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Logged In and Mindset On: Log Data Based Insights on Engagement and Learnings in Programming CBLEs

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Abstract: Mindset has been shown to influence learners' motivation, persistence, and academic outcomes. While extensive research supports the benefits of a growth mindset in traditional classroom settings, little is known about how these beliefs shape learning in autonomous digital environments. This study explores the relationship between students' mindsets (growth vs. fixed) and their performance and engagement in a computer-based learning environment (CBLE) designed for Python programming, called *PyGuru*. Sixty-seven first-year undergraduates participated in a two-day workshop involving mindset surveys, pre- and post-tests, and three hours of CBLE interaction. Learners were grouped into fixed and growth mindset categories using a tertile split. Learning gains were computed via Hake's formula; behavioural data from log traces were analysed using Mann-Whitney U tests with Benjamini-Hochberg correction. Growth mindset students demonstrated significantly higher learning gains despite similar baseline scores. They also engaged more selectively - performing fewer quizzes, readings, and assessments. Whereas fixed mindset learners showed more frequent error-checking. Time-on-task did not differ significantly, indicating that engagement quality, not duration, distinguished the groups. These results highlight that mindset influences not only outcomes but also learning behaviours in CBLEs, even without teacher support. Findings support the integration of mindset-sensitive features into digital learning tools and call for future research across larger, more diverse samples to inform adaptive, growth-oriented learning design.

Keywords: Learner's Mindset, Mindset in Programming Education, Learning Gain, Computer-based Learning Environment

1. Introduction

Mindset - the belief about whether abilities are fixed or malleable, plays a crucial role in learners' motivation, persistence, and academic success (Dweck, 2006). Students with a growth mindset, who see intelligence as developable through effort, tend to embrace challenges and persist through setbacks, consistently outperforming their fixed mindset peers (Blackwell et al., 2007; Yeager & Dweck, 2012). Growth mindset interventions have improved outcomes across educational levels and demographics (Paunesku et al., 2015; Claro et al., 2016; Kattoum & Baillie, 2025), while fixed mindsets are linked to avoidance behaviors and superficial engagement (Dweck & Leggett, 1988; Lopez & Nguyen, 2024).

In programming, a domain requiring iterative problem-solving, debugging, and abstraction, mindset significantly influences learning behaviors. Growth-minded learners persist through logic errors, engage in strategic exploration, and welcome feedback. In contrast, fixed mindset learners often avoid complex tasks, rely on repetition, and disengage when challenged (O'Dell, 2017; Morales-Navarro et al., 2024). These tendencies affect how students approach key programming tasks such as decomposition and code refactoring (Brewer, 2018; Payne et al., 2018).

While most mindset research has occurred in traditional classrooms, where teacher presence influences motivation, less is known about how mindset operates in self-directed settings. Computer-Based Learning Environments (CBLEs) require learners to self-regulate without real-time instructional support. They also offer unique research opportunities through automated log data that captures granular, moment-to-moment behaviors (Singh & Rajendran, 2022; Nishane et al., 2021). However, few studies have leveraged this potential, relying instead on self-reports or observations that may miss subtle behavioral differences (Zhang et al., 2024; Payne et al., 2018).

This study addresses these gaps by investigating how growth and fixed mindsets influence learning gains and interaction patterns in *PyGuru*, a CBLE for Python programming. Sixty-seven first-year undergraduates participated in a two-day workshop involving mindset surveys, pre/post-tests, and interaction with the platform. Using Hake's formula for learning gain and Mann-Whitney U tests for behavior analysis (with Benjamini-Hochberg correction), we compared action frequencies and time-on-task between mindset groups. Growth mindset students achieved significantly higher learning gains ($r = 0.52$) and engaged more selectively, performing fewer resource-intensive actions. Fixed mindset learners showed more frequent error-checking and surface-level repetition. Time spent on tasks did not differ significantly, highlighting that engagement quality - not duration - distinguishes learner outcomes. These findings underscore the need for designing CBLEs that recognize and support mindset-driven learning behaviors through targeted scaffolds and reflective strategies.

