Factor Analysis of Practical Cybersecurity Learning Through Gamified Visual Novel Platform

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Abstract

A method of applying game elements in non-game media is known as gamification. This method is often used for learning environments to enhance learners' motivation. Gamification can be applied to any range of game genres, such as visual novel, a narrative-focused game that needs the user to interact and engage. In this research, ARCS (Attention, Relevance, Confidence, Satisfaction) questionnaire was employed to identify key factors that affect learner motivation during practical learning activities in a course focusing on cybersecurity topics. The Exploratory Factor Analysis (EFA) was utilized to uncover the underlying structure that affects the students' motivation. Through factor analysis, three key factors that influence the students' motivation were found. The first factor involves the students' feelings while using the gamification platform. The second is related to the learning experience of the students. Lastly, the third pertains to how confident the students are in conducting the activities on the gamification platform.

Keywords: Gamification, Visual Novel, ARCS Model, Cybersecurity Education, Exploratory Factor Analysis

Introduction

The more prevalent use of digital technology comes with positive impacts for the efficiency of information exchange. On the other side, it also presents new challenges, foremost in cybersecurity. One of the concerns is cyberattacks, an attack that targets digital systems. Cyberattacks compromise confidentiality, integrity, and availability of information being transmitted through digital technologies (Kumar et al., 2023). The aims of the cyberattacks include gaining unauthorized access to confidential-sensitive data, which can be abused for committing illegal acts, and unauthorized manipulation or destruction of information systems (Al-Hawamleh, 2023).

A report by Hogan et al. (2024) indicates that the supply of cybersecurity practitioners has not met the number of jobs demanded, which requires immediate actions to address this lack (Ramezanian & Neimi, 2024). According to Siqi Hu & Zhou (2022), such actions can take various forms, including the implementation of the Security Education, Training, and Awareness (SETA) program. Within this program, one of the activities is security education, which can be adapted specifically to cybersecurity education in the context of digital technology.

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Ramezanian & Niemi (2024) conducted a study on cybersecurity education activities related to curriculum development for cybersecurity in universities. According to their study, addressing the demand for cybersecurity practitioners can begin at the university level by providing cybersecurity learning activities through curriculum development, such as the CSEC2017 and CyBOK frameworks. However, their study was limited to identifying the essential materials to be taught and ensuring that the learning outcomes correspond with the technical competencies required for cybersecurity profession.

To achieve the intended objectives of the learning activities, the learning model must satisfy effective learning requirements. This view is supported by Bransford et al. (2005), who emphasize that learning activity should not solely focus on instructional material quality, but rather on how well learners can achieve their learning goals. Furthermore, Boyle et al. (2011) contend that effective learning provides an active, dynamic, and flexible learning environment. That learning approach ensures increased learner interaction and is likely to improve learners' comprehension.

Therefore, the implementation of cybersecurity learning activities should be adapted with effective learning methods, for example, implementing gamification on the learning platform. While traditional learning models focus on the interaction between learners and instructors, consequently being rigid and passive (Hannay & Newvine, 2006), gamification encourages learners to be more active without relying on instructors. The gamification method requires active learners to achieve the learning objectives while reducing the perception of rigidity by implementing the game elements that can be adjusted to learner preferences.

However, Silpasuwanchai et al. (2016) found that the gamification method has not been conclusively proven to enhance learner comprehension. Conversely, a study by Nadeem et al. (2023) showed that gamification can effectively enhance learners' interest and motivation in learning activities compared to traditional learning approaches. In addition, Camacho-Sanchez et al. (2024) indicated, through their research, that learners' motivation plays a big role in academic performance, with those with more motivation achieving better grades than the less motivated.

This study designs a gamified visual novel platform for practical cybersecurity learning, aiming to obtain important information about learners' motivation. The visual novel was used due to its emphasis on reading as a central activity (Camingue et al., 2021), aligning with practical cybersecurity learning activities, which were provided in a text-based format. The study by Friedl et al. (2024) also denoted that a visual novel game successfully increases students' knowledge about cybersecurity.

This study uses a visual novel system that contrasts with most previous studies on practical cybersecurity learning, which limit gamification elements to basic reward mechanisms such as point systems and leaderboards, commonly exemplified by Capture-the-Flag (CTF) platforms (Karagiannis et al., 2021). Additionally, most previous studies about gamification mainly focused on evaluating and comparing learning methods aimed at improving learner academic performance, such as Camacho-Sanchez et al. (2024). Although some studies, such as Bernik et al. (2018) and Fotaris et al. (2016), have discussed the effect of gamification on learners' motivation, they do not explain the primary influences that contribute to the level of learners' motivation while using the gamification learning method.

