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Culturally responsive modular arithmetic instruction: Development of digital lucky modal cards inspired by the lucky 9 card game

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Abstract

Properties of modular arithmetic are usually taught through a conventional instructional approach that continuously poses a low level of mastery to many students. The Lucky Modal Card Game is an innovative substitute for the traditional card game embedded in Filipino culture, Lucky 9. Lucky 9, the cultural concept of swerte (luck), is associated with memory enhancement and strategic thinking. Developing learning material from this culturally familiar game provides engaging gameplay for teaching and learning modular arithmetic. The study was guided by the Developmental Research Design ADDIE model, systematically undertaking analysis, design, development, implementation, and evaluation phases. These phases incorporated learners' mastery and speed in solving modular arithmetic, learners' acceptability, and expert validation. Findings revealed that students performed better in modular arithmetic regarding speed of response and accuracy on the operations of addition and multiplication than on operations like inverses (additive and multiplicative inverse), which procedures were not clearly scaffolded, and raising to a power and factorization, which require complex iterative processes. Scheffe tests suggested the following groupings in terms of difficulty: 1) addition and multiplication, 2) inverses (additive and multiplicative inverse), and 3) raising to a power and factorial. The developed learning material demonstrated high usability, instructional quality, and positive learners' acceptability. Students reported increased motivation, ease of navigation, and clearer conceptual understanding. Expert evaluations confirmed that the material was highly valid in content, aligned with curriculum competencies, and appropriately managed cognitive load.

Keywords: Accuracy, Cognitive, Education, Mathematics, Performance, Speed.

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Contents

Contribution of this paper to the literature
This study contributes to the existing literature on game-based mathematics education by introducing a subject-specific digital learning tool design to enhance learners' engagement, motivation, arithmetic fluency, speed, and mastery. It also serves as an intergenerational learning tool that supports cultural preservation while advancing mathematics education through contextualized digital game-based.

1. Introduction

Despite continuous reform in the mathematics curriculum, the program remains challenging for many learners, particularly for abstract reasoning. Most learners obtained low accuracy and were not very fast in solving modular arithmetic problems. Lecture teaching approach using textbook and repetitive worksheets often fails to stimulate mastery learning, increase speed, and sustained engagement, resulting in low motivation and mastery among learners.

According to Hillmayr, Ziernwald, Reinhold, Hofer, and Reiss (2020), even with increased instructional time and policy-driven interventions, secondary school students worldwide continue to struggle with mathematics, especially in topics that demand abstraction. Properties of modular arithmetic are abstract concepts requires procedural approach to solve problems that intensify cognitive load often leads students' low mastery.

In the Philippines, Lucky (*swerte*) 9 a widely played card game among Filipinos across generations. Players with cards with a value equal to (remainder 9) when divided by 10 automatically win the game, an idea that mirrors the core principle of modular arithmetic. Continuous utilization of the game, players unconsciously engage in modulo reasoning and residue recognition. This abstraction gap presents an important opportunity for culturally responsive pedagogy. Culturally grounded learning experiences have been shown to improve relevance, motivation, and conceptual understanding, especially when abstract content is anchored in familiar social practices. However, such indigenous and culturally resonant pedagogy remains underutilized in mathematics instruction.

A meta-analysis conducted by Hillmayr, Ziernwald, Reinhold, Hofer, and Reiss (2020) reported that well-designed digital instructional materials have a statistically significant effect on learning performance. Similarly, Hui and Mahmud (2023) systematically investigate that digital game-based learning significantly improves student learning outcomes, engagement, and persistence. Moreover, interactive digital representations promote a deeper understanding of abstract mathematical concepts and improved problem-solving performance (Ochogboju & Díez-Palomar, 2025; Serin, 2023). Furthermore, digital game-based instruction promotes learner-centered instruction, rule-driven activity into a dynamic, and balanced cognitive demands (Angco, 2023; Nadeem, Oroszlanyova, & Farag, 2023).

Predominantly digital and game-based mathematics instruction is mainly non-specialized, targeting basic numeracy skills such as fundamental operations, signed numbers, and fractions. Studies focusing on specialized game-based approaches, like modular arithmetic, an essential foundation for number theory and abstract algebra, remain scarce. This gap is significant given the subject's role in developing higher-order mathematical reasoning.

Lucky Modal card game is responsive to this need, instructional innovation, a specialized tool, and culturally inspired learning environment. Lucky Modal contextualizes modular arithmetic within a familiar and symbolic logic of the Filipino lucky 9 card game. The tool seeks to reduce the cognitive load of abstraction, promote learners' engagement, enhance motivation, and improve conceptual mastery and computational fluency in modular arithmetic.

Mathematics game-based tasks and gamified learning activities significantly improve students' performance and engagement because they provide measurable outputs reflecting data such as response speed, efficiency, and accuracy, which are reliable indicators of cognitive processing and mastery of mathematical concepts (Alt, 2023; Boom-Cárcamo, Buelvas-Gutiérrez, Acosta-Oñate, & Boom-Cárcamo, 2024). Studies have shown that the effectiveness of educational games depends on game mechanics such as levels of difficulty, scoring, and rewards to enhance learners' conceptual understanding (Angco, 2023). Moreover, Zeng, Sun, Looi, and Fan (2024) reported that challenge-based tasks, progressive difficulty levels, and timed activities help students better understand abstract mathematical topics, especially in number theory and abstract algebra. These findings justify the need to carefully conceptualize the game mechanics of the Digital Lucky-Modal Game to ensure it promotes meaningful learning of modular arithmetic.

Newly developed learning materials need to undergo expert validation to ensure the correctness of the content to represent subject matter, design quality, and usability of the system (Luo, 2024). Research shows that students are willing to adopt educational technology games when they perceived it as easy to use, engaging, and useful (Alt, 2023). Roncal-Belzunce, Gutiérrez-Valencia, Martínez-Velilla, and Ramírez-Vélez (2025) emphasize that functionality, interaction, and engagement are the critical factors for the acceptability of digital learning applications. These findings justify the evaluation of the Digital Lucky-Modal Game in terms of usability, functionality, engagement, and usefulness to ensure that the developed game is not only valid but also acceptable to learners.

1.1. Research Objectives

The study generally aims to develop a digital lucky-modal card game to enhance student engagement and motivation in learning modular arithmetic. Specifically, it aims to determine: 1) the attributes of students in answering modular arithmetic problems in terms of accuracy, response time, and accuracy of response time; 2) the game elements and mechanics to conceptualize effective support for students' understanding of modular arithmetic; 3) the level of validity of the developed lucky-modal card game in terms of content, accuracy of modular arithmetic tasks, instructional design quality, and technology & usability; and 4) the level of acceptability of the developed digital lucky-modal card game in terms of usability, functionality, engagement, and usefulness.

1.2. Contributions of the Study

The development of the Digital Lucky-Modal Card Game contributes significantly to the advancement in mathematics education, subject-specific game-based digital learning, cultural preservation, and community engagement. The contribution of the digital tool is described as follows:

The game can be a supplementary tool in learning Number Theory, Abstract Algebra, and Discrete Mathematics. It is a digital tool for teaching and learning Modular Arithmetic, designed to enhance fluency, mastery, speed in problem-solving skills, and conceptual understanding. Additionally, it serves as a self-assessment tool to track fluency and speed in solving modular arithmetic.

