TIN: Terapan Informatika Nusantara
Vol 6, No 7, December 2025, page 872-885
ISSN 2722-7987 (Media Online)
Website https://ejurnal.seminar-id.com/index.php/tin
DOI 10.47065/tin.v6i7.8744

Calligraphy Style Personalization in Serious Games Using User-Based Collaborative Filtering with Cosine Similarity

Alfina Nurrahma N[1,*], Fresy Nugroho[1,2], Yunifa Miftahul Arif[1,3]

[1] Department of Master Program of Computer Science, Universitas Islam Negeri Maulana Malik Ibrahim, Malang, Indonesia
[2] Department of Electrical Engineering, Universitas Islam Negeri Maulana Malik Ibrahim, Malang, Indonesia
[3] Department of Mechanical Engineering, Universitas Islam Negeri Maulana Malik Ibrahim, Malang, Indonesia
Email: [1,*]240605210009@student.uin-malang, [2]fresy@ti.uin-malang, [3]yunif4@ti.uin-malang
Correspondence Author Email: 240605210009@student.uin-malang

Abstract−This study aims to develop the Try Calligraphy serious game equipped with a personalized recommendation system to assist players in selecting the most suitable Arabic calligraphy style (khat) based on their performance. The primary objective of this research is to optimize learning personalization by implementing a User-Based Collaborative Filtering approach that predicts the most appropriate handwriting styles for new players based on similarity to prior users. Performance data consisting of final scores generated from decoration, neatness, and completion time are recorded and compared to construct player similarity profiles. The system calculates predicted scores for untested calligraphy styles using cosine similarity and subsequently recommends the top three styles with the highest estimated performance potential. Two experimental scenarios were conducted to assess predictive performance. The results show Mean Absolute Error (MAE) values of 16.08 and 13.92, indicating a moderate level of accuracy. These findings suggest that while the system is capable of providing relevant and targeted recommendations, additional training data and improved similarity parameter design can further enhance predictive precision. Usability evaluation using the GUESS-18 instrument involved ten respondents and produced average scores above 3.7 across all constructs, reflecting positive user perceptions in terms of usability, aesthetics, enjoyment, and personal engagement. Overall, the system demonstrates that the integration of User-Based Collaborative Filtering in a serious game environment can enhance personalized learning, increase user involvement, and support the digital preservation and education of Islamic calligraphy art.

Keywords: Calligraphy; Game Adaptation; Game Base Learning; GUESS-18; Knowledge-Based Filtering

1. INTRODUCTION

The global economy has been driven by the rapid growth of the information and communications technology sector in recent decades. One sector that has experienced significant growth is the gaming industry. With increasing internet access and computing devices, gaming has become one of the most popular forms of global entertainment. The gaming industry has experienced rapid and transformative growth through 2024. According to market research data, the global gaming industry is showing a very positive growth trend, with projected revenues reaching US$522.46 billion by 2025. Technological developments such as cloud gaming, virtual reality (VR), and augmented reality (AR) have fundamentally changed the way people play games. The mobile gaming market continues to dominate, particularly in Asia, while subscription-based business models are gaining popularity in North America and Europe. The number of gamers worldwide continues to increase, with a user penetration rate of 34.4%, which is expected to grow to 37.5% by 2029(Games - Worldwide: Statista Market Forecast, 2025).

As the gaming industry evolves, the concept of serious games is gaining attention as an effective educational medium(Yazir et al., 2022). Serious games combine elements of entertainment with elements of learning to provide new insights and skills in an interactive environment. One area that can be integrated with serious games is the art of calligraphy. Alongside entertainment, games are increasingly utilized as serious games to support education, including the learning of Arabic calligraphy. Calligraphy represents a cultural and spiritual heritage with high artistic value, yet traditional learning methods require guidance from experts and dedicated practice sessions that are not always accessible. Digital learning media therefore offer an alternative for improving accessibility, engagement, and learning effectiveness make it easier for teachers and student(Halim et al., 2022). As the main source of teaching, the Al-Quran not only provides understanding in terms of tasyriiyah but also in aspects of knowledge, economics, and the advancement of arts and culture through literary styles, buildings, and visual arts such as calligraphy and Islamic ornaments. This revelation inspired, among other things, Arabic calligraphy.

The art of calligraphy, particularly in the context of Arabic script, is a cultural heritage with high aesthetic value and requires precise technique. However, not everyone has the opportunity to learn calligraphy directly from a teacher or through conventional methods. Islamic calligraphy arguably has a limitless scope, with variations and applications that can be translated into any writing medium(Yunita, 2022). Therefore, a technology-based approach to calligraphy learning is an innovative solution to facilitate access and increase learning effectiveness. In the digital realm, the development of recommendation systems has become one way to enhance the user experience. In the context of serious calligraphy games, time management is a crucial element in measuring a player's perseverance and skill in completing the challenge of writing letters or verses precisely and aesthetically. The time allotted to complete calligraphy exercises or challenges must be utilized efficiently. Players are required to complete tasks within a specific time limit, reflecting the importance of discipline and time management skills, as emphasized in the first verse of Surah Al-Asr. Delays or sluggishness in completing tasks can result in a decrease in the final score. In addition to punctuality, players are also judged on the aesthetic level of their writing, such as neatness of linework, letter proportions, and consistency of handwriting style. These elements reflect pious deeds in the form of maximum effort to produce beautiful and

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meaningful works. Calligraphy, as an art form that represents holy verses, requires a learning process that is not only technical, but also spiritual and consistent. Therefore, the integration of technology such as a recommendation system not only aims to facilitate learning but can also be directed at shaping the character of users to value time more, be diligent in practicing, and understand the values of truth and patience in the journey of seeking knowledge. This letter also serves as a reminder that every activity, including art learning, can be an act of worship if it is based on faith and good deeds.

