Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 12, 817-826
2025
Publisher: Learning Gate
DOI: 10.55214/2576-8484.v9i12.11483

Comparative analysis of students' mathematical problem-solving performance in sequential and concurrent multitasking: Evidence from large-scale computer-based tests

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Abstract: The integration of digital technology in mathematics education has expanded learning opportunities while simultaneously introducing multitasking demands that may impact student performance. Despite substantial research on the negative effects of multitasking, large-scale empirical evidence comparing sequential and concurrent multitasking within mathematical problem-solving contexts remains limited. This study aims to examine and compare the effects of sequential and concurrent multitasking on students' mathematical problem-solving performance using extensive computer-based assessment data. A quantitative, comparative, ex-post-facto design was employed, analyzing 21,484 student responses from digital mathematics assessments. Performance metrics included accuracy rates, response times, and task viewing times across two multitasking conditions. Results showed that concurrent multitasking demonstrated superior performance across all measured indicators: higher accuracy (18.6% vs. 17.7%), faster response times (110.4 vs. 172.6 seconds), and shorter viewing times (119.1 vs. 191.9 seconds) compared to sequential multitasking. Sequential multitasking required 56.3% longer response times, indicating high task-switching costs. These findings challenge conventional assumptions about the detrimental effects of concurrent multitasking in educational contexts. For digital education, the results suggest that interface designs supporting concurrent problem access may enhance learning efficiency by reducing cognitive overhead associated with task switching. Educational technology developers should consider implementing concurrent presentation formats for related mathematical problems rather than enforcing sequential processing approaches.

Keywords: *Computer-based test, Concurrent, Mathematical problem solving, Multitasking, sequential.*

1. Introduction

In the digital era, integrating technology into mathematics learning has opened up new opportunities for enhancing access to content, learner engagement, and the quality of instruction. Ideally, digital learning environments are expected to improve students' problem-solving abilities by fostering cognitive efficiency and adaptive learning strategies. However, the same technological advancements that enable richer learning experiences have also contributed to increased distractions, particularly multitasking. The widespread use of smartphones, laptops, and social media platforms has led students to frequently divide their attention across multiple tasks, even during cognitively demanding activities like solving mathematical problems.

Recent studies have documented that multitasking, whether in sequential (task switching) or concurrent (simultaneous) forms, negatively affects learning outcomes, memory retention, and academic performance [1, 2]. Although some students view multitasking as a modern skill aligned with digital fluency [3], the cognitive costs are well established. Sequential multitasking typically incurs switching

History: Received: 2 October 2025; Revised: 14 November 2025; Accepted: 18 November 2025; Published: 16 December 2025
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costs that slow down performance, while concurrent multitasking, such as texting during a lesson, often results in higher cognitive load and greater performance interference [4, 5]. Despite increased exposure to digital tools, the disadvantages of multitasking persist, reinforcing the need for empirical insights into how these behaviors specifically impact mathematics learning.

In practice, much of the existing research on multitasking remains limited to small-scale experiments and self-report studies. These methods, while insightful, fail to capture the complexity and authenticity of multitasking in digital learning environments, particularly those involving computer-based testing (CBT). For instance, self-reported multitasking often underestimates actual behavior [6], and educational interventions to reduce multitasking have shown limited long-term effectiveness [7]. Furthermore, the existing body of research lacks a rigorous examination of multitasking in mathematics-specific contexts, especially when students must integrate conceptual, procedural, and strategic knowledge.

There remains a notable gap in large-scale studies that directly compare sequential and concurrent multitasking in digital mathematics learning. While some recent studies have begun to address this, such as Sommerhoff et al. [8], which examined instructional approaches for mathematical argumentation, most findings are context-dependent and do not reflect broader patterns across diverse student populations. Research from multimedia learning contexts supports the claim that both types of multitasking impair learning, but concurrent multitasking is consistently more disruptive [9]. No comprehensive empirical framework directly examines the performance implications of multitasking styles using large-scale CBT data.

