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THE IMPACT OF A MOBILE LEARNING APPLICATION ON STUDENTS' COGNITIVE LOAD AND LEARNING PERFORMANCE IN BIOLOGY

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ABSTRACT

Aim/Purpose	This study aims to analyze the cognitive load experienced by secondary school students in Biology within m-learning environments and its impact on learning performance.
Background	Cognitive load has become a critical issue that schools need to address to ensure students can excel in their learning without being overwhelmed. While principles for reducing cognitive load have been extensively discussed in previous research, studies focusing on mobile learning (m-learning) for Biology among students in Malaysia remain limited. This study employed Cognitive Load Theory (CLT) and Cognitive Theory of Multimedia Learning (CTML) to address this gap. By integrating four key principles—segmenting and pretraining, modality, redundancy, and seductive details—into m-learning tasks using the Successive Approximation Model (SAM1), this study aimed to reduce cognitive load and enhance students' learning performance.
Methodology	This study employed a quantitative approach using a randomized pre-test/post-test quasi-experimental design. Students were randomly assigned to either an intervention group (20 students) or a control group (18 students). The study was conducted over four weeks, comprising a three-week intervention period with a one-week interval. Statistical analyses, including independent t-tests, Mann-Whitney U tests, Quade ANCOVA, and Pearson correlation, were used to analyze the quantitative data. Qualitative feedback was analyzed using thematic analysis.

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Contribution	This study contributes by providing instructional design strategies that incorporate principles for reducing cognitive load in mobile learning for Biology. It also demonstrates how Cognitive Load Theory (CLT) and Cognitive Theory of Multimedia Learning (CTML) can be effectively integrated. By examining the cognitive load experienced by secondary school students in m-learning environments, the study offers valuable insights for designing and implementing effective instructional strategies. Identifying the factors influencing cognitive load enables educators to develop targeted interventions that enhance learning experiences and optimize performance.
Findings	The study indicated that the adoption of mobile learning tasks not only significantly reduced cognitive load but also corresponded to enhanced learning performance. Participants engaging in m-learning experienced lower cognitive load, which was positively associated with superior performance in learning tasks, emphasizing the beneficial impact of mobile learning on cognitive load management and academic achievement.
Recommendations for Practitioners	Educators and instructional designers are encouraged to incorporate cognitive load principles into their instructional strategies and learning material design to enhance student performance. Policymakers should consider similar strategies to reduce the cognitive load for students in educational settings to improve learning outcomes.
Recommendations for Researchers	Researchers are encouraged to replicate the design elements used in this study when developing mobile or online learning materials to reduce learners' cognitive load and enhance their performance. They should also consider expanding this research to other topics, subjects, and educational levels to provide further insights and validate the effectiveness of these design elements across different contexts.
Impact on Society	The findings of this study have significant implications for society, particularly in addressing mental health and stress issues among the younger generation. By identifying strategies to manage cognitive load and reduce stress in online learning environments, the study provides valuable insights for educators, parents, and policymakers. These strategies can help mitigate the adverse effects of cognitive overload, improve learning experiences, and promote better mental well-being. Additionally, the study's recommendations can guide the development of more effective and supportive learning environments, contributing to overall societal well-being and academic success.
Future Research	Future studies could explore cognitive load beyond the intrinsic and extraneous components focused on in this study, examining additional elements within the frameworks of cognitive load theory and multimedia learning. In addition to using the cognitive load questionnaire, exploring other measurement tools could ensure a more comprehensive understanding of cognitive load. Future research might also consider enriching mobile learning tasks by diversifying subject matter and conducting longitudinal cohort studies. Such studies could provide valuable insights into memory retention over extended periods, aiding in optimizing mobile learning frameworks and enhancing educational experiences.

Keywords: m-learning, mobile learning, cognitive load, mobile applications

INTRODUCTION

Mobile technologies, characterized by their portability and accessibility, have revolutionized user interactions and opened new learning opportunities beyond traditional classrooms (Criollo-C et al., 2021). These applications, offering multimedia features and communication tools, are integral to mobile learning (m-learning), which utilizes smartphones and tablets as educational aids (Criollo-C et al., 2021; Sobral, 2020; M. Wang & Shen, 2012). The flexibility of m-learning allows learning to occur anytime, anywhere (Faudzi et al., 2022; Kim & Park, 2019), highlighting the need for further development in pedagogy and instructional design.

Recognizing and managing cognitive load in the m-learning context is vital for designing effective instructional strategies and optimizing learning performance (Clark & Mayer, 2011; Krull & Duart, 2017). M-learning environments engage students with multimedia elements, presenting both real-world and digital screens (Chu, 2014; G. J. Hwang et al., 2011). However, limited adaptation of m-learning content to learners' contexts can hinder learning experiences and increase difficulty (Zafar & Hasan, 2014). Analyzing learners' cognitive load based on information flow is essential, as it impacts their learning experience and achievement (Huang et al., 2016). Mobile technology serves as a cognitive tool, offering authentic learning within real-world contexts and potentially alleviating cognitive load (G. J. Hwang et al., 2011).

In the context of m-learning, students often face high cognitive load stemming from factors like irrelevant information, inadequate instructional design, and limited experience with mobile learning (Clark & Mayer, 2011). This overload, particularly challenging for novice learners, underscores the necessity of investigating cognitive load implications within multimedia-rich m-learning contexts (Sweller et al., 2019; van Merriënboer et al., 2006). Mobile technology's potential to either increase or reduce cognitive load highlights the importance of managing cognitive processing effectively to promote learning and transfer (Leppink et al., 2014; van Merriënboer et al., 2006). As learning materials are being adapted to fit mobile screens while facilitating effective knowledge transfer on complex topics, the significance of instructional design principles and cognitive load theories cannot be ignored (Curum & Khedo, 2021).

While prior studies (e.g., Huang et al., 2016; G. J. Hwang et al., 2011) have examined the impact of m-learning systems and traditional instruction strategies on learning performance and cognitive load, comprehensive research specifically addressing secondary school students' cognitive load in m-learning remains scarce. This study aims to fill this gap by investigating the cognitive load of secondary school students in m-learning environments and identifying factors influencing it. As Cognitive Load Theory (CLT) provides a framework through which instructional designers can exert control over the learning conditions within an environment (Agbonifo & Ibam, 2015), this study seeks to inform the development of targeted strategies that mitigate cognitive overload and enhance learning experiences in m-learning by pinpointing the influencing factors.

THEORETICAL FRAMEWORK

The theoretical framework (see Figure 1) for this research study is grounded in Cognitive Load Theory (CLT). CLT, proposed by Sweller (1988), explains how the cognitive load experienced by learners affects their learning performance. According to CLT, cognitive load arises from the limited capacity of a learner's working memory (Sweller, 1994). Key concepts within CLT include elements, schemata, and element interactivity. An element refers to any component that needs to be processed and learned (Chen et al., 2023). Schemata are cognitive frameworks that organize and integrate these elements into coherent structures. Schemata can be retrieved and broken down into elements based on the learner's prior knowledge. Element interactivity describes the degree of interaction between elements, which can be adjusted by modifying the material to have higher or lower levels of interactivity (Sweller, 1994). Task complexity is measured by the number of interactive elements in the material

(Chen et al., 2023). Effective instructional procedures aim to reduce element interactivity, while ineffective ones increase it. Prior knowledge is crucial for integrating new information with existing schemata, leading to a more organized understanding and reducing the cognitive load on working memory (Gerjets et al., 2004).