2. Literature Review

Mindset, defined as beliefs about the malleability of intelligence, is a powerful predictor of motivation, resilience, and academic success (Dweck, 2006). A fixed mindset assumes intelligence is static, leading individuals to avoid challenges and give up when faced with setbacks. In contrast, a growth mindset promotes the idea that abilities can be developed through effort, strategy, and feedback, encouraging persistence and adaptive learning (Dweck, 2006; Dweck & Leggett, 1988). Empirical studies have confirmed these distinctions. For example, Blackwell, Trzesniewski, and Dweck (2007) demonstrated that middle school students taught about growth mindset achieved higher mathematics grades and motivation. Similarly, Paunesku et al. (2015) showed that brief online interventions significantly improved performance, especially for at-risk students. Yeager and Dweck (2012) further highlighted that growth mindset fosters resilience and academic gains across educational contexts.

Programming requires a range of complex problem-solving skills that closely align with learners' underlying mindsets. Students with a growth mindset tend to perceive challenges as opportunities to improve, while those with a fixed mindset often view difficulty as indicative of limited ability (Dweck, 2006; Dweck & Leggett, 1988). This distinction is evident across various programming tasks. For instance, in debugging, growth-minded learners persist through errors, refine their strategies, and treat bugs as opportunities for insight, whereas fixed-minded peers often disengage after repeated failures (O'Dell, 2017; Morales-Navarro et al., 2024). Similarly, in problem decomposition and algorithm design, growth-oriented students are more willing to tackle complexity and experiment with alternatives, while fixed-mindset learners may avoid such tasks due to fear of failure (Yeager & Dweck, 2012; Paunesku et al., 2015). This pattern extends to logic errors and code refactoring, where growth-minded students embrace iteration and continuous improvement, whereas fixed-mindset individuals often perceive the need to revise code as evidence of inadequacy (Brewer, 2018; O'Dell, 2017). When learning new concepts, growth-minded learners actively explore diverse strategies, while fixed-minded students often shy away from unfamiliar material (Blackwell et al., 2007). These differences also shape collaborative programming behaviours: the former group typically welcomes feedback, while the latter may become defensive or disengaged (Morales-Navarro et al., 2024). Even in interpreting error messages or tracing complex code, growth-minded learners show greater persistence, believing that understanding improves with effort, unlike fixed-minded peers who often withdraw early (Payne et al., 2018). Taken together, these alignments suggest that cultivating a growth mindset through strategies such as normalizing failure, encouraging iteration, and fostering peer learning, can significantly enhance students' engagement, resilience, and success in programming. Because learning programming requires the development of all these interrelated skills, novices often struggle to master it. Embedding learning strategies that reflect and reinforce a growth mindset can support students in overcoming these challenges and building long-term proficiency.

Research consistently shows that adopting a growth mindset is associated with higher academic achievement and persistence. Brewer (2018) found that online mindset workshops led to greater perseverance and success in computer-based environments. Similarly, Payne, Babb, and Abdullat (2018) reported better coding performance among growth-minded students. Morales-Navarro et al. (2024) observed that in high school physical computing classes, growth mindset students engaged more actively in debugging and diverse problem-solving strategies. Some more studies reaffirm that a growth mindset positively influences learners' behaviour across educational contexts. In STEM settings, students who perceived instructors as endorsing growth mindsets reported greater comfort and academic success (Kattoum & Baillie, 2025). Growth mindset was also linked to improved learning well-being among high school students, with motivation and grit as mediators (Zhang, Chen, & Li, 2024). College students exposed to mindset interventions reported reduced stress and enhanced academic motivation (Lopez & Nguyen, 2024). Similarly, a large-scale survey showed that growth mindset predicted better mental health and reduced stress impacts among undergraduates (Zhang, Wang, & Zhao, 2022). Together, these studies highlight mindset's role in promoting persistence, emotional resilience, and adaptive learning behaviours. Together, these studies emphasise growth mindset's link to engagement, resilience, and achievement across diverse settings.