The present study introduces a data-driven analytical approach using actual CBT performance metrics to address this gap. It focuses on two key indicators: task switching cost for sequential multitasking and task interference ratio for concurrent multitasking. By analyzing these metrics, the study aims to offer a more accurate depiction of how different multitasking strategies affect accuracy and efficiency during digital mathematics problem solving. This approach provides empirical evidence of student performance and offers a foundation for rethinking how digital learning tasks should be structured concerning students' multitasking behaviors.

The primary objective of this study is to compare the accuracy and completion time associated with sequential and concurrent multitasking to generate actionable recommendations for digital assessment and instructional design. The study's contributions are both theoretical and practical: it introduces a performance-based framework for understanding multitasking in digital learning contexts. It provides insights for educators and assessment developers seeking to optimize task design, reduce cognitive overload, and enhance students' problem-solving experiences in mathematics.

This study employs large-scale CBT data to examine student behavior patterns under sequential and concurrent multitasking conditions, using response accuracy and task duration as primary performance indicators. The results show substantial differences in efficiency and precision between the two multitasking approaches, offering meaningful insights for instructional design and assessment planning. Overall, the research contributes to developing cognitively sustainable digital learning environments by linking multitasking theory with real-world student performance in mathematics.

2. Theoretical Framework

2.1. Multitasking and Mathematical Problem Solving

A suitable theoretical foundation for this study integrates insights from cognitive theories of multitasking and mathematical problem solving, particularly regarding how attention, working memory, and executive control operate under multitasking conditions in digital contexts. Formal cognitive models of multitasking offer structured explanations for performance dynamics in multitasking environments, highlighting mechanisms such as task switching costs in sequential multitasking and interference ratios in concurrent multitasking. These models provide essential tools for quantitatively analyzing efficiency and accuracy, allowing researchers to assess how individuals allocate cognitive resources across tasks [10].

Complementing this, the computational complexity framework emphasizes the intrinsic cognitive demands of mathematical problem solving. It acknowledges that human strategies are often heuristically driven and suboptimal compared to algorithmic ideals, particularly under divided attention. This perspective underscores the necessity of studying real-world performance in multitasking scenarios, focusing on how cognitive limitations and strategy choices influence mathematical outcomes [11]. Integrating this lens allows for a more realistic understanding of problem-solving behavior in digital environments.

The RAMPS (Regulated Attention in Mathematical Problem Solving) framework also brings a metacognitive and affective dimension to the analysis, emphasizing how attention regulation, working memory, and emotional factors such as math anxiety shape problem-solving effectiveness. Particularly relevant in multitasking contexts, RAMPS highlights the critical role of metacognitive monitoring in navigating cognitive load and maintaining focus on mathematical tasks [12]. These three theoretical models, formal cognitive multitasking models, computational complexity, and RAMPS, form a comprehensive foundation to analyze how sequential and concurrent multitasking impact students' mathematical performance in digital learning environments.

2.2. Related Studies on Multitasking and Mathematical Problem Solving

Several prior studies offer essential insights into the effects of multitasking on students' mathematical problem solving, particularly within digital or computer-based environments. While few directly replicate a large-scale comparative design, their findings enrich this research's conceptual and methodological foundation. For instance, Nisa et al. [13] examined students' cognitive strategies in multitasking-based math problems and found that variations in problem-solving approaches were influenced by experience and practice. This suggests that multitasking affects accuracy, time, and the choice of strategy and cognitive stages involved in solving mathematical tasks.