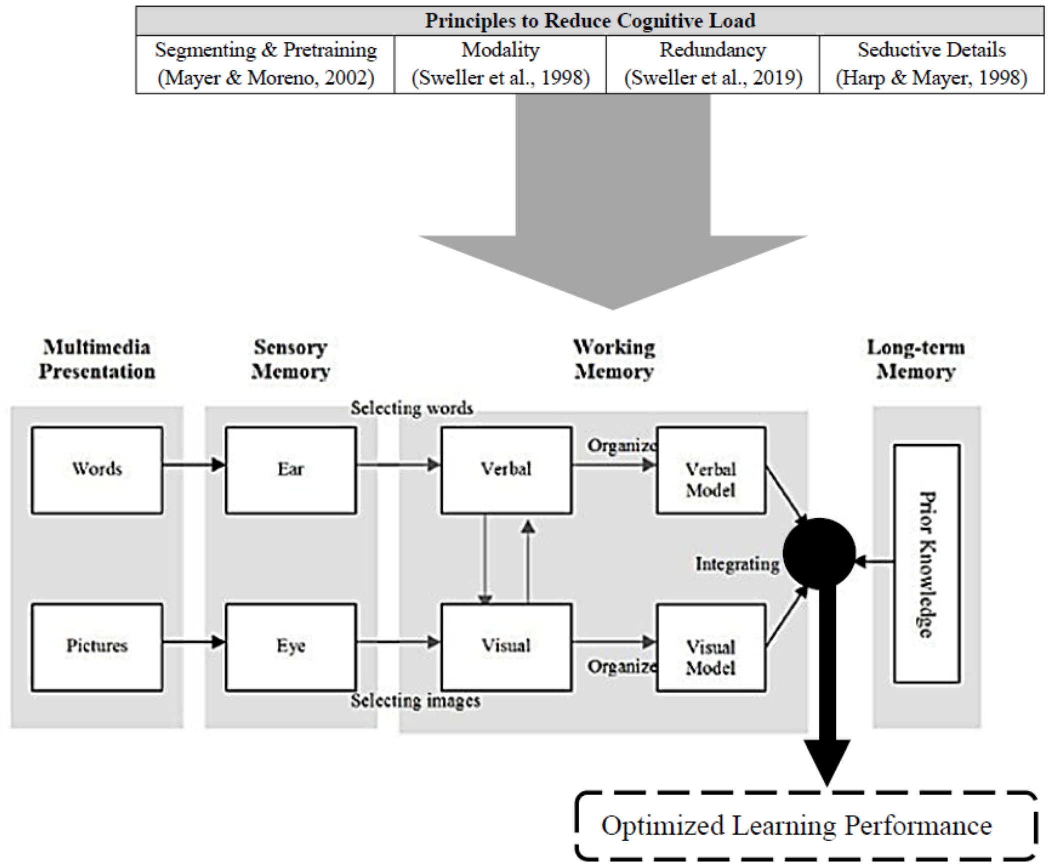

Figure 1. Theoretical framework of m-learning

Cognitive load is categorized into three types: intrinsic, extraneous, and germane (Sweller, 1994). Intrinsic cognitive load is related to the complexity of the information being processed and is linked to element interactivity (Sweller, 1994). Extraneous cognitive load is determined by how information is presented and the tasks required of the learner (Sweller, 1994). Germane cognitive load is the cognitive effort necessary for learning and is concerned with the working memory resources used for processing intrinsic cognitive load rather than extraneous load. When resources are consumed by extraneous load, fewer resources are available for intrinsic load, reducing learning (Sweller, 2010; Sweller et al., 2011). CLT is crucial in teaching and curriculum development as it addresses the limitations of human working memory and its impact on information processing speed (Sweller, 1994).

In mobile learning (m-learning) environments, instructional design aims to enhance learning by promoting meaningful interactivity and avoiding cognitive overload, which can lead to information loss (Agbonifo & Ibam, 2015). By incorporating principles such as segmenting and pretraining (Mayer & Moreno, 2003), modality (Sweller et al., 1998), redundancy (Sweller et al., 2019), and avoiding seductive details (Harp & Mayer, 1998), instructional design in m-learning environments can improve learning performance. CLT provides a solid foundation for understanding how these principles can optimize the learning process in m-learning settings.

Additionally, Mayer and Moreno's (2002) Cognitive Theory of Multimedia Learning (CTML), proposed in 2002, integrates dual coding theory, CLT, and constructivist theory. CTML posits that information is processed through two channels – auditory and visual – within the limited working memory capacity. Instructional design should provide cognitive processing guidance without overwhelming learners. When cognitive overload occurs, essential processing should be prioritized, and incidental processing should be minimized. Multimedia instructional designs that consider cognitive functioning are more likely to facilitate meaningful learning compared to those that do not adhere to these principles. Proper instructional design is crucial to avoid cognitive overload and guide appropriate cognitive processing.

Principles to Reduce Cognitive Load in M-Learning

In m-learning, multimedia elements are incorporated to enhance the learning experience. Mobile devices are well-suited for delivering multimedia content, as they typically have features such as high-resolution screens, audio capabilities, and internet connectivity. M-learning applications and platforms can utilize multimedia elements to present information in a more engaging and interactive manner, catering to different learning styles and preferences. As such, m-learning can leverage multimedia learning principles in instructional design. This includes incorporating strategies such as segmenting content into manageable chunks, providing clear and concise explanations, utilizing visuals to support text-based information, and synchronizing visual and auditory elements.

According to Sweller (1999), cognitive overload occurs when the available cognitive capacity is insufficient to meet the processing demands of complex material, also known as high-intrinsic load. In m-learning, where students engage with educational content on portable devices, it is crucial to optimize the learning experience by reducing cognitive load. In this study, we focused on four principles to reduce cognitive load.

Principle 1: Segmenting and pretraining

According to Spanjers et al. (2011), the effectiveness of segmentation was demonstrated, showing that segmented animations (i.e., divided into parts with pauses in between) were more beneficial for novice learners compared to continuous animations. However, this segmentation effect was not observed in learners with higher levels of prior knowledge. Segmentation involves breaking down the presentation into smaller segments, allowing learners to process and integrate selected words and images from each segment before proceeding to the next (Mayer & Moreno, 2003). This approach provides learners with sufficient time and cognitive capacity to organize and integrate information, thus reducing cognitive load and promoting effective learning (Mayer & Moreno, 2010).

Pretraining, on the other hand, involves providing learners with prior instruction on the components of the system they are about to learn (Mayer & Moreno, 2003). By constructing component models, which represent how each component operates, and causal models, which depict how changes in one part of the system impact another, learners can develop a comprehensive mental model of the subject matter. This process facilitates meaningful learning and reduces cognitive load (Mayer & Moreno, 2010).

Principle 2: Modality

Sweller et al. (2019) proposed that working memory can be divided into independent streams or processors. When a diagram and text are presented together, it can enhance effective working memory compared to situations where only visual working memory is relied upon to process all the information. This is known as the modality effect. According to Sweller et al. (1998), it is better to recall information when it is presented with an auditory channel as this can enhance working memory capacity. The inclusion of elaborate audio or text can provide additional details to support the learning process in m-learning systems. This effect is particularly beneficial for learners with low working memory capacity. By incorporating mixed media, such as combining and dynamically providing learning resources regardless of location and time, it is possible to create a learning environment that is impactful and does not impede the learner's focus (Curum & Khedo, 2021).

Principle 3: Redundancy

The redundancy principle, as proposed by Sweller et al. (2019), aims to provide learners with only essential materials necessary for effective retention. When no animation is presented, students exhibit superior learning outcomes when exposed to a combination of concurrent narration and on-screen text (i.e., verbal redundancy) compared to a presentation with narration alone (Mayer & Moreno, 2010). To enhance comprehensible learning in a mobile environment, it is advantageous to minimize complexities in the delivered learning materials. This optimization process facilitates the management of loading time and enables flexible delivery of learning content to foster a smooth learning flow (Curum & Khedo, 2021).

Principle 4: Seductive details

The seductive details effect (Harp & Mayer, 1998) involves the transformation of informational pieces into captivating and interactive learning components in order to enhance the appeal of course content. However, with the inclusion of additional details within the lessons, seductive details often introduce extraneous cognitive load, which ultimately leads to poor learning performance. Park et al. (2015) suggested that seductive details may promote learning when the cognitive load is low. Specifically, the introduction of extraneous load in the form of seductive details facilitated learning in the narration condition but not in the on-screen text conditions. This is referred to as the seductive details effect.

It is crucial to implement these principles to reduce the cognitive load of students in m-learning to yield several benefits. By optimizing the learning experience, students are more likely to engage with the material, comprehend complex concepts, and transfer their knowledge to new situations. Reducing cognitive load enhances learning effectiveness and can contribute to improved academic performance and long-term retention of knowledge.