Digital Lucky-Modal Card Game tool contributes to the growing field of game-based mathematics education as a subject-specific digital learning tool for modular arithmetic. It is structured around clear learning objectives, game mechanics, and time challenges that promote mastery of modular arithmetic. The game effectively integrates digital learning to increase engagement, participation, and motivation.

By using the familiar structure and mechanics of Lucky Nine, the traditional Filipino card game, the study promotes the preservation and appreciation of Filipino culture while adapting it for educational purposes. Transforming localized games into digital educational tools ensures cultural preservation in the modern technical era and supports both cultural identity and academic learning.

The Digital Lucky-Modal Card Game was also designed for elderly community members who are familiar with the Lucky Nine card game. Because the mechanics are based on a traditional card game, older adults can easily understand and play the digital version, making the tool useful for intergenerational learning activities. The game may help maintain mental alertness, memory skills, promote social interaction, and strengthen cultural connections while supporting lifelong learning.

2. Literature Review

Research on teaching number theory and elementary modular concepts shows learners often struggle when topics are presented abstractly or without meaningful contexts. A qualitative/design research study documenting how secondary students revisit and sometimes "fall back" on school-level discourses when first exposed to modular multiplication highlights the cognitive and representational obstacles students face when modular concepts are taught abstractly (Schüler-Meyer, 2019). Description and pilot evaluation of a Java-based interactive tool (ArtEM) specifically for integer and modular arithmetic, useful as a precedent showing focused digital support for modular topics, but with limited large-scale classroom evidence (Migallón, Penadés, & Penadés, 2025).

A growing body of systematic reviews and empirical studies finds that carefully designed game-based learning and gamification in mathematics improve affective outcomes (motivation, engagement, enjoyment) and often yield positive gains in achievement or practice time. A comprehensive systematic review (2008–2021) of learning games in K–12 mathematics catalogs design features linked to cognitive and affective gains and calls for stronger alignment between gameplay mechanics and mathematical learning goals (Pan, Ke, & Xu, 2022).

According to the study of Hui and Mahmud (2023), a systematic review from 2018 to 2022 showed that game-based learning (GBL) consistently produces positive effects in both cognitive areas (knowledge and skills) and affective aspects (motivation and engagement), but these outcomes vary depending on the quality of instructional design, teacher intervention, and the rigor of research methods used. Similarly, a comprehensive meta-analysis across multiple disciplines reports overall effect sizes for gamification that support the inclusion of gamified features like the Lucky-Modal, while also emphasizing the importance of moderating factors such as duration and design principles (Li, Ma, & Shi, 2023).

Interactive visualizations and virtual manipulatives are consistently recognized as effective tools in helping learners grasp abstract mathematical ideas. Meta-analytic and conceptual findings that are clearly linked to symbolic representations suggest that virtual manipulatives produce moderately positive impacts on mathematics learning. These support the use of interactive visuals for topics like remainders and cyclic patterns (Moyer-Packenham & Westenskow, 2013). As evaluated in the study of Farra, Smith, Johnson, and Williams (2024), virtual and physical manipulatives show effectiveness when scaffolding is implemented and highlight their importance when advocating for virtual teaching concepts in modular arithmetic.

For the systematic development of digital learning tools, ADDIE as an instructional design model continues to be recommended. Meta-analytic evidence on ADDIE underscores its usefulness across distance education contexts; justifies using ADDIE for iterative development of Lucky-Modal and highlights practices (multimedia, feedback, interaction) that should be embedded in the design (Spatioti, Kazanidis, & Pange, 2022).

ArtEM is an instructional tool designed to support the learning of integer and modular arithmetic (Migallón et al., 2025). There is still a need for more comprehensive classroom-based and self-evaluation, while it has demonstrated practical usability and received favorable initial feedback, addressing this need is a key objective and design of Lucky -Modal. Examination of digital game-oriented resources in K–12 mathematics reveals a plethora of general math games but a scarcity of those centered specifically on modular arithmetic, which endorses the claim that dedicated modular game tools are still uncommon (Hussein, Ow, Elaish, & Jensen, 2022).

3. Theoretical and Conceptual Framework

Corbett and Spinello (2020) examined the role of Connectivism in modern digital education, highlighting how learners discover, interpret, and integrate information within modern online learning environments suggested that interconnected digital environments promote learner autonomy and active participation. And this idea is applicable to the creation of tools like Lucky Modal, which emphasize interactive, problem-solving pathways.

Similarly, Bond, Buntins, Bedenlier, Zawacki-Richter, and Kerres (2020) investigated how Web 2.0 technologies reflect connectivist principles, demonstrating that student engagement increases when digital tools promote exploration, collaboration, and rapid access to linked sources of information. Together, these studies indicate that connectivist-based digital tools can enhance student engagement and deepen conceptual understanding, aligning with the goal of improving learning in modular arithmetic.

Research employed in CLT highlights the importance of well-structured digital learning environments for students 'cognitive processes and academic performance. In addition, Leppink (2017) demonstrated that instruction aligned with CLT principles enhances retention and reduces unnecessary mental effort.

Skulmowski and Xu (2022) found that reducing extraneous cognitive load significantly improves comprehension in online learning, particularly for complex subjects like mathematics. Their work underscores the value of intuitive design and immediate feedback features that can strengthen the effectiveness of Lucky Modal in supporting modular arithmetic learning.

Expanding on this, Sweller (2024) emphasized that cognitive load varies among learners, suggesting that adaptive and well-supported digital tools are better suited to meet diverse learning needs. Collectively, these findings provide strong support for integrating CLT principles in creating the design of Lucky Modal digital learning platforms.

The conceptual framework of this study is anchored in Connectivism Theory and Cognitive Load Theory. Connectivism suggests that learning in the digital age occurs through the creation of networks that allow students to access, connect, and interpret information from diverse digital sources. In contrast, Cognitive Load Theory emphasizes managing the mental effort required during the learning process to optimize understanding. Together, these theoretical perspectives explain how Lucky Modal, as an interactive digital learning tool, can enhance learner engagement and motivation, explore modular arithmetic concepts, engage with problems, and build understanding through dynamic learning pathways.