Additionally, Lin et al. [14] explored the dynamics of multitasking, specifically, task switching and dual tasking in virtual collaborative problem-solving settings. Their findings revealed that when paired with peer collaboration, multitasking can enhance efficiency and accuracy, offering an essential nuance to the typical narrative that multitasking is purely detrimental. Lin et al. [14], although not directly studying multitasking, investigated how pressure and working memory load affect mathematical performance. Their findings support distraction theories and show how divided attention, a core feature of multitasking, impairs performance on complex or unfamiliar problems. Furthermore, Ruitenburg et al. [15] demonstrated that active problem solving, as opposed to passive example-based learning, leads to more robust long-term mathematical understanding, underscoring the importance of cognitive engagement, which may be compromised by multitasking.

These studies help contextualize the present research by illustrating how cognitive load, attentional control, collaborative settings, and strategy use interact within digital mathematics learning. They inform the comparative analysis between sequential and concurrent multitasking and support the development of empirically grounded recommendations for digital assessment and instructional design. By situating this study within these empirical contributions, the research builds on existing evidence while addressing the current gap in large-scale performance-based comparisons.

2.3. Research Gap

A significant research gap persists in comparing students' mathematical problem-solving performance under sequential (alternating) and simultaneous (concurrent) multitasking conditions, particularly within large-scale, computer-based settings. While earlier studies have explored students' cognitive processes during multitasking in math tasks, these investigations have been mainly qualitative or based on small samples, without systematically measuring performance metrics such as accuracy and completion time across multitasking types [13]. Moreover, existing research tends to focus on general cognitive flexibility, collaborative problem solving, or the impact of pressure and working memory on mathematical performance [16, 17] rather than directly examining how multitasking structures influence task efficiency and precision in real-world digital environments.

By introducing a large-scale, quantitative approach, this study directly addresses these gaps by comparing students' performance under sequential and concurrent multitasking using computer-based testing data. It incorporates performance metrics such as task switching costs [18-20] and interference ratios [9, 21, 22]. Analyze differences in efficiency and accuracy, providing empirical insights that previous studies have lacked. The findings are expected to contribute to theoretical understanding and practical improvements in the design of digital assessments and instructional strategies. This area remains underexplored in current educational research.

3. Method

3.1. Sampling

The study utilized total sampling, analyzing all available data from the population of students who participated in the computer-based multitasking mathematics assessment. This approach ensures that the sample (21,484 student responses) fully represents the population, minimizing bias and enhancing the generalizability of the findings [23, 24].

3.2. Instrumentation

Two multiple-choice mathematics questions served as the research instruments, each designed to represent a different multitasking condition. One question assessed sequential (alternating) multitasking, while the other evaluated concurrent (simultaneous) multitasking. Careful instrument selection is crucial to ensure the reliability and validity of the data collected [23].

3.3. Data Collection

Data were automatically collected from the computer-based testing (CBT) system. The system recorded student answers, answer keys, the time taken to answer each question, and the time spent viewing each question. Automated data collection enhances precision and reduces the risk of human error, supporting accurate measurement of key variables [23].

3.4. Data analysis

Initial data processing involved determining the correctness of answers and grouping responses by multitasking type. Descriptive statistics were calculated for accuracy, response time, and question viewing time. For inferential analysis, independent t-tests or ANOVA were planned to test for significant differences in performance between the two multitasking conditions. Data visualization, including tables and bar charts or boxplots, was used to clearly present comparative results [23].

4. Results

Descriptive analysis shows differences in student performance between sequential and concurrent multitasking conditions in CBT-based mathematical problem solving. The findings indicate that student accuracy was slightly higher in the concurrent multitasking condition (18.6%) compared to the sequential condition (17.7%). This suggests that performing tasks simultaneously does not necessarily impose a greater cognitive load; instead, the result may be influenced by the nature of the questions or the problem-solving strategies employed by the students.

In contrast, response and question-viewing times were notably longer in the sequential condition (average response time: 172.6 seconds; viewing time: 191.9 seconds) compared to the concurrent condition (average response time: 110.4 seconds; viewing time: 119.1 seconds). This implies that completing one task before switching to another may involve a switching cost or require additional cognitive effort to retain and reactivate contextual information. These patterns highlight that task structure can meaningfully influence the efficiency and effectiveness of students' mathematical problem-solving in digital environments.

