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THE INFLUENCE OF LEARNING STYLE IN INTRODUCTORY PROGRAMMING COURSE OF BIOLOGY STUDENTS

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Abstract: *The critical role of learning styles in programming education is emphasizing the need for instructional approaches that accommodate the diverse ways students absorb, process, and retain information. Integrating learning styles such as visual, auditory, kinesthetic, and reading or writing into programming curricula can improve comprehension, retention, and engagement while fostering problem-solving skills and confidence. Despite the benefits, many programming education programs fail to address these varied learning preferences, leading to diminished understanding and preparedness for diverse work environments. This study aims to identify the relationship between learning styles and student performance, assessing the impact of tailored instructional methods on educational outcomes. Two out of four groups were randomly chosen using cluster sampling who enrolled in a C++ Basic Programming Course among B.Sc. (Hons) Biology students. VARK Questionnaires were distributed and the VARK score was determined for each participant. Meanwhile, the performance of students was determined by four assessments. The data were analyzed using Pearson's correlation coefficient and the results indicate no relationship between learning styles and student performance. However, a significant moderate linear relationship was found between the different learning styles, suggesting the presence of collinearity between variables. This implies that a learner may favor more than two learning styles. This overlap can make it challenging to differentiate the impact of each learning style on educational outcomes, especially in research or when designing instructional methods tailored to specific learning preferences. Recommendations will be provided for effectively incorporating learning styles* *into programming courses, ultimately enhancing students' career readiness and establishing a stronger foundational programming knowledge.*

Keywords: *Learning Style, Biology Students, Programming Course*

Introduction

Learning programming poses several challenges, especially to those with a non-computer science background. Among the reasons why the students find it difficult is due to the nature of the courses generally such as syntax and debugging issues, lack of context, diverse backgrounds, programming style, and balancing the theory with practice (Cawthorne, 2021). A significant number of programming education programs neglect to cater to the varied learning styles of students, resulting in reduced understanding, memory retention, and involvement. In the absence of customized instructional methods that accommodate the learning preferences of visual, auditory, kinesthetic, and reading/writing learners, students may encounter difficulties in establishing solid programming groundwork. This may result in weak problem-solving aptitude, self-assurance, and preparedness for varied job settings particularly for those who do not naturally align with the dominant teaching style of the course.

There are several justifications for integrating learning styles into programming courses, including improving comprehension and retention, offering tailored instruction, boosting motivation and engagement, cultivating problem-solving skills, instilling confidence, encouraging adaptability in learning, enhancing teamwork, and preparing students for varied work environments (Bhat, 2023). On top of that, by recognizing and accommodating the diverse ways in which students learn, educators can help students build a stronger foundation in programming, leading to better outcomes in education and their future careers. The integration of programming into non-computer science curricula, especially in fields such as biology, physics, and engineering, has been driven by the rapid advancements in computer technologies. This has become a growing trend since programming is now recognized as an essential tool for scientific research, data analysis, and modelling across disciplines. For instance, computational thinking (CT) is increasingly seen as a crucial skill not only for computer scientists but for all STEM professionals.

This shift reflects the growing importance of programming for problem-solving, design, and modelling in fields like biology and physics (Li et al., 2020). Despite the increasing need for mastering programming skills across various disciplines, there are many students from non-computer science background still struggling to grab the concept. In response, the objective of this study is to provide the answer to the research question whether student's different learning style have a significant effect on their academic performance in C++ Basic Programming course among B.Sc. (Hons) Biology students. Further, a recommendation for incorporating learning styles into programming curricula to enhance educational outcomes and career readiness can be established. Therefore, to explore and develop effective teaching methodologies, there is a need to identify the relationship between learning style with the student's performance.