LITERATURE REVIEW

MOBILE-LEARNING (M-LEARNING)

With mobile devices becoming the norm for accessing information, individuals of various age groups now rely on their smartphones, tablets, and other devices for retrieving information (Dold, 2016). In Malaysia, computer usage among individuals aged 15 years and above increased from 80.0% in 2020 to 83.5% in 2021. Internet usage rose from 89.6% in 2020 to 96.8% in 2021, while mobile phone usage increased from 98.2% in 2020 to 98.7% in 2021 (Department of Statistics, Malaysia, 2022).

Mobile learning, also known as m-learning, is defined as learning through wireless technological devices that can be conveniently carried and used anywhere the learner's device receives uninterrupted transmission signals (Attewell & Savill-Smith, 2005). Some researchers characterized m-learning as an extension of e-learning (Kadirire, 2009). Other than that, m-learning is characterized as ubiquitous learning (Garcia-Cabot et al., 2015; Ng et al., 2010), meaning it allows students to study at anytime and anywhere (Criollo-C et al., 2018; Faudzi et al., 2022; Kim & Park, 2019). Pedro et al. (2018) provide a definition of m-learning as an educational approach that leverages personal mobile devices like tablets and smartphones, along with internet connectivity, to access learning materials through mobile applications.

RESEARCH ON MOBILE-LEARNING (M-LEARNING)

In recent years, m-learning research has expanded significantly, focusing on various aspects of its design, implementation, and evaluation. Studies have explored m-learning strategies from early mobile systems on PDAs to current applications on smartphones (Anh & Uyen, 2023; Huang et al., 2016; G. J. Hwang et al., 2011; Zhampeissova et al., 2020). A case study by Criollo-C et al. (2022) suggests that educational mobile applications can enhance the teaching-learning process and improve student learning effectiveness (X. Zhang, 2022).

The scopes, designs, and limitations of recent m-learning research on cognitive load are summarized in Table 1. The analysis reveals a lack of research focusing on the participation of secondary school students in m-learning, even though they are part of the iGen generation, which is expected to have strong digital literacy skills. Most studies do not sufficiently consider specific instructional designs aimed at reducing cognitive load, a crucial factor for effective learning in m-learning environments. Incorporating cognitive load management strategies into instructional design, based on Cognitive Load Theory, can optimize student learning outcomes.

Table 1. Critical analysis on m-learning

No	Authors	Scope	Samples	Findings	Research gaps
1	Faudzi et al. (2022)	To evaluate cognitive load in m-learning applications using Nielsen's Heuristics.	University students	Poor interface design hinders knowledge transfer and discourages use; high cognitive load arises from system errors and lack of documentation.	Lack of suitable instructional design for m-learning applications that reduce cognitive load. Focused on HiEd.
2	Zhampeissova et al. (2020)	To examine how cognitive load influences educational outcomes in m-learning.	University students	Effective practices include high-quality content, structured themes and schedules, balanced cognitive load, and active participation.	Not focused on instructional design of m-learning applications. Focused on HiEd.
3	Alasmari (2020)	To investigate the effect of screen size on cognitive load in m-learning.	University students	Smaller screens result in lower cognitive load compared to larger screens.	Not focused on instructional design of m-learning applications. Focused on HiEd.
4	C. X. Wang et al. (2018)	To investigate how interaction complexity impacts learning performance and mental effort in m-learning.	Seventh graders	Interaction complexity affects learning performance and mental effort; higher complexity leads to increased mental effort.	Focused on interaction design, not instructional design.
5	Meng et al. (2016)	To examine issues in mobile micro-learning course design and propose Cognitive Load Theory as a solution.	Mobile micro-learners	Teachers' timely guidance improves germane cognitive load; course design should consider internal cognitive load.	Not focused on instructional design of m-learning applications.

Studies by Meng et al. (2016), C. X. Wang et al. (2018), Alasmari (2020), Zhampeissova et al. (2020), and Faudzi et al. (2022) have explored cognitive load in m-learning. Meng et al. (2016) found that timely guidance from teachers enhances germane cognitive load but did not examine how specific instructional designs, such as Segmenting and Pretraining (Mayer & Moreno, 2003), affect internal cognitive load. C. X. Wang et al. (2018) demonstrated that increased interaction complexity in m-learning correlates with higher mental effort and improved learning performance but did not apply principles like Modality (Sweller et al., 1998) or Redundancy (Sweller et al., 2019) to manage cognitive load effectively. Alasmari (2020) focused on the impact of screen size without considering instructional strategies to minimize cognitive load, such as avoiding Seductive Details (Harp & Mayer, 1998). Zhampeissova et al. (2020) confirmed the benefits of tools designed to reduce cognitive load yet did not incorporate established strategies like those mentioned above. Similarly, Faudzi et al. (2022) highlighted the significance of cognitive load in m-learning, noting that poor interface design can hinder knowledge transfer, but did not employ specific techniques to reduce cognitive load.

While these studies have considered cognitive load, few have specifically focused on secondary school students or instructional designs that effectively reduce cognitive load. Therefore, this study aims to investigate the cognitive load experienced by secondary school students in m-learning environments designed with principles from Cognitive Load Theory (CLT) and the Cognitive Theory of Multimedia Learning (CTML) and its impact on their learning outcomes.

RESEARCH QUESTIONS

This study answers the following questions:

- To what extent does the mobile learning intervention impact students' understanding of biology concepts, as reflected in their test scores?
- What are the differences in cognitive load between students using the mobile learning intervention and those in the control group?
- What is the relationship between cognitive load and learning performance in mobile learning?
- How do students in the experimental group perceive the effectiveness of mobile learning in reducing their cognitive load?

RESEARCH METHODOLOGY

This study adopted a quantitative research approach through a quasi-experimental design with a randomized pre-test and post-test control group design (Table 2). It was considered a quasi-experimental design because it was conducted in a natural setting rather than a laboratory, and variables were isolated, controlled, and manipulated (Cohen et al., 2007). The students were randomly assigned to either the control group or the experimental group.

Table 2. Randomized pre-test post-test control group design

Group	Pre-test	Intervention	Post-test
Control	O1	CL	O2
Experimental	O1	X	O2

**O1 = Pre-test, O2 = Post-test, X = Intervention (m-learning), CL = Conventional Learning*

The experimental group received two mobile learning (m-learning) tasks, administered at a one-week interval, and both were designed using Padlet. These tasks were developed based on principles from Cognitive Load Theory (CLT) and Cognitive Theory of Multimedia Learning (CTML). In contrast, the control group participated in conventional teaching and learning activities, following standard instruction in a regular classroom setting.

PARTICIPANTS

The targeted students for this study were Science stream students from two Form 4 classes (n = 38) at Secondary School A. Biology is one of the compulsory science subjects in the science stream. The students in these classes were aged between 16 and 17. Random assignment was used to assign the students in the two classes to either the control group or the experimental group.

All the students initially took a digital performance pre-test on the m-learning task topic prior to the commencement of the intervention. With the presence of a schoolteacher, the researcher guided the experimental group students through the m-learning task. The m-learning intervention 1 which lasted approximately 40 minutes. After completing the learning task, the experimental group students completed a cognitive load questionnaire to measure their cognitive load. Similarly, the control group students were also given a cognitive load questionnaire upon completing the relevant topic using conventional teaching and learning methods.

A week later, the students in the experimental group attended m-learning intervention 2, which also lasted 40 minutes. While for control group, they learned similar topics using conventional teaching and learning methods in their classroom. After completing the session, both students from the control group and experimental group were asked to fill in the cognitive load questionnaire.

Another week later, all students from both groups took a post-test digital performance test to assess their learning performance. Three students who scored low cognitive load from both m-learning tasks were included in a focus group interview with their teacher to provide their insights on recommendations and strategies for reducing cognitive load and optimizing learning in m-learning tasks.

