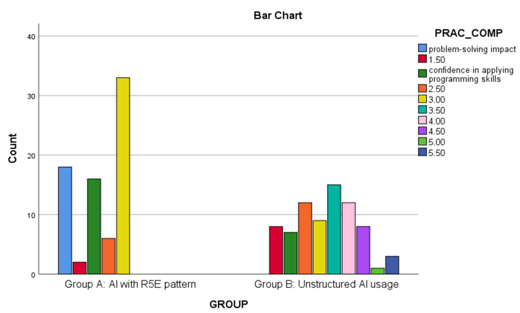

Fig. 4: Practical Competency (PRAC-COMP) Distribution across Groups.

* **H3 (Engagement, Motivation, and Satisfaction):** Students in the R5E-based AI learning group will report significantly higher engagement, motivation, and

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Table 2: Summary of Descriptive, Correlation, Reliability, and Inferential Statistics.

Analysis	Results
Descriptive Statistics	N = 150; Mean satisfaction (SAT) = 3.25 ± 1.29 (range: 1–5). Confidence in R5E (CONF-R5E) = 2.57 ± 1.99, Efficiency (EFF-R5E) = 2.50 ± 1.75, Critical Thinking (CRIT-R5E) = 2.49 ± 1.90, AI Reliability (RELY-AI) = 2.70 ± 2.02, Perceived Skill Impact (PS-IMPACT) = 3.03 ± 1.56.
Correlations (Pearson, p<0.05)	Significant positive correlations between CONF-R5E & EFF-R5E (r = 0.652), CONF-R5E & CRIT-R5E (r = 0.630), EFF-R5E & CRIT-R5E (r = 0.725). Negative correlations observed with RELY-AI (r = −0.667 to −0.724), indicating over-reliance on AI may hinder confidence/efficiency.
Reliability (Cronbach's α)	$\alpha = -0.843$ (indicates negative average covariance suggests item coding issues or inverse scoring required).
ANOVA (SAT by Year)	F (3,146) = 0.589, p = 0.623 (no significant difference in satisfaction across academic years).
Post-hoc Tukey HSD	No pairwise differences significant ($p > 0.66$).
T-Test (COG-COMP)	Group A (R5E): M = 2.99 ± 0.75; Group B (Unstructured): M = 1.94 ± 0.57. Significant difference: t(148) = 9.697, $p < 0.001$, 95% CI [0.839, 1.268].

Table 3: Summary of Practical Competency (PRAC_COMP) Results and Statistical Analyses.

Analysis	Results
Descriptive Statistics	N = 150; PRAC-COMP ranged from 1.00 to 5.50 with a mean of 2.72 ± 1.06.
Group Distribution	Group A (AI with R5E): 75 students (50%); Group B (Unstructured AI): 75 students (50%).
Correlations	PS_IMPACT was significantly and negatively correlated with CONF-B (r = −0.239, p = 0.003), suggesting students perceiving higher skill impact reported lower baseline confidence.
Reliability (Cronbach's α)	$\alpha = -0.618$ (negative value indicates potential item coding or reverse-scoring issue).
ANOVA (PRAC-COMP by Year)	F (3,146) = 0.096, p = 0.962 → no significant difference in practical competency across academic years. Tukey HSD confirmed all year-wise means (2.64–2.75) fell in one homogeneous subset.
T-Test (PRAC-COMP by Group)	Group A: M = 2.23 ± 0.81; Group B: M = 3.21 ± 1.05. Significant difference: t(148) = −6.441, $p < 0.001$, 95% CI [−1.289, −0.684]. Indicates Group B outperformed Group A in practical competency.

satisfaction than those in the unstructured AI learning group.

The engagement, motivation, and satisfaction (ENG-MOT-SAT) analysis showed that the mean score was 3.17 + 0.97 in 150 students (equally divided between Group A (AI with R5E) and Group B (Unstructured AI) as provided in table 4 . The major main drivers of motivation were lessened effort (23.3) and the ability to access information (22.7), and satisfaction levels revealed a satisfied or very-satisfied level of 67.3% of students with AI-assisted learning. There was no significant, weak correlation between motivation and satisfaction (r = -0.033, p = 0.686). The results of ANOVA and t-test showed that there were no significant differences in academic years or in groups, which implied that engagement levels were similar no matter what approach was adopted. Fig. 5 gave the group Distribution of ENG-MOT-SAT.