Although there is a lot of research regarding learning styles and academic performance, there is little evidence regarding the interrelationship between learning styles, instructional design, and the performance of programming among non-CS students. The literature pays much

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attention to cohorts of computer science, which does not address the requirements of students studying other sciences. In addition, many studies focus more on theoretical frameworks without connecting them to actual teaching methods or findings as pass rates or student ratings in programming courses. Thus, this study will fill this gap by investigating the role of learning style preferences in performance in an introductory course on C++ programming among biology students. Empirical evidence that relates the variety of learning styles to programming achievement in non-computer science students is lacking. A common problem faced by many biology students when they take courses in programming can be attributed to the fact that the teaching methods do not match the learning styles that they like. To overcome this, it is important to know the relationship existing between learning styles and academic outcomes to guide pedagogical redesign of the learning styles.

Literature Review

The growing integration of programming into non-CS fields, particularly in disciplines such as biology, physics, and engineering, has become more essential due to the increasing reliance on computational tools for data analysis, modelling, simulation, and problem-solving. This trend reflects the critical need for professionals to develop coding skills that enhance their ability to manage complex datasets and automate processes which can be applied to scientific research and challenges across many disciplines. However, courses designed for computing majors are often not aligned with the background and interests of students from other disciplines (Liu et al., 2023). Studies indicating the challenges and issues in the implementation of computer programming courses to non-computer science students, suggesting that traditional course structures may not be applicable. One of the solutions as suggested by Mafukidze et al. (2024), is using visual programming languages and non-code tools where educators can cater to visual and kinesthetics learners, who may struggle with traditional text-based programming.

These tools help make abstract programming concepts more accessible by providing a visual, drag-and-drop interface, which is more intuitive for students without a computer science background. This approach offers a more engaging and less intimidating introduction to programming for non-CS students, especially those in fields such as biology or engineering. It also enhances their ability to apply skills required in computing without bogging down by syntax, making the learning process more effective. The concept of learning styles refers to the preferred ways in which individuals process information and acquire knowledge. Notable models include Kolb's Experiential Learning Theory (Kolb, 2014) which categorizes learners into four types: converging, diverging, assimilating, and accommodating, and the VARK model that was developed by Fleming and Baume (2006), which identifies visual, auditory, reading or writing, and kinesthetic learners. These frameworks provide a basis for understanding how students approach learning tasks differently, including those related to computer programming. Understanding how different learning styles impact programming performance among undergraduate students in tertiary education can provide insights into optimizing teaching methods and improving learning outcomes, especially among non-computer science backgrounds.

Among recent studies that were taking into consideration is the study conducted by Ho et al. (2021) that focused on personalized learning style among students learning Python programming showing the results for academic performance is increased. Supporting this, a study conducted by Maya et al. (2021) explores the connection between different learning preferences and academic success in higher education, emphasizing the importance of aligning

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teaching methods with student learning styles to improve performance. While it focuses broadly on psychology and education students, its findings on the importance of individualized learning methods are relevant to programming education. Numerous studies have investigated the relationship between learning styles and academic achievement across various fields, including computer programming. These studies aim to understand how different learning preferences impact students' success in mastering complex subjects like programming. The importance and impact of learning style on students' performance is not only focused on a physical class in the sense of conventional classroom setting, but also for the virtual setting such as on-line learning.

El-Sabagh (2021) concluded that learning styles significantly impact student performance and engagement in online learning, by taking into consideration the element of learning style to be included in the learning design. Instructors who implement active teaching approaches tailored to various learning styles can better support different learners. As a result, incorporating these styles into educational materials is essential to address the diverse needs of students, ultimately enhancing their ability to learn and succeed. Programming education often benefits visual and kinesthetic learners significantly. Anindyaputri et al. (2020) highlighted the use of a software tool Java Grader that enhances kinesthetic learners' skills when exposed to a live coding feature of the tool. The more often the students engage in writing codes the better their programming abilities. A study by Ngatirin and Zainol (2020) suggested that many factors have influenced learning styles such as gender and personality traits. Besides, Hong and Chu (2017) investigated the effectiveness of a situated 3D computational problem-solving and programming game-based learning model in enhancing students' cognitive engagement and learning perceptions.