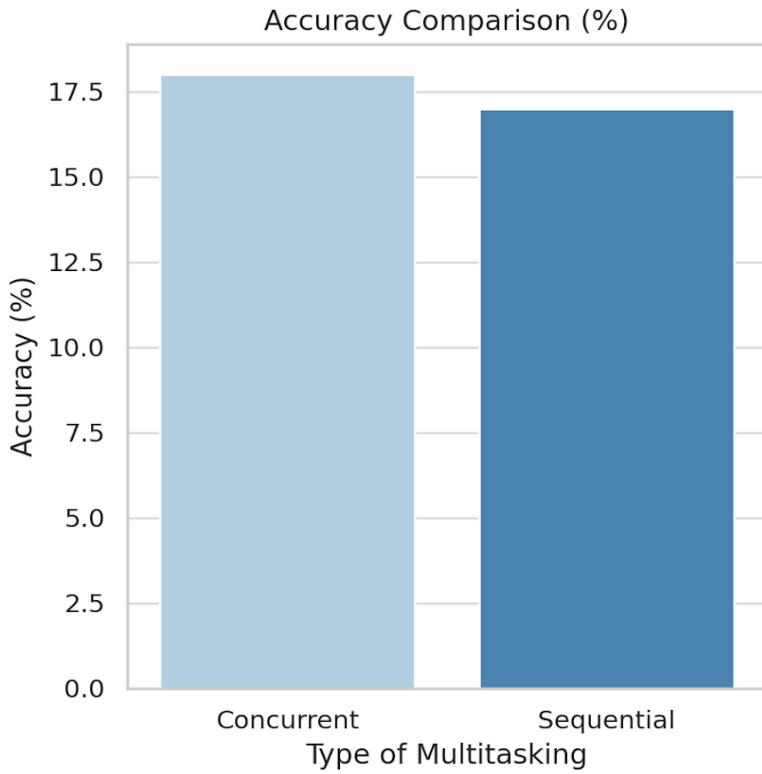

Figure 1.
Accuracy Comparison.

Figure 1 presents a bar chart comparing students' accuracy rates in mathematical problem solving under two multitasking conditions: concurrent and sequential. The results show that accuracy in the concurrent multitasking condition was slightly higher, exceeding 18%, compared to just under 17% in the sequential condition. Although the difference between the two groups is relatively small, it suggests that students employing concurrent multitasking tend to produce more accurate answers than those using a sequential approach. Beyond speed advantages observed in prior analyses, concurrent multitasking also demonstrated a marginal improvement in accuracy, indicating that performing tasks simultaneously does not diminish and may even enhance students' precision in answering. Nevertheless, the statistical significance of this difference requires further validation through inferential tests, such as independent t-tests or Mann–Whitney tests. These findings have potential pedagogical implications, as they suggest that concurrent multitasking could be strategically integrated into mathematics learning activities to improve efficiency and accuracy, provided task design and cognitive load are carefully managed.