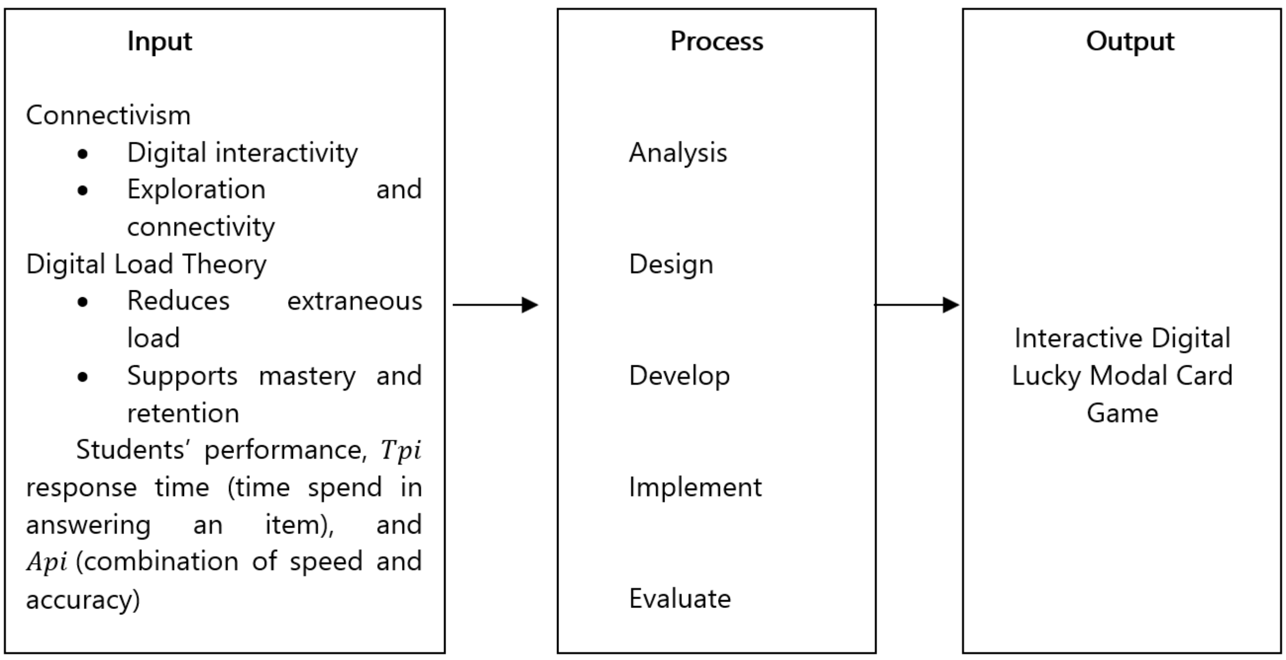

Figure 1. Research paradigm.

Figure 1 presents the research paradigm of the study, illustrating the process in the development of the digital tool. The input includes: 1) connectivism principle, learning happens by forming connections through digital interactivity and exploration; 2) digital load theory, digital tools reduce unnecessary mental effort (extraneous load) for complex operations and support mastery; and 3) students' response time, accuracy, and the combination of response time and accuracy, key variables involved in the analysis phase prior to developing the interactive Lucky Modal Card Game. These inputs are part of the development process for the Digital Lucky Modal Card Game, specifically following the ADDIE (analysis, design, develop, implement, and evaluate) model. The output is an interactive Digital Lucky Modal Card Game, a digital tool supported by educational theories and empirical findings.

4. Methods

This chapter outlines the research design, respondents of the study, research instrument, data gathering procedure, statistical treatment, and ethical considerations. Every phase, from tool conception, development, execution, to assessment, is directed by developmental research employing the ADDIE Model.

4.1. Research Design

The study employed the Analysis, Design, Development, Implementation, and Evaluation (ADDIE) model as a developmental research design. The ADDIE model offers a structured approach suitable for the systematic creation and assessment of educational resources. It ensures that the Lucky Modal Digital Game can achieve its instructional objectives, meet learners' needs, receive constructive feedback, and yield positive evaluation outcomes.

Analysis Phase: The current stage involves determining the difficulties learners experience in modular arithmetic. This includes assessing accuracy, response time (Tpi) and the accuracy of the response time (Api) when answering modular arithmetic problems involving: a) addition; b) subtraction (minuend greater than subtrahend); c) subtraction (minuend less than subtrahend); d) multiplication; e) the product of a number A and the multiplicative inverse of B ($A \times B^{-1}$) where $B < A$; f) exponentiation; and g) factorials. Learner assessments were used to collect the necessary data.

Design Phase: The analysis phase's findings will direct the creation of the user interface and game mechanics. Performance, Tpi, and Api were used to partition the game. Modular arithmetic challenges and a template for the game's components were created.

Development Phase: The framework supplied during the design phase served as the basis for the creation of the digital Lucky Modal. To achieve the framework, researchers, together with an Information Technology expert, collaborated closely.

Implementation Phase: The target learners were presented with the finished Lucky Modal game. During the trial period, students used the tool under the guidance of the researchers and the developer. The faculty experts in mathematics were also introduced to the developed lucky modal. They were given access to the digital material's features and mechanisms. Additionally, a web connection was supplied so that they could play the digital content.

Evaluation Phase: This phase involves the evaluation of the validity and reception of the Lucky Modal Card game. The digital tool was presented to the target learners for one hour and thirty minutes. The acceptance of the developed digital card game was assessed based on usability (user-friendliness), functionality (capabilities and efficiency), engagement (incentive and appeal), and usefulness (perceived value). Validation by experts (faculty teaching number theory and abstract algebra) was conducted to refine the game features and mechanics.

4.2. Respondents of the Study

In this survey, there were two categories of respondents. The main respondents were 191 fourth-year students who completed the Number Theory or Abstract Algebra courses covering modular arithmetic subjects (90 students participated in the analytical phase and 101 students in the evaluative phase). Ninety of the 117 students (at a 95% confidence level) from Asingan, Sta. Maria and Bayambang campuses participated in the analytical phase. The respondents at this phase were selected using simple random sampling. During the try-out of the developed digital material, 101 students were present. All of these students served as evaluators of the digital game. The features, mechanics, and content of the digital lucky modal card game were explained to the students. They then assessed the content for usefulness, usability, functionality, and engagement. The secondary responders were six instructors from Pangasinan State University who taught number theory and abstract algebra. They served as validators for the digital content in terms of content, accuracy, instructional design and quality, technology, and usability.

4.3. Research Instruments

A researcher-made test questionnaire was used to measure the accuracy, response time, and accuracy response time of the students. The questionnaire garnered an internal consistency (Cronbach Alpha) of 0.83 in terms of accuracy and 0.79 in terms of response time.

Student evaluation survey questionnaire**.** A researcher made a survey questionnaire contextualized to digital numeracy instructional material were employed to measure the level of acceptability. The questionnaire comprised four parameters (usability, functionality, engagement, and usefulness with a total of 13 indicators, yielding Cronbach's alpha of 0.864. According to Tabier (2017), the Alpha value could be interpreted as "Good," indicating that the survey's internal consistency was acceptable.

Expert Validation Forms. Mathematics experts rated the game based on content validity, accuracy of modular arithmetic tasks, instructional design quality, and technology & usability. Indicators of the survey questionnaire were derived from the study of Quinto (2022) titled "Development and Validation of Survey Instrument on Game-Based Learning Approach (SIGBLA). The survey instrument garnered a S-CVI average of 0.983, and Cronbach's alpha = 0.839 implies that it is valid and has acceptable internal consistency.

4.4. Data Gathering Procedure

The researchers seek permission from the campus executive directors of the three campuses offering Bachelor of Secondary Mathematics Education to administer tests, conduct surveys, and pilot test the developed lucky modal card game. There were three phases in the data collection process.

Initially, the students were given a test by the researcher to gauge their proficiency and speed in solving modular arithmetic problems related to the content of the lucky modal card games. The students were divided into two groups, and one group kept track of how long the other group took to complete each test question. This procedure was also used with another group, and the test-takers kept an eye on how much time the other group spent.

Second stage: the developed digital learning material undergoes expert validation by providing them with the expert validation form and the digitized learning material. Validators were provided with the link and step-by-step procedure to play the lucky modal card game and the mechanics of the individual and group game. Moreover, a Google form containing the parameters to measure the validity of the developed digitized material was also provided to the validators. The expert validators' recommendations were also sought for additional enhancements to the created digital games.