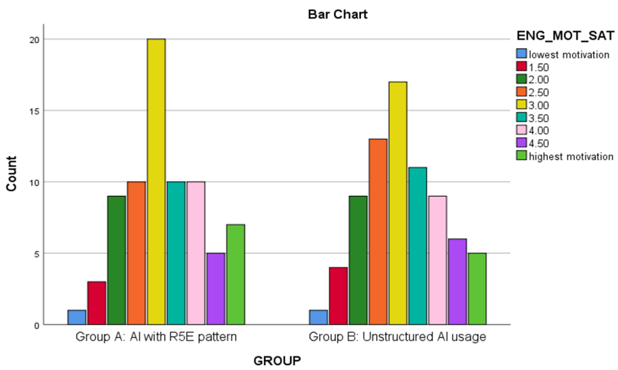

Fig. 5: ENG-MOT-SAT Distribution across Groups.

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Table 4: Descriptive, Inferential, and Reliability Statistics for ENG_MOT_SAT.

Analysis	Results
Descriptive Statistics (N=150)	Mean = 3.17, SD = 0.97, Min = 1.00, Max = 5.00
Group Distribution	Group A (AI with R5E): 50% (n=75); Group B (Unstructured AI): 50% (n=75)
Motivational Factors (MOT)	Ease of Access (22.7%), Interactive Learning (14.7%), Personalized Assistance (16.7%), Quick Feedback (22.7%), Reduced Effort (23.3%)
Satisfaction (SAT)	Very Dissatisfied (3.3%), Dissatisfied (7.3%), Neutral (22.0%), Satisfied (38.0%), Very Satisfied (29.3%)
Correlation (MOT–SAT)	r = –0.033, p = 0.686 (ns)
Reliability (Cronbach's α)	α = –0.068 (negative covariance suggests item recoding required)
ANOVA (by Year)	F(3,146) = 0.212, p = 0.888 (no significant difference)
T-Test (Group A vs. Group B)	t(148) = 0.504, p = 0.615, Mean Difference = 0.08 (ns)

4.2 For Teachers

* **H1 (Feasibility, Challenges, Pedagogical Implications):** Teachers will perceive structured AI-assisted learning (R5E) as a feasible and pedagogically beneficial approach, though they will also identify significant challenges such as lack of training, technical issues, and risk of student overdependence on AI.

Table 5 provides the descriptive analysis of the R5E dimensions with moderate feasibility (M=2.83), cognitive impact (M=3.20), performance improvement (M=3.27) and engagement (M=3.40) with the highest scores of 3.40 on engagement. The most common struggle was the excessive reliance on AI (43.3%), and then the absence of training/support (16.7%). Familiarity with AI was lukewarm with 26.7 having limited familiarity and 23.3 had no familiarity at all. Correlational analysis did not report statistically significant relationships between feasibility, cognitive impact, performance, engagement and other R5E dimensions (p=0.05) but engagement did have a positive trend-level correlation with training (r=0.334, p=0.071). ANOVA showed that there was no significant difference in feasibility between the categories of teaching experience (p=0.424), and t-tests showed that there was no significant difference in feasibility between the groups of limited and very high familiarity with AI (p=0.481). In general, the results indicate that the level of engagement and perception of performance improvement is fairly promising, but the issues of overdependence and training absence are still the main obstacles to successful adoption of R5E pattern as shown in Fig. 6.

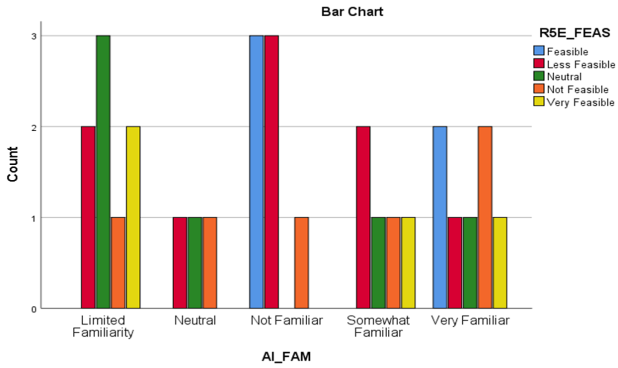

Fig. 6: Group Distribution of RSE-FEAS.