Therefore, the integration of learning styles into academic curricula should begin at an earlier stage in education, allowing for the simultaneous development of individual personalities and learning preferences. This approach ensures that teaching methods align with students' natural learning tendencies, fostering a more personalized and effective learning experience. In conjunction with this, Fernando and Premadasa (2024) indicated in his study, that game-based methods are more suitable for primary school students as opposed to traditional methods as they cater to their interests and keep them motivated. This aligns with the idea that learning style identification should be integrated into curricula at an early stage, allowing for the development of personalized education pathways. Identifying student's learning styles accurately is challenging since there is a wide range of theories, models, and algorithms aimed at understanding individual learning preferences (Lestari et al., 2024). Thus, aiming at improving the algorithm for learning process optimization, particularly in computer science. However, educators can leverage these insights to create more effective programming courses such as suggestions on matching the student's learning style to the lecturers' teaching style (Chetty et al., 2019).

The relationship between cognitive styles and programming performance has also been examined. Pashler et al. (2008) focused on how cognitive styles influence students' success in critical thinking, a skill closely related to programming proficiency. However, they acknowledged that diverse instructional methods could benefit all students by addressing various cognitive processes involved in learning programming. Diverse teaching methods, including lectures, visual aids, hands-on projects, and group activities, can cater to different learning styles, enhancing overall student engagement and performance. Providing

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opportunities for students to explore programming concepts through their preferred learning methods can improve understanding and retention. Regular feedback and adaptive teaching strategies that respond to students' learning preferences can lead to better outcomes. The relationship between learning styles and programming performance among undergraduate students is complex and multifaceted. While there is no one-size-fits-all approach, research indicates that accommodating different learning preferences through diverse instructional methods can positively impact student performance. Further research is needed to explore the long-term impact of tailored instructional methods on programming proficiency and career success.

Learning styles are the way in which a student likes to receive and digest new knowledge, which determines the way a student works with instructional material. VARK model (Fleming & Baume, 2006) directs people to the groups of visual, auditory, reading/writing, and kinesthetic types of learners, whereas the Experiential Learning Theory, provided by Kolb (2014), underlines that people learn by going through the experience, reflection, conceptualization, and experimentation. These models emphasize that successful teaching is not only determined by the knowledge of the learning preferences of students, but also by the ability to create the necessary learning environment. Instructional design is the linking component in the relationship between learning styles and academic performance in the learning context of programming education. Being a programmer is known to need abstract thinking and problem-solving, which is not always easy when a non-computer student is involved (Cawthorne, 2021). Learners can internalize the programming concepts when the instructional materials are created to incorporate various learning modalities including diagrams and flowcharts to reach visual learners, discussions and explanations to reach auditory learners, written syntax drills to reach reading/writing learners and hands-on coding activities to reach the kinesthetics learners.

Several studies prove the significance of the alignment of the instructional design with the learning preferences. Ho et al. (2021) discovered that when the instruction was modified to the learning style of preference, programming students performed relatively well. El-Sabagh (2021) also established that adaptive e-learning settings that adapt to the learning preferences of the students enhance engagement and performance. Similarly, Chetty et al. (2019) pointed out that aligning teaching styles and learning styles with each other enhances student academic performance tremendously. In the case of programming, Anindyaputri et al. (2020) emphasized the advantage of adaptive software-based learning in terms of providing live-coding and instantaneous feedback to improve kinesthetic learning. Mafukidze et al. (2024) recommended visual and physical programming instructions to assist students with no prior coding knowledge- a strategy that is particularly useful to non-computer science students (e.g. biology majors). Simultaneously, other researchers warn that the application of the learning styles cannot be taken strictly. Pashler et al. (2008) and Baker and Robinson (2019) maintained that, although individuals have their preferences, different and interesting methods of teaching are advantageous to all learners irrespective of the dominant style. It implies that the most effective results might be achieved by flexible instructional design and not by learning-style matching. The learning style in this study is theorized to have the ability of influencing how students wish to receive and process information in the process of learning. As soon as the teachers are aware of these preferences and implement the necessary instructional design techniques to use, i.e. to use visual, auditory, reading/writing, and kinesthetics elements, the instructional process will be more inclusive and more interesting. Proper design of instructions is thus a mediating factor,

