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Article

Modeling "Stag and Hare Hunting" Behaviors Using Interaction Data from an mCSCL Application for Grade 5 Mathematics

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Abstract: This study attempted to model the stag and hare hunting behaviors of students using their interaction data in a mobile computer-supported collaborative learning application for Grade 5 mathematics. Twenty-five male and 12 female Grade 5 students with an average age of 10.5 years participated in this study. Stag hunters are more likely to display personality dimensions characterized by Openness while students belonging to hare hunters display personality dimensions characterized by Extraversion and Neuroticism. Students who display personality dimensions characterized by Agreeableness and Conscientiousness may tend to be either hare or stag hunters, depending on the difficulty, types of arithmetic problems solved, and the amount of time spent solving arithmetic problems. Students engaged in a stag hunting behavior performed poorly in mathematics. Decision tree modeling and lag sequential analysis revealed that stag and hare hunting behaviors could be identified based on personality dimensions, types of arithmetic problems solved, difficulty level of problems solved, time spent solving problems, and problem-solving patterns. Future research and practical implications were also discussed.

Keywords: decision tree; educational technology; mobile games; personality; personality dimensions

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1. Contribution to the Literature

Stag and hare hunting behaviors are not well understood in the context of mobile CSCL. This paper sheds light on what features describe these gaming behaviors. Furthermore, this study discovered that students who displayed the Neuroticism personality dimension appeared to be helpful and cooperative, which is contradictory to the existing literature and studies.

2. Introduction

Computer-supported collaborative learning (CSCL) is the "field concerned with how information and communication technology (ICT) might support learning in groups (co-located and distributed)" (p. 290) [1]. This group is usually composed of 2 to 6 students working together to solve a problem [2]. ICT covers a wide range of technological tools and devices such as computers, the Internet, live broadcasting technologies (e.g., radio and television), broadcasting technologies (e.g., podcasting and video players), and telephony (e.g., mobile, or fixed) [3]. In the scoping review conducted by Bringula and Atienza (2022) [4], it was shown that CSCL had positive effects on students' social aspects, attitudes, and mathematics competencies.

Within a CSCL learning environment, it is assumed that students can work together towards a common academic goal and, consequently, learn in a social group [5,6]. It is also assumed that students have equal participation in this learning environment. However, these assumptions are not always true because students have different personalities. Understanding the students' personalities is important because these could influence their academic performance in a learning environment [7]. For example, highly individualistic students prefer to work alone. In addition, some students do not perform their assigned tasks; instead, they resort to leaving the group to avoid dealing with the responsibility [8]. Furthermore, some dominant students monopolize discussions [8], whereas some team members share and agree on a common decision [9,10]. As a result, unique information is ignored [11]. Students who have unique ideas may be forced to agree with the rest of the group, resulting in a phenomenon known as groupthink [11]. Other students may reduce or cease efforts to contribute to the welfare of the group [12–15]. They may also have varying degrees of participation in a learning activity [16]. Some students were very competitive and outspoken, while others were timid, shy, and afraid to commit mistakes. As pointed out by [17], these challenges are related to group cohesion, participation, communication, collaboration, and trust.

The behaviors previously discussed are well-documented. The stag and hare hunting behaviors, on the other hand, are underrepresented in the CSCL literature. In a game-based, mobile-supported collaborative learning environment, stag and hare hunting behaviors refer to learners' tendency to choose either a high-risk game mode with higher payoffs (i.e., the stag) or a low-risk game mode with fewer points (i.e., the hare) [18]. Since learners are in a collaborative learning environment, their interactions with the system may be influenced by their personalities. A student who is not afraid to make mistakes may choose an answer passively to contribute to the group's points. On the one hand, a student who does not want to be blamed if his or her answer is incorrect may choose a question with a lower point value. These students may not necessarily contribute to the overall well-being of the group and, as a result, do not achieve learning.

This study adapted the stag hunt behavior proposed by Rousseau [19], as discussed in the papers of Skyrms [20,21]. The stag hunt behavior means that a hunter must hunt for a stag, though he may, nonetheless, opt for a hare, if given the chance. The contributions of the members of the team in the stag hunting behavior are based on the risks associated with the options. Given this context, this study aimed to investigate stag and hare hunting behaviors of students who used a mobile-based CSCL in mathematics and to develop a model that would characterize these behaviors.

3. Literature Review and Research Questions

3.1. CSCL and Academic Achievement

Prior studies categorized students in the CSCL environment and reported their learning achievements. Lipponen et al. [22] used social network analysis (SNA) to classify students as active and inactive participants based on levels of activity. In a recent similar study, Kim and Ketenci [23] classified learners into three groups based on their conversations and quantified their participation using SNA. Kim and Ketenci [23] showed that there were three types of participants in their study: full, inbound, and peripheral. A full participant whose inputs involve frequent interactions and feedback is the most active contributor in the group. An inbound participant participates actively in conversations, raises questions, and provides meaningful feedback. The peripheral participants are those learners who are not engaged in any of the activities. The full participants had the highest final scores.

Noroozi et al. [24] investigated the learning outcomes of human nutrition and health students in a CSCL environment. They discovered that the learning outcomes of successful and less successful students differed in terms of relevance, justification, reasoning, and the breadth and depth of discussion about food and nutrient intake assessment. Similarly, Siqin, Van Aalst, and Chu [25] demonstrated that as students become more involved in the course, their domain knowledge of introductory research methods grows, and students in groups who engage in constructive discussions are more likely to generate higher-level questions and ideas. These findings are consistent with the findings of Tirado-Morueta, Maraver-Lopez and Hernado-Gomez [26].

Kapur and Kinzer [27] analyzed the problem-solving strategies in CSCL. Their study showed that students solving ill-structured problems produced more problem-centered interactional activities (e.g., problem definition, identification of relevant parameters, brainstorming solutions, evaluation and elaboration of suggestions, selection of solutions, and negotiation of a final decision) in Newtonian kinematics. However, students in this group tended to dominate a discussion more than those students solving well-structured problems. The inequities in member participation decreased the quality of discussion, which adversely affected the group's problem-solving performance.

In this study, even though students worked as a group in a CSCL environment, their individual gaming behaviors were classified as either stag or hare hunters. Subsequently, their mathematics achievement was collected. Therefore, this current study attempted to answer the question below and forwarded a null hypothesis:

Research Question 1 (RQ1). *Which of the stag and hare behaviors is beneficial to mathematics achievement?*

Hypothesis (H_{0a}). *None of these behaviors are beneficial to mathematics achievement.*

3.2. Types of CSCL Interactions and Personality

Some studies attempted to classify CSCL learners based on their levels of participation. Fields et al. [28] categorized the Scratch online community profile users into five classes: "high", "download", "social + download", "download + comment", and "low-level". "High" class users are the most active type of online community users, exhibiting all forms of participation such as posting a remix, downloading a project, commenting on a project, showing interest in a project, and making a friend request. The "download" class is the type of user that is most likely to download a Scratch project. Users that are active in the social networking features of Scratch and download Scratch projects are sorted in the "social + download" class.

Piki [29] classified the forms of participation of postgraduate students engaged in CSCL through behavioral (e.g., contributions to blogs, videoconferencing, and activities), intellectual (e.g., academic motivation, approach to studying, degree of self-awareness), and affective (expressed feelings) variables. Other variables like learning preference and assignment mark of engagement were also used. Using these variables, the author suggested four classifications of learners: Withdrawn, Impulsive, Strategic, and Enthusiastic (WISE). Withdrawn learners have low behavioral, intellectual, and affective engagement. Impulsive learners describe themselves as solo learners but are active in collaborative activities. Strategic learners tend to ignore the value of CSCL; thus, they have moderate to low engagement in collaborative learning and are more active in face-to-face discussions. Enthusiastic learners are those who highly participate in a CSCL environment.

Marcos-García, Martínez-Monés, and Dimitriadis [30] proposed a comprehensive model of learner roles in CSCL. Their research centered on emergent roles characterized by different learners' participation in online discussions. Their extensive literature review resulted in seven student roles, from most to least participation. They are leader, coordinator (or moderator), animator (starter), active (participatory), peripheral (marginal participant), quiet (observer or lurker), and missing (outsider or isolated).

Moreover, the personality dimensions of each learner may influence the interaction with the learning systems [7]. Various models measure personality dimensions (e.g., Big Five Personality, [31]; Neuroticism-Extraversion-Openness Personality Inventory, [32]; Trait Descriptive Adjectives, [33]). Among these models, the Big Five Personality Model is the most relevant in this study because the questions are intended for children [31]. The Big Five personality dimensions are characteristics of a person's personality: Openness (or Openness to experience) if they are more conventional or imaginative; Conscientiousness if they are more spontaneous or organized; Extraversion if they like solitude or are more outgoing; Agreeableness if they are skeptical or more trusting; and Neuroticism if they are emotionally stable or unstable (OCEAN). Based on the study of McCrae and John ([34], cited in Müller & Schwieren [35]), people who display a highly Open personality like to learn new things and enjoy a new experience. People with this personality trait have a wide variety of interests. They are also imaginative and creative, which enable them to perform better in a group [36,37].