Finally, the updated digital content was shown to students after incorporating experts' recommendations. The researchers conducted a 30-minute review in modular arithmetic, a 15-minute orientation, and a 45-minute utilization of the digitized learning material. Afterwards, they solicited students' perceptions of the digital material by providing an acceptability survey questionnaire.

4.5. Treatment of Data

Learners' performance in answering modular arithmetic problems was analyzed using frequency distribution and mean percentage score. These tools were best suited if you aimed to describe the performance of the learners. The tools provide information regarding the prevailing attributes in learners' skills in answering modular arithmetic. Learners' performance in modular arithmetic was classified into four categories according to their mean percentage scores. Learners' speed in answering modular arithmetic problems was analyzed using Response Time (Tpi). The notation used in response – time modelling in educational measurement and psychometrics. Modular arithmetic problems require mental computation, pattern recognition, decision speed, and fluency with modulo operations. These are cognitive processes that naturally vary in the time students take to solve each item. Response-time (RT) models were developed precisely to analyze this type of cognitive processing (De Boeck & Jeon, 2019). Accuracy Response Time (Api) was used to evaluate learners' accuracy and speed in solving modular arithmetic problems. Api was categorized by De Boeck and Jeon (2019) based on the following:

Table 1. Accuracy response time.

Case	Interpretation
Fast (<31 s) & correct	High fluency/mastery
Slow (>31 s) & correct	Careful reasoning
Fast (<31 s) & incorrect	Guessing / low effort
Slow (>31 s) & incorrect	Struggle or confusion

Table 1 presents the four cases to evaluate the accuracy and speed of learners in solving modular arithmetic problems. The speed is categorized into fast (<31 s) and slow (>31 s), and accuracy is categorized into correct and incorrect. The combination of these parameters was used to develop an accuracy response time evaluation tool. Each parameter combination is explained in the interpretation column.

Frequency count and percentage were used to evaluate the digital learning material's acceptability and validity levels. The following ranges were used to interpret the acceptability and validity of the developed digital learning material:

Table 2. Level of acceptability and validity descriptions.

Mean	Acceptability	Validity
1.00 – 1.49	Highly Not Acceptable	Not Valid
1.50 – 2.49	Not Acceptable	Less Valid
2.50 – 3.49	Slightly Acceptable	Moderately Valid
3.50 – 4.49	Acceptable	Highly Valid
4.50 – 5.00	Highly Acceptable	Very Highly Valid

Table 2 presents the range for the mean parameter, along with the relevant description as to acceptability and validity for each range. The ranges were derived from a five-point Likert scale survey questionnaire, with 1 representing the lowest and 5 indicating the highest. The boundary of each range is the midpoint of the five ordered response options.

4.6. Ethical Consideration

In this study, the researchers obtained ethical clearance from an accredited ethics review board. The study was approved by the University Research Ethics Board of Pangasinan State University under protocol number 2025-0143C-GARIN-MODULAR, dated March 31, 2025. Afterward, the researchers informed the participants about the nature and purpose of the study, including the risks, benefits, and any other relevant information that may help them make an informed decision. The participants were allowed to ask questions before they could give their voluntary consent to participate. This ensures that the students and teacher participants were fully aware of what they agreed to and that they had the right to withdraw their consent at any time.

The participants must understand the information provided, so they will be allowed to ask questions before they can give their voluntary consent to participate. The ICD will ensure that the student and researchers conduct the study fairly and equitably. This means that all the participants are treated equally regardless of their race, gender, ethnicity, or any other characteristics. Moreover, researchers took necessary steps to ensure that their data were kept confidential and secure. This includes obtaining participants' consent to use their data and ensuring that it is not shared with unauthorized individuals or entities. Furthermore, the names were not required to be included during the conduct of tests and surveys to protect the participants' identities and assess the acceptability of the digital tool. In addition, the researchers ensure that the study does not harm the participants in any way. This means that the researchers minimized any potential risks and ensured that the potential benefits of the project outweigh any risks involved.

5. Results

This chapter presents the results organized according to the research problems. It begins with the ability of student respondents to answer modular arithmetic tasks, response time, and accuracy. The chapter further discusses the framework for game elements and mechanics. Additionally, the validity and acceptability of the developed tool are presented.

Table 3. Performance of the BSE math students in modular arithmetic.

Operation	Percentage Score	Frequency	%	Mean Percentage Score
Addition	Above 75 (Very Satisfactory)	87	96.7	98.52 (Very Satisfactory)
	51 – 75 (Satisfactory)	2	2.2	
	25 – 50 (Fair)	1	1.1	
Subtraction (A>B)	Above 75 (Very Satisfactory)	77	85.6	88.88 (Very Satisfactory)
	51 – 75 (Satisfactory)	3	3.3	
	25 – 50 (Fair)	3	3.3	
	below 25 (Poor)	7	7.8	
Subtraction (A<B)	Above 75 (Very Satisfactory)	32	35.6	48.68 (Fair)
	51 – 75 (Satisfactory)	12	13.3	
	25 – 50 (Fair)	16	17.8	
	below 25 (Poor)	30	33.3	
Multiplication	Above 75 (Very Satisfactory)	74	82.2	91.11 (Very Satisfactory)
	51 – 75 (Satisfactory)	16	17.8	
Multiplicative Inverse	51 – 75 (Satisfactory)	45	50.0	41.10 (Fair)
	25 – 50 (Fair)	21	23.3	
	below 25 (Poor)	24	26.7	
Raise to Power	Above 75 (Very Satisfactory)	21	23.3	64.81 (Satisfactory)
	51 – 75 (Satisfactory)	51	56.7	
	25 – 50 (Fair)	7	7.8	
	below 25 (Poor)	10	11.1	
Factorial	Above 75 (Very Satisfactory)	61	67.8	77.41 (Satisfactory)
	51 – 75 (Satisfactory)	10	11.1	
	25 – 50 (Fair)	6	6.7	
	below 25 (Poor)	13	14.4	

Table 3 shows the frequency distribution of the performance of the BSE Mathematics students in modular arithmetic with the specified operations. The results show a high level of proficiency in addition and multiplication, with average percentage scores of 98.52% and 91.11%, respectively. However, notable lower performance was observed in more cognitively demanding tasks such as Multiplication Inverse ($\bar{x} = 41.10\%$), Subtraction ($\bar{x} = 48.68\%$) where $A < B$, and Raise to Power ($\bar{x} = 64.81\%$).

From the perspective of Connectivism Theory and Cognitive Load Theory, learning occurs through the formation of networks that link prior knowledge, digital tools, peers, and instructional content. Tasks like addition and multiplication are familiar operations and pose a low cognitive load to which students are able to connect existing schema, and allow students to process them effectively. However, operations requiring more abstract reasoning, such as multiplicative inverse, non-intuitive subtraction ($A < B$), Raising to a power and factorial require more advanced connections across concepts, symbols, and rules, and require students to manage multiple steps. When these networked connections are weak or insufficiently scaffolded, performance declines. The study of Naidoo and Govender (2021) shows that technology-supported environments enhance mathematical understanding when learners can access and navigate rich informational networks. Tasks requiring complex problem-solving lead to poorer outcomes when instructional design fails to reduce unnecessary cognitive load (Adhikari & Anbuchelvan, 2025).

Table 4. Response time by operation.