Despite these insights, most prior research has been conducted in instructor-led environments, where teachers offer personalised feedback and motivation. In such settings, disentangling mindset effects from teacher influence is difficult. It remains unclear whether growth mindset alone can enhance learning in self-directed, computer-based environments (CBLEs), where teacher support is absent and learners must independently manage their learning processes (Nishane et al., 2023).

Furthermore, existing mindset studies have largely relied on self-reports and observations (Blackwell et al., 2007; Yeager & Dweck, 2012), which fail to capture granular, moment-to-moment behaviours. Log data from CBLEs offers an alternative - recording every click, code submission, error check, and navigation step which can give us detailed record of learner activities (Singh & Rajendran, 2022; Singh et. al., 2022; Nishane et al., 2021). This enables researchers to directly map mindset-related behaviours, such as debugging frequency or exploration breadth, providing a richer understanding of learning processes.

To address these gaps, our study investigates how mindset impacts learning gains and engagement in Python programming within a CBLE. Using detailed clickstream data and learning gain analysis, we explore how growth- and fixed-mindset learners differ in action frequency and time spent on various learning activities. By analysing behavioural traces rather than self-reports, we aim to offer clearer insights into how mindset influences autonomous learning and inform the design of adaptive, mindset-sensitive learning environments.

3. Research Questions

To address the identified gaps, this study investigates how learners' mindsets influence their behaviour and performance in a fully computer-based learning environment (CBLE). Specifically, it examines the relationship between mindset and learning gains in Python programming (RQ1), as well as how mindset shapes interaction patterns, including frequency of clicks and time spent within the CBLE (RQ2).

- RQ1: How much does learners' mindset (growth vs. fixed) affect their learning gains in Python programming when using a CBLE without the presence of a teacher to influence the learning process and learning outcomes?
- RQ2: How does learners' mindset (growth vs. fixed) influence the programming learning in a computer-based learning environment (CBLE) using the log data beyond what can be gathered using self-report and researcher observation data?
    - What is the impact of learners' mindset on the number of actions performed and
    - How does the learners' mindset influence the time spent on those actions in a CBLE?

4. Background : CBLE - PyGuru

We developed PyGuru, a computer-based learning environment aimed at enhancing Python programming education (Singh & Rajendran, 2022; Singh et al., 2022). As depicted in Figure 1, PyGuru comprises four key components.

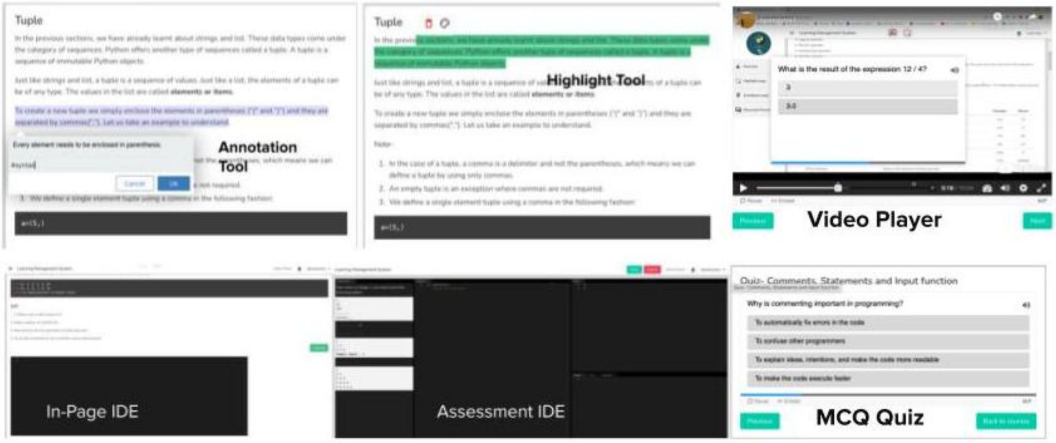

Figure 1. PyGuru environment includes book reader components, such as annotation tool, highlight tool, video player, in-page IDE, assessment IDE, and MCQ quiz.