Responsible, controlled, orderly, cautious, meticulous, hard-working, self-disciplined, reliable, and having a high sense of goal achievement are the distinctive traits of people with a high Conscientiousness personality type ([32] cited in [38]; [39]). People who belong to this category are known to perform their assigned tasks [40] and have high achievement motivation [41]. People who belong to the Conscientious personality dimension are found to be beneficial to individual and group success [42]. High conscientiousness, on the other hand, tends to make one a perfectionist. This may lead to tension in the group, which may also lead to the loss of a sense of belongingness in an organization and, eventually, failure in achieving the organization's goal ([43] cited in [38]).

People displaying a high Extrovert personality dimension are characterized as emotionally positive, spontaneous, energetic, assertive, dominant, and confident [35,44], while people displaying high Agreeableness are described as compassionate, caring, cooperative, altruistic, and emotionally supportive [35,44]. Curşeu et al. (2019) [38] concluded that people displaying high Extraversion, Conscientiousness, and Agreeableness personality dimensions are suitable for teamwork. On the other hand, people displaying high Neuroticism are characterized by negative interpersonal dynamics, emotional instability [35], and affectivity in teams [45]. Taking into account the cited literature, the purpose of this study was to add to the existing literature by describing the stag and hare behaviors of students as they used the mobile-based CSCL and their personalities. For this reason, this study attempted to answer this question:

RQ2. *Do learners' game interaction data and personality dimensions describe the stag and hare hunting behaviors of the students?*

It is hypothesized that

Hypothesis (H_{0b}). *Learners' game interaction data and personality dimensions do not describe the stag and hunting behaviors of the students*.

3.3. Lag Sequential Analysis and Usage Behaviors

Lag sequential analysis (LSA) is a method that could describe the learning or usage behaviors of learners in CSCL. Through LSA, Shukor et al. [46] explained the knowledge construction behavior of web development students in a collaborative discussion. The study reported that students' argumentation and emphasis on problem-solving tasks are helpful to their learning. In a similar study on knowledge construction, Yang et al. [47] showed that there is a significant difference in the behavioral sequences between higher- and lower-engagement groups in terms of negotiation of meaning and co-construction of knowledge.

In a related study, Wu, Chen and Hou [48] found that the usage behavior of learners in an online concept map discussion environment includes frequent moving of nodes, talking among themselves to produce a concept map, and adding or deleting multiple nodes and relationships. Another team of researchers, Yang et al. [47], studied the usage behaviors (e.g., editing content, commenting on an entry, posting a discussion, etc.) of open online knowledge communities (OKC) users. Their transitional diagram of usage behaviors showed that users are not sharing adequate materials to boost knowledge communities and that there are no behavioral sequences that improve the content of OKC.

Examining the usefulness of LSA to describe the usage behaviors of learners, this research utilized it as the method of analysis to answer the question below:

RQ3. *What is the usage behavior of students in terms of the level of difficulty and types of a problem solved?*

It is hypothesized that

Hypothesis (H_{0c}). *The problem-solving behavior of students in terms of the level of difficulty and types of arithmetic problem solved (subsequently referred as types of problem solved) do not exhibit a significant pattern.*

4. Methodology

4.1. Software Utilized

The method of this study was already reported in our previous work [16]. The study utilized Ibigkas! Math, a mobile-based learning application for students in grades 1–6. It is a collaborative game that generates and displays arithmetic problems (addition, subtraction, multiplication, and division of whole numbers and fractions). The given and possible answers appear on all the students' devices. The correct answer, however, appears only on one of the mobile Android devices of the team members. The answer must be stated aloud by the players. At least two students must play the game. Each player was given a chance to host the game. Only the host can select the game setting. The game setting includes selection of the arithmetic operation, difficulty level, and speed (Figure 1; [16]).

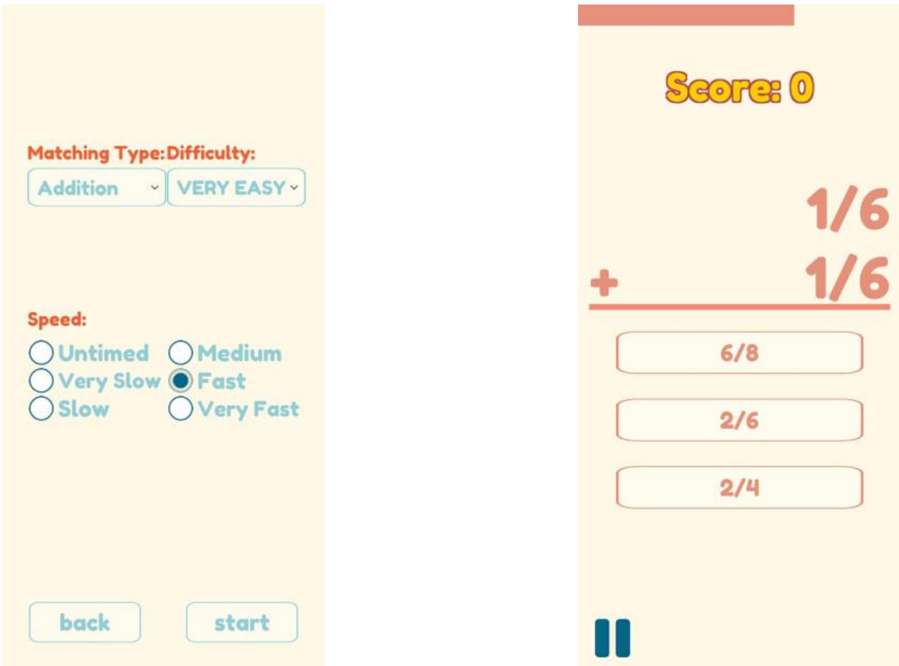

Figure 1. A sample game setting and actual arithmetic problem in Ibigkas! Math.

4.2. Research Design, Data Gathering Procedure and Participants

Two research designs were used in this study. One of the research designs used was a one-group pretest-posttest design [49]. Prior to the intervention period, a pretest was administered. A three-day intervention period followed the pretest. All participants used the same version of Ibigkas! Math. Finally, a posttest was given. A descriptive design was also used because the collected log files were analyzed to determine the participants' usage behaviors [49].

There were two sections of grade 5 students, each of which had 40 students, but only one section participated in the study. Of the 40 students in that section, only 37 participated in the study. The demographics of the participants are shown in Table 1.

Table 1. The demographics of the participants in terms of their age, gender, math abilities, and personality dimensions. Most of the participants are male, have high mathematical abilities, and belong to the Agreeableness personality dimension.

Demographics	Frequency	Percentage
Age *M* = 10.5 years old	-	-
Gender		
Male	25	68
Female	12	32
Math Ability		
Low	8	22
Average	13	35
High	16	43
Personality		
Agreeableness	13	35
Conscientiousness	4	11
Extraversion	3	8
Neuroticism	6	16
Openness	11	30
Total	37	100

Grade 5 students from a private university in Manila participated in this study. The university has an elementary department. They were grouped into three-person teams in terms of mathematical competencies and personality dimensions. Every team consisted of students with different levels of mathematical competencies (struggling/low-, average-, and high-performing) and personality dimensions. The team is homogenous. Teachers identified the mathematical competencies of the students. The classifications are reliable because teachers know the abilities of their students [18,50–52]. The results of the pretest (Table 2) confirmed that the teachers' classifications were correct. Thus, in the study, there were eight struggling students, 13 average students, and 16 high-performing students. Meanwhile, the Big Five personality dimensions (OCEAN) [31] were used to identify the personality dimensions of the students because the items of this instrument are intended to capture the dominant personality dimensions of the children. The descriptions of OCEAN are further discussed in the results section.

Table 2. The mathematics performance of stag and hare students in terms of pretest, posttest, and learning gain.

Mathematics Performance	Stag		Hare	
	M	SD	*M*	SD
Pretest (n = 12)	10.8	0.9	9.2	2.0
Posttest (n = 12)	10.2	1.3	9.4	1.8
Learning Gain	−50.0	99.7	7.1	146.4

The team used the game for a total of 45 min without any interventions from the software or facilitators. Each team member was given equal chances to host the game. The host of the game chose the game settings that include the type of problem solved (addition, subtraction, multiplication, and division), difficulty levels (very easy, easy, medium, hard, and very hard), and speed (very slow, slow, medium, fast, and very fast). The times for each speed setting are as follows: very slow is 35 s, slow is 30 s, medium is 27 s, fast is 20 s, and very fast is 15 s. The game scores are based on the speed setting, but untimed speed has no equivalent points. The points for the other settings are as follows: very slow corresponds to 2 points, slow to 5 points, medium to 10 points, fast to 15 points, and very fast to 20 points. All students were given a token of participation, and the three groups with the highest game scores received prizes. During this process, interactions with the applications were tracked and automatically recorded on the mobile phones.