RESEARCH INSTRUMENTS

Learning performance test

To assess the learning performance of the students, a pre-test and a post-test were administered based on the learning topic in a digital format to evaluate students' knowledge and understanding of the specific biology topic selected for the study, which was Chapter 11 on Immunity in Humans. The pre-test was administered before the intervention to establish baseline performance levels, while the post-test was conducted a week later to assess the impact of the m-learning task on students' learning performances.

The assessment consisted of a combination of 21 multiple-choice questions and 5 short, structured questions, providing a comprehensive assessment of students' knowledge acquisition and application. Multiple-choice questions were used to evaluate students' ability to recognize and select correct answers among several options, while short, structured questions allowed for more in-depth responses, requiring students to demonstrate their understanding and provide explanations.

Cognitive load scale

A cognitive load scale was employed as a research instrument to measure the cognitive load experienced by the students during the learning activities. The cognitive load scale was adapted from the questionnaire developed by Leppink and van den Heuvel (2015), which specifically addresses the two components of cognitive load: intrinsic load and extraneous load. The cognitive load scale consisted of eight questions that focused on assessing the perceived complexity of the learning activity and the clarity and effectiveness of the explanations and instructions provided.

However, to suit the target students, who were secondary students with an average age of 16 years old, the questions in the questionnaire were modified in terms of sentence structure and the rating scale. Additionally, the response scale was modified from 10 to a 5-point format. The modified questionnaire is presented in Table 3. Each question in the questionnaire refers to the learning activity that the students had just completed. The students were asked to rate their agreement or disagreement on a scale of 0 to 4, where '0' indicates 'No Load' and '4' indicates 'High Load.'

These questions were designed to capture students' perceptions of the cognitive demands imposed by the learning activity, including the complexity of the content, the level of mental effort required, and the clarity and effectiveness of the instructional materials. The cognitive load scale was administered to both the control and experimental groups upon completion of the learning activity. Students were asked to reflect on their cognitive processes and provide self-ratings on the presented scale. The scale aimed to capture the students' subjective experiences and insights regarding the cognitive load they experienced during the learning task.

The Cronbach's alpha value obtained for the cognitive load questionnaire was exceptionally high, calculated at 0.960. Such a high alpha coefficient signifies an extraordinarily strong level of internal consistency among the questionnaire items measuring cognitive load. This suggests an exceptional agreement and coherence among the various items, indicating that they collectively and reliably measure the same underlying construct of cognitive load. While high values like this generally denote robust internal consistency, such extremely high values might occasionally indicate a possibility of some items being overly similar or redundant in capturing the construct. Nonetheless, the 0.960 alpha value underscores the questionnaire's reliability and consistency in assessing cognitive load experiences among participants within the experimental framework of this study.

Table 3. Cognitive load questionnaire adapted from Leppink and van den Heuvel (2015)

No	Modified Questions
1	The cognitive load that the content of the activities in the mobile application has on my thinking
2	The cognitive load that the problems in the mobile application activities have on my thinking.
3	The cognitive load that the terms used in the mobile application activities have on my thinking.
4	The cognitive load that the complexity of the activities in the mobile application has on my thinking.
5	The cognitive load that the explanations in the activities of the mobile application have on my thinking.
6	The cognitive load that the language used in the explanations of the mobile application activities has on my thinking.
7	The cognitive load that the helpfulness of the explanations in the mobile application activities has on my thinking.
8	The cognitive load that the complexity of the explanations in the mobile application activities has on my thinking.

Focus group interview questionnaire

Focus group interviews were conducted after obtaining the cognitive load data and consisted of open-ended questions to encourage detailed responses. The focus group interview questionnaire was designed to gather in-depth insights from students who scored low cognitive load in the m-learning task, as well as their teachers. The questionnaire consisted of open-ended questions aimed at exploring their experiences, perceptions, and strategies related to reducing cognitive load and optimizing learning in the m-learning task. The following questions were included in the focus group interview questionnaire:

1. **Questions for students:**
   - Can you describe your experience during the m-learning task? What aspects of the task were engaging or effective for your learning?
   - How did the m-learning app help you understand and process the content? Were there any specific features or tools that you found particularly helpful?
   - How did the use of multimedia elements (such as videos, images, or interactive features) in the m-learning task affect your cognitive load and learning experience?
   - How did the m-learning task compare to traditional learning methods in terms of your understanding and retention of the subject matter?

- How did the level of interactivity and engagement in the m-learning task influence your cognitive load?

2. **Questions for teachers:**
   - What are your observations regarding the students who scored low on cognitive load after the m-learning intervention? How do you think the intervention contributed to their learning performances?
   - In your opinion, what are the key factors or design features of the m-learning app that helped reduce cognitive load for these students?
   - How did you support the students during the m-learning task to optimize their learning experience and manage their cognitive load?
   - Were there any specific instructional strategies or approaches that you used in conjunction with the m-learning app to enhance student understanding and reduce cognitive load?
   - Based on your experience and the feedback from students, what recommendations or strategies would you suggest for further reducing cognitive load and improving learning performances in future m-learning tasks?

These questions aimed to elicit rich qualitative data and provide valuable insights into the factors influencing cognitive load and effective strategies for optimizing learning in the m-learning task. The responses obtained from the focus group interviews were carefully analyzed to inform recommendations and strategies for enhancing the m-learning experience and reducing cognitive load for students.

Design and Development of The M-Learning Task

Although the SAM1 ID model has three phases, namely Design, Develop, and Evaluate, for designing instructional material, this study adds a Background phase to analyze targeted students and learning material.

During the Background phase, the learning objectives and desired outcomes of the m-learning task were identified, and the target audience and their specific needs and characteristics were determined. A thorough analysis of the content (Chapter 11: Immunity in Humans) to be delivered through the m-learning task was conducted. The m-learning tasks had two sessions, each lasting 40 minutes, which covered the topics in the chosen chapter. The details of the subtopics covered are illustrated in Table 4.

In the Design phase, the principles of segmenting and pretraining were applied to break down the content into manageable and meaningful segments. Segmentation involves breaking down the presentation into smaller segments, allowing learners to process and integrate selected words and images from each segment before proceeding to the next (Mayer & Moreno, 2003). This approach gives learners sufficient time and cognitive capacity to organize and integrate information, thus reducing cognitive load and promoting effective learning (Mayer & Moreno, 2010). Figure 2 illustrates how these principles were implemented in the m-learning task. The educational YouTube videos were sourced from the internet (see Appendix A), carefully selected, and edited into smaller segments, ensuring shorter clips that students could learn from effectively without overloading their cognitive load.

Pretraining, on the other hand, involves providing learners with prior instruction on the components of the system they are about to learn (Mayer & Moreno, 2003). Constructing component models, illustrating the operation of each part, and causal models, showing how changes affect the system, helps learners form a thorough mental model of the subject, fostering meaningful learning and lessening cognitive load (Mayer & Moreno, 2010). In Figure 2, a red-colored post marks the beginning of a new section to inform and prepare students for the content they are about to learn next. The content is listed in point form, focusing only on the necessary parts they are going to learn in that section.