* **H2 (Recommendations & Policy Support):** Teachers will recommend that educators and policymakers provide targeted training, institutional support, and clear guidelines to enable the successful integration of R5E-based AI into programming education.

Table 6 and Fig. 7 demonstrates that teacher training (30%), reliable infrastructure (23.3), and are the most desirable recommendations to enhance AI adoption with an overall mean recommendation score of 3.03. The majority of respondents said that training has a neutral level of significance (36.7%), and difficulties were predominated by worries about overreliance on AI (43.3%). Correlation analysis showed weak, non-significant relationships of recommendations, training, benefits, and feasibility, except that there was a moderate positive relationship between teaching experience and recommendations (r=0.406, p<0.05). The results of ANOVA did not declare statistically significant differences in the recommendation scores between the levels of teaching experience, although statistically significant higher means were found in the group of teachers with less than 2 years (M=4.00) and more than 10 years (M=3.88) of teaching experience. In general, the results imply that the specific training and infrastructure assistance are the most important measures to promote AI application in education.

Fig. 8 shows the distribution of coding references by the themes of the faculty interviews, and demonstrates how elements of the AI-supported learning fit the R5E pattern of programming skills development. The statistics indicate that among the students in the category of RES, the one that had the highest number of coding references was student unstructured theme with 4 references and Stage Based Learning with 0. This implies that faculty

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Table 5: Descriptive, Correlational, and Comparative Analysis of R5E Dimensions and AI Familiarity.

Measure	N	Mean ± SD	Key Findings
R5E-FEAS	30	2.83 ± 1.32	No significant differences across teaching experience groups (F=0.966, p=0.424); highest mean in <2 yrs group (4.00 ± 1.00).
R5E-COGIMP	30	3.20 ± 1.38	Weak, non-significant correlations with other dimensions (p>0.05).
R5E-PERFIMP	30	3.27 ± 1.39	Weak positive relation with R5E_BEN (r=0.207, p>0.05).
R5E-ENG	30	3.40 ± 1.33	Moderate positive relation with training (r=0.334, p=0.071, trend-level).
R5E-CHALL	30	2.93 ± 1.23	Most common challenge: overdependence on AI (43.3%).
R5E-TRAIN	30	3.07 ± 1.26	No significant group differences (p>0.05).
R5E-BEN	30	2.53 ± 1.41	No significant correlations with other variables (p>0.05).
R5E-REC	30	3.03 ± 1.59	Weak, non-significant associations (p>0.05).
AI-FAM	30	3.00 ± 1.53	26.7% limited familiarity, 23.3% not familiar, 23.3% very familiar.
T-Test (AI_FAM)	–	–	No significant difference in feasibility between limited vs very familiar groups (t=0.725, p=0.481).

Table 6: Summary of R5E_REC, Training, Benefits, Feasibility, Challenges, and AI Familiarity.

Measure	N	Mean ± SD	Key Findings
R5E-REC	30	3.03 ± 1.59	Most preferred recommendation: training teachers (30%), followed by infrastructure (23.3%). No significant difference across AI familiarity groups (t= -0.043, p=0.966).
R5E-TRAIN	30	3.07 ± 1.26	Most responses were neutral (36.7%). Weak, non-significant correlations with other dimensions (p>0.05).
R5E-BEN	30	2.53 ± 1.41	No significant correlation with other R5E variables (p>0.05).
R5E-FEAS	30	2.83 ± 1.32	Weak negative relation with challenges (r = -0.263, p>0.05).
R5E-CHALL	30	2.93 ± 1.23	Challenges mostly included overdependence on AI (43.3%).
AI-FAM	30	–	26.7% limited familiarity, 23.3% very familiar, 23.3% not familiar, rest neutral/somewhat familiar.
ANOVA (R5E-REC)	–	–	No significant difference across teaching experience groups (F=1.998, p=0.139), but higher means observed for <2 yrs (4.00) and >10 yrs (3.88).