Operation	Response Time	Frequency	Percent	Mean
Addition	Less than 11 s (Very fast)	83	92.2	5.21 (Very fast)
	11 - 20 s (Fast)	6	6.7	
	21 - 40 s (Moderate)	1	1.1	
Subtraction ($A > B$)	Less than 11 s (Very fast)	73	81.1	7.38 (Very fast)
	11 - 20 s (Fast)	15	16.7	
	21 - 40 s (Moderate)	2	2.2	
Subtraction ($A < B$)	Less than 11 s (Very fast)	33	36.7	16.69 (Fast)
	11 - 20 s (Fast)	40	44.4	
	21 - 40 s (Moderate)	15	16.7	
	41 - 60 s (Slow)	2	2.2	
Multiplication	Less than 11 s (Very fast)	46	51.1	17.01 (Fast)
	11 - 20 s (Fast)	28	31.1	
	21 - 40 s (Moderate)	9	10.0	
	41 - 60 s (Slow)	5	5.6	
	above 90s (Extremely Slow)	2	2.2	
The product of a number and the multiplicative inverse of the other number	Less than 11 s (Very fast)	26	28.9	30.92 (Moderate)
	11 - 20 s (Fast)	27	30.0	
	21 - 40 s (Moderate)	20	22.2	
	41 - 60 s (Slow)	9	10.0	
	61 - 90 s (Very Slow)	2	2.2	
	above 90s (Extremely Slow)	6	6.7	
Raise to Power	Less than 11 s (Very fast)	3	3.3	84.09 (Very Slow)
	11 - 20 s (Fast)	11	12.2	
	21 - 40 s (Moderate)	21	23.3	
	41 - 60 s (Slow)	23	25.6	
	61 - 90 s (Very Slow)	7	7.8	
	above 90s (Extremely Slow)	25	27.8	
Factorial	Less than 11 s (Very fast)	8	8.9	72.77 (Very Slow)
	11 - 20 s (Fast)	5	5.6	
	21 - 40 s (Moderate)	18	20.0	
	41 - 60 s (Slow)	24	26.7	
	61 - 90 s (Very Slow)	21	23.3	
	above 90s (Extremely Slow)	14	15.6	

Table 4 shows the response time of the students across different operations. The students demonstrated very fast in Addition (M = 5.21 s) and Subtraction, where A > B (M = 7.38 s), with more than 80% completing these tasks in under 11 seconds.

From a connectivist perspective, these operations are highly familiar, having been reinforced through repeated exposure for efficient retrieval of answers. However, tasks involving greater complexity, such as finding the product of a number and its multiplicative inverse (M = 30.92 s), raising numbers to a power (M = 84.09 s), and computing factorials (M = 72.77 s) required substantially longer processing time. These operations demand multiple layers of reasoning, including identifying modular inverses, recognizing repeated multiplication patterns, and handling large numerical computations. According to Cognitive Load Theory (CLT), such tasks impose a high intrinsic cognitive load because they involve numerous interacting elements that must be processed simultaneously. As the burden on working memory increases, slower response times are expected.

The longest response times were observed in exponentiation and factorial tasks, where many students fell into the “slow” or “extremely slow” categories. These operations involve iterative and multi-step procedures, increasing both intrinsic load due to mathematical difficulty and extraneous load, particularly when instructional support is insufficient. Supporting this, Adhikari and Anbuchelvan (2025) found that high-complexity mathematical tasks significantly reduce processing speed unless instructional strategies such as worked examples are used to minimize unnecessary cognitive demands.

Table 5. Multivariate tests by operation in the respondents' performance and response time.

Effect		Value	F	Sig.	Partial Eta Squared
Operation	Wilks' Lambda	0.497	43.411^b	0.000	0.295

The multivariate test results in Table 5 reveal that the effect of operation on the performance and response time is statistically significant, as indicated by $Wilks' \, Lambda = 0.497, F = 43.411, p < .001$. The Partial Eta Squared of 0.295 represent the large effect size, meaning that approximately 29.5% of the variance in the students' accuracy and response time is explained by the modular arithmetic operation. When interpreted in terms of CLT, the large value multivariate effect suggests that high-level modular operations place substantially greater demands on working memory and response time. In the lens of Connectivism Theory, high-level modular arithmetic operations require richer and more specialized network knowledge. When such networks are inadequately developed, students rely on slower, step-based computation, explaining the large operational differences captured by Wilks' Lambda. Naidoo and Govender (2021) strong digital and continuous practice significantly enhances mathematical efficiency and cognitive processing.

Table 6. Tests of Between-Subjects Effects by Operation in the Respondents' Performance and Response Time.

Source		F	Sig.	Partial Eta Squared
Operation	Score	44.857	0.000	0.302
	Time	41.840	0.000	0.287

Table 6 affirmed that the type of modular arithmetic operation significantly influences students' performance score and response time, with $F = 44.857, p < 0.001, \eta^2 = 0.302$ for performance and $F = 41.840, p < 0.001, \eta^2 = 0.287$ for response time. The effect sizes fall within the large effect range, indicating that the aforementioned operations account for approximately 30.2% of the performance score variances and 28.7 of the response time variances. This means that the specific operation students work on plays a crucial role in measuring the accuracy and quickness with which they can produce correct responses. More complex operations demand lower accuracy and slower response time, while basic operation students perform significantly better and respond faster.

The results parallel Sweller's CLT; task complexity elevates intrinsic cognitive load, resulting in decreased performance and longer response time. This aligns with the present study, high-level cognitive operations such as multiplicative inverse, raise to power, and factorial were associated with poorer and longer responses.

Table 7. Pairwise comparison by operation in the response time of the respondents.

Dependent Variable	Operation (I)	Operation (J)	Mean Difference (I-J)	Sig.
Time	Addition	Subtraction(A>B)	-2.1656	1.000
		Subtraction(A<B)	-11.4767	0.846
		Multiplication	-11.8017	0.828
		Multiplicative Inverse	-25.7100*	0.037
		Raise to Power	-78.8804*	0.000
		Factorial	-67.5544*	0.000
	Subtraction(A>B)	Subtraction(A<B)	-9.3111	0.939
		Multiplication	-9.6361	0.929
		Multiplicative Inverse	-23.5444	0.081
		Raise to Power	-76.7148*	0.000
		Factorial	-65.3889*	0.000
	Subtraction(A<B)	Multiplication	-0.3250	1.000
		Multiplicative Inverse	-14.2333	0.658
		Raise to Power	-67.4037*	0.000
		Factorial	-56.0778*	0.000
	Multiplication	Multiplicative Inverse	-13.9083	0.683
		Raise to Power	-67.0787*	0.000
		Factorial	-55.7528*	0.000
	Multiplicative Inverse	Raise to Power	-53.1704*	0.000
		Factorial	-41.8444*	0.000
	Raise to Power	Factorial	11.3259	0.854

Table 7 demonstrates significant variations in response times among different modular arithmetic operations. Basic operations such as addition, multiplication, and subtraction result in considerably reduced processing times compared to operations like exponentiation and factorial (e.g., Addition vs. Exponentiation: -78.8804^*, p = 0.000).