The Book Reader allows learners to navigate textual content, highlight important sections, and add annotations with personalised notes and tags. The Video Player presents interactive videos embedded with questions that pause playback until answered, promoting active learner engagement. PyGuru also includes two integrated development environments (IDEs): an In-page IDE for immediate code experimentation alongside textual content and an Assessment IDE, which formally evaluates learners' programming skills by running their code against predefined test cases. Additionally, the platform offers an MCQ Assessment Module, providing multiple-choice questions that reinforce conceptual understanding and offer instant feedback. The learners' interactions with the CBLE comprised several key actions. First, they "Read" textual content and "Watch_Video" tutorials to acquire foundational information on each topic. While viewing videos, they paused to answer In-video questions, which served to verify their understanding of the material. After completing a topic, students attempted a "Quiz" covering the same topics to further assess their comprehension. To practice coding concepts, they used the "Practice_Code" environment within the page, entering syntax and experimenting with examples. More formal "Assessment" code tasks required learners to expand or modify pseudocode and "Verify_assessment" code against the test cases.

5. Methodology

5.1 Study Design

The study was conducted over two days in a workshop-style format with first-year non-CS undergraduate students. All participants were from non-CS major background with no prior programming experience using Python. On Day 1, participants completed a demographic survey (age, degree, year of study, perceived programming proficiency, and prior experience), provided consent for log data collection, filled out the 20-item Growth Mindset Scale (Dweck, 1999, 2006), and undertook a 30-minute pre-test. This was followed by 1.5 hours of interaction with the PyGuru environment. On Day 2, learners continued using PyGuru for another 1.5 hours and concluded with a 30-minute post-test. The process is shown in Figure 2.

The pre- and post-tests, adapted from Lewis (2016), assessed Python programming knowledge and were scored out of 25 marks: 13 from multiple-choice questions (1 mark each) and 4 from three open-ended questions (3 marks each), such as code completion and output prediction.

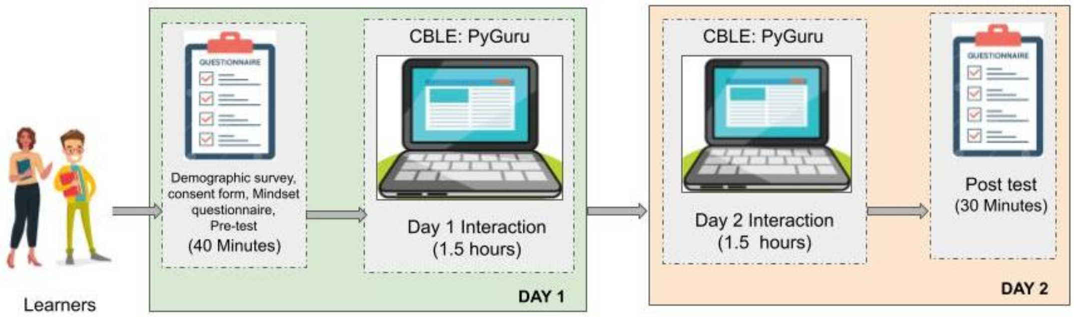

Figure 2. Block diagram of the study design

5.2 Data Collection Procedure

Data were collected from 72 first-year undergraduate students. After excluding five students with missing pre-test, post-test, mindset, or demographic data and the learners with fewer than 10 actions, the final sample comprised 67 participants. The mindset survey demonstrated acceptable internal consistency with Cronbach's alpha value of 0.72. Using a tertile-split approach based on mindset questionnaire scores, students were categorised into three groups: growth mindset (top 33%, n = 24), fixed mindset (bottom 33%, n = 22), and mixed mindset (middle 33%, n = 21).

This grouping enabled us to focus on the extremes of the mindset continuum, a method commonly used in educational research. For example, Ma and Xu (2004) used tertile splits to study math anxiety, and Guthrie et al. (2012) applied a similar approach to examine reading engagement. In this study, only the growth and fixed mindset groups were retained for comparative analysis.