DOI: 10.55214/2576-8484.v9i12.11483

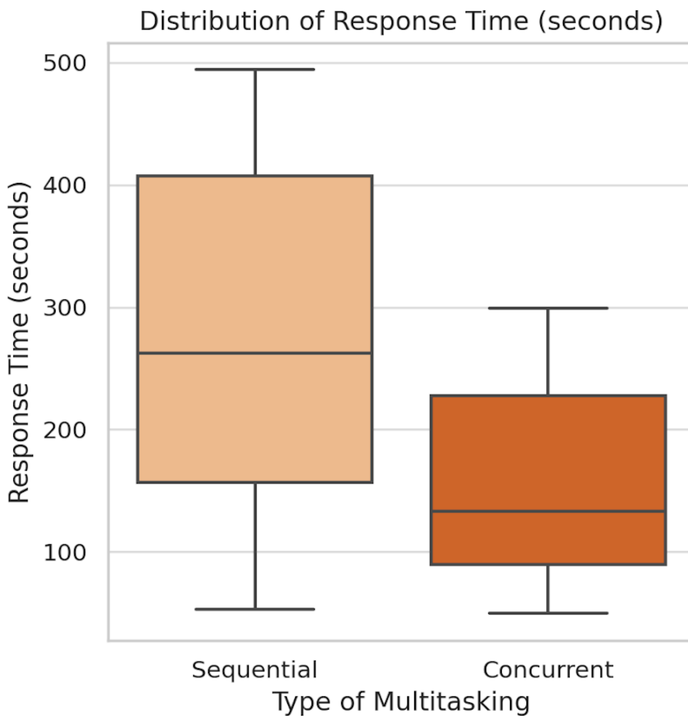

Figure 2.
Distribution of Response Time.

Figure 2 presents a boxplot illustrating the distribution of students' response times (in seconds) for mathematics problems under two multitasking conditions: sequential (performed step-by-step) and concurrent (performed simultaneously). The descriptive statistics indicate that the median response time in the sequential condition was higher than in the concurrent condition, reflecting generally slower task completion. Sequential multitasking also displayed a wider range of response times and more extreme outliers, as shown by longer whiskers and more data points outside the box. In contrast, concurrent multitasking exhibited a more concentrated and narrower distribution, albeit with some outliers remaining. Visually, students in the sequential condition tended to require more time to complete the tasks than those in the concurrent condition. These results suggest that concurrent multitasking enabled students to work more efficiently overall, with a more stable distribution of response times. In contrast, sequential multitasking showed greater variability in performance, possibly indicating inconsistent effectiveness across students. Outliers in both conditions highlight that specific individuals took unusually long to respond, particularly in the sequential group. Overall, the findings support the potential of concurrent multitasking to improve time efficiency in mathematical problem solving, provided that questions of answer quality and cognitive load are addressed in future research.

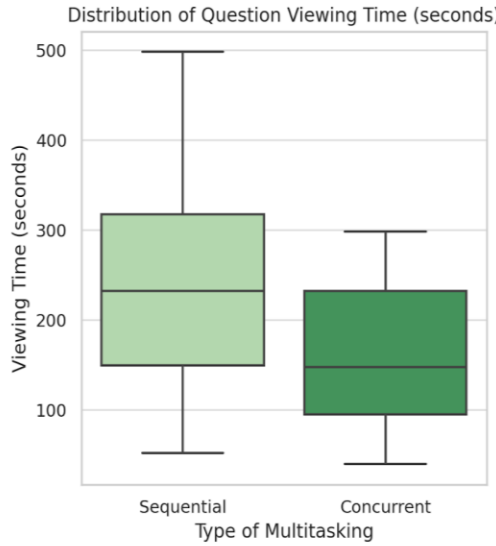

Figure 3.
Distribution of Question Viewing Time.

The descriptive analysis of Figure 3, which compares question-viewing times under sequential and concurrent multitasking conditions, reveals distinct differences in students' engagement patterns. The median viewing time was higher in the sequential condition, with a wide interquartile range (IQR) indicating substantial variability. Viewing times ranged from nearly 0 seconds to almost 500 seconds, and several extreme outliers exceeded 450 seconds. By contrast, the concurrent condition showed a lower median viewing time and a narrower IQR, suggesting more consistent viewing behavior, with maximum times reaching only around 400 seconds despite multiple outliers. These patterns indicate that students in the sequential condition generally spent more time viewing questions, with greater variability. In contrast, those in the concurrent condition tended to have shorter and more uniform viewing durations. This may suggest that sequential multitasking gives students a greater opportunity to focus and reflect on the problem. In contrast, concurrent multitasking could impose additional cognitive load, leading to shorter or fragmented viewing periods. From an instructional perspective, these findings imply that the choice of multitasking strategy should align with learning objectives and task complexity. Sequential multitasking may be more effective for tasks requiring deep comprehension and sustained attention, allowing students sufficient time and focus to process the problem thoroughly.