The results align with CLT's explanations on task advancement, with tasks that necessitate considerable processing (high intrinsic and extrinsic load) to achieve the desired solution leading to reduced response time. The findings align with Paas and Sweller (2012) report, indicating that tasks needing a high cognitive level demand significant working memory resources, resulting in slower response times. Significant time gaps exist between basic and advanced tasks, leading students to invest greater cognitive energy in high-level activities that involve multi-step or abstract procedural computations. Aldalalah and Ababneh (2020) noted that complex tasks require increased cognitive effort and longer reaction times in digital mathematics settings. Siemens (2014) highlights that as learners build stronger knowledge nodes, the digital pathways improve efficiency and facilitate faster decision-making in problem-solving. Likewise, Sofroniou, Patel, Premnath, and Wall (2025) indicates that tackling complex problem tasks greatly enhances cognitive links among interconnected concepts. Almulla (2022) stated that in technology-enhanced learning environments, learners facing tasks with greater conceptual difficulty take longer to respond unless robust learning networks are established beforehand.

Table 8. Pairwise comparison by score of the respondents.

Dependent Variable	Operation (I)	Operation (J)	Mean Difference (I-J)	Sig.
Score	Addition	Subtraction(A>B)	9.6296	0.639
		Subtraction(A<B)	49.6296*	0.000
		Multiplication	7.4074	0.865
		Multiplicative Inverse	57.4074*	0.000
		Raise to Power	33.7037*	0.000
		Factorial	21.1111*	0.002
	Subtraction(A>B)	Subtraction(A<B)	40.0000*	0.000
		Multiplication	-2.2222	1.000
		Multiplicative Inverse	47.7778*	0.000
		Raise to Power	24.0741*	0.000
		Factorial	11.4815	0.415
	Subtraction(A<B)	Multiplication	-42.2222*	0.000
		Multiplicative Inverse	7.7778	0.834
		Raise to Power	-15.9259	0.071
		Factorial	-28.5185*	0.000
	Multiplication	Multiplicative Inverse	50.0000*	0.000
		Raise to Power	26.2963*	0.000
		Factorial	13.7037	0.195
	Multiplicative Inverse	Raise to Power	-23.7037*	0.000
		Factorial	-36.2963*	0.000
		Subtraction(A<B)	-7.7778	0.834
		Multiplication	-50.0000*	0.000
	Raise to Power	Factorial	-12.5926	0.294

Table 8 presents the results of the pairwise comparisons for the respondents' scores, indicating notable performance variations in modular arithmetic operations. Specifically, functions such as additive and multiplicative inverses, exponentiation, and factorial calculations consistently resulted in markedly lower scores than the modular arithmetic addition and multiplication (e.g., Addition vs. Subtraction difference=49.6296*, $p = .000$; Addition vs. Multiplicative Inverse: difference=57.4074*, $p = 0.000$). This pattern suggests that more intricate tasks lead to a greater cognitive load, potentially resulting in a higher likelihood of making errors or having misconceptions. This corresponds with theories CT and CLT, emphasizing learners' conceptual frameworks for these processes and clarifying that complex concepts result in a greater likelihood of errors because of their increased task difficulty.

This aligns with the findings of Aldalalah and Ababneh (2020) as well as Almulla (2022), which indicated that students' performance declines significantly as task complexity rises. Students assert that learning efficiency and fluency occur when learners create interconnected networks of ideas, particularly in digital learning settings (Siemens, 2014). Additionally, students' precision in mathematically complex tasks is enhanced solely when technology-enhanced learning fosters the development of robust conceptual links between related mathematical frameworks (Kop & Hill, 2008; Sofroniou et al., 2025).

Table 9. Scheffe tests based on observed response performance means in homogeneous subsets.

Operation	Subset				
	1	2	3	4	5
Multiplicative Inverse	41.1111				
Subtraction(A<B)	48.8889	48.8889			
Raise to Power		64.8148	64.8148		
Factorial			77.4074	77.4074	
Subtraction(A>B)				88.8889	88.8889
Multiplication				91.1111	91.1111
Addition					98.5185
Sig.	0.834	0.071	0.294	0.195	0.639

Table 9 displays the Scheffé post-hoc analysis, which reveals homogeneous subsets of students regarding their performance in modular arithmetic operations. High-scoring operations, addition, subtraction, and multiplication, comprise a first grouping. Multiplicative and additive inverse form the lowest performing group, the 2nd group, followed by the exponentiation and factorial 3rd group. From the perspective of connectivism, high-scoring operations enable faster retrieval and stronger performance. The strength of conceptual networks determines the accuracy of learners' responses (Siemens, 2014). Mathematics learners perform significantly better only when complex mathematical tasks are coherently structured, and digital tools strengthen linkages for complex procedures.

Table 10. Scheffe tests based on observed response time harmonic means in homogeneous subsets.

Operation	Subset		
	1	2	3
Addition	5.2122		
Subtraction(A>B)	7.3778	7.3778	
Subtraction(A<B)	16.6889	16.6889	
Multiplication	17.0139	17.0139	
Multiplicative Inverse		30.9222	
Factorial			72.7667
Raise to Power			84.0926
Sig.	0.828	0.081	0.854

Table 10 displays the results of the Scheffé test for response time; the tool identifies homogeneous subsets based on their harmonic mean completion time. The categorization relies on the time taken for completion, arranged from quickest to slowest. The initial subsets include addition, subtraction, and multiplication. The collection includes nearly all fundamental modular arithmetic operations except for inverse addition. The second set of operations includes subtraction, multiplication, additive inverses, and multiplicative inverses. The third category of operations includes exponentiation and factorial. It is the most time-consuming subset since the tasks necessitate multi-step and abstract reasoning, which significantly extends the response duration.

Table 11. Accuracy response time of the digital lucky modal card game.

Operation	High fluency/ Mastery	Careful Reasoning	Guessing/Low effort	Struggle or confusion
Addition	98.52	0.00	1.48	0.00
Subtraction (Minuend > Subtrahend)	88.89	0.00	11.11	0.00
Subtraction (Minuend < Subtrahend)	46.67	2.22	46.67	4.44
Multiplication	67.78	14.44	17.78	0.00
The product of a number and the multiplicative inverse of the other number	31.85	14.07	51.48	13.33
Raise to Power	22.96	41.85	12.96	22.22
Factorial	18.15	59.26	12.59	10.00

Table 11 shows the students' performance regarding accuracy and response time for modular arithmetic across different operations. In the process of addition, subtraction (where the minuend exceeds the subtrahend), and multiplication, there was a strong level of mastery shown, with almost no instances of struggle or confusion, careful reasoning, and guessing. This suggests that during the mentioned operation, students exhibited automatic mastery and had strong schemas for fundamental modular arithmetic. This signifies that the task related to the aforementioned operations pertains to CLT. Minimize intrinsic cognitive load, enabling learners to use minimal mental effort so they can respond quickly and accurately.

In the inverses (addition and multiplication) demonstrated moderate mastery with almost no instances of struggle or confusion and careful reasoning. Nevertheless, a notable percentage (46.67 and 51.48) of students depend on a minimal effort strategy (guessing). This suggests that the task of operation inverses creates a greater cognitive burden than the earlier operations, leading learners to employ guessing strategies. In the research by Aldalalah and Ababneh (2020), it was found that complex mathematical tasks demand sequential reasoning and heighten cognitive effort and reasoning.

The most notable cognitive change is seen in the operations Raise to power and factorial, falling to 22.96% and 18.15%. A notable shift in strategy is observed in detailed reasoning, rising to 41.85% and 59.26%. This suggests that the majority of students take more time to solve modular arithmetic involving exponentiation and factorials, yet they still show low fluency. Additionally, the operations demonstrate high levels of difficulty (22.22%), suggesting that tasks involving exponentiation and factorials remain conceptually unstable for many students.