The pretest-and-posttest research design was adopted from Rodrigo et al. [53]. The pretest was administered before the start of the game, and the posttest was given after the game. Both tests consisted of 12 items (three questions on each of the four arithmetic operations on fractions). Mathematics teachers validated the items on the pretest and posttest. This ensured that the items of the tests were appropriate for the grade levels of the students and conformed to the curriculum [53].

4.3. Data Collection, Pre-Processing, Preparation, Feature Selection, and Data Analysis

The interaction log files from mobile phones were manually collected and encoded in a spreadsheet. The dataset included interaction logs with eight distinct features (i.e., game host, difficulty level, speed, type of problem solved, time start, time end, number of attempts, and correct attempts). The game host (coded as 1 and 0) displays the student who selected the game setting. Correct attempts refer to whether the response is correct or not. Nominal data include the difficulty level, type of problem solved, and correct attempts. Time spent is a derived feature that indicates the time spent answering problems. It is calculated by subtracting time end from time start. The total number of responses provided by learners in answering a given problem is referred to as the number of attempts. Accuracy is calculated by dividing the number of correct attempts by the number of attempts, and numeric data is normalized using z-scores.

The stag and hare hunting behaviors were based on the speed setting that a student chose. Students were labeled as stag hunters if they chose fast or very fast game settings; otherwise, they were labeled as hare hunters [16]. A stag hunter is a student who chooses a faster game setting that entails higher points as well as higher penalties for incorrect answers (e.g., deductions on time). A hare hunter is the exact opposite of a stag hunter—that is, a student who chooses a slower game setting in which there are fewer points and penalties for incorrect answers. Personality dimensions were also included as one of the hypothesized features. Incomplete records (e.g., incomplete or invalid data) were removed from the dataset, whereas log files generated in single-player mode were discarded. Accuracy was excluded in the decision tree modeling.

Seventy percent of the dataset served as the training dataset. Employing forward feature selection using k-NN 10-fold cross-validation with Weight by Chi-Squared Statistic ($\chi 2$(Difficulty Level) = 5159.1; $\chi 2$(Type of Problem Solved) = 951.7; $\chi 2$(Correct Attempts) = 123.9; $\chi 2$(Personality) = 15076.0) and Weight by Correlation (Time Spent, $r = 0.11$; Number of Attempts, $r = 0.09$), all features except Number of Attempts were retained.

Decision tree modeling with accuracy criterion was employed using the selected features to model the behavior of the students in using the application. Using the decision tree modeling dataset, the data for the lag sequential analysis (LSA) was derived. The LSA data was composed of a sequence of game settings in terms of difficulty level and types of problems solved of stag and hare hunters. The data was then analyzed through Generalized Sequential Querier version 5.1.

Normalized learning gain was computed to describe the increase (or decrease) in the scores of the students. Moreover, normalized gain g was computed to determine how much the students learned from the game session. The formula, which is shown in Equation (1), denotes the ratio of the mathematics performance of students to the maximum achievable improvement [54,55].

$$g = \frac{\text{Posttest scores } - \text{ Pretest scores}}{\text{Number of items} - \text{ Pretest scores}} \tag{1}$$

Due to the small sample size, the Mann-Whitney U test was used to establish whether there is a significant difference in game interaction data between the hare and stag hunters [56]. Spearman's rho correlation was employed to determine the relationship between learners' game interaction data and learning gain. To determine the significance of the findings, all statistical tests adopted a 0.05 level of significance with 95% reliability.

5. Results

RQ1: Which of the stag and hare behaviors is beneficial (or harmful) to mathematics achievement?

Table 2 shows the pretest and posttest results. Stag hunters have higher prior knowledge than the hare hunters. The standard deviations of the scores and learning gains show that the mathematics performance of stag hunters is less dispersed than that of the hare hunters. The stag hunters had negative learning gains ($M = -50\%$). On the other hand, the hare hunters had positive learning gains ($M = 7.1\%$). Nevertheless, the test scores of both students were above the passing mark (i.e., half of the number of items).

There are 1745 game sessions (Table 3). A game session refers to the state where a student chooses a game mode. The stag hunters are more likely to choose the very fast game mode, while the hare hunters tend to select a medium speed game mode. This is confirmed in the z-scores shown in Table 4. Stag hunters tend to avoid division problems, while hare hunters try to solve more diverse types of problems. While both tend to solve more addition problems, the z-scores indicate that stag hunters solve addition problems higher than the average. The z-scores also suggest stag hunters tend to avoid subtraction and multiplication problems, which is the opposite of what the hare hunters do.

Table 3. The selected game modes of the students in the Ibigkas! Math in terms of level of difficulty, and types of arithmetic problems solved.

	Hare		Stag			
Game Modes	**Frequency**	**Percentage**	**Frequency**	**Percentage**	**Total**	**Percentage**
Level of Difficulty						
Very easy	377	21.6	237	13.6	614	35.2
Easy	389	22.3	382	21.9	771	44.2
Medium	165	9.5	159	9.1	324	18.6
Hard	4	0.2	0	0.0	4	0.2
Very hard	5	0.3	27	1.5	32	1.8
Speed						
Very slow	66	3.8	35	2.0	101	5.8
Slow	112	6.4	43	2.5	155	8.9
Medium	673	38.6	147	8.4	820	47.0
Fast	27	1.5	128	7.3	155	8.9
Very fast	62	3.6	452	25.9	514	29.5
Types of Problem						
Addition	898	51.4	788	45.2	1686	96.6
Subtraction	23	1.31	5	0.3	28	1.6
Multiplication	14	0.81	12	0.7	26	1.5
Division	5	0.28	0	0	5	0.29
Total	940	53.8	805	46.2	1745	100%

Table 4. The frequencies of game mode settings were standardized by using z-scores. Hare hunters solved a more diverse range of arithmetic problems, while stag hunters were more inclined to solve addition problems.

	Hare (n = 25)					Stag (n = 12)				
Game Modes	***M***	**SD**	**Min**	**Max**	**z-Score**	***M***	**SD**	**Min**	**Max**	**z-Score**
Level of Difficulty										
Very easy	41	54	0	159	−0.09	53	42	0	108	0.19
Easy	28	66	0	334	−0.25	106	136	0	334	0.52
Medium	19	19	0	52	−0.07	26	48	0	127	0.14
Hard	0.48	1.33	0	4	0.12	0	0	0	0	–
Very hard	3	7	0	27	−0.01	3	8	0	27	0.01
Speed										
Very slow	3	6	0	24	−0.01	3	8	0	29	0.03
Slow	4	9	0	30	0.04	4	7	0	21	−0.07
Medium	27	54	0	276	0.11	12	16	0	40	−0.22
Fast	1	4	0	13	−0.33	11	13	0	40	0.69
Very fast	2	10	0	50	−0.33	37	52	0	170	0.70
Types of Problem										
Addition	88	75	7	366	−0.30	188	137	61	371	0.63
Subtraction	2	6	0	21	0.01	2	6	0	20	−0.03
Multiplication	2	4	0	12	0.06	1	3	0	12	−0.13
Division	0.4	1	0	5	−0.004	0	0	0	0	–

The game sessions generated 4628 solved arithmetic problems (Table 5). On average, students solved 2.7 problems per minute (4628 arithmetic problems/(37 students × 3 sessions × 15 min per session)). This result is achievable because each game setting could last from 15 to 35 s. Stag hunters (M = 1.2 s, z-score = −0.61) answered the questions more quickly than did the hare hunters (M = 1.6 s, z-score = 0.29). Stag hunters had more attempts to answer a problem before getting the correct one (M = 535.7, SD = 712.5, z-score = 0.44). When the average number of attempts is divided by the average number of problems (535.7/173.3~3.1), an average of 3.1 is computed. This is the average number of attempts per problem. This result implies that stag hunters select all the possible choices just to get the correct answer, which, in turn, increases the accuracy rate. On the one hand, hare hunters (M = 182.4, SD = 420.3, z-score = −0.21) take about 1 to 2 selections (182.4/125.5~1.5) before they can hit the correct answer. The z-scores of average attempts confirm that stag hunters took more attempts on average than did the hare hunters.

Stag hunters had more correct attempts (M = 68.7, SD = 54.3, z-score = 0.56) than did the hare hunters (M = 30.4, SD = 36.0, z-score = −0.27). Similarly, the stag hunter (M = 46.9, SD = 49.2, z-score = 0.47) had higher chances of getting the correct answer than the hare hunters did (M = 25.3, SD = 12.6, z-score = −0.23). This is because stag hunters selected all three given choices. Stag hunters (M = 188.3, SD = 137.4, z-score = 0.63) were more likely to answer addition problems than their counterparts (M = 87.7, SD = 75.2, z-score = −0.30). Mann-Whitney U tests show that there is a significant difference between the game interactions of the two groups in terms of time spent answering a problem, number of attempts, number of correct attempts, accuracy, and number of addition problems (Table 6).