5.3 Data Analysis

Learning gain, a commonly used metric in educational research, was employed to assess the impact of learners' mindsets on their programming performance. It was computed using Hake's formula (Hake, 1998):

$$\textit{Learning Gain} = \frac{(Post-test - Pre-test)}{(100 - Pre-test)}$$

This formula quantifies the proportion of possible improvement a learner achieves, accounting for ceiling effects and enables comparison across students with different starting scores. This metric captured knowledge improvement after interacting with the CBLE, *PyGuru*, and allowed us to compare learning outcomes between growth and fixed mindset groups. We also analysed differences in action frequencies and average time spent on learning activities. Actions with mean frequency below 1 in either group were excluded. Due to non-normal data and unequal group sizes (growth: 24; fixed: 22), we used the non-parametric Mann-Whitney U test for group comparisons. To address multiple comparisons, we applied the Benjamini-Hochberg correction, which controls the False Discovery Rate and is suitable for identifying meaningful behavioural differences in educational datasets.

6. Results

6.1 Learning Gain (RQ1)

To assess the impact of mindset on academic performance, we compared pre-test scores using the Mann-Whitney U test, which revealed no significant difference between growth and fixed mindset groups, $U(23, 22) = 352$, $p = .053$, $r = .29$. The mean pre-test score for growth mindset students was 37.50 (Median = 40), and 30.55 (Median = 24) for fixed mindset students. Figure 3 shows comparison of the learning gain across the groups of students with fixed and growth mindset. Boxplot shows the differences in distribution of learning gain and highlights the significance in the difference.

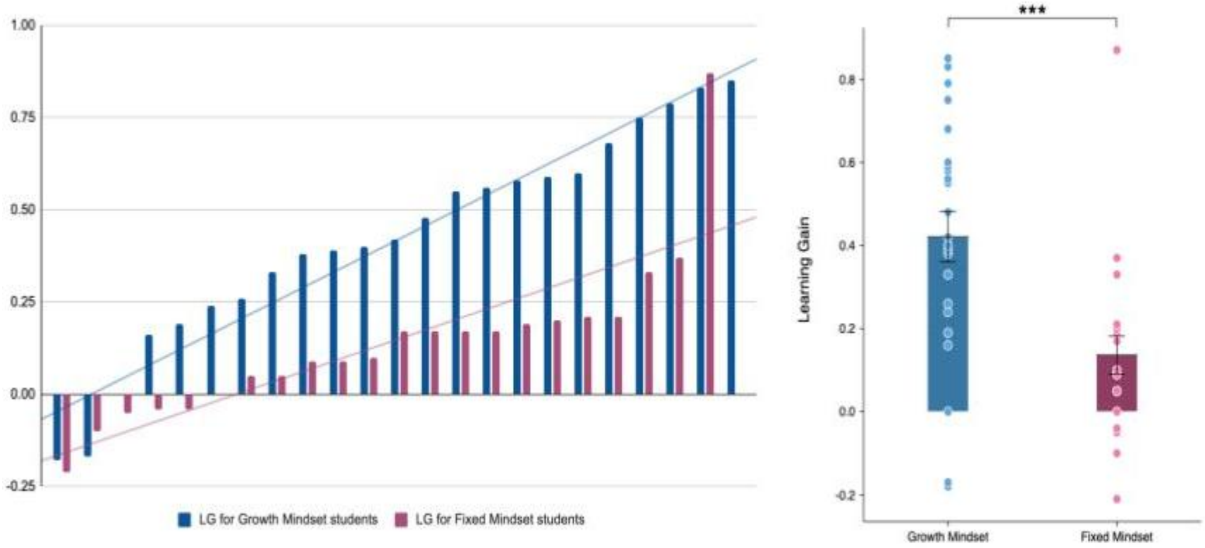

Figure 3. Comparison between the learning gains of students with Growth and Fixed mindset student-wise and group-wise.

Due to unequal group sizes and non-normal distributions, we again used the Mann-Whitney U test. Results showed a significant difference in learning gains, $U = 406.5, p = .0005, z = 3.49$, with a large effect size ($r = 0.52$, Cohen's $d = 1.11$), favouring growth mindset students. Their mean learning gain was 0.421 ($SD = 0.136$), compared to 0.291 ($SD = 0.214$) for fixed mindset students. Growth mindset students achieved significantly higher learning gains compared to fixed mindset students, with a large effect size, highlighting a strong relationship between mindset and academic improvement.