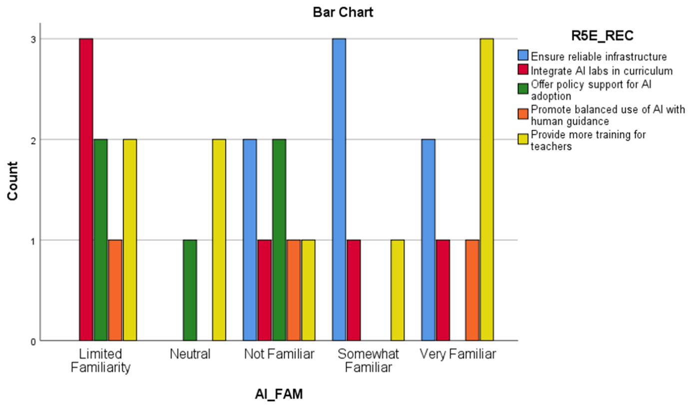

Fig. 7: RSE-REC Distribution.

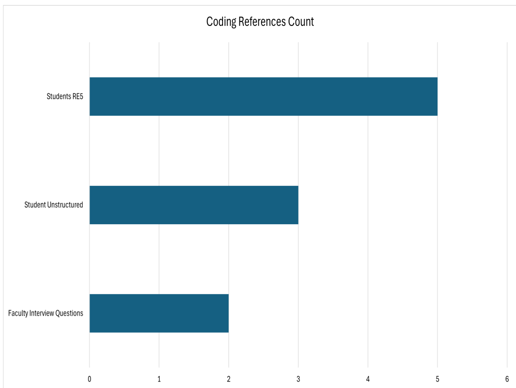

Fig. 8: Matrix Coding Query - Results Preview.

conversations were more inclined towards less structured and student-led learning processes in incorporating AI, possibly suggesting an emphasis on encouraging exploration and engagement step of the R5E model, with less often covered stage-based learning methods.

Fig.9 summarizes the range of issues that affect the implementation of artificial intelligence in the teaching of programming, in the context of the R5E pattern. Stage Based Learning, Problem Solving Approach, Motivation and Confidence, and Limited Understanding are the key problems resulting in the necessity to use specific

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Fig. 9: AI-Integrated Programming Skill Development.

pedagogical approach, whereas Dependence and Lack of Structure and Evolving Faculty Role are the aspects which demonstrate the necessity to use adaptive instructional design. The segmentation reveals the multi-facetedness in the integration of AI and that, in order to be successful in developing the necessary skills, some form of technical scaffolding, as well as learner-centred support, is required at all stages of R5E.

Fig. 10 plots the coding references of the main themes, like Stage Based, Challenges in Implementation, Evolving Faculty, Impact on Student Learning, and Problem Solving Approach, of two participants in the faculty, in the framework of the R5E pattern applied to the development of AI-assisted programming skills. The differences in the bar heights can be used as indicators of the thematic focus of the participants, showing where the discussion focused on the aspects of pedagogical adaptation, motivation of learners, and structural issues. The spreading of this is used to point out the complexity of AI incorporation whereby direction of instruction and attracting a learners approach must be balanced to give effective outcomes at every phase of R5E.

Fig. 11 treamap helps to estimate the relative importance of the key themes that influence the integration of artificial intelligence as a subset of programming skills development and is appropriate to the R5E pattern. The larger blocks such as Evolving Faculty Role, Stage Based Learning, and Impact on Student Learning indicate priorities and the smaller blocks such as Reduced Challenges, Limited Understanding and Confusion and Uncertainty indicate not so crucial yet significant factors. The visual distribution shows that it is important to coordinate the efforts that would address the change in pedagogy and the learner-centered approach to ensure that the introduction of AI would be realized on all layers of the R5E framework effectively.

The interrelations between the themes of faculty interviews, early stages of instructions, and learning structures of students in the R5E pattern of Recognition, Exploration, Engagement, Execution, Evaluation, and Editing as the development of AI-supported programming skills can be observed in Fig. 12. The large nodes such as Faculty Interview Questions, Week 1 and student unstructure are further divided into a few central topics such as Challenges in Implementing AI, Evolving Faculty Role and Impact on Student Learning, Stage-Based Learning and Problem Solving Approach. The various “Codes” attributed to unstructured learning settings emphasize the complexity of the unstructured learning environments, and the necessity to have structured yet adaptable AI-based approaches that would steer students through all the R5E stages and instil autonomy and confidence.