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interpreting the preferences in learning into meaningful learning experiences, which mediate in understanding and remembering. Consequently, it enhances the ability of students to practice programming concepts, solve coding problems, and perform well in examinations. Essentially, the relationship between the learning styles and instructional design has a direct impact on the performance of the programming, and it creates a logical chain of events where the former (learning styles) governs the latter (instructional design), and vice versa, the latter (instructional design) improves performance. When instructional design considers studying various learning styles, students outside the computer science major (like biology) will be better equipped to gain a deeper understanding, feel confident, and have the willingness to use computational thinking in their respective subjects (Li et al., 2020; Zilan et al., 2011).

Despite all the findings, there is still a gap in understanding how learning styles specifically impact programming performance among undergraduate biology students, which this study aims to address. By investigating the relationship between learning styles and programming performance in a C++ Basic Programming course for B.Sc. (Hons) Biology students, this study builds upon previous research by applying learning style theories to a non-CS academic setting. Unlike previous works that focus primarily on computer science or general education students, this study will provide discipline-specific insights, potentially guiding curriculum design to better support biology students in acquiring computational skills.

Methodology

This study involved B.Sc. (Hons) Biology students who enrolled in a C++ Basic Programming Course. There are 43 participants in the population of B.Sc. (Hons) Biology students who enrolled in a C++ Basic Programming Course. All 43 students enrolled in C++ Basic Programming Course participated in the survey which are non-computer sciences major academic programs at UiTM. The present study involved a total of 43 respondents, which represented the entire population of the selected course cohort. Although the number of participants was below the conventional recommendation for large-sample correlation and regression analyses (Tabachnick & Fidell, 2019), it was considered sufficient for this investigation, as all accessible participants were included. According to Gay et al. (2021), when the total population is small (fewer than 50), it is appropriate to include all individuals to minimise sampling error and to ensure representativeness. In the context of this study, which explores the relationships between students' VARK learning style preferences and their mathematics learning outcomes, the aim was to obtain comprehensive relational insights rather than generalise findings to a larger population. Correlation analysis remains acceptable with smaller datasets when assumptions of normality are satisfied or when nonparametric alternatives are applied (Bonett & Wright, 2000; De Winter et al., 2016). Moreover, Creswell and Creswell (2017) emphasised that in educational settings with bounded populations, full participation of available respondents enhances contextual validity and provides meaningful interpretation within that specific learning environment. Therefore, the sample size of 43 was deemed adequate to examine the relationships between VARK learning styles and mathematics learning variables within the studied group.

All 43 students were given a set of questionnaires which consisted of 16 questions with four multiple choice questions to identify which four learning styles will be the best categories for each student. The questionnaire on VARK was adapted from the VARK website (VARK, 2025) and is used in this study to ensure standardized data collection regarding students' preferences. Students may choose more than one option with priority numbering attached to

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each option. This is to identify the domination of each learning style for each question. The instrument was adapted to the local context with minor linguistic adjustments for clarity and administered in English. Respondents completed the instrument during class sessions guided by the researcher. Then, the internal consistency of the VARK instrument was examined using Cronbach's alpha. The VARK questionnaire demonstrated high internal consistency (Cronbach's α = 0.878), indicating strong reliability in measuring students' learning style preferences. This value exceeds the recommended threshold of 0.70 for acceptable reliability in educational research (Nunnally & Bernstein, 1994).

Student performance is measured by a quiz, group project, test, and final examinations of C++ programming skills for a semester as shown in Table 1. The data on learning styles (visual, auditory, kinesthetic, reading/writing) are treated as independent variables by assigning scores based on questionnaire responses, while student performance is treated as dependent variable by assigning assessment scores or exam scores. These two variables are quantified into scores, then Pearson's correlation coefficient is appropriate to examine the strength and direction of relationships between variables.