To evaluate the information about learners' motivation, this study employs the ARCS questionnaire, the Reduced Instructional Materials Motivation Survey (RIMMS). Based on the collected data, a factor analysis will be conducted to identify the key factors that influence learners' motivation during practical learning in cybersecurity through a gamified visual novel platform.

Literature Review

This section presents a detailed explanation of the works relevant to our proposed work.

Security Education, Training, and Awareness (SETA)

SETA (Security Education, Training, and Awareness) is a program conducted by an organization to help its users become more cautious in their actions (Amankwa et al., 2015). SETA aims to explain the importance of implementing security regulations for minimizing security-related incidents. The security context of SETA can be adjusted to align with the objectives of the organization, such as cybersecurity. SETA consists of three activities: security education, security training, and security awareness.

Each activity in the SETA program serves different purposes. According to Amankwa et al. (2015), cybersecurity education intends to educate cybersecurity practitioners with the industrial-standard necessary skills. Cybersecurity training focuses on enhancing individual skills and knowledge related to cybersecurity. Lastly, cybersecurity awareness aims to help individuals recognize cybersecurity-related issues and respond appropriately.

ARCS Model

The ARCS model is a motivational theory developed to enhance learners' motivation in learning activities (Keller, 1987). This model is applicable to any learning activity strategy. To assess the levels of learners' motivation, this model splits motivational feeling into four components: Attention, Relevance, Confidence, and Satisfaction. Each of these components has a distinct purpose in maintaining and enhancing learners' interest during learning activities.

- Attention is related to the ability of learners to maintain focus and concentration during learning activities.
- Relevance intends to establish the perception that the learning activities are relevant and meaningful to the learners.
- Confidence aims to enhance learners' belief in succeeding and achieving their goals throughout the learning activities.
- Satisfaction is related to the satisfaction experience of the learners because their efforts are appreciated and thereby increase their motivation to engage in learning activities

The effectiveness of a learning method to enhance learners' motivation depends on the implementation of the ARCS model principles within the learning environment (Keller, 2009). In the gamification method, as demonstrated by Wan Hamzah et al. (2015), the principles can be integrated into the platform design. Each design should be adjusted with specific aspects of the ARCS model principles to ensure that the platform influences the learner's learning motivation. More details for the implementation of ARCS Model into the gamification platform will be explained in the Development part of the Methodology section.

Gamification

Gamification is the use of game design or elements in a non-game context with the purpose of enhancing engagement in non-game activities (Tobarra et al., 2020). Gamification is not similar to game-based learning, as it does not involve actual playing. However, gamification's concept originates from game-based learning methods (Dahalan et al., 2024). The selection of game elements in gamification can follow MDA framework, the theory of game design, which stands for Mechanics, Dynamics, and Aesthetics (Wan Hamzah et al., 2015). Mechanics are the core components and rules of the game; Dynamics describe how these mechanics are implemented; and Aesthetics focus on the emotional responses and engagement of users, to make them interested in using the gamified system (Buchem et al., 2021).

Visual Novel

A visual novel game is a game that focuses on the narrative and storytelling aspect (Camingue et al., 2021). These aspects, narrative and storytelling, are the main attraction of the game, and thus, an engaging and well-created plot becomes a major element in maintaining the players' interest. Apart from its focus on narrative and storytelling aspects, this game also includes player interactivity elements (Lai & Chen, 2023) by adding various common game features (Lynch et al., 2019).

Methodology

In this section, we will provide the explanation of our conducted experiment.

Participants

The participants in this study were 27 students who enrolled in the Ethical Hacking course of Even Semester 2024/2025 at the Faculty of Computer Science, Universitas Indonesia. They also served as the population of the experiment. To determine the minimum number of the sample, the formula from *Table for Determining Sample Size* (Krejcie & Morgan, 1970) was used, which stated a minimum of 26 respondents. However, the study utilized the entire population of 27 students rather than selecting a sample.