Table 5. Learners' game interaction data (e.g., number of problems solved, time spent answering a problem, number of attempts, etc.) were standardized using z-scores.

Learners' Game Interaction Data	Game Behavior									
	Hare (n = 25)					Stag (n = 12)				
	M	SD	z-Score	Min	Max	M	SD	z-Score	Min	Max
Number of Problems Solved (NPS)	125.5	90.7	−0.15	51	316	173.3	127.3	0.31	63	371
Time Spent Answering a Problem (s)	1.6	0.5	0.29	0.6	2.84	1.2	0.5	−0.61	0.61	1.88
Number of Attempts	182.4	420.3	−0.21	11	1857	535.7	712.5	0.44	15	2033
Number of Correct Attempts (NCA)	30.4	36.0	−0.27	1	177	68.7	54.3	0.56	13	181
Accuracy (NCA/NPS)	25.3	12.6	−0.23	0.95	56	46.9	49.2	0.47	21	201
Number of Problems Solved—Very Easy	40.9	54.2	−0.09	0	159	54.9	42.3	0.19	0	108
Number of Problems Solved—Easy	28.8	65.7	−0.25	0	334	105.6	136.5	0.52	0	334
Number of Problems Solved—Medium	19.9	19.5	−0.07	0	52	26.3	48.5	0.14	0	127
Number of Problems Solved—Hard	0.5	1.3	0.14	0	4	–	0	–	0	0
Problems Solved—Very Hard	2.6	7.5	−0.01	0	27	2.7	7.8	0.01	0	27
Number of Problems Solved—Addition	87.7	75.2	−0.30	7	366	188.3	137.4	0.63	61	371
Number of Problems Solved—Subtraction	2.3	5.8	0.01	0	21	2.1	5.8	−0.03	0	20
Number of Problems Solved—Multiplication	2.1	4.1	0.06	0	12	1.3	3.5	−0.13	0	12
Number of Problems Solved—Division	0.4	1.4	−0.004	0	5	0.4	1.4	0.01	0	5

Table 6. Mann-Whitney *U* test was employed to determine whether there is significant difference on the game interaction data between hare and stag hunters. This statistical test confirms that there is a significant difference between the interactions of the groups in terms of time spent, number of attempts, number of correct attempts, accuracy, and number of addition problems solved.

Learners' Game Setting Data	Mann-Whitney *U*	*p*-Value
Number of Problems Solved	98.5	0.094
Time Spent Answering a Problem (in seconds)	76.0	0.016 *
Number of Attempts	86.5	0.039 *
Number of Correct Attempts	64.0	0.005 **
Accuracy	75.0	0.015 *
Number of Problems Solved—Very Easy	120.0	0.315
Number of Problems Solved—Easy	130.0	0.514
Number of Problems Solved—Medium	117.0	0.267
Number of Problems Solved—Hard	132.0	0.217
Number of Problems Solved—Very Hard	149.0	0.960
Number of Problems Solved—Addition	57.0	0.002 **
Number of Problems Solved—Subtraction	135.0	0.518
Number of Problems Solved—Multiplication	138.5	0.643
Number of Problems Solved—Division	149.5	0.973

* Difference is significant at 0.05. ** Difference is significant at 0.01.

Answering easy problems for the hare hunters has a moderately positive relationship with their learning gain (Spearman r = 0.475, $p < 0.05$) (Table 7). The result suggests that hare hunters are more cautious in answering problems (Table 7). For the stag hunters, all game settings data relating to number of attempts (Spearman r = −0.54, $p < 0.05$), number of correct attempts (Spearman r = −0.77, $p < 0.05$), accuracy (Spearman r= −0.61, $p < 0.05$), and addition problems (Spearman r = −0.60, $p < 0.05$) have a moderate to strong negative relationship with their learning gains. While high interaction data may seem favorable to students, the findings suggest otherwise.

Table 7. Spearman's rho rank correlation showed that the number of problems solved by hare hunters was positively related to their learning gain. Meanwhile, the interactions of the stag hunters were negatively related to their learning gains.

Learners' Game Interaction Data	Learning Gain			
	Hare (n = 25)		Stag (n = 12)	
	R	p-Value	r	p-Value
Number of Problems Solved	0.18	0.381	−0.56	0.061
Time Spent Answering a Problem (in seconds)	−0.08	0.707	0.06	0.859
Number of Attempts	0.18	0.376	−0.54	0.068 *
Number of Correct Attempts	0.27	0.197	−0.77	0.004 **
Accuracy	0.165	0.431	−0.61	0.036 *
Number of Problems Solved—Very Easy	0.16	0.438	0.272	0.393
Number of Problems Solved—Easy	0.475	0.016 *	−0.279	0.379
Number of Problems Solved—Medium	−0.074	0.725	−0.415	0.179
Number of Problems Solved—Hard	0.112	0.595	–	–
Number of Problems Solved—Very Hard	0.257	0.215	0.083	0.798
Number of Problems Solved—Addition	0.195	0.351	−0.60	0.040 *
Number of Problems Solved—Subtraction	0.288	0.163	0.265	0.405
Number of Problems Solved—Multiplication	0.031	0.884	0.523	0.081
Number of Problems Solved—Division	0.319	0.120	−0.090	0.782

* Correlation significant at 0.05. ** Correlation significant at 0.01.

6. RQ2: What Features Describe the Stag and Hunting Behaviors of the Students?

The model correctly classified 76.1% of the instances classified using the decision tree model (Figure 2). The precision means that 83.3% of the students belong to the actual "stag" class among all the students predicted to be "stag" (Table 8). Under the class "stag", the classifier can correctly label 83.3% of the students who are stag hunters. In other words, when the decision tree model predicts the student as a stag hunter, the model is correct 83.3% of the time. Recall signifies that 72.2% of the "stag" students have been correctly identified as "stag-hunter" students.

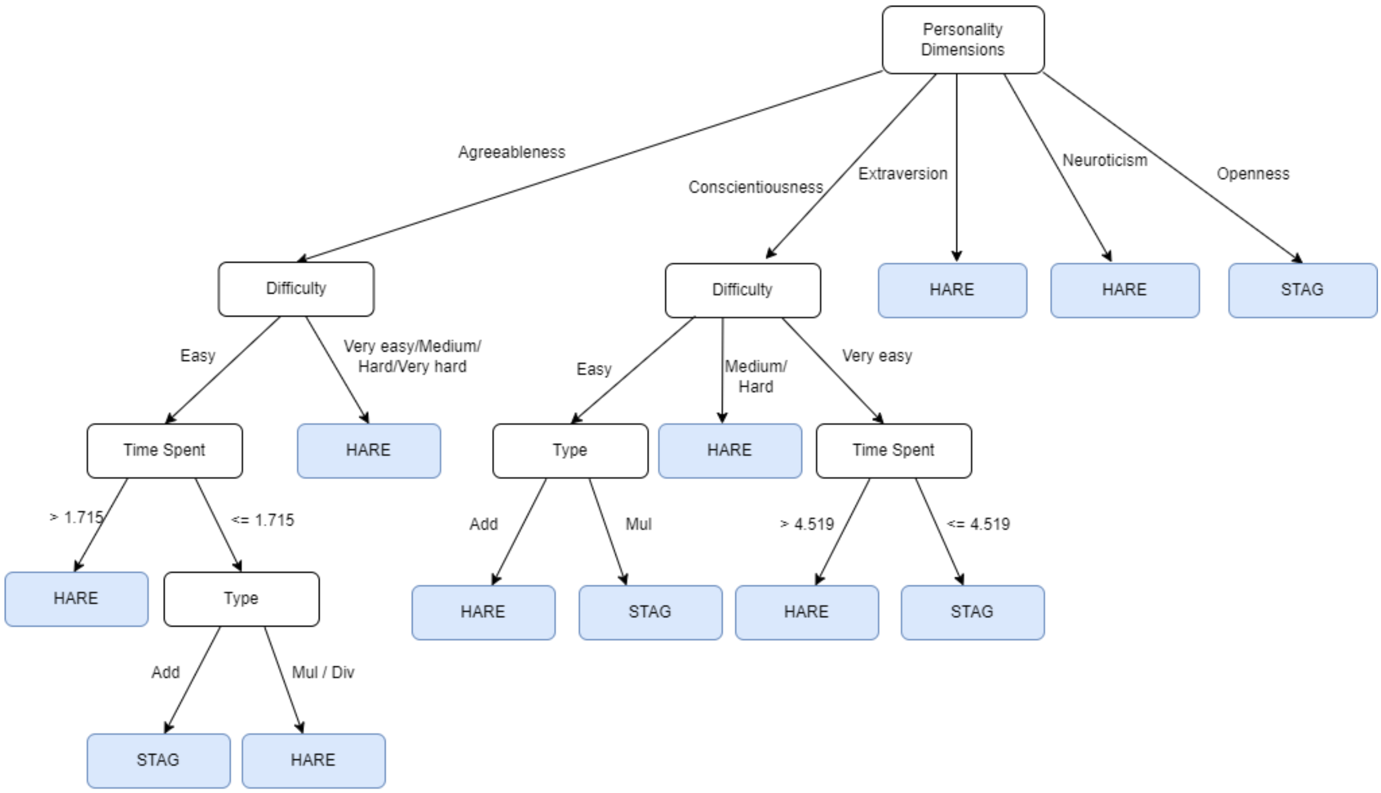

Figure 2. This decision tree shows the characteristics of stag and hare hunter students. Personality dimensions are the primary predictor of stag and hare hunting behavior.

