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Using Gamification along with Recommender Models in Learning of Data Science

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Abstract

Gamification is a persuasive technology widely utilized in education to enhance learning and productivity. A common challenge in gamification design is the application of a uniform content strategy for all users, which often results in suboptimal performance. Personal gamification tailors game content to individual user characteristics. Although various personalization methods target students' traits and learning styles, few studies have examined the use of machine learning algorithms in this area. This paper presents a model for personalized gamification in data science education, employing recommender system algorithms to improve data quality. The model incorporates real-time implicit and explicit voting, creating a dynamic learning environment. We developed a gamified platform for 680 students across eight classes. After three months, user feedback and log data revealed that the singular value decomposition (SVD) algorithm performed best among the recommender systems, positively influencing learning outcomes, as confirmed by t-tests and A/B testing.

Keywords: Gamification, Personalization, Recommender System, Algorithms, Learning, Data science

1. Introduction

Gamification can be called the use of game design elements in non-game fields, which will improve user interaction and motivation. Game design elements can include points, badges, and scoreboards (Pereira et al., 2023). Gamification in Various areas is being used as a persuasive technology (Fogg, 2002; Lin et al., 2023). The purpose of using gamification in educational environments is to use game elements in a learning environment to improve experiences, and motivations, and increase the learning process of the students (Caporarello et al., 2019; Kopcha et al., 2016). The most important factor of students' learning curve which

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should be paid attention to, is Motivation (Buckley & Doyle, 2017). Some studies have also been conducted in relation to the verification of gamification and increase of motivation (Hallifax et al., 2020) . Although many studies showed positive effects of gamification, there are some reports that mentioned negative consequences (Andrade et al., 2016; Mekler et al., 2013; Toda et al., 2017). Various factors (Werbach et al., 2012), such as incorrect use of game elements (Andrade et al., 2016), wrong implementation of the game environment (Yasemin & Samur, 2018), and lack of consideration of the personality and behaviors of the users in the design of the gamification environment will spoil the students' learning.

Gamification is used in many fields. One example is education, which will improve the process of learning and productivity in this area such as business education, learning in schools, and lifestyle learning, where gamification enhances people's participation, motivation, and continuity of activity (Codish & Ravid, 2015).

1.1 Personality Gamification

One of the mistakes during the design of game elements that causes the low performance of gamification is having the same content creation strategy for all users (Codish & Ravid, 2015). Their character can affect their understanding and performance in using different gamification elements (Khoshkangini et al., 2021) . Each player has his skills, abilities, and preferences (Codish & Ravid, 2014), which should be used in the concepts of personalization and design of the game environment and elements for each person to increase the performance of the game. There are two approaches for personal learning. Using a psychological approach to adapt game environments is one of these methods that deal with the psychological aspects of gamification of a person. There are studies based on parameters such as the type of player, learning styles, personality traits, and based on psychological tools such as Brainhex, Bartel, Hexad, Felder-Silverman learning style, and the Big Five.

Generally the drawbacks of the mentioned method are lack of using tools and human aspects and also statistical evidence in review of gamification learning.

The second approach is providing models, using tools, models, process studies, and computational approaches. A few studies have utilized machine algorithms and were able to use models (Khoshkangini et al., 2021). There are disadvantages of this method such as lack of review of personalized and not personalized versions in the process of learning, not providing auto adaptability on systems, lack of architecture, a small dataset with low quality for machine algorithms, and also the study of users behaviors in a long-term period.

1.2 Recommender system algorithms in Personality Gamification

Recommender systems include techniques and tools that suggest things to users that they may require (Santos et al., 2022). Recommender systems are used in various fields. But the most popular one is learning (Hariyale et al., 2022). To build a recommender system, there are two popular methods, content-based and collaborative filtering. Each of the methods has its weaknesses and strengths. In collaborative filtering, there are limitations such as cold start, dispersion, and scalability which will cause the low performance of the systems. There are also hybrid approaches to deal with the weaknesses of each method in making recommender systems (Rahayu et al., 2022). Concerning personal gamification, only one study on its model has been proposed (Sharma et al., 2022). However, an important method in personal gamification is recommender algorithms.