Instruments

The RIMMS (Reduced Instructional Materials Motivation Survey) questionnaire was used to assess participants' motivational reactions (Wang et al., 2020). The reduced version was preferred over the original IMMS (Instructional Materials Motivation Survey) (Keller, 2009) due to the small number of respondents. According to de Winter et al. (2009), the number of respondents must exceed the number of variables to conduct a factor analysis. The IMMS contains 36 variables (Keller, 2009), whereas the RIMMS only has 12 variables (Loorbach et al., 2015), making it more suitable for the available participant size. This survey employs a five-point Likert scale: (1) Strongly Disagree, (2) Disagree, (3) Neutral, (4) Agree, and (5) Strongly Agree. Table 1 presents the questionnaire items along with their corresponding variables for each component of the ARCS model.

Table 1. RIMMS Indicators

Components	Var.	Questions in Indonesia	Questions in English
Attention	A3	Pemilihan elemen gim dalam platform gamifikasi dapat mempertahankan atensi saya.	The selection of game elements in the gamification platform helped to hold my attention.
	A6	Penataan elemen gim dalam platform gamifikasi membantu saya untuk menjaga atensi.	The way the game elements are arranged on the gamification platform helped keep my attention.
	A10	Variasi jalan cerita dan desain visual membantu saya untuk menjaga atensi selama mengerjakan tugas menggunakan platform gamifikasi.	The variety of storylines and visual designs helped keep my attention on the lesson.
Relevance	R1	Tugas pada platform gamifikasi cukup relevan dengan materi yang saya ketahui.	It is clear to me how the tasks on the gamification platform relate to things I already know.
	R6	Elemen gim dalam platform gamifikasi memberikan impresi bahwa tugas yang diberikan layak untuk dikerjakan.	The game elements on the gamification platform convey the impression that its tasks are worth doing.
	R9	Tugas-tugas pada platform gamifikasi sangat berguna bagi saya.	The tasks on the gamification platform will be useful to me.

Confidence	C5	Saat menggunakan platform gamifikasi, saya yakin bahwa saya dapat menyelesaikan tugas yang diberikan.	As I used the gamification platform, I was confident that I could finish the task.
	C7	Setelah mengerjakan tugas pada platform gamifikasi, saya yakin bahwa saya dapat menyelesaikan UTS dengan baik.	After doing the task on the gamification platform for awhile, I was confident that I would be able to pass a midterm test on it.
	C9	Penataan elemen gim yang baik dalam platform gamifikasi membuat saya lebih yakin dalam mengerjakan tugas yang diberikan.	The good organization of the game element helped me be confident that I would complete the task.
Satisfaction	S2	Saya sangat menyukai platform gamifikasi hingga ingin menggunakannya di tempat lain.	I enjoyed this gamification platform so much that I would like to use it in another place.
	S3	Saya sangat suka mengerjakan tugas melalui platform gamifikasi.	I really enjoyed doing the task on the gamification platform.
	S6	Saya merasa gembira selama mengerjakan tugas pada platform gamifikasi.	It was a pleasure to complete the task on the gamification platform.

Procedures

The experiment was conducted for six weeks. Each week, participants were assigned different task instructions and objectives. Participants used the gamification platform that facilitated practical and self-directed learning activities to accomplish the task during the experiment. After the experiment, participants were asked to complete the ARCS questionnaire anonymously, which had been translated into Bahasa Indonesia. The exploratory factor analysis will be conducted on the collected data using IBM SPSS Statistics Version 26 to find the correlations. The selection of the factor analysis method will be explained in the Factor Analysis part, as it depends on the characteristics of the collected data.

Development

Game Elements and Gamification Framework

When developing a gamification platform, there are two main considerations. First, the selected game elements should align with the components of the MDA framework. Second, the platform's design must implement motivational principles from the ARCS model.

The gamification platform, that we built, will use common game elements found in visual novel games. However, the game elements are only used as platform interfaces. Based on Ferro (2021) and Camingue et al. (2021), the following game elements are particularly well-suited for visual novel gamification:

- Narrative-Focused; emphasizes storytelling as a core engagement element.
- Background; presents scenery of the story settings.
- Quest; specific tasks or challenges for learners to complete.
- Static Character; features non-animated character representations.
- Traditional Textbox; delivers information and dialogue through a classic text interface.
- On-Click Progression; advances the progress through user interactions.
- Action Menu Choice; offers multiple actions to be chosen by the learner.