Personalization in games can increase user participation and learning outcomes by tailoring the gaming experience to each individual's needs and preferences(B. Bontchev et al., 2020). In the context of educational games, the application of personalization can strengthen player engagement and learning effectiveness, as the material provided is tailored to the user's character and preferences. Customizing content and gameplay based on user profiles also positively contributes to increased motivation and learning outcomes(B. P. Bontchev et al., 2020). Recommendations are a form of enhancing the user experience through relevant and contextual approaches. This is achieved through a method-based approach, which in this case is incorporated into the game itself. Recommendations in serious games generally apply to several aspects such as gameplay, characters, environments, and strategies. Games adopt this approach to increase user engagement and provide a personalized experience. A recommendation system for serious games was previously developed by Arif (2021). This study demonstrated the gameplay scenarios players would encounter through a tourism education game about Batu City. This research was then further developed to consider more factors, such as location, ratings , and previous experience with halal tourism (Arif et al., 2022) .

Recommendation systems can also utilize deep learning for team selection in multiplayer games. Dallmann (2021) states that a sequential item recommendation model can be used in Dota 2 to provide item recommendations based on player play patterns. The model utilizes historical player data as input to predict the most appropriate items in a given game situation. Meanwhile, Dota 2 data is processed using a combination of Recurrent Neural Networks (RNNs). (RNN) or Long Short-Term Memory (LSTM) to capture sequence patterns and time dependencies in matches (H. Lee et al., 2022), and using Random Forest for feature-based classification of match data (S.K. Lee et al., 2020) . Then, Chen (2023) developed a model called MOBARec-GCNFP based on Graph Convolution Network used in MOBA games . In the text processing section, data from League of Legends was also processed using Word2Vec techniques (CBOW and Skip-gram) to understand semantic relationships between in- game elements , such as in-game chat or character attributes (Shen et al., 2022) . To address the problem of players having difficulty selecting items in the In-App Purchase (IAP) system as well as concerns about the security of digital assets, this study proposed a multi-criteria recommendation system (MCRS) combined with Non-Fungible Token (NFT) technology to improve the accuracy of recommendations and the security of players' digital assets (Pradana et al., 2022) . Then, research by Zang & Luo (2022) used enhanced user -based Collaborative Filtering with player profiles to recommend effective Clash Royale decks.

Recommendations in serious games are not only limited to character or item selection, but also include game strategies. Hong (2020) champion recommendation system in the game. League of Legends, which considers various factors such as team synergy and player playstyles. This model helps players choose optimal champions based on historical game data. Furthermore, Zhang et al. (2020) proposed an in- game lineup recommendation model Dota 2 is based on the Bidirectional LSTM approach. Using this model, the system can predict the best lineup combination that provides a strategic advantage in a match. This model shows that the use of deep learning in recommendation systems can improve the quality of player decisions in strategy-based games. The CF method can be used to recommend content, levels, or features that match individual player preferences and behaviors in the game. Collaborative Filtering can be used to recommend game features or mechanics that players might like based on the preferences and interaction patterns of other similar players (Viljanen et al., 2020) .

Existing research on personalization and recommendation systems in serious games has mainly focused on gameplay optimization, item or character recommendations, and strategic decision support in domains such as MOBA games or tourism simulations. These works utilize approaches such as Collaborative Filtering, deep learning, or user profiling but are generally intended to enhance in-game performance rather than skill-based artistic learning. Meanwhile, studies outside the gaming context have applied Collaborative Filtering to domains such as tourism, culinary preferences, and product selection, yet none address the prediction of player performance in calligraphy learning. This gap indicates that there is limited research integrating recommendation systems into serious games for Islamic calligraphy education, particularly for selecting appropriate khat styles based on player ability. Therefore, this study aims to develop a serious game that supports digital calligraphy learning, implement a User-Based Collaborative Filtering method to predict player performance on untested calligraphy styles, and generate personalized recommendations to enhance learning effectiveness and user engagement.

This research differs from prior studies by applying performance-based personalization not for entertainment outcomes but to support artistic skill development and cultural preservation in a digital learning environment. The application of this method to the system is expected to build a profile of each player's preferences based on their interactions with various calligraphy elements. This allows for more relevant and tailored recommendations based on styles that have proven to attract players, resulting in a more focused and enjoyable learning experience. This approach can help beginners explore suitable styles without being overwhelmed by the complexity of traditional calligraphy, while allowing more advanced users to refine their preferences in a structured manner. Furthermore, the use of personalization within a cultural-arts context represents an important shift in how digital tools are commonly applied.

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The application of this technology shows great potential in optimizing the gaming experience, while simultaneously supporting the preservation and digital learning of calligraphy through a personalized approach in serious games.

2. RESEARCH METHODOLOGY

2.1 Conceptual framework

A series of steps have been carried out sequentially and systematically to make it easier for researchers to determine the next steps, so that the expected results can be achieved. The approach used in this recommendation system is Collaborative Filtering (CF). Collaborative Filtering (CF) is a recommendation technique that predicts user preferences based on similarities among users or items(Hartatik et al., 2021). CF is divided into two main approaches: User-Based and Item-Based. The User-Based approach predicts a user's preference by identifying other users with similar rating patterns using similarity measures such as Pearson Correlation or Cosine Similarity(Khusna et al., 2021). Previous studies have successfully applied CF conducted by Oktavika (2023) designed a tourism recommendation system in Bandar Lampung using the Collaborative Filtering algorithm. This system was developed to address the difficulties faced by the public and tourists in finding suitable tourist destinations in Lampung Province.

On the User-Based CF model, predictions are generated by identifying groups of users who have similar rating patterns, and then using their preferences to estimate the target user's rating. In contrast, the Item-Based CF model measures the similarity among items, not users, and generates predictions based on items that share similar rating behavior. User-Based CF is generally more effective when users exhibit strong behavioral patterns and variations in preferences, while Item-Based CF performs better in systems with large and stable item datasets where item similarity is more consistent over time(Ajaegbu, 2021). In this research, the User-Based Collaborative Filtering approach is selected because learning outcomes in calligraphy serious games are strongly influenced by player performance patterns, interaction characteristics, and individual learning behavior. Since different players may show similar strengths and weaknesses in handwriting neatness, proportion, or time management, the use of User-Based CF allows the system to identify users with comparable learning progress and utilize their performance profiles as the basis for generating more personalized recommendations. Additionally, the number of calligraphy styles used in this game is relatively limited, whereas the number of players as the system grows will continue to increase. Under these conditions, User-Based CF provides better flexibility for modeling player similarity compared to Item-Based CF, making it more suitable for adaptive learning environments where user variation is a critical factor. Therefore, this method ensures that system recommendations are not only relevant but also aligned with how real players perform and improve throughout gameplay(Permana, 2024).