Although many studies have been done in the past regarding the use of machine learning and gamification technologies together and many efforts have been made in this field using psychology approaches and the use of supervised and unsupervised learning algorithms in personalization and increasing efficiency, a few machine learning research was done in gamification efficiency in education. Some research gaps such as a general model and architecture in learning data science, recommender systems, and their implementation are mentioned in our study.

In this paper, a personalized model has been designed using recommender systems for students to learn data science. Many elements have been considered to increase the efficiency of the designed system. In the proposed models, recommender systems were used to personalize gamification for providing different suggestions and increase the efficiency of students' data science learning. The purpose of the model is to simultaneously use recommender system techniques in gamification and its effect on better student learning. A large set of data was created in educational systems that can be used for better decision-making (Tondello et al., 2017). Information processing along with recommender systems was used to improve the educational process of learning data science.

The structure of this study is as follows: In part one, we will the approach and system of gamification in the field of data science learning and the use of the recommender model. In part two, the recommender algorithms and their model will be presented in the gamification environment. The evaluation will be discussed in the third part. Finally is the conclusion.

2. Related work

As listed in Fig. 1 the studies in personal gamification are divided into two main categories: with and without machine algorithms. In the first area, students' characteristics, learning styles, mental states, motivation, and demographic factors are considered to design systems according to the personality and characteristics of people. The psychological models of all types of players are employed to identify their personalities. The most utilized model in studies is Brain Hexad. Research was done with player personality recognition in this model to personalize the gaming environment (Abu Saa et al., 2019; Monterrat, Desmarais, et al., 2015; Monterrat, Lavoué, et al., 2015; Monterrat et al., 2017; Oliveira et al., 2020). 4 personality models of Bartel were also used to personalize this gaming environment (Lavoué et al., 2018). Learning styles (Borges et al., 2016), characteristics, the 5-factor personality model (Zaric et al., 2017), designing personalization games based on students' characteristics such as age and gender (Denden et al., 2017), and using demographic data (Monterrat et al., 2014) are other works in this field. Psychological approaches, tools, and models for personalization are also used for personalization. In these studies, questionnaires and people's personality checks were used for personal gamification, and the suggestions that were given to users were done after evaluating and checking the people's personalities causes the stability of the gamification environment. Also, many studies did not make the game development environment and were just more theoretical. Furthermore, some convincing strategies were studied. On top of this, for each game characters were suggested suitable elements. Finally, for the personalization of gaming environments, computational approaches, tools, models, processes, architectures, and ontology were employed.