The gamification model follows the MDA framework. The selection of game components can vary across various gamification platforms, as the selection is adjusted to specific implementation needs. Kusuma et al. (2018) have identified several common components that are frequently used in gamified systems. In this study, the mechanics are tasks, game content, and additional features. The dynamics are rewards, non-linear progression, and hints. The aesthetics are sensation, challenge, and narrative.

Subsequently, the gamification platform will implement ARCS motivational principles to assess participants' learning motivation. Each component of the ARCS model has a distinct purpose in motivating participants (Keller, 2009; Wan Hamzah et al., 2015). Table 2 shows the purpose and implementation of each ARCS model component within the gamification platform.

Table 2. Purpose and Implementation of ARCS Model in Gamification Platform

Components	Subcomponent	Purpose	Implementation
Attention	Perceptual Arousal	Capture student attention to use the gamification platform.	Using the attractive visual designs on the gamification platform.
	Inquiry Arousal	Encourage student curiosity to use the gamification platform.	Using interactive elements on the gamification platform, such as on-click progression.
	Variability	Maintain student attention while using the gamification platform.	Split the story into six chapters.
Relevance	Goal Orientation	Meet student learning goals while using the gamification platform.	Informing the purpose for each task.
	Motive Matching	Link the gamification platform to student interests.	The gamification platform was developed to allow students to complete tasks at their own pace, without being tied to a fixed schedule.
	Familiarity	Familiarize the gamification platform with a visual novel gaming experience.	Using common visual novel game mechanics.
Confidence	Learning Requirements	Build positive expectations for success.	The gamification platform was developed to ensure that every student feels capable of success.
	Success Opportunities	Improve student competence.	Create multiple difficulties on the tasks.
	Personal Control	Show the results of student competencies personally.	Students can view both their completed and incomplete tasks.
Satisfaction	Intrinsic Reinforcement	Provide a pleasure feeling after using the gamification platform.	Provide feedback if successfully complete the task.
	Extrinsic Rewards	Give rewards for students' success.	Provide an epilogue of the story for students who complete all tasks.
	Equity	Fair treatment for all students.	Using the same tasks for all students.

Implementation of Gamification Platform

We used DeepAI for visual graphics, such as character and background images. The gamification was integrated into the learning platform using Pixi'VN. The game element can have different designs for each chapter, especially background images, based on the theme of the chapter. Some of the game element implementations were displayed in Figure 1.

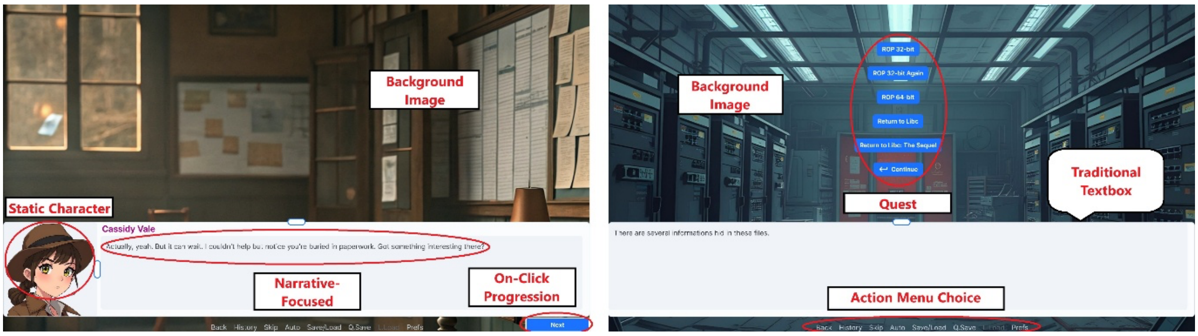

Figure 1. Example of Game Element Implementations

Results

This section presents the distribution of questionnaire responses and analyzes the underlying factors between the questionnaire items.

ARCS Questionnaire

The questionnaire responses are summarized using the mean and standard deviation, as presented in Table 3. There are several interesting insights about the participants' motivation level. In general, all variable scores exceed 3.00, suggesting a high level of participant motivation when using the gamification platform (Sasada et al., 2023).

Table 3. Mean and Standard Deviation on ARCS Questionnaire

Variable	Mean	Standard Deviation
A3	3.70	1.103
A6	3.70	1.031
A10	3.48	1.122
R1	3.96	0.898
R6	3.70	1.031
R9	4.07	0.829
C5	3.30	1.325
C7	3.56	1.155
C9	3.70	0.993
S2	3.41	1.185
S3	3.44	1.311
S6	3.74	1.259

The relevance component has the highest mean score compared to the other components. Notably, there is only one variable, R9, with a mean higher than 4.00, which indicates that participants are particularly focused on practical learning activities with a direct impact on their needs. Furthermore, attention's mean score is slightly higher than confidence and satisfaction, which reflects that the gamification platform has been effective in attracting and maintaining participants' attention.