Table 1: Assessment Type and Marks Distribution

Assessment type	Weightage Contribution	Type	Occurrences/Duration
Quiz	Quiz	Quiz	Quiz
15%	15%	15%	15%
Written	Written	Written	Written
1/1hour	1/1hour	1/1hour	1/1hour

Thus, the objective of the study can be successfully achieved to provide a precise numerical value of how strongly two variables are related. This design allows for the exploration of the strength and direction of the relationships between variables (learning styles and performance) and an explanation of the interactions between different learning styles. It can also lead to (clear and interpretable result) recommendations for instructional design based on the patterns identified. In conclusion, Pearson's correlation is the most appropriate technique compared to descriptive statistics. Besides that, Pearson's correlation is preferred because it is more sensitive to actual numerical relationships because learning styles preferences are converted into numerical scores and the data meet normality assumptions.

Result and Discussion

The number of respondents in this study was 43 B.Sc. (Hons) Biology students, of which 30.2 and 69.8 respectively were male and female learners. The students had to take a course in C++ Basic Programming as the degree requirement. Overall, every student has his or her own learning style that may influence the results of the educational process positively. The analysis of data was done around four main learning styles namely: visual, auditory, kinaesthetic and reading/writing with reference to programming education. Table 2 presents the findings, indicating that the distribution of all variables follows a normal distribution, with skewness values ranging from -0.048 to 0.654. Among the learning styles, the highest mean score was observed for kinesthetic learning (9.1395), followed by auditory (7.3953), visual (7.3023), and reading/writing (6.0698). These findings are also illustrated graphically in Fig. 1. This finding also supports study by Gangadharan et al. (2025) indicating that health sciences students scored

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higher in the kinesthetic modality and in total VARK scores, indicating a stronger preference for hands-on, experiential learning activities. The standard deviation for all learning styles was approximately 3 which are same and consistent for all learning styles. Additionally, the mean academic performance score for the 43 students was 68.6744, with a standard deviation of 9.2960 and a mark range of 43 (95-52).

Table 2: Descriptives Statistics for Learning Styles and Academic Performance

	N	Minimum	Maximum	*M*	*1 SD*	Skewness
Visual	43	1.00	13.00	7.3023	3.2844	.209
Auditory	43	2.00	14.00	7.3953	2.9531	.396
Read/writing	43	1.00	14.00	6.0698	3.2396	.481
Kinesthetic	43	3.00	14.00	9.1395	3.1440	-.048
Academic Performance	43	52.00	95.00	68.6744	9.2960	.654