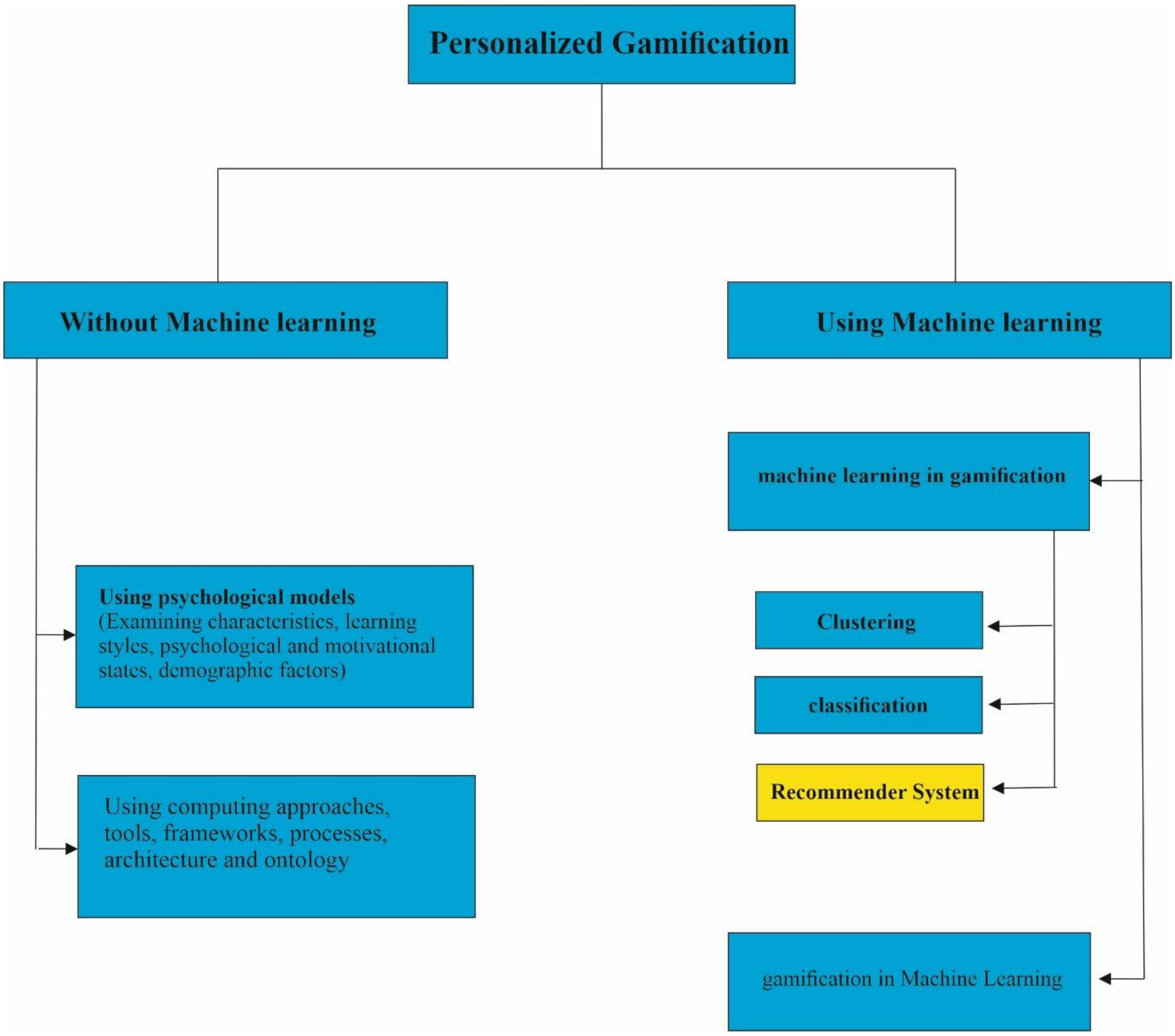

Fig. 1 Gamification Categories

2-1 Gamification in Machine Algorithm

Gamification and machine learning can increase each other's performance cooperatively (Calle-Archila & Drews, 2017). One of the areas in which gamification can improve machine learning processes is better data collection, especially labeling data. It will increase the motivation of users to collect and label data and generate machine learning algorithms with more data quality which increase the prediction accuracy of machine learning methods used serious games in a study to collect data (Khakpour & Colomo-Palacios, 2021). Authors used these data to increase the accuracy of random forest algorithms and linear regressions for their applications (L'Heureux et al., 2017). Another research for collecting datasets related to gamification was used to improve the deep learning algorithm model (Murphy et al., 2018). Some studies also employed the power of gamification to create motivation to increase the quality of collected data for machine learning purposes. In their software, user data were collected and then labeled. Gamification helped to label data (Li et al., 2016). In majority of the research the power of gamification was used for supervised algorithms, while, it also improved unsupervised learning. It also were used as a reinforcement learning which gamification can contribute to verifying the results and help to optimize the algorithm (Urh &

Pejović, 2016). In most papers gamification can be used to generate suitable data for analysis with the help of machine learning (Holzinger, 2016).