Table 8. A confusion matrix was employed to determine the accuracy and precision of the model shown in Figure 2.

		Labels Returned by the Classifier	
		Stag	**Hare**
True labels	Stag	350	135
	Hare	70	304
Accuracy = 76.1%			
Precision(Stag) = 83.3%			
Recall(Stag) = 72.2%			
Precision(Hare) = 69.3%			
Recall(Hare) = 81.3%			

Personality dimensions primarily predict stag and hare hunting behaviors. Students who display high Openness personality traits are more likely to become stag hunters. The keenness to try new things and experiences—the dominant characteristics of people displaying Openness personality traits—explains why students are thrilled to have faster game settings. Students who display high Extraversion personality traits are known to be talkative, energetic, and assertive. Students who display high Neuroticism personality traits are more likely to be hare hunters. They are known to be moody and tense. They regulate these traits by choosing a slow-paced game setting.

Students who display high Conscientiousness are also categorized as hare hunters. They are characterized as being organized, methodical, and thorough. Students who display an enhanced Agreeableness personality trait tend to be classified as hare hunters. However, they also display characteristics of stag hunters when they solve addition problems. They are characterized as friendly and cooperative. They may consult other team members when choosing which game setting the group may want to play and agree to such recommendations. This explains why they tend to exhibit both gaming behaviors.

7. RQ3: What Is the Usage Behavior of Students in Terms of the Level of Difficulty and Types of a Problem Solved?

States are defined as different game modes. A state transition is the shifting of game mode to another game mode per game session. The transition labels are in the form of a conditional probability/z-score. A z-score of at least 1.96 is considered significant [57]. Arrows in darker lines show significant transitions. Students are given all equal chances to choose game settings.

There is a high probability (95%) that stag hunters will choose problems with a medium level of difficulty (Figure 3). They are more likely to switch from easy to medium and vice versa. This means that they will choose a step lower or a step higher level of difficulty. Stag hunters are more likely to choose only the first-three levels of difficulty (very easy, easy, and medium levels). This is because they are more interested in increasing their game scores.

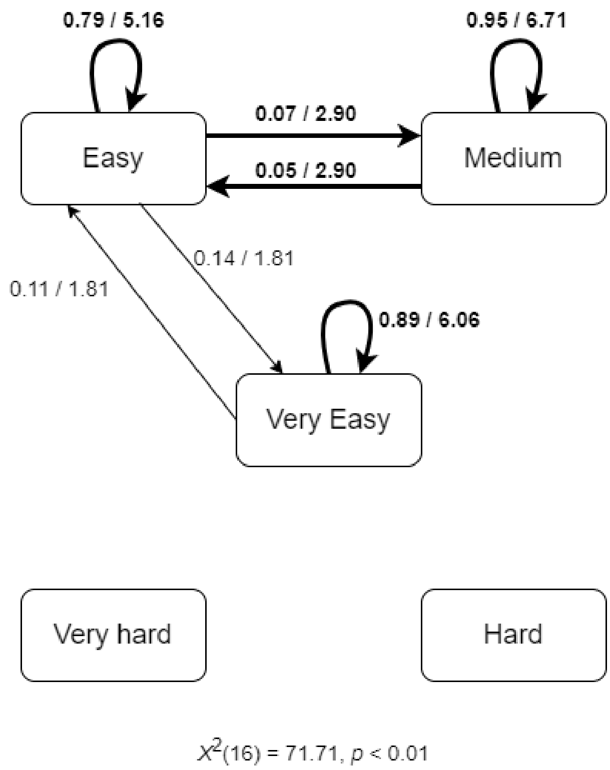

Figure 3. This figure shows the sequential problem-solving behavior of stag hunters in terms of difficulty of problem solved. Stag hunters avoid hard and very hard problems.

Hare hunters have a high tendency (83%) to solve very easy problems (Figure 4). Unlike the stag hunters, the hare hunters will switch from very easy to medium problems (and vice versa), which are two steps lower (or higher) in level of difficulty. Even though there are insignificant transitions, the result shown in Figure 4 suggests that hare hunters will attempt to answer problems of varying difficulties. Although there is a small possibility (6%), hare hunters will shift from medium to hard problems. It is an indication that hare hunters try to advance their problem-solving skills. Hare hunters are more explorative and cautious problem solvers. For hare hunters, the primary motivation in the game is learning the content, not the possible prize they could win.

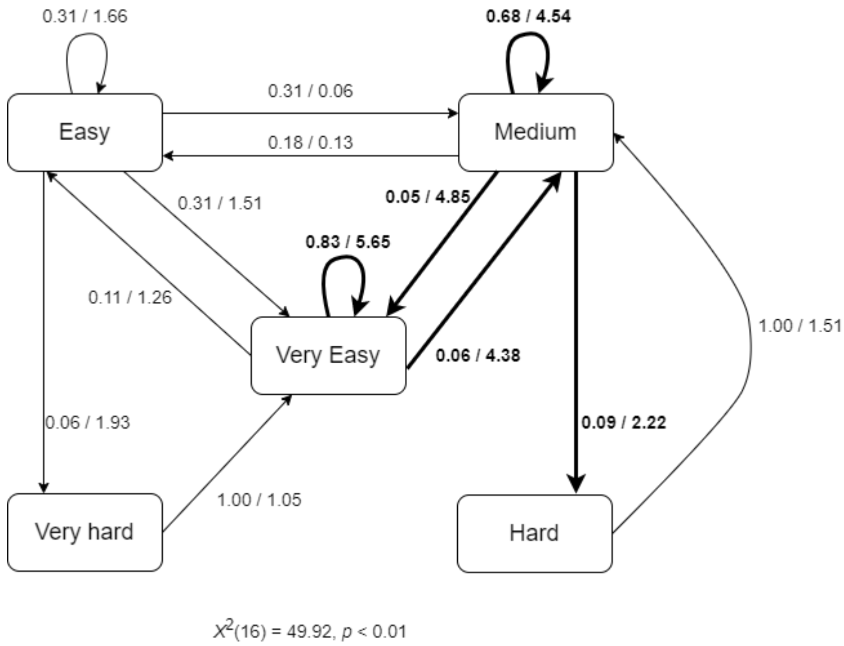

Figure 4. The sequential problem-solving behavior of hare hunters in terms of difficulty of problem solved shows that hare hunters solved diverse types of arithmetic problems.

There are no significant transitions in terms of the types of problems solved by stag hunters (Figure 5). This discovery is attributed to uneven frequency distributions of state transitions in terms of problem types solved. Nevertheless, the state transition diagram in Figure 6 shows that the hare hunters are more likely to shift to and from addition and multiplication. Furthermore, Figure 5 shows that, 98% of the time, addition problems will be selected in the next game setting. Stag hunters will avoid changing the operations to division.

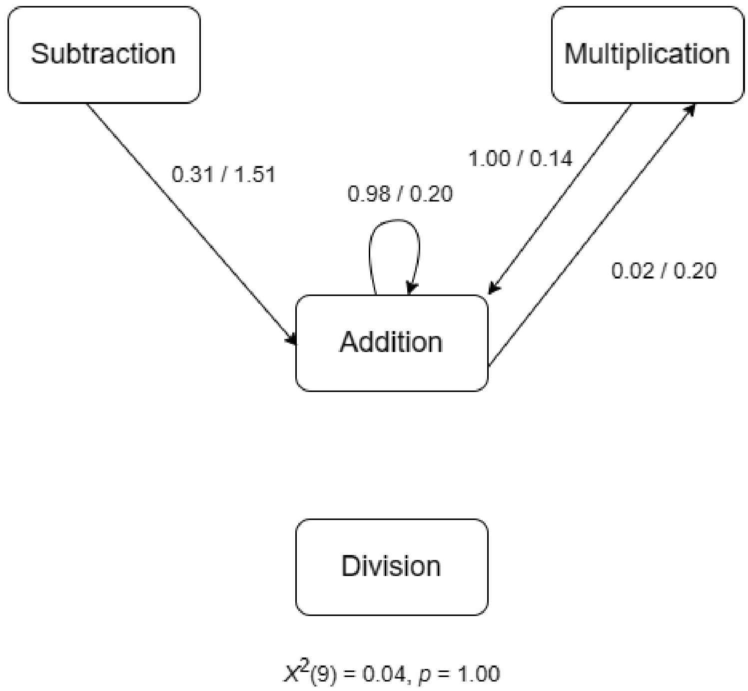

Figure 5. The sequential problem-solving behavior of stag hunters in terms of types of problem solved disclosed that stag hunters are more likely to choose an addition or multiplication arithmetic problems.