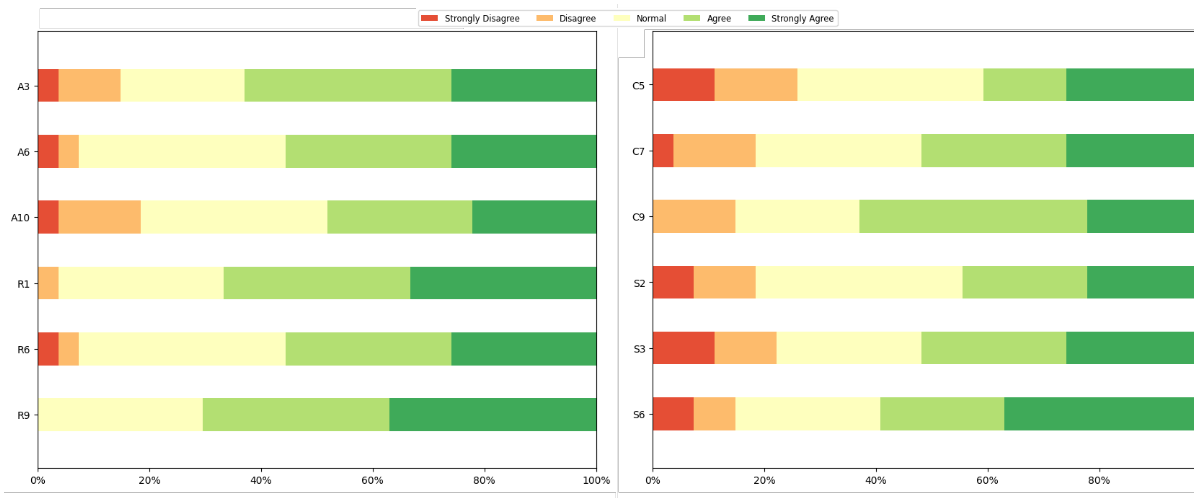

Figure 2. ARCS Questionnaire Distribution

Figure 2 shows the distribution of participants' responses for each variable on the questionnaires. Higher-scoring items are represented in green bars, while lower-scoring items are in red bars. The bar is skewed toward higher-scoring items, consistent with the mean scores, which reflect an overall high level of participant motivation.

However, several variables were responded with more lower-scoring items from participants, such as C5 and S3. These variables are associated with participants' low confidence levels in completing tasks and their low favorability levels in using the gamification platform. This suggests that despite having a high overall level of motivation, there may be implied concerns for self-efficacy and user experience of the platform.

Furthermore, the satisfaction component has the most variables with low-score responses across all components. This indicates that there is room for improvement in the gamification platform on participant satisfaction. Enhancing satisfaction can have a positive influence on participants' learning motivation.

Reliability and Normality Test

The questionnaire data were validated for reliability using Cronbach's alpha (Keller, 2009). The overall reliability coefficient score was 0.938, which is greater than the minimum acceptable threshold of 0.7 (Watkins, 2018). The Cronbach's alpha coefficients for each component were: Attention (0.845), Relevance (0.716), Confidence (0.811), and Satisfaction (0.889).

Normality of the data was tested using Shapiro-Wilk. In this test, data are assumed to be normally distributed if the ρ-value for all variables is greater than 0.05 (de Souza et al., 2023). After conducting the test, results showed that the highest ρ-value was 0.019 for A10, which is below the normally distributed threshold, indicating that the data from the questionnaire is non-normal distribution.

Correlation Analysis

Table 4 presents the results of the Spearman rank correlation analysis. According to Asuero et al. (2006), pairs with a correlation coefficient score higher than 0.7 are considered to have a strong correlation. From the analysis, several pairs of variables have strong correlations. Three of these pairs belong to the same component: C5–C7, S2–S3, and S3–S6. Ten other pairs are variables from different components: A3–R1, A3–S2, A3–S3, A6–S3, A6–S6, R1–C9, R6–C5, R6–C7, R6–S3, and R6–S6.