2-2 Machine algorithms in Gamification

There are papers that try to use machine learning techniques or approaches and algorithms to strengthen and support gamification tasks. Personalization is one of the methods used to enhance processes and improve gamification programs. Personal gamification changes or suggests the content of games and elements based on the specifications and characteristics of users. In each gamification environment, a special algorithm is required to improve the performance, and different algorithms can be selected for the appropriate purpose. In many studies in this field, classification algorithms have been used. These algorithms perform personalization on the data that people extract by working with gamification programs. In a large set of studies, the classification of students was used to provide different suggestions and environments based on each category. In 2014, a web gamification environment utilizing data mining of the students' logs was presented (Murphy et al., 2018; Nozari et al., 2022). In 2017, authors implemented the Bayesian algorithm to personalize challenges (Monterrat et al., 2014, Nozari & Aliahmadi, 2022). In an article published in 2018, machine algorithms were proposed to specify personalized strategies and gamification activities. They are used for classification between different situations in the field of cooperative learning (Psaltis et al., 2017). In another article, to increase the efficiency of students in gamification environments, EM algorithms were used to cluster students and categorize them into 5 groups. (successful, disabled, low-achieving, and slow-witted) and created a smarter environment for each of the categories with this classification (Khoshkangini et al., 2017; Nozari, 2024). In another study, ϵ-greedy and ϵ-decreasing algorithms were used to improve and personalization of gamification environments (Barata et al., 2015)]. Another paper, utilized gamification for children's brain development, the K-means clustering algorithm was used to evaluate brain development with respect to children's age, and finally, appropriate games for each part were used (Anparasanesan et al., 2019). An adaptive management system was designed based on the specifications and features of users with machine algorithms. Different scenarios and elements are suggested online and offline. Also, machine algorithms were used to select suitable content for each person in gamification and automation environments (Stefanidis et al., 2019). Some models for producing content and providing suitable challenges according to the profile and characteristics of different people were generated (Knutas et al., 2019; Ghahremani-Nahr et al., 2023) .

2-3 Gamification in Learning

Studies were conducted in the field of using gamification to learn machine learning processes. In 2018, a gamification environment was used to simplify and gain a better understanding of the knowledge of machine learning in a technical manner. Authors improved the performance of students in learning machine algorithms (Khoshkangini et al., 2017). In another paper, the processes of learning were minimized by using gamification. In all cases, reports mentioned more enjoyment in machine learning (Sakulkueakulsuk et al., 2018). In another article, clustering tools were used to design an intelligent learning environment for learning different engineering courses. Better performance in learning was reported in their environment (Rattadilok et al., 2018).

While personalization and gamification methods were reviewed separately in previous studies, the use of gamification to create a personalized e-learning environment that matches the personality and motivation of students was not fully studied. Research in this area can be beneficial due to considering the positive effects of individual characteristics of learners on their performance in e-learning environments and the possibility of strengthening these effects by using gamification as a personalization method.

The employment of machine learning in this gamified learning platform helps to expand the learning context by dynamically and intelligently creating game elements that lead to optimization (Ghaleb et al., 2018). The most important item among the mentioned advantages of personalization is creating game plans and content for each user, which is not an easy task. Therefore, efforts were made to simplify the structures and processes of personalization games. Despite the difficulties in the implementation of personalization for gamification tasks, this is one of the most prominent reasons for using machine learning methods in human-computer interaction systems. This research question is exactly in contrast with the previous question and it investigates the contribution of machine learning in increasing gamification processes which few studies have done before it.

3. Proposed Method

To evaluate the acceptance and use of recommender system models in personal gamification, initially, a gamification system was created in the field of data science learning which is accessible at https://www.teamdatascience.ir/. The purpose of this system is to teach the fields of data science according to Table 1. This environment has a social network of experts and scholars together. Different professors also were present in this network to upload classes and content. In this social network, there is a lot of information, including news, posts, experiences, brochures, articles, and files, related to various professors in the field. In this social network, a group of experts and scholars gathered together and exchanged knowledge and ideas in the field of data science. In addition, members also found their colleagues and made active teams in the field of data science for their business. Various facilities such as presenting work experiences, chat rooms, categorizing members, and generating challenges were provided to the users. To increase students' motivation and achieve effective game design, game design elements should be designed based on students' needs (Knutas et al., 2019). Game design elements, such as scores and badges are used in the proposed method. In the four groups containing activities, network activities, research credits, and completing the resume, game elements were used, which are stated in Table 1. The functions of each of the elements are stated.