Table 4. Content of m-learning tasks

M-learning task	Topics and contents covered
1	PART 1: Fighting Against Diseases SHORT-CLIP: Guardians of Health: Your Body's Immune System NOTE: Body Defense System: An Overview KAHOOT!: Overview of The Guardians Within PART 2: First Line of Defense SHORT-CLIP: Guarding the Gates: Your Body's Barriers Against Invaders NOTE: The Frontliners SHORT-CLIP: Skin: Your Body's Shield Against Invaders! NOTE: Skin as a barrier KAHOOT!: Overview of The Frontliners COGNITIVE LOAD QUESTIONNAIRE: Unlocking Your Learning Potential
2	PART 1: The Second Line of Defense SHORT-CLIP: Phagocytosis NOTES: Phagocytosis: How Cells Eat Germs SHORT-CLIP: Fever Fighters: How Your Body Battles Invaders NOTES: Fever Fighters KAHOOT!: Immune System Defenders Showdown SHORT-CLIP: How Your Body Responds to a Stab Wound NOTES: Inflammatory Response KAHOOT!: Flames of Healing! PART 2: Third Line of Defense SHORT-CLIP: Guardians of Health: White Blood Cells Unveiled! NOTES: The Protection by White Blood Cells SHORT-CLIP: Immune System's Memory: The Key to Long-Term Defence NOTES: Immunity's Memory Magic KAHOOT!: Immune System and Long-Term Immunity Challenge COGNITIVE LOAD QUESTIONNAIRE: Unlocking Your Learning Potential

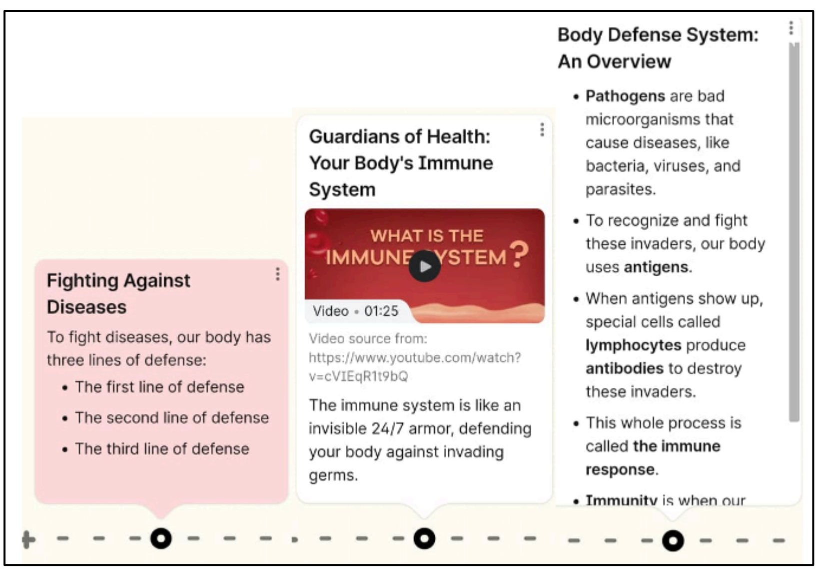

Figure 2. m-learning task in Padlet

In applying the principle of redundancy, emphasis was placed on reinforcing crucial information through multiple modalities to enhance learning outcomes. As depicted in Figure 2, this principle was tactfully implemented, wherein a concise summary in note form accompanied the lesson watched. By providing learners with a condensed overview of the material, the aim was to streamline the learning process, ensuring that only essential information crucial for effective retention was presented. This approach not only reinforces key concepts but also caters to diverse learning preferences, thereby maximizing comprehension and knowledge retention. Through the strategic use of redundancy, learners are equipped with supplementary aids that reinforce their understanding, ultimately promoting more robust and enduring learning outcomes.

Aligned with the modality principle, the instructional design integrates multimedia elements and interactive features to accommodate diverse learning styles and preferences, as illustrated in Figure 3. Each segmented clip is thoughtfully complemented by narratives presented with both text and subtitles, enriching students' comprehension by leveraging dual channels of information reception, encompassing both visual/pictorial and auditory/verbal modalities.

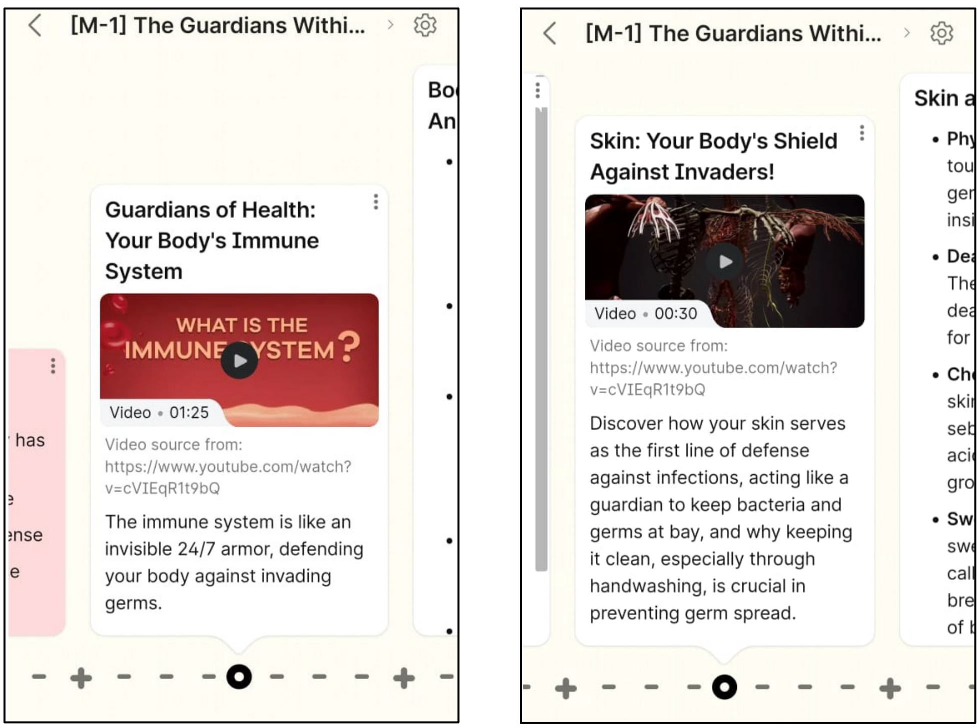

Figure 3. Multimedia elements such as edited YouTube videos were embedded as a post

By providing comprehensive audio or textual content, additional details are seamlessly incorporated to bolster the learning process within m-learning systems. Figure 4 offers a visual depiction of the meticulous implementation of this principle, highlighting the concerted effort to optimize learning experiences by catering to various sensory modalities and reinforcing engagement through interactive elements. This strategic approach not only enhances comprehension but also fosters a dynamic and immersive learning environment conducive to effective knowledge acquisition and retention.

Seductive details were strategically integrated to capture learners' attention and enhance engagement. Seductive details can promote learning when the cognitive load is low (Park et al., 2015). An interactive Kahoot! Game, as shown in Figure 5, was employed after each subtopic as part of the transformation of informational pieces into captivating and interactive learning components to enhance the appeal of course content.

Figure 4. Text and subtitles of narration were shown in all short clips

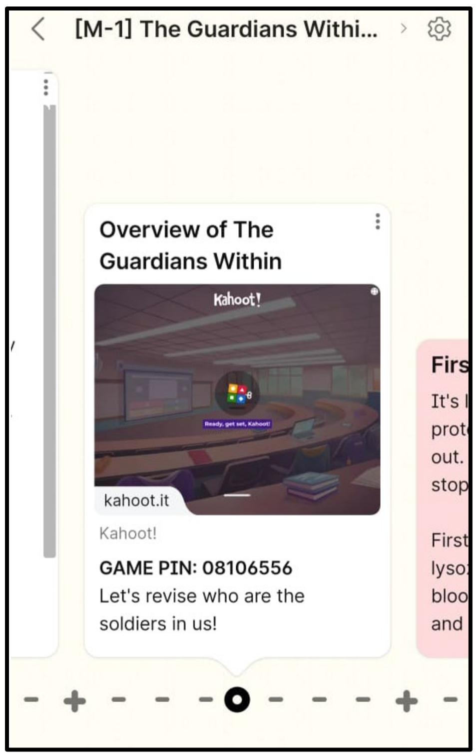

Figure 5. A short gamify quiz as part of the interactive features to further reinforce lesson learned

To provide a clear roadmap for learners, a visual representation of the m-learning task was carefully designed, outlining the sequence of content and interactions in a comprehensible manner. This visual guide serves as a digital map for students, aiding them in understanding the structure of the learning journey and facilitating seamless navigation through the educational material. Figure 6 showcases the interface of the meticulously designed m-learning task, offering students a user-friendly platform to engage them with the course content. Notably, the layout of the interface adheres to the intuitive left-to-right orientation commonly found in digital interfaces, ensuring ease of use and familiarity for students. This design choice enables students to effortlessly progress from one lesson to another, fostering a smooth and intuitive learning experience within the Padlet interface environment.