Table 4. Matrix Correlation

	A3	A6	A10	R1	R6	R9	C5	C7	C9	S2	S3	S6
A3	1.00	-	-	-	-	-	-	-	-	-	-	-
A6	0.68	1.00	-	-	-	-	-	-	-	-	-	-
A10	0.59	0.64	1.00	-	-	-	-	-	-	-	-	-
R1	0.88	0.64	0.42	1.00	-	-	-	-	-	-	-	-
R6	0.62	0.52	0.64	0.65	1.00	-	-	-	-	-	-	-
R9	0.33	0.48	0.24	0.52	0.34	1.00	-	-	-	-	-	-
C5	0.49	0.40	0.54	0.43	0.77	0.30	1.00	-	-	-	-	-
C7	0.68	0.57	0.62	0.64	0.71	0.51	0.74	1.00	-	-	-	-
C9	0.66	0.54	0.60	0.71	0.59	0.54	0.56	0.63	1.00	-	-	-
S2	0.72	0.61	0.58	0.57	0.42	0.17	0.32	0.52	0.49	1.00	-	-
S3	0.74	0.73	0.69	0.59	0.73	0.19	0.56	0.69	0.59	0.71	1.00	-
S6	0.56	0.73	0.55	0.55	0.72	0.49	0.52	0.60	0.59	0.56	0.81	1.00

Factor Analysis

The results of the correlation analysis can be utilized to identify strongly correlated items. Several of these correlations involve variable pairs from different components of the ARCS model, suggesting that the dimensional structure of practical learning may differ from the ARCS model (Sasada et al., 2023). Consequently, a factor analysis will be conducted to identify the underlying factors that influence students' motivation in practical learning activities.

The response data will be evaluated for appropriateness before conducting factor analysis to discover the compatible variables. The results revealed a ρ-value of 0.000 for the Bartlett's test of sphericity, which is smaller than the significance threshold of 0.001 (Wu et al., 2023). The Kaiser-Meyer-Olkin (KMO) value was 0.738, which is greater than the minimum recommended value of 0.7 (Watkins, 2018). Moreover, the anti-image correlation scored that all variables had values greater than 0.53, which is surpassing the generally accepted minimum of 0.5 (Wu et al., 2023). Based on these results, the response data are considered appropriate for factor analysis.

The factor analysis in this study uses the principal axis factoring method to identify the common factors from the questionnaire data. This method is more suitable given the non-normal distribution of the data (Watkins, 2018; Cudeck, 2000). Then, the analysis uses the promax rotation method with *kappa* = 4, which produces intercorrelated factors (Watkins, 2018), to simplify the factors.

The scree plot, interpreted using the elbow method, suggests a two-factor solution. However, the three-factor solution also has a comparable eigenvalue; therefore, both solutions were examined. The factor extraction process generated communalities scores, which represent the proportion of a variable's variance that is explained by the extracted factors. Table 5 presents the communalities scores for both solutions, revealing that R9 does not meet the minimum threshold of 0.55 (MacCallum et al., 2001) in both solutions and will be excluded from the interpretation. As a result of this exclusion, the appropriateness tests were repeated using the new data without R9.

Table 5. Communalities Score for Initial Data

Variable	Initial	Extraction Two Factor	Extraction Three Factor
A3	0.912	0.696	0.759
A6	0.779	0.649	0.694
A10	0.793	0.652	0.648
R1	0.935	0.784	0.936
R6	0.886	0.664	0.735
R9	0.757	0.442	0.381
C5	0.767	0.395	0.840
C7	0.818	0.668	0.699
C9	0.675	0.617	0.604
S2	0.704	0.575	0.726
S3	0.884	0.920	0.898
S6	0.860	0.679	0.680

The appropriateness test for the new data has a ρ-value of 0.000 for Bartlett's test of sphericity, and the KMO test was 0.730. All variable scores in the anti-image correlation were above 0.57, confirming that the new data is suitable for factor analysis.

The scree plot results for the new data also suggest a possible solution of either two or three factors. To determine the best ideal solution, the communalities score in both solutions was examined. As shown in Table 6, the variables C5, C9, and S2 in the two-factor solution do not meet the minimum required communalities score, while all variables in the three-factor solution satisfy the required criteria. Therefore, the three-factor solution is considered the right solution.