Also, 170 pieces of educational content in three topics, posts, articles, and books were uploaded by professors in this system. It is also possible to hold special classes and privileges in this field. C# and SQL SERVER databases were used. Bootstrap, jQuery, and JSON technologies were used to transfer data. Also, different access levels were considered for entering. In fig. 2 a view from the first page of the website is pictured.
The goal of the designed system is to create a game-based educational environment in the field of data science. The educational categories in different fields of data science are given in Table 1.

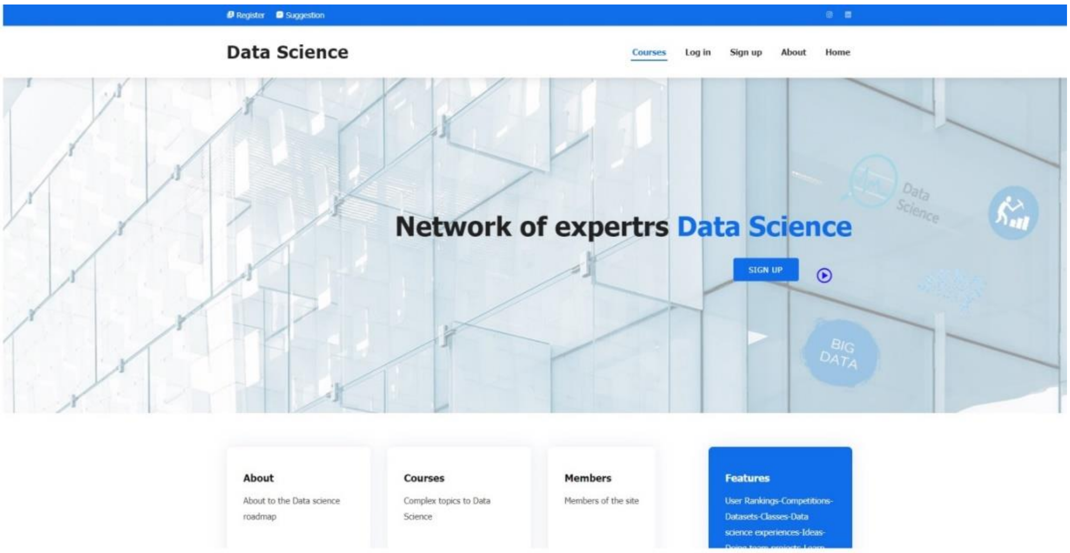

Fig. 2 A view from the website

Table 1 Content

Content
Data management
Machine learning
Data mining tools
Big data
Text mining
Data analysis
Business Intelligence
Neural Networks
Recommender systems

- **Scores:**

In (Denden et al., 2022) researchers recommended the use of different types of scores to increase students' participation in gamification systems. This method was considered for different activities in the system. Also, there are different standings for receiving points. Finally, scores are considered for each standing.

- **Levels:**

4 levels are considered in this course. The levels are different in each dimension. These levels should change from the easiest to the hardest (Zichermann & Cunningham, 2011). For performing activities, the user receives various points and can reach the desired level after passing the minimum points. For example, 120 points are required to reach the class activities in this course. In the fig. 3, we will see those activities.