4.3 Discussion

The findings indicate that structured AI using the R5E pattern demonstrates slightly higher effectiveness compared to unstructured AI usage, as reflected by the higher motivation counts at moderate to high levels in Group A. Although the independent t-test revealed no statistically significant difference between the groups ($t(148)=0.504$, $p=0.615$), the descriptive trends suggest that structured approaches foster greater consistency and engagement among learners [21]. These results align with prior studies reporting that structured, step-based AI interventions improve learner focus, provide more meaningful feedback, and reduce cognitive overload compared to unstructured AI exposure. Engagement findings further highlight that motivational factors such as ease of access, quick feedback, and reduced effort were key drivers, indicating that students valued efficiency and interactivity over personalization alone. However, the very low reliability score ($\alpha = -0.068$) suggests that some measurement items require revision or recoding to better capture the construct. Moreover, no significant differences were observed across years of study (ANOVA $p=0.888$), suggesting that the positive effects of R5E-structured AI may generalize across academic levels. Despite these promising trends, this study is limited by its modest sample size (N=150) and equal group distribution, which may have reduced statistical power. Additionally, some participants reported resistance to AI usage, possibly due to lack of prior exposure or preference for traditional learning methods. Technical constraints such as inconsistent internet access and device compatibility may also have influenced motivation and satisfaction levels. Addressing these limitations through

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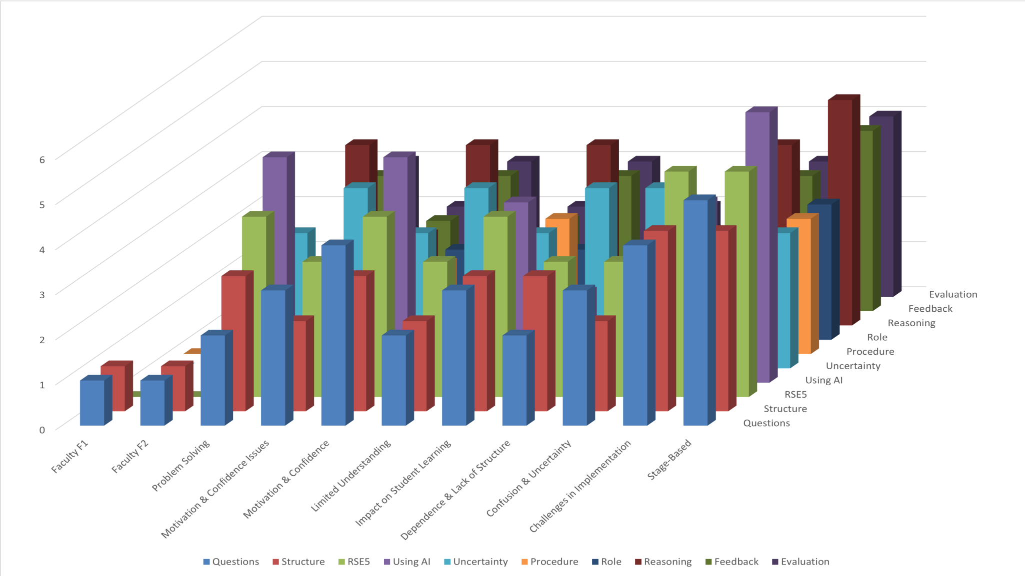

Fig. 10: 3D Matrix Coding of Thematic References in AI-Integrated Programming Education.