Table 6. Communalities Score for New Data (Without R9)

Variable	Initial	Extraction Two Factor	Extraction Three Factor
A3	0.906	0.859	0.860
A6	0.778	0.638	0.725
A10	0.791	0.647	0.638
R1	0.926	0.969	0.966
R6	0.873	0.694	0.743
C5	0.767	0.415	0.986
C7	0.759	0.626	0.656
C9	0.636	0.543	0.556
S2	0.686	0.540	0.676
S3	0.849	0.823	0.845
S6	0.792	0.733	0.749

Based on the factor loading values shown in Table 7, two issues were identified in the factor structure. First, some variables reveal cross-loadings, which complicate the factor interpretation; therefore, only variables with factor loading values above 0.8 will be retained for further analysis (de Winter et al., 2009). Second, the third factor appears to be unstable because it contains only one variable.

Table 7. Factor Loading for Three Factor Solution

Variable	Factor 1	Factor 2	Factor 3
A3	0.176	0.807	-0.022
A6	0.854	0.096	-0.120
A10	0.680	-0.006	0.174
R1	-0.122	1.073	-0.015
R6	0.371	0.068	0.525
C5	-0.160	-0.035	1.105
C7	0.278	0.239	0.414
C9	0.139	0.466	0.243
S2	0.822	0.187	-0.250
S3	0.897	-0.045	0.081
S6	0.896	-0.149	0.104

Unstable factors are relatively common issues in non-normal distribution data. Even though such factors usually get excluded from interpretation (Watkins, 2018), there are some situations where retaining them is a more proper solution. In this study, the third factor was retained since it had good discriminant validity. This can be seen from the values of interfactor correlations in Table 8, all of which were below the threshold value of 0.80 (Brown, 2015), demonstrating that all extraction factors are sufficiently different from one another.

Table 8. Interfactor Correlation Matrix

Factor	1	2	3
1	1.000	-	-
2	0.709	1.000	-
3	0.642	0.550	1.000

Aside from interfactor correlations, a factor can be retained if it can significantly explain the variance (Williams et al., 2010). As shown in Table 9, the third factor also contributes significantly to explaining variance in the extraction factors with 8.124%, only slightly lower than the 8.958% explained by the second factor. Meanwhile, for the other factor solutions that were not selected, the explained variance is not significantly increased.

Table 9. Total Variance Explained

No. of Factor	Eigenvalues	% of Variance	Cumulative (%)
1	7.056	64.149	64.149
2	0.985	8.958	73.107
3	0.894	8.124	81.231
4	0.474	4.306	85.538
5	0.446	4.054	89.582
6	0.342	3.108	92.700
7	0.307	2.791	95.491
8	0.196	1.782	97.274
9	0.157	1.431	98.705
10	0.113	1.027	99.732
11	0.029	0.268	100.000

The selected solution needs to be assessed. The relationship between the factors can be seen by interfactor correlations, while the association between the factors and their constructed variables is reflected in the structure coefficient scores. Additionally, the relationship among the constructed variables within their factor should be checked using Spearman rank correlations.