6.2 Differences in the action counts performed by the students with Growth and Fixed mindsets (RQ 2a)

We present the visual comparison of action counts of both the groups in Figure 4. Differences can be seen for the actions such as reading, video watching, quiz, assessment, and practice coding. Apart from the frequency of "Verify_assessment" against the test cases per student, frequency of other actions seem to be different for group of students with growth and fixed mindset. A Mann-Whitney U test was conducted to compare the frequency of various actions between growth and fixed mindset students. The Benjamini-Hochberg procedure was applied to control for multiple comparisons, with an FDR (False Discovery Rate) threshold of 0.05.

A Mann-Whitney U test was conducted to compare the frequencies of various learning actions between growth and fixed mindset students. After applying the Benjamini-Hochberg correction, several actions showed statistically significant differences between the groups as shown in Table 1. Growth mindset students performed significantly fewer quiz ($U = 61.5, p < .001, r = -0.66$, $Mean_{Growth}=3.38$, $Std_{Growth}= 3.98$, $Mean_{Fixed}= 11.86$, $Std_{Fixed}= 5.96$), video watching ($U = 69.5, p < .001, r = -0.63$, $Mean_{Growth}= 12.33$, , $Std_{Growth}= 38.96$, $Mean_{Fixed}= 16.05$, $Std_{Fixed}= 8.69$), reading ($U = 95, p = .00021, r = -0.55$, $Mean_{Growth}= 15.38$, $Std_{Growth}= 14.42$, $Mean_{Fixed}= 36.18$, $Std_{Fixed}= 18.03$), and assessment ($U = 118, p = .00119, r = -0.47$, $Mean_{Growth}= 2.58$, $Std_{Growth}= 3.31$, $Mean_{Fixed}= 7.27$, $Std_{Fixed}= 5.69$) actions compared to fixed mindset students.

However, no significant differences were found for actions like practice coding, and verifying assessments, as indicated by non-significant corrected p-values. Details are presented in the Table 1.

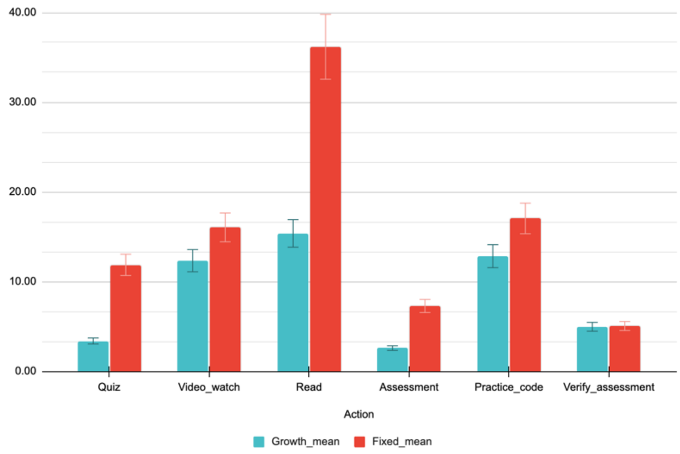

Figure 4. Graph comparing mean value of action counts/frequency for groups of students with Growth mindset and Fixed mindset.

Table 1. *Results of the Mann-Whitney U test along with the Benjamini-Hochberg post-hoc test results for comparison of frequency for each action performed for groups of students with Growth and Fixed mindsets.*

Action	MW_statistic	p_value	z_value	effect_ size_r	cohens_d	corrected_p_ value	significance
Quiz	61.5	7.55E-06	-4.45	-0.66	-1.68	6.04E-05	TRUE
Video_watch	69.5	1.84E-05	-4.28	-0.63	-0.13	7.37E-05	TRUE
Read	95	0.00021	-3.72	-0.55	-1.27	0.000554	TRUE
Assessment	118	0.00119	-3.21	-0.47	-1.01	0.002383	TRUE
Practice_code	178.5	0.06106	-1.88	-0.28	-0.27	0.081410	FALSE
Verify_assess ment	222	0.34807	-0.92	-0.14	-0.01	0.397793	FALSE

Overall, growth mindset students engaged less frequently in certain resource-heavy activities like quizzes, reading, and assessments compared to fixed mindset students.