System development must begin with data collection. The goal is to gain insight into user preferences through two collection methods: implicit and explicit. Implicit data collection involves recording gameplay results, while explicit data collection requires rating items. A recommendation system based on Collaborative Filtering (CF) is utilized to personalize learning by suggesting font types and calligraphy styles based on features of content previously liked or selected by other users. This approach can help players choose the type of handwriting that best suits their gameplay outcomes in the context of serious calligraphy games. CF is used to exploit the similarity of preferences between users in providing additional suggestions.

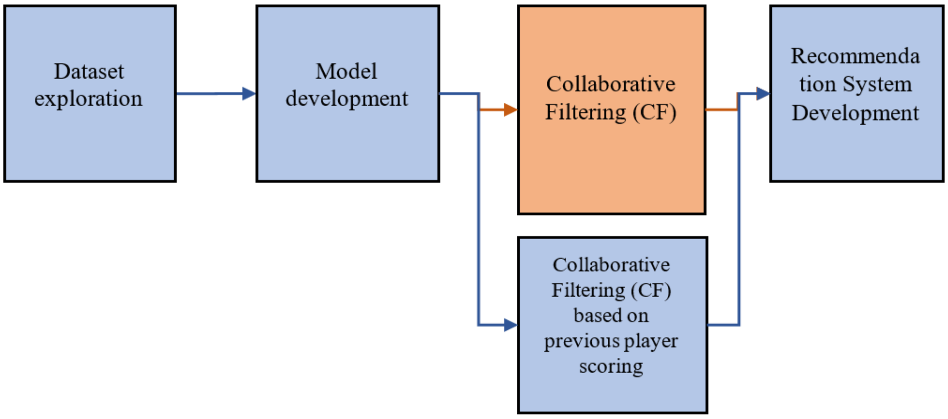

Figure 1. Conceptual framework

Figure 1 illustrates the recommendation system's workflow, which begins with dataset exploration players' performance data from the calligraphy learning game is collected in the form of final scores for each khat type. This dataset is then used as the basis for model development. At this stage, two layers of Collaborative Filtering (CF) are shown: the general CF process referenced from existing literature and the customized CF process implemented in this research. The first CF branch represents standard approaches commonly used in related studies, while the second branch (CF based on previous players) reflects the contribution of this research, which focuses on calculating similarity

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between players to generate personalized recommendations. After the model development stage, the system proceeds to the scoring process, where player similarity is computed using historical data. Based on these similarity scores, the system predicts the performance of a target player on khat types they have not yet attempted.

Finally, the predicted scores are processed into a recommendation output, in which the system proposes the most suitable calligraphy type for the player. Thus, Figure 1 not only visualizes the flow of system development but also highlights the added value of this research, namely the implementation of user-based Collaborative Filtering to enhance personalization within a serious gaming environment.

2.2 Research Stages

System design contains a series of steps carried out sequentially and systematically to make it easier for researchers to determine the next steps, so that the expected results can be achieved

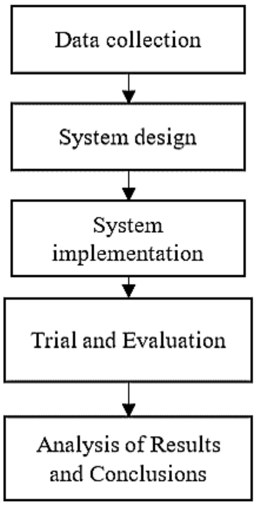

Figure 2. Research design

Based on the research design in Figure 2, the first step begins with data collection and then continues with creating a system design consisting of a series of processes within the system. To enable the model to learn from the data provided, the system design is implemented within the system. Finally, the steps that must be taken are testing and discussing the results obtained from the system implementation, then concluding with an analysis of the results and conclusions.

2.2.1 Data Collection

In the data collection stage, the main sources came from previous research that had developed an information system-based calligraphy assessment system, as well as assessments from experts in the field of calligraphy art. The data collected included evaluation scores on several important aspects in assessing calligraphy works, such as decoration, neatness , and time . Each aspect has its own weight, namely decoration (50 %), neatness (30 %), and time (20%) , which are used to calculate the final score of the user's writing results (Zayadi, 2023) . Data from previous research and expert input are used as the basis for developing a user-based recommendation system. Collaborative Filtering (CF). In this approach Using player names as identifiers and the final game scores as the primary data, each player writes several different scripts, and the final scores for each script are stored as a rating matrix. In addition, the calligraphy style references used in this study include seven main types of script, namely Naskhi, Tsulus, Diwani, Diwani Jaly, Farisi, Riq'ah, and Kufi. The assessment of each script is carried out by experts or refers to previous evaluation systems to ensure the quality and accuracy of the scores used in the system.

Using previous players' score histories, the recommendation system will learn patterns of similarity between players in scoring different types of khat. New players, who only have initial scores for a few khat types, will be given khat recommendations based on similarity in scoring patterns to those of players who have played before.

a. Khat Types
   This study used seven types of khat as recommendation objects. Each type has distinct visual characteristics, aesthetics, and difficulty levels, which can serve as the basis for the assessment process and recommendation score calculation. The list of khat types includes: Naskhi, Tsulus, Diwani, Diwani Jaly, Farisi, Riq'ah, and Kufi (Achmad & Jamaluddin, 2022).
b. Khat Color
   The colors used for this costume are primary and secondary colors. These color references sometimes have common differences in each gender. There are significant differences in color preferences between men and women. Men show a very strong preference for cool colors, especially blue and green, while women have a more even preference with a dominance of green and blue, followed by purple and red(Baniani, 2022). Then, differences in location and culture also influence color preferences, for example, women in various cultures (English, Chinese, Arabic, and

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Indian) show a particular preference for pink. It is important to note that there are color symbols in Chinese culture that also influence some colors, such as red is considered a lucky color, and white symbolizes cleanliness and purity.