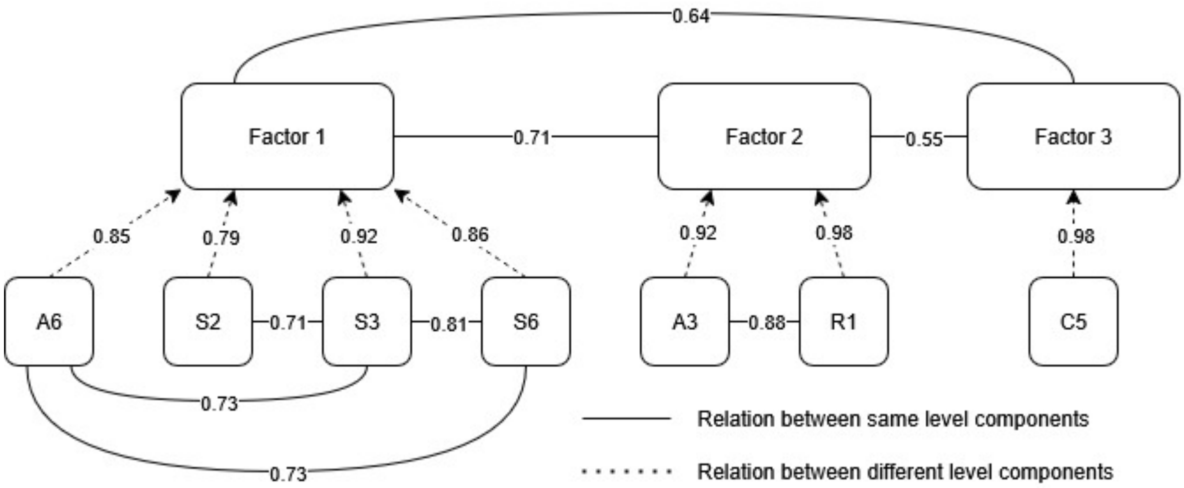

Figure 3. Relationship Between Factors and Variables

A low score of interfactor correlation for all factor pairs, which is below 0.8 (Brown, 2015), indicates that each factor contains different information and is unlikely to affect the other factors. It contrasts with the correlation scores between constructed-variables within the factor, which are accepted as strongly correlated because the coefficient scores exceed 0.7 (Asuero et al., 2006). The similarity of information among constructed-variables reflects the same underlying factor structure they represent. However, having a direct correlation with each variable is not required. The more complex of constructed-variables, the number of direct correlations tends to decrease. The last relationship to be assessed is the correlation between the factors and their constructed-variables. This correlation should be as strong as the correlation between constructed-variables, as they share similar information about the same factor.

Discussion

The study results indicate that the ARCS questionnaire, RIMMS, can be used to identify factors influencing student motivation. Although the ARCS model was originally designed for assessing motivation in the general learning environment, the factor analysis revealed a tendency for certain variables to be more dominant in the practical learning activities. The following part presents an interpretation of the three factors that were successfully identified.

- The first factor consists of variables A6, S2, S3, and S6. Variables S2, S3, and S6 represent components of satisfaction, reflecting a learner's enjoyment while learning on the gamification platform. Variable A6, on the other hand, indicates a learner's interest in continuing to use the platform. In general, these variables capture learners' feelings when using the gamification platform and can thus be interpreted as "Learning Affectivity".
- Then, variables A3 and R1 create the second factor. Even though this factor comprises only two variables, it can still be meaningfully interpreted when supported by a strong theoretical basis, as demonstrated in Sasada et al. (2023). Variable A3 reflects the use of the gamification platform to maintain a learner's attention, while variable R1 represents the relevance between the platform and the learner's personal experience. Although these variables appear distinct due to different components, both contribute to creating an effective learning experience. Therefore, this factor can be interpreted as "Learning Effectiveness".
- Despite the third factor consisting solely of variable C5, analysis of interfactor correlation and its contribution to explained variance indicates that this factor captures distinct information not represented by the other factors and makes a meaningful interpretation to the solution. Variable C5 reflects a learner's self-belief in completing the given tasks. Accordingly, this factor is interpreted as "Learning Assertiveness", representing the learner's self-confidence in the learning activities.

A study by Wang et al. (2020) reveals that, in general learning environments, the structure of extracted factors should align with the structure of the ARCS model. However, Sasada et al. (2023) revealed a different latent structure for the cybersecurity educational training context, which is similar to the finding in this study. These differences in latent structures were also indicated by the correlation analysis, which showed strong correlations among several cross-component variables.

Although this study used an exploratory approach, one identified factor was similar to Sasada et al. (2023) findings. That factor relates to learners' motivation to complete learning activities, which is interpreted as "Learning Assertiveness" in this study. The other two factors may be considered as unique latent structures that appeared specifically from the use of visual novels on the learning platform.

Conclusion

This study aims to identify the underlying factors that influence learners' motivation in practical learning activities. The ARCS questionnaire was used to assess learners' motivation for learning activities, and factor analysis was conducted to extract the relevant key factors for practical learning. The findings revealed that learners' motivation is influenced by three key factors: The first factor relates to learners' feelings while using the gamification platform, the second relates to learners' learning experience, and the last factor describes learners' confidence in completing the tasks on the gamification platform.

Overall, the findings provide a basis for the development of gamified visual novel systems. In future relevant studies, these results can be used to refine the platforms by focusing the development on the main aspects that most effectively influence learners' motivation. Additionally, instructors may utilize these findings to prioritize key elements for implementing the gamification platform, thereby improving the overall learning experience.

Limitations and Future Works

This study involved 27 respondents, which limits the findings to small and specific populations. Future work will include a larger respondent to enhance the accuracy and applicability of the results to broader populations. Additionally, the visual design of the gamification platform will be adjusted to align with current design trends.

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