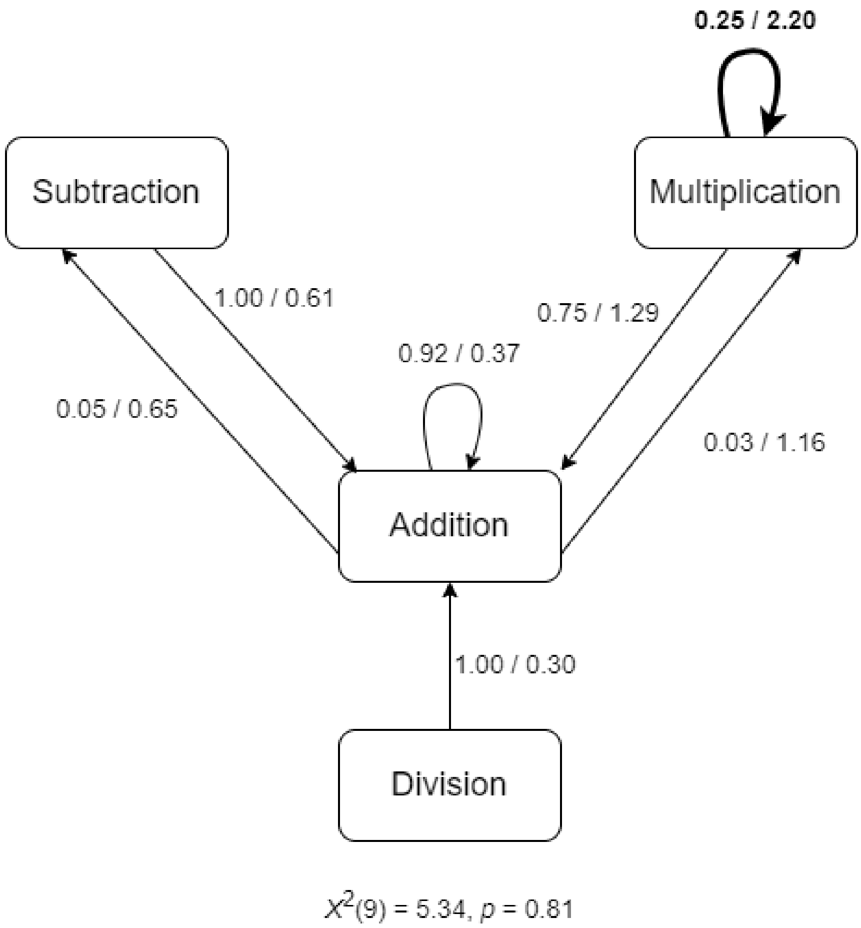

Figure 6. The sequential problem-solving behavior of hare hunters in terms of types of problem solved revealed that they were solving all types of arithmetic problems.

Meanwhile, there is a 25% chance to choose a multiplication type of problem (Figure 6). All other transitions are not significant. Nonetheless, hare hunters are open to solving diverse types of problems (Figure 6). It is worth noting that hare hunters attempted to answer subtraction and division problems. If they find it difficult, they switch back to answering problems in addition.

Overall, the types of problems solved, and the level of difficulty have between four and five options. There are 20 (4×5) possible combinations of states (or game settings) that a student may choose. There are 400 (20×20 states) transitional probabilities. Students chose 10 out of the 20 possible game modes. Out of the 400 possible transitional probabilities, addition with varying difficulty levels is the most preferred setting. Among these settings, addition with very easy difficulty level is the most preferred. When the students chose to switch from easy division problems to addition with a hard difficulty level, they chose addition with a hard difficulty level. Also, it is most probable that students will choose their current game modes again for the next game session (EA_ADD → EA_ADD = 53%; VE_ADD → VE_ADD = 78%; MD_ADD → MD_ADD = 76%).

8. Discussion

The purpose of this study was to describe students' stag and hare hunting behaviors in a mobile-based CSCL. According to the findings of this study, stag and hare hunters prefer easy problems. They prefer the addition of fractions because it is the easiest type of problem that can be solved in a time-constrained game. Statistical analysis shows that the interaction data in terms of the number of problems solved are also similar, which suggests that both sets of participants are engaged in the experiment.

The study found empirical evidence for the distinct traits of stag and hare hunters in choosing game modes and game interaction. Hare hunters would attempt to solve different types of arithmetic problems solved with varying degrees of difficulty. This game behavior may not be beneficial for the game since it would entail lower game scores. On the other hand, stag hunters stick to solving addition problems in a fast or very fast mode. Consistent with the definition of Skyrms [20,21], stag hunters are more inclined to choose game settings with higher payoffs but higher risk. The findings of this study indicate that the game interactions of stag hunters are higher than those of hare hunters. While these results seem to be desirable since higher interactions with CSCL are positively related to academic performance [23,25–27], the results of this current study suggest otherwise.

The correlation coefficients reveal that the game interactions of the stag hunters are negatively related to learning gain. In the context of this study, the high number of interactions with the mobile-based CSCL does not positively contribute to students' learning since it is an indication that the stag hunters passively select answers. This would result in a superficial indication that students get a higher number of correct answers in a short time. On the other hand, hare hunters are cautious before they choose an answer. This process is slower, which leads to more time spent but with a lower number of attempts and accuracy rate. Nevertheless, this "slow but sure" attitude can lead to a 7% increase in their mathematics scores. The finding of the study that higher interactions or engagements in a computerized learning environment can lead to higher academic performance contradicts the findings of Siqin et al. [25] and Tirado-Morueta et al. [26]. This disagreement could be attributed to the context of the current study. The current study was carried out in a setting where students compete for higher points, and the results of the tests had no bearing on their grades in their subject. As a result, the engagements measured in this study may only reflect the students' desire to win the game.

The stag and hunting behaviors of the students are primarily attributed to personality dimensions. This current study provides empirical evidence that personalities do influence the interaction with the learning systems [7]. It also contributes to the existing literature by showing that stag and hare hunting behaviors exist in mobile-based CSCL, which consequently extends the current classifications of learners in this learning environment. Mathematics teachers benefit from this result as it suggests that personality dimensions and prior mathematics achievement can be considered when forming groups in collaborative mathematics learning activities.

Students who exhibited high Open personality trait are more likely to engage a stag behavior. This finding confirms the findings of the studies of Sánchez Hórreo and Carro [36] and Baer et al. [37] that the characteristics of people in this personality dimension (i.e., open to experience) contribute to the welfare of the group (i.e., higher engagement). However, this characteristic does not contribute to learning performance. Students with this characteristic are more focused on experiencing the creative and fun aspects of the game ([34] cited in [35]). In other words, they are distracted by the creative components of the game and may not focus on the true goal of the mobile CSCL.

Students who exhibit high Conscientiousness, Agreeableness, Extraversion, and Neuroticism personality traits are classified as hare hunters while students who show high Conscientiousness personality traits are motivated to learn from the activity [32,38,41]. This characteristic is shared by a student who belongs to the Agreeableness personality dimension. According to different studies [35,44], a person in this personality dimension is expected to be cooperative. Hence, students in this personality dimension are expected to perform in accordance with the team's goal. Meanwhile, students in the Extraversion personality exude positive behaviors (e.g., emotionally positive, energetic, confident, etc.) that could contribute to the welfare of the team [35,44]. These traits may influence other members of the team to achieve the goal of the game. In summary, previous studies showed [40,41] that people with enhanced personality traits of Conscientiousness, Agreeableness, and Extraversion are mostly task and group performers—traits that are desirable in a team member [38]. Therefore, hare hunters have the sought-after characteristics of a team member.

Students who show personality traits of high Neuroticism are also hare hunters. People in this taxon are known for being moody, easily getting upset, tense, and worrisome, all of which harm group dynamics [35] and affectivity [45]. However, the result of this study contradicts the image of people in this taxon reported in the existing literature. Although the characteristics of people showing high Neuroticism personality traits have negative connotations, these characteristics turn out to be helpful traits in this study. For example, students tend to regulate these traits by lowering their expectations. They do this by selecting a game mode with a slower pace and fewer penalties. Consequently, their game interactions with the mCSCL are substantial enough to be categorized as hare hunters. The disagreement of this finding with prior research can be attributed to the fact that students are driven by a common learning goal. Future researchers may further investigate the goal-setting behaviors of students who fall in the Neuroticism personality dimension and how these behaviors influence gameplay.