Another study found that age is a factor influencing color preference. Girls prefer pink over boys at an early age. However, blue remains a favorite across all age groups. Furthermore, red preferences increase among adult women due to social norms and biological or emotional factors. Consumers purchase more colors that align with their preferences. The higher a person's preference for a color, the more likely they are to purchase products in that color (Yu et al., 2021)

2.2.2 System Design

A system design is created to generally describe the calligraphy handwriting recommendation system developed based on the collected and processed data. The steps taken include user input, Collaborative Filtering (CF) , score calculation, and finally, handwriting recommendation output. The system design for this study is shown in Figure 3.

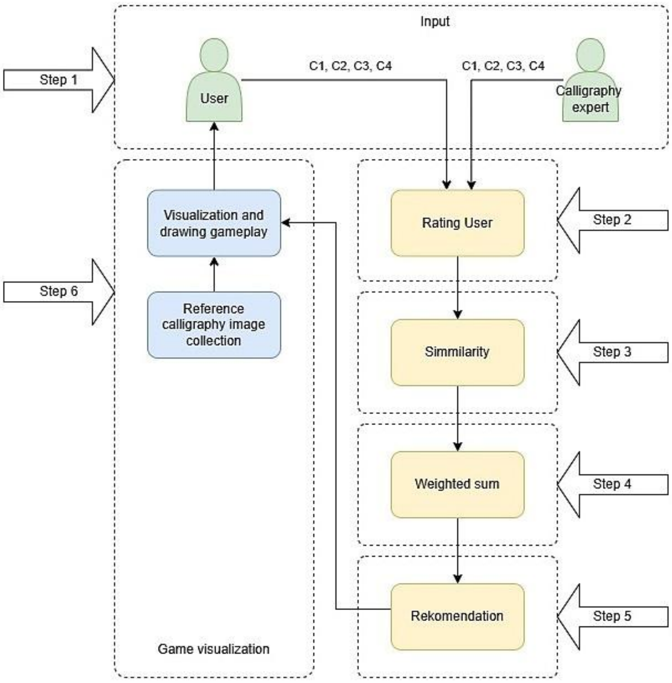

Figure 3. Propose system with Knowladge based for challigraphy game

Figure 3 illustrates the workflow of the calligraphy recommendation system, which operates through six sequential stages. In Step 1, the system receives input from users and calligraphy experts, including handwriting results and scoring criteria. In Step 2, these inputs are converted into numerical ratings that represent player performance for each calligraphy style. Step 3 involves calculating similarity between players using a User-Based Collaborative Filtering approach, identifying users with similar evaluation patterns. In Step 4, the system applies the Weighted Sum prediction formula to estimate player performance for calligraphy styles they have not yet attempted. Based on these predicted values, Step 5 generates ranked recommendations of the most suitable calligraphy styles. Finally, in Step 6, the recommended style is visualized in the game, enabling players to directly experience the handwriting style in subsequent gameplay. This systematic process ensures that recommendations are data-driven and tailored to player performance patterns.

a. Dataset

The dataset in this study was obtained through player interactions in a developed digital calligraphy game . Each piece of data collected represents a player's performance when writing a specific type of script. Recorded attributes include the player's name, the type of script chosen, and scores based on three main criteria: decoration (50 %), neatness (30 %), and time (20%). According to expert calligraphy sources, the scores for each criterion range from 0 to 100, and are then calculated into a standardized final score based on a predetermined percentage weight.

This dataset is dynamic and continues to grow as more players try the game . Game results from previous players are used as the basis for the user-based process. Collaborative Filtering compares player rating patterns to recommend appropriate handwriting styles for new players. With this data structure, the system can learn player relationships and tendencies toward specific handwriting styles based on actual game results, not personal preferences

b. Recommendation System Design

In this section, we will explain in general terms how the system will operate, using flowcharts and sequence diagrams to provide a more detailed overview of the constraint-based approach. This process flow can be seen in the flowchart shown in Figure 4.

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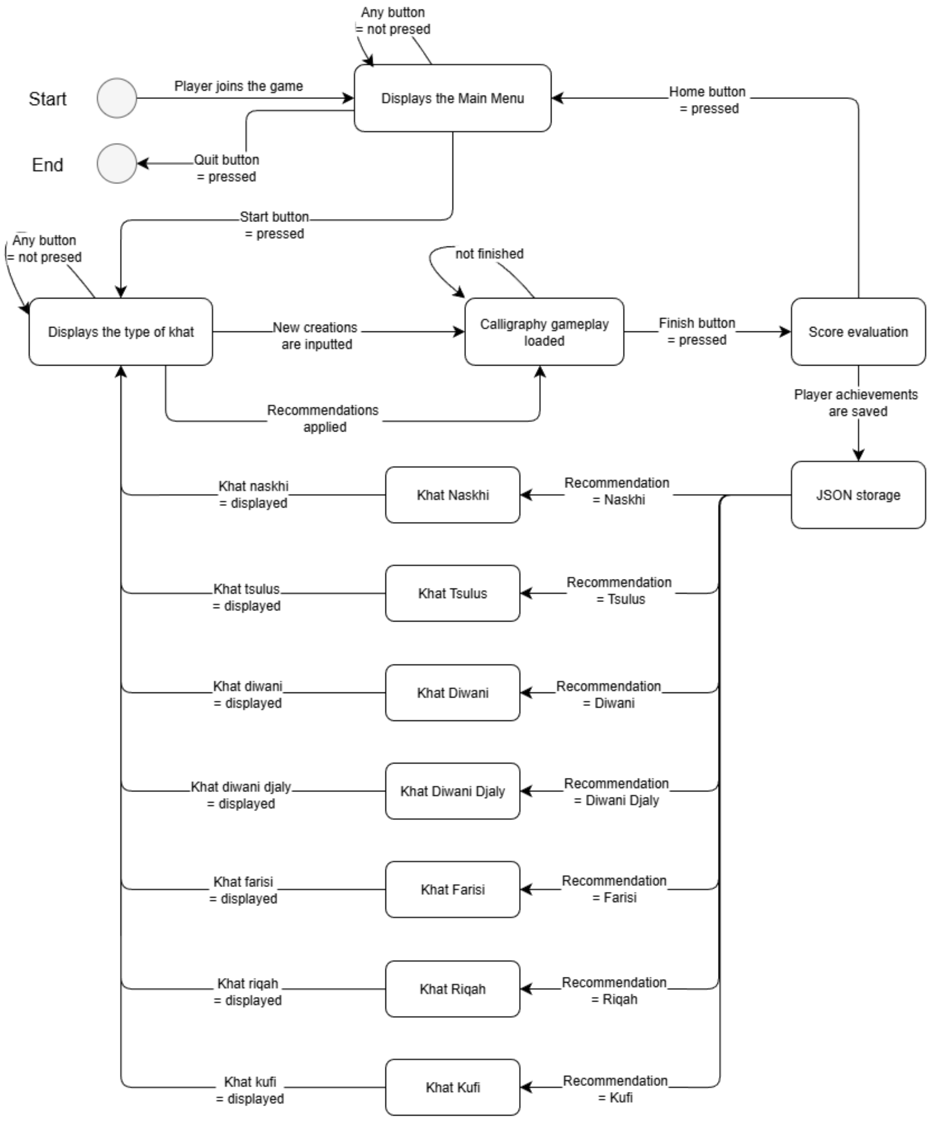