m mean, 1 *SD* standard deviation

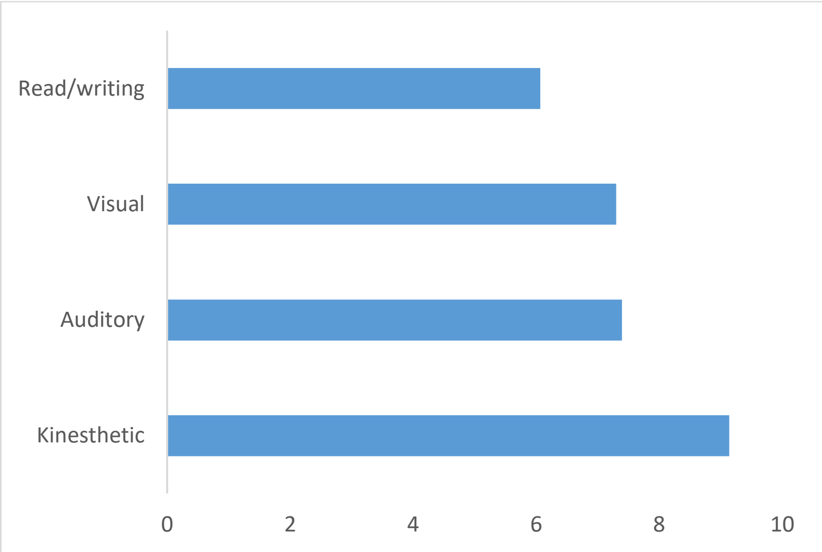

Figure 1: Average Learning Style Score Among Students

Data analysis was thus done using SPSS software to determine the Pearson correlation to determine the relationship between the academic performance and the learning styles in attaining the objective of this study. The correlation coefficient r goes between -1 to +1. Values that are close to +1 indicate strong positive linear relationship between the two variables, and values that are close to -1, there exists strong negative linear relationship. A value of zero indicates that there is no linear relationship between two variables (Gogtay & Thatte, 2017). Table 3 showed that the learning styles (visual, auditory, reading or writing and kinesthetic) had weak positive but statistically insignificant correlation with academic performance (p-value > 0.05). This indicates that students studying programming do not have any learning style that they use to improve their performance.

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Table 3: Pearson Correlation for Academic Performance and Learning Styles

		Visual	Auditory	Read/writing	Kinesthetic
Academic Performance	Pearson correlation, r	.112	.047	.091	.137
	Sig. (2-tailed)	.476	.763	.562	.382
	N	43	43	43	43

These results correspond to the argument presented by Pashler et al. (2008) that the scientific evidence behind the inclusion of learning style tests into the educational programs, such as the programming courses, is rather inadequate. Although learning styles have become a common practice, matching the instructional modes with the original preference of the students may not always be accompanied with better results. Baker and Robinson (2019) said that the priority of the engagement and processing of information can be a more effective way of enhancing learning experiences in students. This implies that learning style should not be the sole tool in delivering an otherwise complex subject like programming. Learning style and academic performance studies are not limited to the programming education but also to other fields like medical science, dentistry, health sciences, and engineering.

Mustafa et al. (2024) studied on relationship between learning styles and academic performance in Medical Students at Jazan University, Kingdom of Saudi Arabia with 431 medical students where the researcher did not find any significant correlation between learning styles and grade point averages, which indicates that learning styles are not a determinant of academic success in medical education. In a similar manner, Mozaffari et al. (2020) found that preferred learning styles were not significantly correlated with academic achievement in dental education, which supports the assumption that learning styles had no powerful impact on academic performance. Similar results were also found by a study by Gangadharan et al. (2025) in the field of health sciences, which did not indicate any direct relationship between certain learning style preferences and academic performance. The results indicate that many students tend to utilize several learning styles, which can be more influential in the academic achievement. This is consistent with the findings of Table 4 of this study, which still makes learning styles not the only factor in defining academic performance.

Table 4: Pearson Correlation between Learning Styles

		Visual	Auditory	Read/writing
Kinesthetic	Pearson correlation, r	.584**	.681**	.600**
	Sig. (2-tailed)	.000	.000	.000
	N	43	43	43

An interesting finding in this study reveals the presence of collinearity among learning styles (visual, auditory, read/writing, and kinesthetic). As shown in Table 4, there is a significant moderate positive relationship between these styles, suggesting that they are not entirely independent but rather exhibit substantial overlap. This collinearity implies that students who favor one learning style (e.g., visual) might also benefit from or prefer another (e.g., kinesthetic), making it challenging to isolate the impact of each style on academic performance. Consequently, this overlap complicates the determination of which specific learning style contributes most to a student’s success. The concept of collinearity among learning styles aligns

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with Neil Fleming's VARK model, which classifies individuals based on sensory preferences but acknowledges that these modalities are often interrelated (Fleming & Baume, 2006). Rather than relying exclusively on a single learning style, students may adopt a combination of approaches, reinforcing the idea that learning styles function in an integrated manner (Cherry, 2024; Mustafa et al., 2024).