It can be observed from the decision tree model that three out of the five hypothesized game interaction variables are significant features to detect stag and hare hunting behaviors. This study provides further evidence from the study of Piki [29] that behavior engagement in a CSCL could serve as a basis for classifying CSCL learners. Therefore, stag and hare hunters could be distinguished in terms of their personality dimensions, types of problems they solve, level of difficulty they choose, and time they spend solving problems.

Lag sequential analyses further describe the engagement of stag and hare hunters in terms of the sequence of types of problems solved and the level of problem difficulty. The findings of this study extend the current literature in two ways. First, this current study shows that mathematics learners in an mCSCL can be characterized through decision tree and lag sequential analysis. This extends the learners' classification of previous studies [22–27,46,47]. Second, it was shown that mathematics mCSCL can be classified through their gaming behaviors based on the concept proposed by Skyrms [20,21]. Particularly, stag and hare hunters have distinct patterns of problem-solving behaviors. Stag hunters are complacent when solving easy or medium-level problems, while hare hunters are the exact opposite of stag hunters.

Meanwhile, hare hunters explore all difficulty levels even though the game scores do not depend on the level of problem difficulty. The transition labels in Figure 4 show that the transitions from Very Easy $\rightarrow$ Medium $\rightarrow$ Difficult are significant, indicating that hare hunters attempt to progress their level of mathematics skills. These distinct problem-solving behaviors could further explain why the hare hunters managed to increase their mathematics scores. The overall LSA suggests that all students are more focused on solving addition problems with varying degrees of difficulty. These findings provide important key points in the development of mCSCL.

9. Conclusions, Recommendations, and Implications

This study attempted to determine whether the stag and hare behaviors are beneficial to mathematics achievement, whether the learners' game interaction and personality dimensions describe these behaviors, and whether the problem-solving behavior of students exhibits a significant pattern. The study provided empirical evidence to conclude that (a) hare hunting behavior is beneficial to mathematics achievement, (b) learners' game interaction in terms of difficulty level, time spent, type of problem solved, and personality dimensions do describe gaming behaviors, and (c) students exhibit a significant pattern of problem-solving behaviors. Therefore, all hypotheses in this study are partially supported.

Stag and hare hunters could be distinguished in terms of their personality dimensions, the types of problems they solve, the level of difficulty they choose, the time they spend solving problems, and their problem-solving patterns. More specifically, stag hunters are most likely to belong to the Openness personality dimension that describes them as imaginative, insightful, daring, and creative. They are also likely to solve problems more quickly than hare hunters, and to stick to the same levels and types of problems. Meanwhile, hare hunters may display four of the Big Five personality traits, which are Conscientiousness, Extraversion, Agreeableness, and Neuroticism. They tend to solve problems slower than the stag hunters and tend to attempt problems of varying degrees and types.

There are theoretical and practical implications derived from the findings. First, this study shows that students' engagement in an mCSCL goes beyond being classified as social loafers or bystanders. Unlike social loafers, who have no intention to interact with other team members, students in this study reduced their participation because of associated risks (e.g., wrong answers entail deduction of time). The second theoretical implication relates to this finding. When students are given the freedom to choose the level of participation that they are comfortable with, they are expected to perform in that chosen environment. Their low game interactions do not necessarily mean that they are not engaged in the mCSCL; rather, it reflects being careful. The third theoretical implication is that this study discovered a new perspective about the group interaction of people with neurotic personalities. Further research is recommended to understand the academic goals of students displaying high level of Neuroticism personality trait and how this affects their interactions in an mCSCL.

The practical implications of the results of the study include the following: (1) detect the stag and hare hunting behaviors and make it adaptive to these gaming behaviors; (2) increase the points for types of problems and level of difficulty; (3) encourage game users to explore more problems; (4) include a more stringent penalty to avoid stag behaviors; and (5) provide post-game support to address the problem-solving weaknesses of the students.

Finally, future research could be conducted to determine the impact of these game design changes on game interaction and mathematics learning, and the results of this study could inform mathematics educators that, to achieve optimal mathematics learning in collaborative activities, gender, personality dimensions, and prior mathematics performance could serve as the basis for group composition.

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Informed Consent Statement: Informed consent was obtained from the students, teachers, and parents before students could participate in this study. Informed consent was included in the document used to obtain ethics approval. Informed consent was obtained from all subjects involved in the study.

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Abbreviations

ADD	Addition
CSCL	Computer-Supported Collaborative Learning
DIV	Division
EA	Easy
g	Learning gain
HA	Hard
ICT	Information and Communication Technology
ID	Identification
k-NN	k-nearest neighbor
LSA	Lag Sequential Analysis
M	Mean
Max	Maximum
MD	Medium
Min	Minimum
MUL	Multiplication
RQ	Research Question
SNA	Social Network Analysis
STEM	science, technology, engineering, and mathematics education
WISE	Withdrawn, Impulsive, Strategic, and Enthusiastic
OCEAN	Openness (or Openness to experience), Conscientiousness, Extraversion, Agreeableness, and Neuroticism
OKC	Online Knowledge Communities
SD	Standard Deviation
SUB	Subtraction
VE	Very easy
VH	Very hard

References

1. Ludvigsen, S.; Mørch, A. Computer-supported collaborative learning: Basic concepts, multiple perspectives, and emerging trends. In *The International Encyclopedia of Education*; McGaw, B., Peterson, P., Baker, E., Eds.; Elsevier: Amsterdam, The Netherlands, 2010; Volume 5, pp. 290–296.
2. Udvari-Solner, A. Collaborative learning. In *Encyclopedia of the Sciences of Learning*; Seel, N.M., Ed.; Springer: Boston, MA, USA, 2012; pp. 631–634. [CrossRef]
3. UNESCO. Information and Communication Technologies. 2017. Available online: https://learningportal.iiep.unesco.org/en/glossary/information-and-communication-technologies-ict (accessed on 10 January 2023).
4. Bringula, R.P.; Atienza, F.A.L. Mobile computer-supported collaborative learning for mathematics: A scoping review. *Educ. Inf. Technol.* **2022**, 1–26. [CrossRef] [PubMed]
5. Gillies, R.M. Cooperative learning: Review of research and practice. *Aust. J. Teach. Educ.* **2016**, *41*, 39–54. [CrossRef]
6. Gokhale, A.A. Collaborative learning enhances critical thinking. *J. Technol. Educ.* **1995**, *7*, 22–30. [CrossRef]
7. Chen, Z.; Lin, T. Automatic personality identification using writing behaviours: An exploratory study. *Behav. Inf. Technol.* **2017**, *36*, 839–845. [CrossRef]
8. Shea, J.H. Problems with collaborative learning. *J. Geol. Educ.* **1995**, *43*, 306–308. [CrossRef]
9. Collett, D.; Kanuka, H.; Blanchette, J.; Goodale, C. *Learning Technologies in Distance Education*; University of Alberta: Edmonton, AB, Canada, 1999.
10. Kanuka, H.; Garrison, D.R. Cognitive presence in online learning. *J. Comput. High. Educ.* **2004**, *15*, 21–39. [CrossRef]
11. Osman, G.; Duffy, T.M.; Chang, J.Y.; Lee, J. Learning through collaboration: Student perspectives. *Asia Pac. Educ. Rev.* **2011**, *12*, 547–558. [CrossRef]
12. Williams, K.D.; Karau, S.J. Social loafing and social compensation: The effects of expectations of co-worker performance. *J. Personal. Soc. Psychol.* **1991**, *61*, 570. [CrossRef]
13. Chidambaram, L.; Tung, L.L. Is out of sight, out of mind? An empirical study of social loafing in technology-supported groups. *Inf. Syst. Res.* **2005**, *16*, 149–168. [CrossRef]
14. Piezon, S.L.; Donaldson, R.L. Online groups and social loafing: Understanding student-group interactions. *Online J. Distance Learn. Adm.* **2005**, *8*, 1–11.
15. Shiue, Y.C.; Chiu, C.M.; Chang, C.C. Exploring and mitigating social loafing in online communities. *Comput. Hum. Behav.* **2010**, *26*, 768–777. [CrossRef]