Figure 4. FSM calligraphy game

Figure 4 illustrates the complete gameplay workflow implemented in the system. The process begins when the player starts the game and arrives at the main menu interface. After the Start button is selected, the system displays the available Arabic calligraphy styles (khat) that the player may choose from. The selected style is then used in the next step, where a new calligraphy writing session is generated, and the calligraphy gameplay scene is loaded. Once the player completes the writing process and presses the Finish button, the system proceeds to the score evaluation stage, where the handwriting is assessed based on predefined criteria. The resulting performance data and player achievements are then stored in JSON format, forming part of the dataset used for recommendation processing. The recommendation engine subsequently calculates predicted performance values for each khat style and determines the most suitable options. Finally, the system displays the recommended calligraphy styles to the player, and the recommendation is applied in the next gameplay session. This process ensures that the system continuously adapts to player performance and supports personalized learning experiences.

2.2.3 System Implementation

The implementation of a calligraphy handwriting recommendation system in this study focuses on helping new players choose the type of handwriting that best suits their abilities. The system does not ask players to directly enter demographic information, such as age, gender, or color preferences. Instead, it only uses game results data, namely decoration scores and neatness from previous players.User-Based system approach Collaborative Filtering (CF) analyzes the similarity of game results between players. When a new player completes a calligraphy session on a particular script, the system compares their results with those of other players who have written the same script. Based on the similarity of scores and result patterns, the system recommends the next script that best matches the new player's performance. The system can provide personalized and adaptive recommendations, not based on subjective preferences but on concrete data from playing experience. The recommendations are displayed interactively, allowing players to view the recommended characters and select one for further practice.

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2.2.4 Evaluation

Game system developed using Unity 3D was tested on a heterogeneous user base to measure system performance and user satisfaction. The system evaluation was conducted using the Mean Absolute Error (MAE) method , which calculates the average difference between the recommendation value generated by the system and the actual value selected by the user (Hartatik et al., 2021) . MAE is used to measure the accuracy of the Collaborative Filtering- based recommendation system, where a smaller MAE value indicates a more accurate system in predicting user preferences for combinations of font type, writing color, and background. Furthermore , to assess the quality of the gaming experience subjectively from the user's perspective, the 18- item version of The Game User Experience Satisfaction Scale was used. (Keebler Assoc et al., 2020) . GUESS-18 is a shortened version of the original GUESS containing 55 items(Mittmann et al., 2024), but still maintains the validity and coverage of nine main constructs such as engagement, challenge, aesthetic value, and overall satisfaction. The use of GUESS-18 is considered effective for iterative game evaluation because it is concise but still able to describe user perceptions comprehensively. The data from this test results serve as the basis for analyzing the strengths and weaknesses of the system and become input for further development. This question is shown in Table 1.

Table 1. GUESS-18 questions

No	Construct	Statement
1.	Usability / Playability	I found the controls in this game easy to understand
		I found the game's interface easy to navigate
2.	Narratives	I was intrigued by the story of this game from the start
		I enjoy the fantasy or storyline presented in this game
3.	Play Engrossment	I feel detached from the outside world while playing this game
		I don't care about real world events while playing this game
4.	Enjoyment	I find this game fun
		I feel bored when playing this game (reverse/negative score)
5.	Creative Freedom	I feel like this game allows me to imagine
		I feel creative when playing this game
6.	Audio Aesthetics	I enjoyed the sound effects in this game
		I feel the in- game audio (e.g. sound effects, music) enhances my gaming experience
7.	Personal Gratification	I am very focused on my own performance when playing
		I want to get the best possible results when playing this game
8.	Social Connectivity	I feel this game supports social interaction (e.g. through chat) between players
		I love playing this game with other players
9.	Visual Aesthetics	I enjoyed the graphical look of this game
		I found this game visually appealing

Table 1 presents the questionnaire instrument used to measure player perceptions of the developed serious game. The instrument consists of 18 statements grouped into nine constructs that assess different aspects of user experience. The Usability/Playability construct evaluates how easily the player understands and navigates the game interface. Narratives reflects the player's interest and engagement in the storyline provided. The Play Engrossment construct measures how immersed players feel while playing, including their detachment from real-world activities. Enjoyment assesses the level of fun experienced by the player, including one reversed negative statement to maintain response balance. Creative Freedom examines the extent to which players feel free to express imagination during gameplay. Audio Aesthetics measures how much sound effects and in-game audio contribute to the playing experience. Personal Gratification evaluates the player's focus on performance and achievement while playing. The Social Connectivity construct assesses the perception of interaction and communication among players. Finally, Visual Aesthetics evaluates user impressions of the graphical presentation of the game. Together, the statements in Table 1 form the basis for evaluating player experience as part of the post-game assessment.

2.2.4 Experiment

The system was conducted to test the performance of a handwriting recommendation system in the educational game "Try Calligraphy," developed using Unity 3D and employing the Collaborative Filtering method. The purpose of this experiment was to evaluate the system's ability to provide accurate and appropriate recommendations, as well as the user's level of satisfaction with the game shown in table 2. By varying the number of initial users and training data, the evaluation showed how prediction quality changed as the system had more player behavior patterns to learn. This was crucial to ensure that the system not only performed well on a small dataset but also maintained accuracy as the user base increased, as in real-world implementations.