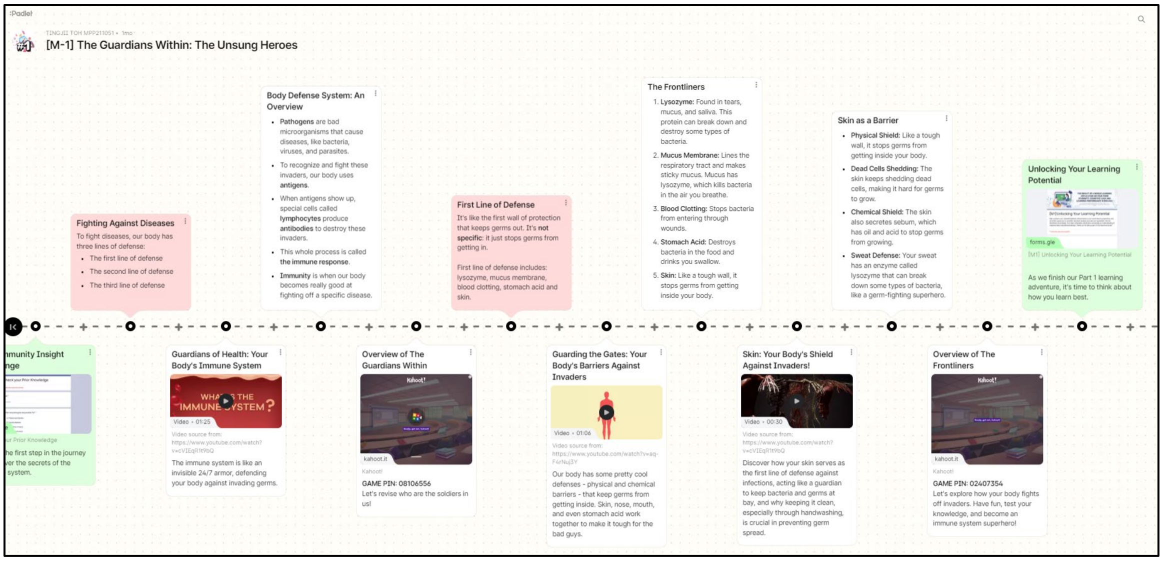

Figure 6. Visual representation of the m-learning task that outlined the sequence of content and interactions

In the development phase, the digital assessment of the pre-test and post-test cognitive load questionnaires were embedded on the same platform. Students were able to access all necessary steps within the same platform. During the pilot test, the Google Feedback Form was embedded and used to gather feedback from students on the pilot test. Revisions and improvements are made based on the feedback received. The functionality and usability of the m-learning task were tested on different devices and platforms. The effectiveness of design elements and instructional strategies was also validated through pilot testing.

During the Evaluation phase, the final version of the m-learning task was deployed on the Padlet platform. Clear instructions and access were provided to learners, ensuring they could easily navigate and engage with the task. Learner progress and engagement were monitored during the m-learning task.

Pilot Study

A pilot study was conducted to assess the feasibility and effectiveness of the research instruments used in this study, including the m-learning tasks. It involved 27 respondents from school B Biology students who represented the target population. During the pilot study, participant feedback, technical issues, and any challenges encountered were carefully evaluated. This evaluation process aimed to identify and address any shortcomings or difficulties that arose, allowing for adjustments and refinements to be made to the study design, instruments, or procedures as necessary.

The pilot test data provides valuable insights into the initial evaluation of the m-learning app's effectiveness and user experience among participants. Approximately 25.9% encountered technical difficulties, signaling potential usability issues, while around 68.3% found the app easy to navigate, indicating a positive experience with navigation. Moreover, roughly 66.6% found the learning activities engaging, and nearly 77.8% rated the learning content as effective, suggesting usefulness. Multimedia elements were well-received by about 88.9% of participants. Most (77.8%) found the learning materials clear and comprehensive, and approximately 70.4% perceived instructions as easy to understand. Responses regarding relevance and helpfulness of learning resources were positive (77.8%). While the pre-test effectively assessed prior knowledge (81.5%), fewer (63%) felt the questionnaire accurately captured cognitive load experiences. Suggestions for improvement included additional games and optimization for mobile devices, with few participants citing challenges in understanding the lymphatic system. Overall, participants praised the app's convenience and engaging videos, though some faced issues with video accessibility due to slow internet speeds, which could be mitigated by extending the allotted exploration time in formal studies.

ETHICAL CONSIDERATION

Prior to commencing the study, each student received a letter that outlined the objectives of the study and emphasized that participation was voluntary. Along with the letter, a consent form was provided, requesting the students' consent to take part in the study by completing the questionnaire for research purposes. It was made clear to the students that their data would be treated confidentially. They were also informed about their right to withdraw from the study at any point without facing any negative consequences. All completed consent forms were collected before the study began.

Furthermore, this study sought approval from the Educational Department through the Educational Research Application System. The study strictly adheres to the protocols set by the relevant authorities, ensuring that all ethical guidelines and standards are followed to safeguard the rights and well-being of the students.

RESULTS AND DISCUSSIONS

Table 5 shows the distribution of respondents' gender. In the Intervention Group (n = 20), comprising students from one Biology science class, there are 12 female participants and 8 male participants. Conversely, the Control Group (n = 18), selected from another Biology science class, includes an equal count of 9 female and 9 male participants.

Table 5. Distribution of respondents' gender

	Intervention group	Control group
Female	12	9
Male	8	9
Total (n)	20	18

THE IMPACT OF M-LEARNING INTERVENTION ON STUDENTS' PERFORMANCE

Students' prior knowledge and learning performance were assessed before and after the intervention. They underwent a performance test in the form of a Google Form embedded within the m-learning platform. This assessment comprised 21 multiple-choice questions: the initial 20 questions carried 4 marks each, and the 21st question carried 5 marks. Additionally, there were 5 short, structured questions, each carrying 3 marks. The total marks for the assessment equated to 100 marks. A score of 100 indicated high learning performance, while a score of 0 signified no performance at all.

The evaluation of learning performance among secondary school students engaged in m-learning activities demonstrates significant outcomes (Table 6). The intervention group achieved a higher mean assessment score of 77.65 ($SD = 5.00$) compared to the control group's mean score of 69.89 ($SD = 9.02$), indicating greater consistency in performance within the intervention group. The difference in mean scores suggests that students in the intervention group generally outperformed those in the control group on the post-test. Furthermore, the substantial increase in mean mark from pre-test to post-test for the intervention group (13.35 points increase, from 64.30 to 77.65) contrasts starkly with the minimal increase for the control group (from 68.89 to 69.89), emphasizing the positive impact of m-learning tasks on learning performance and highlighting significant improvements among students in the intervention group.

Statistical analysis using Quade ANCOVA (Table 7) validates a significant difference between control and intervention groups in post-test scores ($F = 7.268$, $p = 0.011 < 0.05$), even after adjusting for pre-test scores. This significance indicates the intervention's influence on post-test scores, affirming distinct learning performance differences between the groups. The effect size (Partial Eta Squared, η^2 p=0.168) suggests that 16.8% of post-test score variance can be attributed to group differences, emphasizing the intervention's notable impact on enhancing learning performances.

Table 6. Descriptive analysis of pre-test and post-test scores for both groups

Group	Pre-test		Post-test	
	Mean	Standard deviation	Mean	Standard deviation
Intervention (n= 20)	64.30	6.26	77.65	5.00
Control (n = 18)	68.89	15.73	69.89	9.02

Table 7. Result of (Quade's) ANCOVA with the pre-test scores as covariate

Source	Type III sum of squares	df	Mean square	F	Sig.	Partial Eta Squared
Corrected model	760.446[a]	1	760.446	7.268	0.011	0.168
Intercept	2.106	1	2.106	0.020	0.888	0.001
GROUP	760.446	1	760.446	7.268	0.011	0.168
Error	3766.906	36	104.636			
Total	4527.352	38				
Corrected total	4527.352	37				

[a] R *Squared = 0.168 (Adjusted* R *Squared = 0.145)*

Numerous studies, including Alturki and Aldraiweesh (2022), X. Zhang (2022), and Ozer and Kılıç (2018), support m-learning's positive impact on student achievement. Additionally, research by Cross et al. (2019), B.-L. Hwang et al. (2021) and J. Zhang and Crompton (2021) has supported these findings but has mainly focused on tertiary education students. Conversely, Hoque et al. (2023) proposed an m-learning system without empirical evidence supporting its effectiveness for secondary students in Malaysia. This study further reinforces these findings, showcasing how a well-designed m-learning application rooted in Cognitive Load Theory and Cognitive Theory of Multimedia Learning significantly enhances learning performance.