16. Bringula, R.; Rodrigo, M.M.T. Can "Stag-and-Hare Hunt" Behavior be Modeled using Interaction Data from a Mobile-Supported Collaborative Learning Application? In Proceedings of the 27th International Conference on Computers in Education, Taoyuan County, Taiwan, 2–6 December 2019; Volume 2, pp. 763–766.
17. Uz Bilgin, C.; Gul, A. Investigating the effectiveness of gamification on group cohesion, attitude, and academic achievement in collaborative learning environments. *TechTrends* **2020**, *64*, 124–136. [CrossRef]
18. Bringula, R.P.; Fosgate, I.C.O., Jr.; Garcia, N.P.R.; Yorobe, J.L.M. Effects of pedagogical agents on students' mathematics performance: A comparison between two versions. *J. Educ. Comput. Res.* **2018**, *56*, 701–722. [CrossRef]
19. Rousseau, J.-J. *Discourse on the Origin of Inequality*; Hackett Publishing Co.: Indianapolis, Indiana, 1992.
20. Skyrms, B. The stag hunt. *Proc. Address Am. Philos. Assoc.* **2001**, *75*, 31–41. [CrossRef]
21. Skyrms, B. *The Stag Hunt and the Evolution of Social Structure*; Cambridge University Press: Cambridge, UK, 2004.
22. Lipponen, L.; Rahikainen, M.; Lallimo, J.; Hakkarainen, K. Patterns of participation and discourse in elementary students' computer-supported collaborative learning. *Learn. Instr.* **2003**, *13*, 487–509. [CrossRef]
23. Kim, M.K.; Ketenci, T. Learner participation profiles in an asynchronous online collaboration context. *Internet High. Educ.* **2019**, *41*, 62–76. [CrossRef]
24. Noroozi, O.; Biemans, H.J.; Busstra, M.C.; Mulder, M.; Chizari, M. Differences in learning processes between successful and less successful students in computer-supported collaborative learning in the field of human nutrition and health. *Comput. Hum. Behav.* **2011**, *27*, 309–318. [CrossRef]
25. Siqin, T.; Van Aalst, J.; Chu, S.K.W. Fixed group and opportunistic collaboration in a CSCL environment. *Int. J. Comput. Support. Collab. Learn.* **2015**, *10*, 161–181. [CrossRef]
26. Tirado-Morueta, R.; Maraver-López, P.; Hernando-Gómez, Á. Patterns of participation and social connections in online discussion forums. *Small Group Res.* **2017**, *48*, 639–664. [CrossRef]
27. Kapur, M.; Kinzer, C.K. Examining the effect of problem type in a synchronous computer-supported collaborative learning (CSCL) environment. *Educ. Technol. Res. Dev.* **2007**, *55*, 439–459. [CrossRef]
28. Fields, D.; Giang, M.; Kafai, Y. Understanding Collaborative Practices in the Scratch Online Community: Patterns of Participation among Youth Designers. CSCL Proceedings Volume 1 (pp. 200–207). 2013. Available online: https://repository.isls.org/handle/1/1810 (accessed on 10 January 2023).
29. Piki, A. Learner Engagement in Computer-Supported Collaborative Learning Activities: Natural or Nurtured? In *International Conference on Learning and Collaboration Technologies*; Springer: Cham, Switzerland, 2014; pp. 107–118.
30. Marcos-García, J.A.; Martínez-Monés, A.; Dimitriadis, Y. DESPRO: A method based on roles to provide collaboration analysis support adapted to the participants in CSCL situations. *Comput. Educ.* **2015**, *82*, 335–353. [CrossRef]
31. John, O.P.; Srivastava, S. The Big-Five trait taxonomy: History, measurement, and theoretical perspectives. In *Handbook of Personality: Theory and Research*, 2nd ed.; Pervin, L.A., John, O.P., Eds.; Guilford Press: New York, NY, USA, 1999; pp. 102–138.
32. Costa, P.T.; McCrae, R.R. *Neo Personality Inventory-Revised (NEO PI-R)*; Psychological Assessment Resources: Lutz, FL, USA, 1992.
33. Goldberg, L.R. The development of markers for the Big-Five factor structure. *Psychol. Assess.* **1992**, *4*, 26–42. [CrossRef]
34. McCrae, R.R.; John, O.P. An introduction to the five-factor model and its applications. *J. Personal.* **1992**, *60*, 175–215. [CrossRef]
35. Müller, J.; Schwieren, C. Big five personality factors in the trust game. *J. Bus. Econ.* **2020**, *90*, 37–55. [CrossRef]
36. Sánchez Hórreo, V.; Carro, R.M. Studying the impact of personality and group formation on learner performance. In *International Conference on Collaboration and Technology*; Springer: Berlin/Heidelberg, Germany, 2007; pp. 287–294.
37. Baer, M.; Oldham, G.R.; Jacobsohn, G.C.; Hollingshead, A.B. The personality composition of teams and creativity: The moderating role of team creative confidence. *J. Creat. Behav.* **2008**, *42*, 255–282. [CrossRef]
38. Curşeu, P.L.; Ilies, R.; Vîrgă, D.; Maricuţoiu, L.; Sava, F.A. Personality characteristics that are valued in teams: Not always "more is better"? *Int. J. Psychol.* **2019**, *54*, 638–649. [CrossRef]
39. Kucukozer-Cavdar, S.; Taskaya-Temizel, T. Analyzing the effects of the personality traits on the success of online collaborative groups. *Procedia-Soc. Behav. Sci.* **2016**, *228*, 383–389. [CrossRef]
40. Barrick, M.R.; Stewart, G.L.; Neubert, M.J.; Mount, M.K. Relating member ability and personality to work-team processes and team effectiveness. *J. Appl. Psychol.* **1998**, *83*, 377. [CrossRef]
41. Richardson, M.; Abraham, C. Conscientiousness and achievement motivation predict performance. *Eur. J. Personal.* **2009**, *23*, 589–605. [CrossRef]
42. Peeters, M.A.; Van Tuijl, H.F.; Rutte, C.G.; Reymen, I.M. Personality and team performance: A meta-analysis. *Eur. J. Personal.* **2006**, *20*, 377–396. [CrossRef]
43. Carter, N.T.; Dalal, D.K.; Boyce, A.S.; O'Connell, M.S.; Kung, M.C.; Delgado, K.M. Uncovering curvilinear relationships between conscientiousness and job performance: How theoretically appropriate measurement makes an empirical difference. *J. Appl. Psychol.* **2014**, *99*, 564–586. [CrossRef]
44. Carver, C.S.; Scheier, M.F. *Perspectives on Personality*; Pearson Education: London, UK, 2008.
45. LePine, J.A.; Buckman, B.R.; Crawford, E.R.; Methot, J.R. A review of research on personality in teams: Accounting for pathways spanning levels of theory and analysis. *Hum. Resour. Manag. Rev.* **2011**, *21*, 311–330. [CrossRef]
46. Shukor, N.B.A.; Tasir, Z.; van der Meijden, H.A.T.; Harun, J. Exploring students' knowledge construction strategies in computer-supported collaborative learning discussions using sequential analysis. *J. Educ. Technol. Soc.* **2014**, *17*, 216–228.

47. Yang, X.; Song, S.; Zhao, X.; Yu, S. Understanding user behavioral patterns in open knowledge communities. *Interact. Learn. Environ.* **2018**, *26*, 245–255. [CrossRef]
48. Wu, S.Y.; Chen, S.Y.; Hou, H.T. Exploring the interactive patterns of concept map-based online discussion: A sequential analysis of users' operations, cognitive processing, and knowledge construction. *Interact. Learn. Environ.* **2016**, *24*, 1778–1794. [CrossRef]
49. Leavy, P. *Research Design: Quantitative, Qualitative, Mixed Methods, Arts-Based, and Community-Based Participatory Research Approaches*; The Guilford Press: New York, NY, USA, 2017.
50. Cheong, Y.F.; Pajares, F.; Oberman, P.S. Motivation and academic help-seeking in high school computer science. *Comput. Sci. Educ.* **2004**, *14*, 3–19. [CrossRef]
51. Lambert, L. A framework for shared leadership. *Educ. Leadersh.* **2002**, *59*, 37–40.
52. Reeve, J. Teachers as facilitators: What autonomy-supportive teachers do and why their students benefit. *Elem. Sch. J.* **2006**, *106*, 225–236. [CrossRef]
53. Rodrigo, M.M.T.; Ocumpaugh, J.; Diy, W.D.; Moreno, M.; De Santos, M.; Cargo, N.; Lacson, J.; Santos, D.; Aduna, D.; Beraquit, J.I.; et al. Ibigkas!: The Iterative Development of a Mobile Collaborative Game for Building Phonemic Awareness and Vocabular. *Comput. Based Learn. Context* **2019**, *1*, 28–42.
54. Hake, R.R. Socratic pedagogy in the introductory physics laboratory. *Phys. Teach.* **1992**, *30*, 546–552. [CrossRef]
55. Nissen, J.M.; Talbot, R.M.; Thompson, A.N.; Van Dusen, B. Comparison of normalized gain and Cohen's d for analyzing gains on concept inventories. *Phys. Rev. Phys. Educ. Res.* **2018**, *14*, 010115. [CrossRef]
56. Nachar, N. The Mann-Whitney U: A test for assessing whether two independent samples come from the same distribution. *Tutor. Quant. Methods Psychol.* **2008**, *4*, 13–20. [CrossRef]
57. Bakeman, R.; Gottman, J.M. *Observing Interaction: An Introduction to Sequential Analysis*; Cambridge University Press: Cambridge, UK, 1997.