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Table 2. Experimental Scenario

Scenario	Initial Number of Users	Initial Data Amount	Number of Players	Notes
A	5 dummy users	15	10 players	Recommendations are given after 1 session
B	20 dummy users	60	10 players	Focus on evaluating performance predictions

Table 2 presents the experimental scenarios used to evaluate the performance of the handwriting recommendation system in the "Try Calligraphy" game. Each scenario differs in terms of dataset size and testing objectives. Scenario A utilizes five dummy users and a small data volume consisting of 15 records. A total of ten real players participates, and recommendations are generated after a single gameplay session. This scenario is designed to examine the basic functionality of the system and determine whether the recommendation engine can produce relevant suggestions with minimal initial information.

Meanwhile, Scenario B employs a larger dataset, consisting of 20 dummy users and 60 data entries, also involving ten players. This scenario focuses on assessing the system's predictive performance when provided with more comprehensive data. With a broader user base and interaction records, Scenario B enables a deeper analysis of the accuracy and reliability of the Collaborative Filtering predictions. Together, the scenarios in Table 2 ensure that the recommendation system is tested under both limited and more realistic data conditions, providing a balanced evaluation of system capability and adaptability.

3. RESULTS AND DISCUSSION

3.1 System Implementation

The implementation stages were carried out in Unity 3D version 2022.3 (LTS) using the C# programming language. This system is implemented as a desktop application that displays calligraphy handwriting style recommendations in text and image form, based on user preferences. The system consists of three main components:

1. User Data Input: Stores user ratings or preferences for several handwriting styles.
2. Collaborative Filtering Engine: Calculates similarities between users based on stored JSON data.
3. Recommendation Output: Displays a list of recommended handwriting styles along with representative images

All user data and scores are stored in a JSON file, which serves as a local data repository for easy access by Unity without requiring a connection to an external database. The JSON format contains a list of users, their scores, and handwriting styles they have or are currently learning. Each time a user completes a training session, the score is saved to a JSON file, and the system performs a similarity calculation between users using a score-based collaborative filtering approach. The user similarity calculation is performed using the Cosine Similarity method using a C# script in Unity. This section describes the results of the study. Results should be presented clearly and concisely. Authors should explore the novelty or contribution of the research to the literature used. Present clearly the results of testing, analysis and discussion using primary, relevant and up-to-date references. The following example of the main code snippet is shown in Table 3.

Table 3. Cosine similarity calculation pseudocode

Name

BEGIN
INPUT: Two lists of player data, userA and userB, each containing pairs (KhatType, FinalScore)
 	
# Step 1: Find the same Khat type 	
SET commonKhat ← list of Khat types that appear in userA and userB
 	
IF sum(commonKhat) = 0 THEN
RETURN 0 # No similar Khats
END IF
 	
# Step 2: Calculate the total similarity for each common Khat 	
INIT sum ← 0
 	
FOR each Khat in commonKhat DO
SET skorA ← userA's FinalScore for that Khat
SET skorB ← userB's FinalScore for that Khat
 	
SET difference ← |skorA - skorB| # Calculate the score difference
SET similarity ← 1 - (difference / 100) # Scale 0–1

Name
UPDATE sum ← sum + similarity END FOR # Step 3: Calculate the average similarity between players SET result ← sum / sum(commonKhat) RETURN result # Final similarity score END

The Table 3 explains the process of calculating khat style recommendations. The process begins by collecting data from all users and all khat types available in the system. The system then calculates the similarity between users based on the scores they give for the same khat (common khat). The method used here is similar to rating-based cosine similarity, where the difference in scores between users for each khat is converted into a similarity value between 0 and 1: the smaller the difference in scores, the higher the similarity. After the similarity value is calculated, for each khat that has not yet been rated by the target user, the system calculates a predicted score by taking a weighted average of the scores of other users with high similarity. The weights are based on these similarity values, so that scores from more similar users contribute more to the prediction. The final step is to compile a list of recommendations consisting of several (e.g., three to five) khat styles with the highest predicted scores, which are then presented to the user as recommendations. In this way, the system can provide relevant suggestions based on the user's preference patterns, even if they have not tried all khat styles.

3.2 Test Result

The testing phase is conducted to ensure the system functions as intended and provides relevant recommendations based on user scores. Testing is divided into two main parts: functional system testing and usability testing using the GUESS-18 method.

3.2.1 Experiment A

Experiment A was conducted to simulate the initial performance of the calligraphy handwriting style recommendation system using dummy data before testing it directly on real users. The main objective of this experiment was to determine the system's accuracy in predicting new user preferences based on the rating patterns of other users using the User-Based Collaborative Filtering method. In this stage, the system was trained using five dummy data sets representing five users' ratings of four types of handwriting: Diwani, Naskhi, Kufi, and Tsuluts. Each user received a performance score between 60 and 95, resulting from a combination of ratings for decoration, neatness, and completion time. A blank (-) value indicates a type of handwriting that the user has never played before. Using the five dummy data sets, we added a new player who only played Naskhi handwriting. This player received a final score of 70. Therefore, the system searched for other users who had also played Naskhi to measure similarity. This scenario is shown in table 4.

Table 4. Experimental results of scenario A

Player	Naskhi	Tsulus	Diwani	Kufi
U1	75	92	87	-
U2	-	81	78	64
U3	73	-	66	70
U4	69	75	-	82
U5	85	95	93	-
U6	70	-	-	-

Once the similarity scores between players are calculated, this section of code predicts the target player's score for a khat type they haven't tried yet. The system explores each khat type in the dataset, ignoring those already played, and then calculates a predicted score using a similarity-based weighting formula: each other player's score is multiplied by its similarity, summed (numerator), and divided by the total similarity score (denominator). This average score is the final predicted score for each khat. All predictions are displayed via Debug.Log, sorted from highest to lowest to yield the top three recommendations. These scores then form in Table 5, which displays the predicted scores and the order of recommendations based on the most potential performance for the target player. Using the script above, the results are shown in the table 5.