5.1. Framework for the Development of the Digitized Modular Arithmetic Card

The evaluations in Tables 7-11 relating to response time accuracy trends, along with uniform groups, would contribute to a more defined framework regarding the structural and scaffolding elements required for the digital tool to improve user mastery and engagement. These results indicate a developmental trajectory that corresponds with the cognitive and system frameworks outlined by CLT and Connectivism.

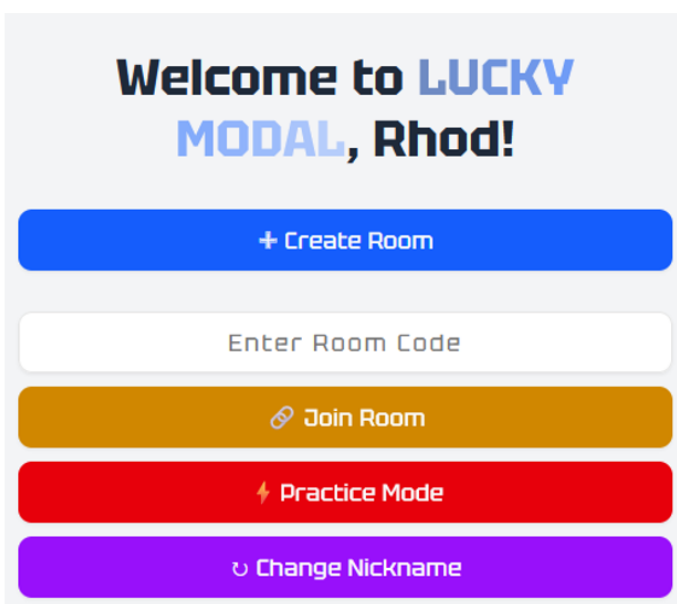

Figure 2. Mode selection.

Figure 2 presents the mode selection interface of the digital game. In this window, the player must choose the game modality – either a group or an individual game. If the player chooses the group game, they may press "Create Room" or "Join Room". The player should select "Join Room" if another player has already created a room, then enter the room code provided by the creator. If the player creates the room, the player needs to share the room code with other players. The maximum number of players for a group game is four. If the player chooses to play an individual game, they must use the practice mode. Moreover, in this window, the player can change their identity by changing their nickname.

Accuracy–Response Time Profiles as the basis for user-level classification. In Table 11, the performance profile shows high fluency, careful reasoning, guessing, and struggle or confusion. The game categorizes players based on their accuracy-speed profile. Results reveal distinct behavioral patterns that provide insights for adjusting difficulty within the game. Learners with high fluency should progress to more complex operations, careful reasoners should focus on intermediate levels, guessing or low-effort learners may use the easy level for motivation and longer engagement, and struggling learners require remedial pathways such as tutorials, worked examples, and simplified question variants.

Table 7, 9, and 10 provide progressive subsets for the game difficulty. The results confirmed the following hierarchy of difficulty across modular arithmetic operations. The operations addition, multiplication, and subtraction (A>B) are the most accurate and fastest subset, forming the foundation of gameplay. Operations with medium accuracy or response time, like subtraction (A<B) and multiplicative inverse, occupy the intermediate task. Operations with high cognitive load, such as raising to a power and factorial characterized by slow response and low accuracy from upper tiers.

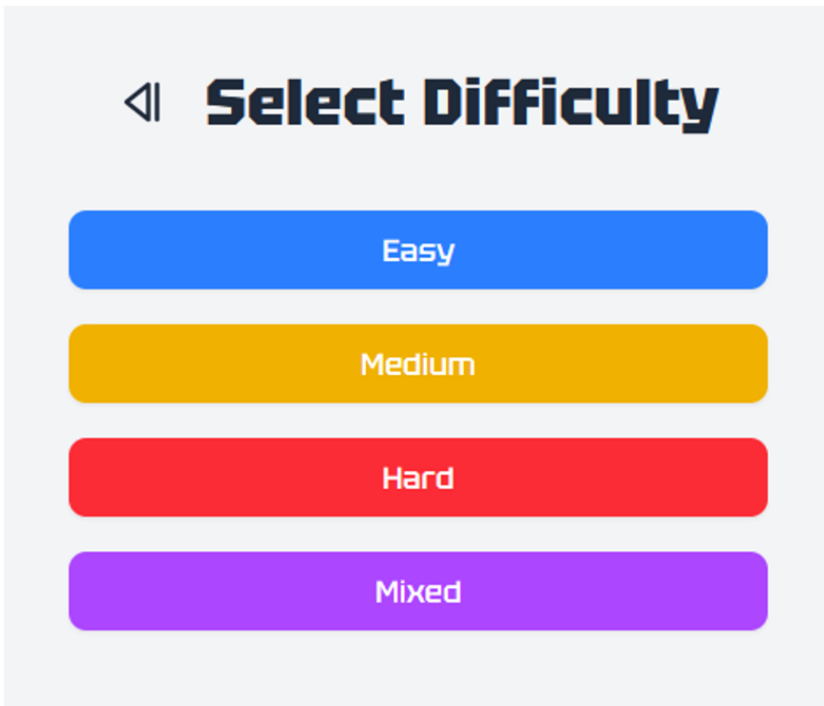

Figure 3. Level of difficulty.

Figure 3 illustrates the level of difficulty window. The player(s) must agree on the level of difficulty they want to play. The easy level includes addition and multiplication; the medium level includes inverse addition and inverse multiplication; the hard level includes exponentiation and factorial; and the mixed level includes all operations from easy to difficult.

Table 7, 10, and 11 demonstrated that operations involving high structural complexity (such as multiplicative and additive inverses, exponentiation, and factorial) place a greater intrinsic cognitive load. The game offered guides (Structured Hint) to minimize unnecessary extraneous load in the operations of inverse, exponent, and factorial. This aligns with cognitive load theory; the game should avoid overload and maintain balance during difficult tasks to help learners progress toward mastery.

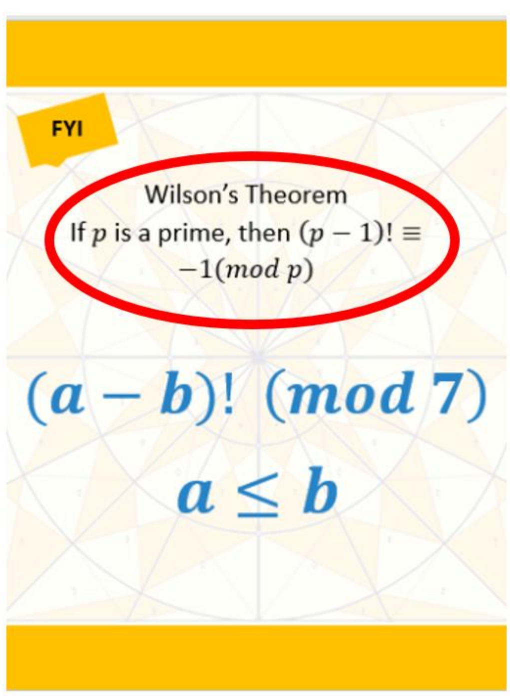

Figure 4. Structured hints.