Data visualization (Figures 1–3) supports these findings. The bar chart in Figure 1 shows that although the difference in accuracy is slight, it consistently favors the concurrent condition. The boxplot in Figure 2 shows a narrower distribution of response times in the simultaneous condition, with a lower median, while the sequential condition shows a broader range and many outliers. Figure 3 shows that the time spent viewing questions in the sequential condition tends to be longer and more variable than in the concurrent condition.

5. Discussion

These findings indicate that concurrent multitasking does not always reduce students' performance in solving mathematical problems. In fact, in the context of this study, concurrent multitasking resulted in shorter completion times with slightly higher accuracy than sequential multitasking. This contradicts some literature emphasizing the negative impact of multitasking on academic performance [4, 5] but aligns with the findings of Lin et al. [14], who discovered that under certain conditions, multitasking can enhance efficiency.

ISSN: 2576-8484
Vol. 9, No. 12: 817-826, 2025
DOI: 10.55214/2576-8484.v9i12.11483

Cognitively, these results can be explained by task-switching costs in sequential multitasking. When students complete one task and move on to another, they must reactivate their mental context and working memory, which requires additional time and cognitive resources [10]. Conversely, in concurrent multitasking, although there is the potential for increased cognitive load, tasks can be completed simultaneously, reducing the need to reactivate the context.

However, it should be noted that the difference in accuracy between the two types of multitasking is relatively small. This indicates that the kind of multitasking is not the only factor determining performance; other factors, such as the level of difficulty of the questions, the strategy used to solve them, and the students' numerical abilities, are likely to play a role [13, 16].

The practical implication of these findings is that digital-based learning strategies may consider using concurrent multitasking models if time efficiency is a priority, such as in quick drills or short quizzes. However, if the learning objective is deep understanding and complex conceptual processing, sequential multitasking may be more appropriate as it allows for more extended periods of focus on each subtask.

The limitations of this study include: (1) only two questions were analyzed, limiting the generalizability of the results; (2) there was no control for individual student factors such as working memory or math anxiety; (3) multitasking was classified based on question numbers without an explicit experimental design; and (4) the analysis was still descriptive without inferential tests to examine the significance of differences. Therefore, further research is recommended to apply a randomized experimental design, include more questions with varying cognitive levels, and incorporate students' mental and affective variables. Qualitative analysis of students' strategies is also essential to understand the thinking patterns that occur during multitasking.

6. Conclusion

This study shows that students' abilities in mathematical multitasking are not necessarily worse in concurrent situations. Sequential multitasking tends to be more time-consuming, most likely due to the need to store and manage information sequentially. These findings support previous studies suggesting that students' multitasking strategies should be adjusted according to the context of the mathematical tasks they face.

This study has several limitations, including the analysis of only two problems, which restricts the generalizability of the results. There was no control over individual student factors such as mathematical ability or working memory, which could affect multitasking performance. The classification of multitasking types based on item numbers was not based on an explicit experimental design, which may introduce bias. Moreover, the large data scale was not accompanied by response quality filtering, and the analysis was purely descriptive without any inferential statistical testing to confirm the significance of differences.

Future research should use an explicit experimental design by randomly assigning students to sequential and concurrent conditions. Cognitive variables such as working memory and attentional focus should also be included, as well as variation in problem types and mental levels. Inferential statistical tests such as t-tests or ANOVA should be employed to test for significance. A qualitative approach is also recommended to understand students' strategies during multitasking and to categorize them based on learning profiles, thereby examining the influence of individual factors.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

Acknowledgements:
The authors would like to express their sincere gratitude to the Doctoral Program in Mathematics Education at Universitas Negeri Surabaya for its academic support and the constructive scholarly environment it provided throughout this research.

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