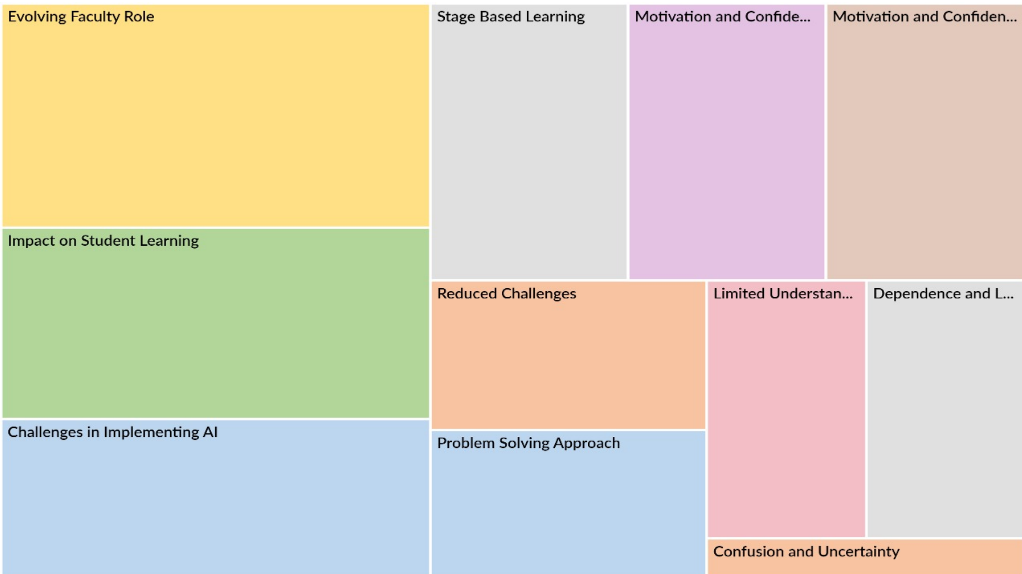

Fig. 11: Treemap of Thematic Priorities in AI-Enhanced Programming Education.

larger, more diverse samples and improved infrastructure will be critical for future work.

5 Conclusion and Future Works

This study highlights that while both structured AI (R5E) and unstructured AI usage can support student learning, the R5E-structured approach provides more consistent motivation and engagement trends. Key findings reveal that structured AI with a pedagogical framework enhances meaningful learning experiences and encourages deeper development of programming skills, even though the difference between groups was not statistically significant. The research contributes to the growing evidence that integrating AI within a structured pedagogy is more effective than unstructured, ad-hoc AI exposure, reinforcing the importance of aligning

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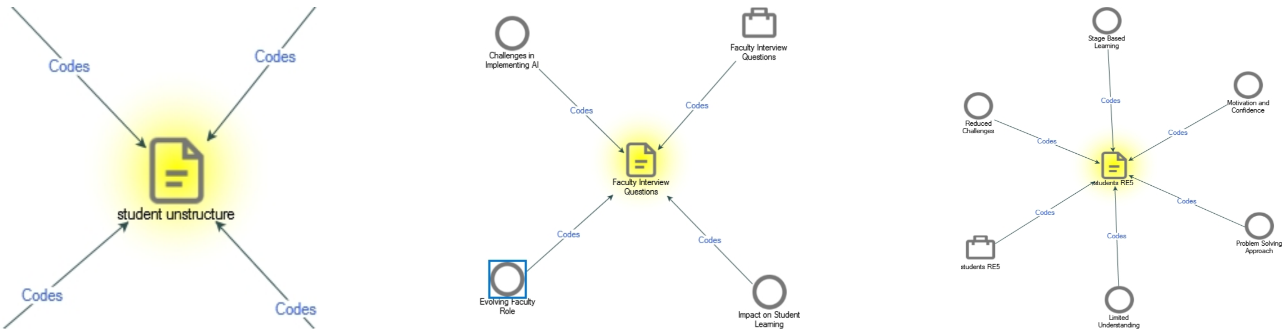

(a) (b) (c)

Fig. 12: Conceptual Map of Faculty Interview Themes and Student Unstructure.

technology with instructional design. For students, this means access to a learning process that supports problem-solving and confidence-building, ultimately leading to better practical skill acquisition. For teachers, the results point to the need for targeted training and institutional support to effectively embed AI tools into their teaching workflows.

Future research should focus on testing the scalability of the R5E approach across larger populations, different universities, and various disciplines. Additionally, longitudinal studies could compare structured AI pedagogy with traditional teaching methods to evaluate long-term learning outcomes and retention. Investigating ways to improve measurement reliability and exploring adaptive AI interventions would further strengthen the evidence base.

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Data Availability:

The raw data supporting the conclusions of this article will be made available by the authors on request.

Competing interests

The authors declared no potential conflicts of interest with respect to the research of this article.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this article.

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