Figure 4 presents one of the special features of the cards, the "structured hints". These structured hints in the modulo card correspond to the randomly selected operations. For example, Figure 4 presents the factorial operation; therefore, the structured hint provided is Wilson's theorem. The feature aims to promote mastery and reduce cognitive load associated with the selected problem.

The findings confirmed that precision and response duration are dependable indicators of cognitive condition. This implies a need for a real-time analytics dashboard or heat maps for a digital tool displaying precise responses and mistakes.

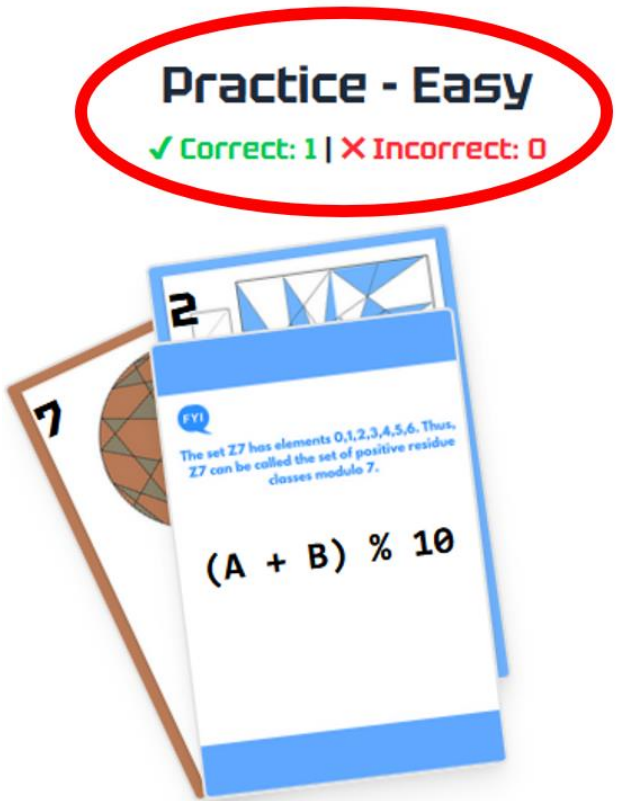

Figure 5. Game analytics.

Figure 5 illustrates the analytics for the practice mode game. The developed digital game provides real-time analytics, displaying the correct and incorrect responses. In the group game mode, the tool also shows the scores for each player. Additionally, players immediately determine whether they won the game after each shuffle of the cards.

Table 12. Evidence-based sequencing of game levels.

Level	Interpretation	Operation
Easy	Foundational Operation (High Mastery + Low Cognitive Load)	Addition Multiplication Subtraction (A>B)
Medium	Intermediate Conceptual Adjustment (Moderate - High Load + Emerging Confusion/Increased Guessing)	Subtraction (A<B) Multiplicative inverse
Hard	Abstract and Multi-Step Operations (Very High Load + High Confusion)	Raise to power Factorial

Table 12 presents a unified perspective of Tables 5-9, outlining the three-tier instructional progression. The development linked conceptual frameworks and strong schemas prior to advancing to complex tasks. This suggests that the game encourages low-entry, high-potential play, enabling newcomers to thrive while providing challenges for more experienced players. This approach is backed by modern digital learning studies and the trends identified in the data.

Table 13. Level of acceptability of the digital lucky modal card game.

Parameters	Mean	Description
A. Usability (Ease of Use)	4.81	Highly Acceptable
B. Functionality (Features & Performance)	4.88	Highly Acceptable
C. Engagement (Motivation & Interest)	4.85	Highly Acceptable
D. Perceived Usefulness (Learning Impact)	4.92	Highly Acceptable
Grand-mean	4.86	Highly Acceptable

The results in Table 13 reveal that the Lucky Modal Digital Card Game obtained a high level of acceptability (Grand Mean = 4.86, Highly Acceptable) across the domains of usability (Sub-mean=4.81, Highly Acceptable), functionality (Sub-mean = 4.88, Highly Acceptable), engagement (Sub-mean = 4.85, Highly Acceptable), and perceived usefulness (Sub-mean = 4.92, Highly Acceptable). Well-designed learning applications enrich their learning experience and improve students' ability to navigate learning pathways (Kim & Choudhury, 2021). The app functionality supports real-time knowledge construction, relevant features, and organized numeracy tasks that reinforce conectivist principles.

The perceived usefulness obtained the highest sub-mean (4.92), which implies that the learner agreed that the tool enhanced their numeracy skills and comprehension. In the CLT term, the tool increases the germane cognitive load, leading to automation in modular arithmetic. According to Gil-Flores, Torres-Gordillo, and Perera-Rodríguez

(2012), instructional tools designed with CLT principles significantly enhance motivation and improve learning performance.

Table 14. Level of validity of the digital lucky modal card game.

Parameters	Mean	Description
Content Validity (Mathematics & Instructional Content)	4.9	Very Highly Valid
Accuracy of Modular Arithmetic Tasks.	4.67	Very Highly Valid
Instructional Design Quality (Game Mechanics & Learning Design)	4.78	Very Highly Valid
Technology & Usability	4.94	Very Highly Valid
Grand-mean	4.83 (Very Highly Valid)	

Based on the results in Table 14 reveal that the Digital Lucky Modal Card Game obtained very high content validity (grand mean = 4.83) across content, task accuracy, instructional design quality, and technology and usability parameters. This finding corroborates Imron and Nababan (2022) report that when the features of the instructional material are designed for interactivity to increase motivation and conceptual and conceptual clarity, improve knowledge networks, and learner engagement.

The game interface research-based structured task of the developed digital tool minimizes extraneous load, making the material very highly valid on usability (Mean=4.94). Well-structured digital instructional material reduces extraneous cognitive load and enhances accuracy and response time (Chiu, 2021; Maries & Singh, 2023).

The table also shows balanced ratings for task accuracy (Mean = 4.67), especially in the promotion of speed suited for mastery. Well-designed drills enhance fluency, which aligns with the CLT principle of automaticity. According to Uzun and Kilis (2020), speed-based mechanics align with structured cognitive processing and enhance computational fluency.

6. Conclusion

The students exhibited strong performance and rapid response in the operations of addition, multiplication, and subtraction (minuend A is greater than subtrahend B). They experienced low precision and medium rapid response in the inverses, and they faced low accuracy and substantially low response time with exponentiation and factorial. The findings affirmed that modular arithmetic, a foundational topic in number theory, abstract algebra, and discrete mathematics, poses cognitive and conceptual challenges that are not addressed by conventional instruction.

The created digital tool aids in progressive subsets for gameplay challenges. The operations addition, multiplication, and subtraction (A>B) are the most accurate and fastest subset; the operations' inverses occupy the intermediate task. Operations raised to a power and factorial, characterized by slow response and low accuracy, form upper tiers. Moreover, the game presents structured hints to minimize unnecessary extraneous load and features a real-time analytics dashboard or heat maps displaying precise responses and mistakes. Furthermore, the digital tool affirms sufficient scaffolding and interconnected knowledge, forming well-structured digital material.

The developed digital tools recorded a high level of validity across content, task accuracy, instructional design quality, and usability, providing empirical support for their pedagogical value. Students perceived high acceptability regarding usability, functionality, engagement, and usefulness. These outcomes confirmed that the material is well-structured and could contribute to the design of digital tools aimed at reducing cognitive load and strengthening conceptual networks for teaching and learning.

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