Table 5. Predicted U6 value for untested khat

Prediction	Value	Recommendation
Diwani	81.5	2
Kufi	76.1	3
Tsulus	86.9	1

TIN: Terapan Informatika Nusantara
Vol 6, No 7, December 2025, page 872-885
ISSN 2722-7987 (Media Online)
Website https://ejurnal.seminar-id.com/index.php/tin
DOI 10.47065/tin.v6i7.8744

Table 5 shows the predicted values for each recommendation. These predictions are then represented by three images, as shown in Figure 5. Table 5 presents the prediction values generated by the system for several handwriting style recommendations. These numerical results are then visualized in Figure 5, which displays three selected calligraphy types—Tsulus, Diwani, and Kufi—as the highest-ranked recommendations. Figure 5 illustrates how the system transforms rating predictions into visual output, presenting the recommended handwriting styles directly to the player within the game interface. This visual presentation allows players to clearly see the types of calligraphy that best match their performance patterns based on similarity calculations from previous users.

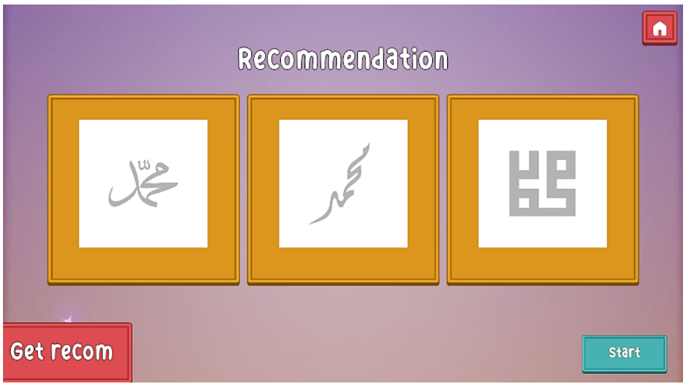

Figure 5. Recommendations for small stake players

3.2.2 Experiment B

This experiment conducted to directly test the effectiveness of a calligraphy handwriting style recommendation system on improving performance and user experience. Unlike Scenario A, which used simulated data, in this scenario, testing was conducted with 10–20 real respondents consisting of school and university students interested in Arabic calligraphy. The goal of this experiment was to measure the extent to which the recommendation system could improve user performance compared to if they freely selected handwriting styles.

1. Recommendation System Simulation
   Each respondent was asked to play at least three practice sessions with different handwriting styles. In the first session, players freely chose a handwriting style (without system recommendations). After the first session, the system calculated a performance score based on three main components. Based on this score, the system provided recommendations for the next handwriting style using User-Based Collaborative Filtering.
2. User Performance Improvement Results
   One player, with the condition that he has played twice, used the Diwani Jaly script with a final score of 64.0 and Kufi with a final score of 54.0. The system recommends the Tsulus, Diwani, and Naskhi script styles.

Figure 6. Recommendations for large number of players

Figure 6 visualizes the recommendation results generated by the system in Experiment B after analyzing the player's performance during their initial gameplay sessions. In this example, a player had completed two handwriting attempts, Diwani Jaly with a score of 64.0 and Kufi with a score of 54.0. Based on the similarity calculation among users, the system predicted which calligraphy styles would be most suitable for the player. Figure 6 displays three recommended calligraphy types Tsulus, Diwani, and Naskh as the top-ranked predictions, and these visual outputs correspond directly to the numerical prediction values shown in Table 6.

Table 6. Comparison between predicted and actual values

Khat style	System Prediction Value	Player Actual Value	Error
Tsulus	56.9	54.0	2.94

TIN: Terapan Informatika Nusantara
Vol 6, No 7, December 2025, page 872-885
ISSN 2722-7987 (Media Online)
Website https://ejurnal.seminar-id.com/index.php/tin
DOI 10.47065/tin.v6i7.8744

Khat style	System Prediction Value	Player Actual Value	Error
Diwani	64.6	73.0	8.41
Naskhi	62.6	93.00	30.39

Mean Absolute Error (MAE) = 13.92

Table 6 presents a comparison between the system's predicted performance values and the actual scores achieved by the player for three recommended calligraphy styles. The goal of this table is to evaluate how accurately the User-Based Collaborative Filtering method can anticipate a player's expected performance in subsequent gameplay sessions. The table shows that the system predicted performance values of 56.9 for Tsulus, 64.6 for Diwani, and 62.6 for Naskhi, compared to the player's actual scores of 54.0, 73.0, and 93.0, respectively. The resulting errors reflect the absolute difference between prediction and outcome, which vary noticeably across the three styles, with Naskhi showing the highest deviation.

The MAE value of 13.92 in the table 6 indicates that the recommendation system still has a relatively high level of prediction error. This means that the difference between the system's predicted performance and the player's actual performance is still quite large, especially for the Naskhi style. This could be due to the limited amount of training data and the high variation in user performance. Nevertheless, these results still demonstrate that the system is capable of generating targeted and relevant recommendations based on user preferences, although its accuracy still needs to be improved through additional data and optimization of parameters for calculating user similarity.

3.2 Usability Testing

In addition to functional testing, usability testing was conducted using the application. This testing involved 10 respondents from school and university backgrounds who were interested in Arabic calligraphy and had tried the application, as shown in the table 7.

Table 7. Respondent demographics

Demographic Characteristics	Category	Number of Respondents (N)	Percentage (%)
Age	Adults (17 years and over)	6	60%
	Teenagers (12-17 years)	1	10%
	Children (12 years and under)tahun)	3	30%
Playing Experience	Ever	9	90%
	Never	1	10%
Playing Platform	Smartphone	7	70%
	Computer/ Laptop	3	30%
Playing Experience	More than 3 months	7	70%
	1 to 3 months	2	20%
	Less than 1 month	1	10%
Playing Duration	More than 6 hours	0	0%
	3 to 6 hours	3	30%
	Less than 3 hours	7	70%
Playing Frequency	Every day	4	40%
	2 to 3 times a week	4	40%
	1 time a week	1	10%
	Does not play	1	10%

Table 7 presents the demographic characteristics of the 10 respondents involved in the usability testing of the calligraphy learning application. The data show that the majority of users were adults aged 17 years and above (60%), followed by children under 12 years (30%), and a smaller proportion of teenagers (10%). Most respondents (90%) had prior gaming experience, indicating familiarity with digital games as a learning medium. The table also shows that smartphones were the most common platform used (70%), while the remaining 30% utilized computers or laptops. In terms of gaming experience duration, most users had been playing for more than three months (70%), while others had between one and three months (20%), and only one respondent had been playing for less than a month (10%). Furthermore, the majority of respondents (70%) played less than three hours per session, and the frequency of play was relatively high, with 40% playing daily and another 40% playing two to three times per week.