6.3 Differences in the average time spent on various actions by the students with Growth and Fixed mindsets (RQ2b)

To explore how mindset affects learning behaviour, the Figure 5 below compares the average time spent on key educational actions by students with growth and fixed mindsets. It highlights where their engagement strategies differ across the CBLE - PyGuru. For the actions like – quiz, video watching, reading and assessment, the time spent seems to be different for both the groups.

A Mann-Whitney U test was conducted to compare the average time spent on various actions between growth and fixed mindset students. The Benjamini-Hochberg procedure was applied to control for multiple comparisons, maintaining an FDR (False Discovery Rate) threshold of 0.05.

A Mann-Whitney U test was conducted to compare the average time spent on various learning actions between growth and fixed mindset students as shown in Table 4. After applying the Benjamini-Hochberg correction, no statistically significant differences were observed across any of the actions. Although quiz activities ($U = 173$, $p = .045$, $r = -0.30$, $Mean_{Growth} = 141.5$, $Std_{Growth} = 409.38$, $Mean_{Fixed} = 122.56$, $Std_{Fixed} = 108.56$)) initially showed low p-values, they did not remain significant after correction (corrected $p = .120$). Similarly, no significant differences were found in time spent on assessments, reading, video watching, or practising code. These results suggest that mindset groups did not differ significantly in the amount of time they allocated to individual learning actions. Detailed results are in Table 2.

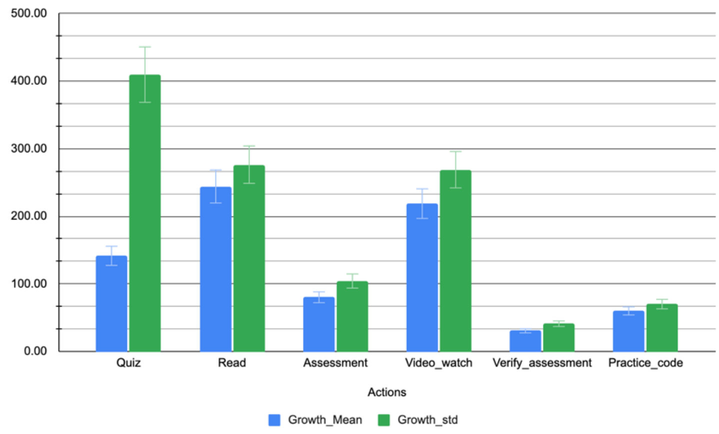

Figure 5. Graph comparing mean value of average time spent on the actions by the groups of students with Fixed and Growth mindsets.

Table 2. *Results of the Mann-Whitney U test for comparison of times spent in seconds for each action performed for groups of students with Growth and Fixed mindsets.*

Action	MW_statistic	p_value	z_value	effect_size_r	cohens_d	corrected_p_value	Significance
Assessment	179	0.0602	-1.8691	-0.2756	-0.3992	0.1204	FALSE
Quiz	173	0.0451	-2.0011	-0.2950	0.0632	0.1204	FALSE
Read	352	0.0543	1.9351	0.2853	0.6560	0.1204	FALSE
Video_watch	200	0.1615	-1.4074	-0.2075	-0.1674	0.2295	FALSE
Verify_assessment	203	0.1721	-1.3414	-0.1978	-0.4246	0.2295	FALSE
Practice_code	218.5	0.3219	-1.0005	-0.1475	-0.1719	0.3678	FALSE

7. Discussion

Our findings show that learners' mindsets significantly influence academic performance in a computer-based learning environment (CBLE) in the absence of teacher/instructor. Growth mindset students achieved notably higher learning gains than their fixed mindset peers, as shown by a statistically significant Mann-Whitney U result (U = 406.5, p = 0.0005, r = 0.52, Cohen's d = 1.11).