Integration of effective multimedia design principles and pedagogical strategies such as segmenting and pretraining (Mayer & Moreno, 2003, 2010), modality (Sweller et al., 1998), redundancy (Sweller et al., 2019), and the Seductive Details effect (Harp & Mayer, 1998) optimizes learning within the m-learning context, affirming its superiority over traditional teaching methods in improving secondary school students' learning performance in Biology.

Cognitive Load of Students Using M-learning vs Conventional Learning

The study highlights the significant impact of mobile learning (m-learning) on the cognitive load of secondary school students, as shown in Table 8. In the intervention group, 70% of students reported low cognitive load during the first learning activity, contrasting sharply with the control group, where only one student experienced low cognitive load. This trend continued in the second activity, with 85% of m-learning students reporting low cognitive load compared to 22.2% in the control group. Furthermore, while most of the control group experienced moderate cognitive load (72.2%), none in the m-learning group reported high cognitive load. The comparison between the two m-learning tasks demonstrated a positive shift, with more students experiencing low cognitive load, highlighting the efficacy of m-learning in reducing mental burden compared to traditional teaching methods.

Table 8. Range of cognitive score by participants in both groups

Range of score	Descriptions	Learning activities	Intervention group (n = 20)	Learning activities	Control group (n = 18)
α ≤ 10	Low cognitive load	Cognitive load for m-learning task 1 (CL-M1)	14 (70%)	Conventional Teaching & Learning 1 (CTL1)	1 (5.6%)
10 < α < 22	Moderate cognitive load		5 (25%)		10 (55.6%)
α ≥ 22	High cognitive load		1 (5%)		7 (3.8%)
α ≤ 10	Low cognitive load	Cognitive load for m-learning task 2 (CL-M2)	17 (85%)	Conventional Teaching & Learning 2 (CTL2)	4 (22.2%)
10 < α < 22	Moderate cognitive load		3 (15%)		13 (72.2%)
α ≥ 22	High cognitive load		0		1 (5.6%)

The t-test results (Table 9) reveal a significant disparity in cognitive load scores between the intervention and control groups during learning activity 1. The intervention group exhibited a mean cognitive load score of 8.20 (SD = 7.001), significantly lower than the control group's mean score of 19.50 (SD = 5.021), with a t-test statistic of -5.659 (p = 0.000). This indicates a substantial difference in cognitive load, aligning with the research's aim to decrease cognitive load through m-learning. The effect size of 1.886 signifies a large effect, underscoring the intervention's impact on reducing cognitive load during the task.

Table 9. Results of cognitive load scores and t-test for m-learning task 1 (CL-M1 vs CTL1)

Group	N	Mean	Standard deviation	F	Sig.	t	df	p	Effect size (d)
Intervention (CL-M1)	20	8.20	7.001	2.418	0.129	-5.659	36	0.000	-1.886
Control (CTL1)	18	19.50	5.021						

Similarly, the Mann-Whitney U test results (Table 10) show a significant difference in cognitive load scores between the intervention and control groups for learning activity 2 (U = 44.000, Z = -4.009, p = 0.000). The intervention group reported notably lower mean ranks (mean rank = 12.70) compared to the control group (mean rank = 27.06), indicating significantly lower cognitive load during m-learning task 2. The effect size of approximately -0.651 suggests a moderate to moderately strong effect, highlighting the meaningful difference between the groups and reaffirming the efficacy of the intervention in reducing cognitive load. These statistical findings are supported by qualitative insights and previous literature, indicating the positive impact of m-learning on cognitive load reduction and enhancing the learning experience, particularly in secondary school settings.

Table 10. Results of cognitive load scores and Mann-Whitney Test for m-learning task 2 (CL-M2 vs CTL2)

Group	N	Mean rank	Sum of ranks	Mann-Whitney U	Z	p	Effect size (r)
Intervention (CL-M2)	20	12.70	254.00	44.000	-4.009	0.000	-0.651
Control (CTL2)	18	27.06	487.00				

These findings align with previous studies, such as Salhab and Daher (2023), Alasmari (2020) and G. J. Hwang et al. (2011), affirming the positive effect of m-learning in reducing students' cognitive load.

Qualitative insights further supplement these results, revealing that students appreciated the accessibility and organized flow of lessons in m-learning, allowing them to review content at their own pace. The contrast with traditional methods, where learning resources were less interactive and less readily available outside the classroom, suggests that factors such as limited access to supplementary materials might contribute to increased cognitive load in conventional learning environments.

These findings further extend our understanding of the impact of m-learning applications on students' cognitive load in Biology education among Malaysian school students. Previous studies predominantly centered on students' cognitive load in learning English (Huang et al., 2016; Ozer & Kılıç, 2018; Yeh et al., 2017) and cultural studies (B.-L. Hwang et al., 2021; G. J. Hwang et al., 2011). Other studies focused on m-learning without specifically addressing cognitive load, such as those in renewable energy education (Hoque et al., 2023), engineering (Criollo-C et al., 2022), forestry education (Tereshchenko et al., 2020), and programming (Halim & Eh Phon, 2020). Most of these studies were conducted at the tertiary education level, whereas our research targets secondary school students, a younger demographic owning mobile devices in large numbers.

The design of the m-learning tasks has tackled the concern by van Merriënboer et al. (2006) on the issue of the constant influx of information significantly increasing the cognitive load on students. Both tasks integrated segmenting and pretraining principles to reduce cognitive load, which have been proven to reduce students' cognitive load in the experimental group. In conclusion, the study evidences the significant role of m-learning in reducing cognitive load for secondary school students, offering a more accessible, organized, and less mentally taxing learning experience compared to conventional teaching methods.

The Relationship of Cognitive Load to Learning Performance

The cognitive load scores for both groups were totaled to compute their average mean values, facilitating analysis of their relationship with learning performances. As illustrated in Table 11, the mean for the variable Cognitive load questionnaire in the intervention group is 0.731, with a standard deviation of 0.651. The mean for the Cognitive load questionnaire in the control group is 2.056, with a standard deviation of 0.596. The Cognitive load questionnaire variable appears to have a lower mean in the intervention group compared to the control group, with less variability around the mean in the control group for this measure.

Table 11. Correlations between post-test scores and cognitive load scores

Group	Mean	SD	Pearson correlation	Sig. (2-tailed)	Sum of squares and cross-products	Covariance	n
Intervention	0.731	0.651	-0.665	0.001	-41.069	-2.162	20
Control	2.056	0.596	-0.549	0.018	-50.139	-2.949	18

The significant negative correlation observed between cognitive load and learning performance across both intervention and control groups (Table 11) underscores an inverse relationship: higher assessment scores correspond with lower cognitive load scores, indicative of reduced mental effort. In the intervention group, this correlation is particularly strong (-0.665), whereas the control group exhibits a slightly weaker correlation (-0.549). These findings emphasize the consistent trend wherein improved learning performance coincides with decreased cognitive load, with the intervention group demonstrating a slightly more pronounced association.

These results align with previous studies such as Chu et al. (2019) and Choi and Lee (2022), which highlight the detrimental effects of high cognitive load on academic achievement and the potential of integrated m-learning approaches to alleviate student pressure. The study's conceptual framework, integrating design principles rooted in Cognitive Load Theory (CLT) and Cognitive Theory of Multimedia Learning (CTML), effectively reduces cognitive load. Specifically, multimedia elements optimized through CTML principles facilitate memory retention and engagement, aligning with CLT to minimize mental effort during the learning process. This theoretical foundation not only elucidates the mechanisms underlying cognitive load reduction but also underscores the pivotal role of these principles in optimizing learning performance within m-learning environments, offering educators and instructional designers valuable insights for enhancing student outcomes. These results showing low cognitive load is closely linked to higher learning performance are aligned with previous studies such as Chu et al. (2019), who found that low-achieving students in the intervention group had significantly higher cognitive load than high-achieving students, suggesting that an integrated m-learning approach could reduce pressure on students. Similarly, Choi and Lee (2022) found that higher extraneous cognitive load and intrinsic cognitive load result in lower academic achievement in online learning environments.