The majority users were adults and had previous gaming experience. Most used smartphones to play games and had been playing for more than three months, typically spending less than three hours per session. Playing frequency varied, but the majority played almost daily or two to three times a week. This data indicates that respondents were quite familiar with the games and devices they used, allowing them to provide valid feedback on the GUESS-18 evaluation of their gaming experience.

The usage patterns evident in this demographic data indicate that respondents have a fairly consistent engagement with gaming activities, allowing them to evaluate the app's user experience more comprehensively. The high proportion of experienced users and their regular play frequency provided an advantage in testing, as respondents

TIN: Terapan Informatika Nusantara
Vol 6, No 7, December 2025, page 872-885
ISSN 2722-7987 (Media Online)
Website https://ejurnal.seminar-id.com/index.php/tin
DOI 10.47065/tin.v6i7.8744

were able to compare the quality of the app's gameplay, interface, and aesthetics with those of other games they had previously tried. The variety of devices also provided a broader perspective on the app's performance on different platforms. Thus, the diversity of respondents' experiences and playing habits further strengthens the reliability of the data obtained for assessing user satisfaction and the effectiveness of the app's learning features. The average scores for each construct are presented in Table 8 below.

Table 8. GUESS-18 Evaluation

Respondent	Usability	Narratives	Play Engrossment	Enjoyment	Creative Freedom	Audio Aesthetics	Personal Gratification	Social Connectivity	Visual Aesthetics
R1	5.5	2.5	4	6.5	7	5.5	7	3	6.5
R2	6.5	2.5	5	6	7	5.5	7	4.5	6.5
R3	6	3	3.5	6.5	7	6	7	4.5	7
R4	7	3	4	6.5	7	5.5	7	4	6.5
R5	6.5	3	4.5	6.5	7	6	7	3	7
R6	6	2.5	3.5	5	6.5	6	6.5	3	5.5
R7	6.5	2.5	4.5	5.5	7	6	7	4	6.5
R8	5.5	3	3	5.5	7	6	7	3.5	6.5
R9	7	2.5	4.5	5	7	6	7	4.5	7
R10	7	1.5	4.5	5.5	6.5	6.5	7	4.5	7
Average	5.86	2.55	4.00	5.68	6.73	5.91	6.95	4.23	6.82

The complete evaluation results of the GUESS-18 instrument are presented in Table 8, which summarizes the scores from 10 respondents across nine assessment constructs. Based on the table, the highest average scores were obtained in Personal Gratification (6.95), Visual Aesthetics (6.82), and Creative Freedom (6.73). These scores indicate that players felt satisfied with their performance, appreciated the visual presentation of the game, and experienced a high degree of creative expression during gameplay. In contrast, the constructs with lower scores were Narratives (2.55) and Social Connectivity (4.23), suggesting that the game's storyline and social interaction features are still limited and could be further improved in future development. Thus, Table 8 clearly shows the distribution of player perceptions regarding the usability, enjoyment, learning experience, and presentation quality of the “Try Calligraphy” game, supporting the overall evaluation discussion presented in this study.

3.2 Discussion

Based on testing in Scenario A, the User-Based Collaborative Filtering system was able to calculate similarities between users and predict scores for new players by considering the scores of other users with similar scoring patterns. Simulation experiments, predicting scores for U6 players on untested khat styles, showed that the system could suggest the three best khat styles (Tsulus, Diwani, and Kufi), with predicted scores close to the actual performance of other players. This confirms that the similarity algorithm and score-based weighted average calculation are quite effective in a simulated context.

In Scenario B, which involved 10 real respondents, performance evaluations revealed discrepancies between the system's predicted values and the players' actual scores. The MAE of 24.02 indicates a relatively high prediction error, particularly for the Diwani and Kufi styles, which could be influenced by the limited amount of training data and individual performance variations. Nevertheless, the system demonstrated adaptive capabilities in providing relevant and targeted recommendations, ensuring players received useful guidance to improve their performance. Usability testing using the GUESS-18 instrument showed positive results across all constructs, with an average score for each construct ranging from 4.0 to 6.9 on a maximum scale of 7, indicating a positive to excellent user experience. Therefore, it can be concluded that the game "Try Calligraphy" provides a fun, easy-to-use gaming experience, and facilitates player creativity. Constructs with slightly lower scores indicate that the storyline and social interaction aspects of the game are not yet prominent or still need improvement.

From the combination of simulation results, real-world testing, and GUESS-18 evaluation, it can be concluded that the handwriting style recommendation system in the game "Try Calligraphy" functions functionally with fairly accurate predictions and provides a positive user experience. However, prediction accuracy can be improved by adding training data, optimizing similarity parameters, and strengthening social interaction features to increase user engagement

TIN: Terapan Informatika Nusantara
Vol 6, No 7, December 2025, page 872-885
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DOI 10.47065/tin.v6i7.8744

4. CONCLUSION

The “Try Calligraphy” game system, which uses the User-Based Collaborative Filtering method, is able to provide relevant handwriting style recommendations based on the score patterns of other users. Predicted scores for handwriting styles that players have not yet tried are quite close to actual performance, although there are differences in some handwriting types due to limited training data and individual performance variations. MAE values of 16.08 and 13.92 indicate that the system's prediction accuracy can still be improved, but the system has successfully provided useful guidance for players to improve their performance. Usability testing using the GUESS-18 instrument showed that all constructs obtained an average score above 4.0, indicating a positive to excellent gaming experience. Players rated the game controls as easy to use, the visuals attractive, and the gameplay able to support creativity and provide personal satisfaction. However, the Social Connectivity aspect scored relatively lower than the other constructs, indicating that the game's social interaction features can still be improved to strengthen engagement between players. Overall, the evaluation results show that the recommendation system and gameplay in “Try Calligraphy” have successfully met the development objectives, both in terms of system functionality and user experience satisfaction.

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