This aligns with psychological theories asserting that a growth mindset which believe that intelligence can be developed through effort - enhances motivation, persistence, and performance (Dweck, 2006; Blackwell et al., 2007; Paunesku et al., 2015). Our study extends these insights to programming in CBLEs, where growth mindset learners not only started at similar baselines but progressed further. These findings suggest the value of early mindset assessments to personalise instruction. More broadly, they reinforce the importance of understanding not just *what* students learn, but *how* they engage, particularly in self-paced digital environments.

Beyond learning gains, our results reveal behavioural differences between mindset groups. Growth mindset learners engaged in significantly fewer quizzes, videos, readings, and assessments than fixed mindset learners (all p < .001, $r \geq 0.47$), while fixed mindset students checked errors more frequently (p = .028, r = –0.27). No significant differences were found in coding practice, verification, or submission actions. This suggests growth mindset students interact more selectively and efficiently, reflecting mastery-oriented behaviours (Morales-Navarro et al., 2024; Murphy & Thomas, 2008), while fixed mindset learners may rely on repetition and surface-level engagement (Dweck, 2006). Frequent error-checking among fixed mindset learners may indicate trial-and-error strategies or avoidance of deeper conceptual effort (Yeager & Dweck, 2012). Despite these action differences, time-on-task did not significantly differ after correction. This suggests mindset effects are better reflected in engagement quality than in the amount of time spent supporting earlier findings (Claro et al., 2016).

Together, the data highlight that growth mindset learners optimize their time and actions, while fixed mindset learners show more frequent but potentially less effective behaviours. These distinct engagement strategies underlie the stronger outcomes seen among growth mindset students. This study reinforces the impact of mindset on how learners engage with CBLEs. Growth mindset students demonstrated better learning with fewer but more strategic actions, while fixed mindset learners showed heavier, less productive engagement. These patterns suggest that mindset affects not only outcomes, but also how cognitive resources are allocated. For educators and instructional designers, this underscores the importance of mindset-informed CBLE design. Systems should track not just what learners do, but how and why they engage. Embedding metacognitive prompts and adaptive feedback may help fixed mindset learners adopt more effective strategies.

8. Conclusion

This study investigated how learners' mindsets influence their performance and engagement in a self-regulated computer-based learning environment (CBLE) for Python programming. By combining mindset surveys with log data and learning gain analysis, we demonstrated that students with a growth mindset achieved significantly higher learning gains and exhibited more strategic engagement patterns compared to those with a fixed mindset. While fixed mindset learners engaged in more frequent actions like quizzes and error-checking, growth mindset students demonstrated greater efficiency and selectivity in their interactions by emphasizing quality over quantity.

The findings underscore the importance of integrating mindset-aware instructional strategies into CBLEs. By identifying how learners with different mindsets behave, educators and designers can create adaptive systems that scaffold productive engagement, encourage metacognitive reflection, and support the development of growth-oriented strategies.

Although our results have broader implications for self-directed learning environments beyond programming, their generalizability is shaped by certain constraints. The study focused on a specific CBLE (PyGuru), a limited sample of first-year non-CS undergraduates, and short-term learning sessions. Moreover, the mindset categorization relied on a tertile split, which simplifies the mindset continuum. These assumptions may influence the observed behavioural patterns and learning outcomes.

Future research should also leverage log data analysis more deeply to uncover nuanced patterns in learner behaviour. Specifically, pattern mining techniques can help identify recurring sequences of actions that distinguish growth and fixed mindset learners, offering a richer understanding of how mindset manifests in real-time interactions. This could reveal not only what learners do, but when and how they engage with different components of the CBLE. Such insights can guide the design of targeted interventions that adaptively respond to learners' behavioural patterns and support mindset development through system-level scaffolding. Future work should extend this analysis to larger and more diverse learner populations, explore longitudinal learning effects, and evaluate how similar mindset-behaviour relationships manifest across other domains. Additionally, deeper log analysis and qualitative data (e.g., interviews or think-aloud protocols) could provide richer insight into the mechanisms through which mindset shapes self-regulated learning in digital environments. This can help in development of more robust, mindset-sensitive digital learning environments.

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