Students' Perceptions Towards M-Learning Towards Reducing Cognitive Load

Qualitative data supports the effectiveness of these principles within the framework, illustrating their role in reducing cognitive load and optimizing learning performance. Students' positive reactions to the well-organized, bite-sized learning materials, readily accessible for revision, contribute significantly to their reduced cognitive load. Multimedia elements like bite-sized videos enhance learning experiences by infusing fun and promoting better memory retention compared to traditional static methods. Table 12 shows the summary of the themes formulated as strategies used to reduce cognitive load and enhance learning experiences in m-learning.

The strategic use of modality includes deploying multimedia elements like visual aids, diagrams, videos, and audio recordings, catering to diverse learning preferences and thereby enhancing comprehension and engagement (Sweller et al., 2019). Similarly, the redundancy principle advocates for the removal of unnecessary information, ensuring the content focuses solely on essential components, thus reducing the cognitive load (Curum & Khedo, 2021). Videos are segmented into bite-sized portions to ensure students receive the lesson content effectively.

The deliberate consideration of seductive details within the m-learning environment is paramount. By identifying and limiting the inclusion of attention-grabbing yet extraneous information, the focus remains committed to core content, fostering deeper understanding and retention of knowledge. Additionally, interactive elements like gamified quizzes reinforce memory retention and newly processed information, as affirmed by students M2 and M4 (see Table 12). Their responses confirm the efficacy of interactive elements in lowering cognitive load and bolstering memory retention.

Table 12. Findings from the interviews

No	Themes	Samples of student's responses
1.	Multimedia elements and notes	M2: "The video and note were very helpful, especially the cute and easy-to-understand videos." M4: "The video and the note given are clear and easy to understand. The task helped me understand the chapter better." M9: "I like it, it feels like a game."
2.	Comparison with traditional learning	M4: "In traditional learning, I couldn't understand certain aspects because it was only pictures. M-learning allows me to see the movements of cells or other details."

Unlike traditional classroom settings where videos are often used passively as supplementary material, m-learning platforms like Padlet integrate videos within an interactive framework that continuously engages students through gamified elements and immediate feedback. This approach not only enhances comprehension but also fosters active learning and adaptation to individual needs, which is less feasible in conventional learning environments. Padlet provides a unique advantage by allowing students to interact with multimedia resources at their own pace, supporting diverse learning styles and reducing cognitive overload. This flexibility and personalization are key differentiators that enhance the learning experience beyond what is typically achievable in a standard classroom setting.

They added that these elements made learning fun and improved memory retention. They appreciated the engaging nature of the videos and found them fun, enhancing their memory and making learning more interesting. The m-learning tasks were considered more convenient than traditional learning methods, allowing them to grasp the topics faster and have easy access to notes and videos.

The teacher observed that students who scored low on cognitive load after the m-learning intervention showed improved understanding of chapter concepts facilitated using videos. She noted that videos were instrumental in aiding students' comprehension and learning performances.

When asked about the impact on cognitive load, their responses ranged from "very good" to "moderate," expressing satisfaction with the overall experience. Student M2 appreciated the convenience of accessing notes and videos together, allowing them to learn faster and review content effortlessly.

All three students appreciated the interactivity and engagement of m-learning, mentioning it was more interesting and easier to remember. Multimedia elements like videos and interactive features positively impacted their learning experiences by offering a clearer understanding of topics compared to static images in traditional methods. The engagement level in m-learning tasks seemed to make content more memorable and understandable, reducing cognitive load.

The teacher highlighted visual learning as a key factor in reducing cognitive load for these students. The incorporation of visual elements within the m-learning app seemed to be particularly effective in facilitating learning and reducing cognitive burden.

Regarding the comparison to traditional learning methods, one student, M4, highlighted the limitations of traditional methods. Students found m-learning more engaging, informative, and accessible compared to traditional methods. They highlighted that m-learning's interactive nature and availability of resources enhanced their learning experience. In traditional learning, the teacher's support strategies involved informing students to focus on key points during the m-learning task. This guidance was aimed at optimizing the students' learning experiences and managing cognitive load, possibly helping them concentrate on critical aspects of the content.

Thematic analysis of student and teacher perspectives underscores the positive reception of m-learning, highlighting its effectiveness, engagement, convenience, and superior learning experience compared to traditional methods (Alturki & Aldraiweesh, 2022; J. Zhang & Crompton, 2021). Multimedia elements, particularly visual learning through videos, play a pivotal role in facilitating learning and reducing cognitive load, aligning with instructional design principles rooted in Cognitive Load Theory and Cognitive Theory of Multimedia Learning (CTML) (Harp & Mayer, 1998; Mayer & Moreno, 2003, 2010; Sweller et al., 1998). Segmentation and pretraining activities aid in breaking down learning materials into digestible units, enhancing concentration and reducing cognitive load, while modality considerations cater to diverse learning preferences, improving comprehension and engagement (Curum & Khedo, 2021). Furthermore, the redundancy principle ensures content focuses solely on essential components, minimizing cognitive load, while interactive elements like gamified quizzes reinforce memory retention and alleviate cognitive strain (J. Zhang & Crompton, 2021).

Within the m-learning environment, instructional design principles serve as guiding beacons, fostering meaningful interactivity while safeguarding against cognitive overload—a common trigger for memory information loss (Agbonifo & Ibam, 2015). The strategic integration of these principles has a positive impact on elevating students' learning performance and reducing cognitive load, as evidenced by thematic analysis and empirical research (Alturki & Aldraiweesh, 2022; Curum & Khedo, 2021). For instance, segmentation into digestible units allows learners to focus on one concept at a time, enhancing comprehension and reducing cognitive strain (Mayer & Moreno, 2003). Similarly, pretraining activities activate prior knowledge, facilitating effective learning (Mayer & Moreno, 2010). Modality considerations, including multimedia elements, cater to diverse learning preferences, enhancing engagement and understanding (Sweller et al., 2019). Moreover, the redundancy principle ensures content focuses solely on essential components, minimizing cognitive load and optimizing learning outcomes (Curum & Khedo, 2021). Additionally, deliberate consideration of seductive details within the m-learning environment ensures the focus remains on core content, fostering deeper understanding and retention of knowledge (Harp & Mayer, 1998).

CONCLUSIONS

The meticulously crafted m-learning tasks have significantly decreased students' cognitive load while optimizing their learning performance, leveraging principles from Cognitive Load Theory (CLT) and Cognitive Theory of Multimedia Learning (CTML). This integration serves as a model for educators, highlighting the transformative potential of targeted instructional strategies on cognitive load and learning outcomes. These tailored tasks provide students with seamless access to lessons, reducing the need for supplementary materials and lowering cognitive strain. Integration of interactive multimedia elements enhances memory retention and simplifies lesson recall, fostering student confidence and establishing a robust foundation for future educational practices.

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APPENDIX: YOUTUBE VIDEOS' SOURCES

YouTube Channel	Video Title	Link
Learn Bright	What Is the Immune System for Kids | Learn all about how the body fights off bad germs	https://www.youtube.com/watch?v=cVIEqR1t9bQ
FuseSchool - Global Education	Human Defense Systems Against Pathogens | Health | Biology | FuseSchool	https://www.youtube.com/watch?v=aq-F4rNuj3Y
The Partnership In Education	Phagocytosis Animation	https://www.youtube.com/watch?v=TNK3WyEI3r8
TED-Ed	How does your immune system work? - Emma Bryce	https://www.youtube.com/watch?v=PSRJfaAYkW4
Biotech Review	Inflammation | Histamine | Phagocyte	https://www.youtube.com/watch?v=vQzzbTxnjjI

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