Furthermore, Howard Gardner's theory of multiple intelligences supports this perspective by emphasizing that individuals possess various forms of intelligence, such as linguistic, logical-mathematical, spatial, and bodily-kinesthetic. Gardner challenges the notion of strictly categorizing learners into specific intelligence types, arguing that these intelligences interact and overlap. This reinforces the idea that learning styles are interrelated and should be adapted to accommodate different student strengths (Armstrong, 2009). Biology students typically do not have a strong programming background, making them an ideal group to study the impact of different learning styles in programming education. Since programming is a relatively new subject for them, they may exhibit diverse learning preferences. The increasing integration of computational skills across various disciplines highlights the importance of understanding how students from non-computer science backgrounds adapt to programming education. Insights from this study could help tailor instructional methods to accommodate learners from diverse academic fields, making programming more accessible to students outside traditional computer science disciplines.

Previous research has suggested that blended learning an approach that combines online and face-to-face instruction, can effectively support different learning styles in programming courses. By allowing students to engage with content in multiple ways, blended learning enhances student engagement and improves overall learning outcomes. Adapting teaching methods to accommodate diverse learning preferences can not only boost student motivation but also create a more effective and inclusive learning environment. By selecting B.Sc. (Hons) Biology students as the study sample, this research extends the applicability of its findings beyond conventional programming students. The results contribute to a broader understanding of how diverse learners, particularly those from non-computer science disciplines, can develop computational skills necessary for modern, technology-driven work environments. Overall, these findings suggest that students may not strictly adhere to a single learning style but instead engage with multiple modalities, highlighting the complexity of learning processes and the need for flexible, multifaceted instructional approaches.

Similarly, Zilan et al. (2011) explored strategies to improve computer skills among non-computer science students, emphasizing the need for instructional methods that align with learners' diverse cognitive and learning preferences. They proposed integrating hands-on, task-oriented instruction supported by visual demonstrations and interactive exercises to enhance comprehension and retention. Regression analysis was not performed in this study because the preliminary correlation analysis revealed no statistically significant relationships between any of the learning style variables and students' academic performance. According to Tabachnick and Fidell (2019), regression analysis is only appropriate when there is evidence of a linear association between the independent and dependent variables. When correlations are weak or non-significant, including such predictors in a regression model does not yield meaningful or interpretable results.

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In addition, the assumption of the absence of multicollinearity among the independent variables was violated. The learning style dimensions demonstrated high intercorrelations, suggesting redundancy among predictors. As highlighted by Nunnally and Bernstein (1994) and Hair et al. (2019), multicollinearity inflates the standard errors of regression coefficients and undermines the stability and interpretability of the model. Therefore, given both the non-significant bivariate correlations and the presence of multicollinearity among learning style variables, it was deemed statistically inappropriate to proceed with multiple regression analysis.

Conclusion

This paper provides valuable insights into the relationship between learning styles and academic performance in a C++ Basic Programming course among B.Sc. (Hons) Biology students. Further, this study suggests that focusing solely on learning styles may not be effective for improving student outcomes in programming courses. Instead, educators may need to adopt a more flexible and holistic approach to teaching complex subjects like programming, rather than relying on predefined learning style frameworks. Among these, kinaesthetic learning had the highest mean score, suggesting that students in this course tend to benefit more from hands-on, practical learning approaches. On the other hand, the relatively high scores for auditory and visual learning indicate that multiple learning styles play a role in student engagement and success in programming education. Another interesting finding from this study is the presence of collinearity implies that it is challenging to isolate the impact of individual learning styles on academic performance, as students may engage with multiple styles simultaneously. This overlap complicates the identification of any single learning style that significantly influences educational outcomes.

Future work could explore more effective methods for accurately identifying learning styles and their direct impact on student performance across different subject areas over time to find more concrete evidence of the adopted learning style. Sample size may be increased in number and cover a broad range of student environments. There is also a need to examine other cognitive or environmental factors (e.g., motivation, prior knowledge, or classroom dynamics) that might interact with learning styles to influence programming performance. Finally, investigating whether encouraging students to develop flexibility in their learning styles can lead to better adaptation and performance in challenging subjects like programming.

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