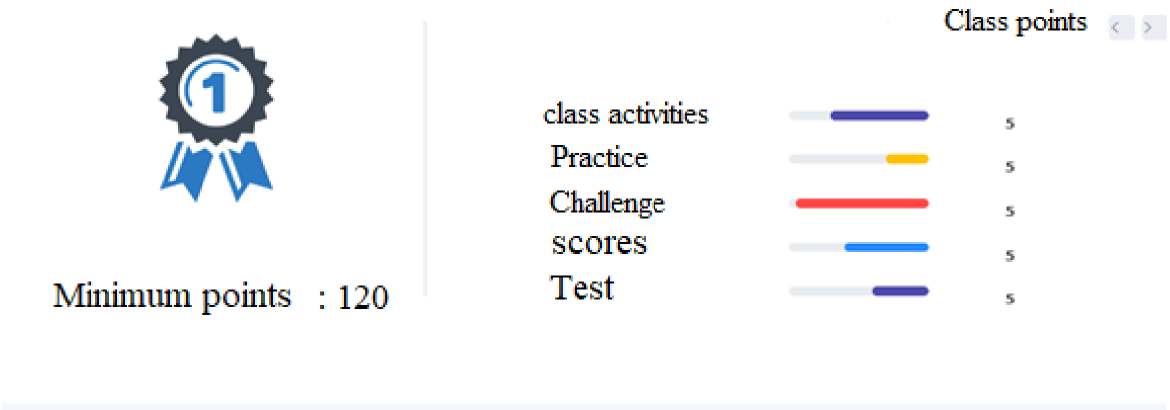

Fig. 3 Class activities and minimum point to reach

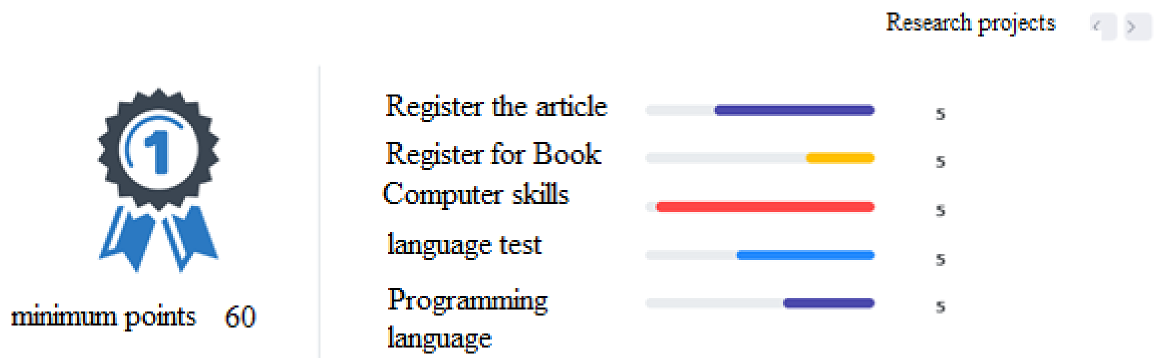

Fig. 4 Research Points

Badges and Scoreboard: Badges are defined in two ways in the system. The first is related to the time when users earned the most points in research activities, class, or a summation of both. The second method is reaching the minimum points that are stated at each level. The use of badges should be defined based on the meaningful achievements that have been considered in the design of this system (Simões et al., 2013). The rank of each student is also displayed on the scoreboard based on their rank. In this case, the feeling of having chance to win will be created in students (Montiel-Ruiz et al., 2023).

Fig. 5 Different Rankings

- **Avatars:**

Avatars make gamification more enjoyable and increase students' motivation (Alaswad & Nadolny, 2015). In this section, it is also possible to update the avatars.

- **Feedback:**

Various feedbacks were considered to increase students' motivation and also to collect information for the input of recommender systems, which is shown in the figure below. These feedbacks are designed based on the Likert scale of 1 to 5, which includes game elements and educational content in two parts. Fig. 6 shows a feedback question with categorized elements.

- **Polls survey:**

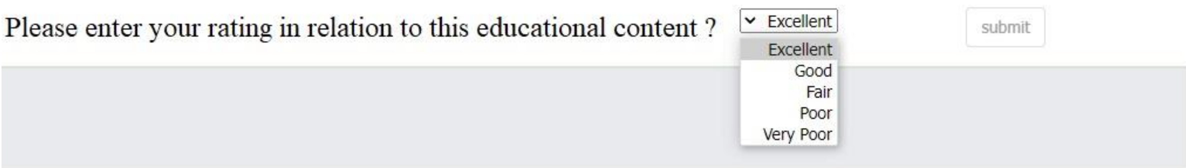

Fig. 6 Polls survey

- **Polls related to game elements:**

A sample poll question is mentioned in Fig. 7.

Fig. 7 Rating

- **Progress bar:**

One of the elements of the game that makes a course meaningful is the progress bar (Korn, 2022). As you can see in Fig. 8, the student can see his score status in each section.

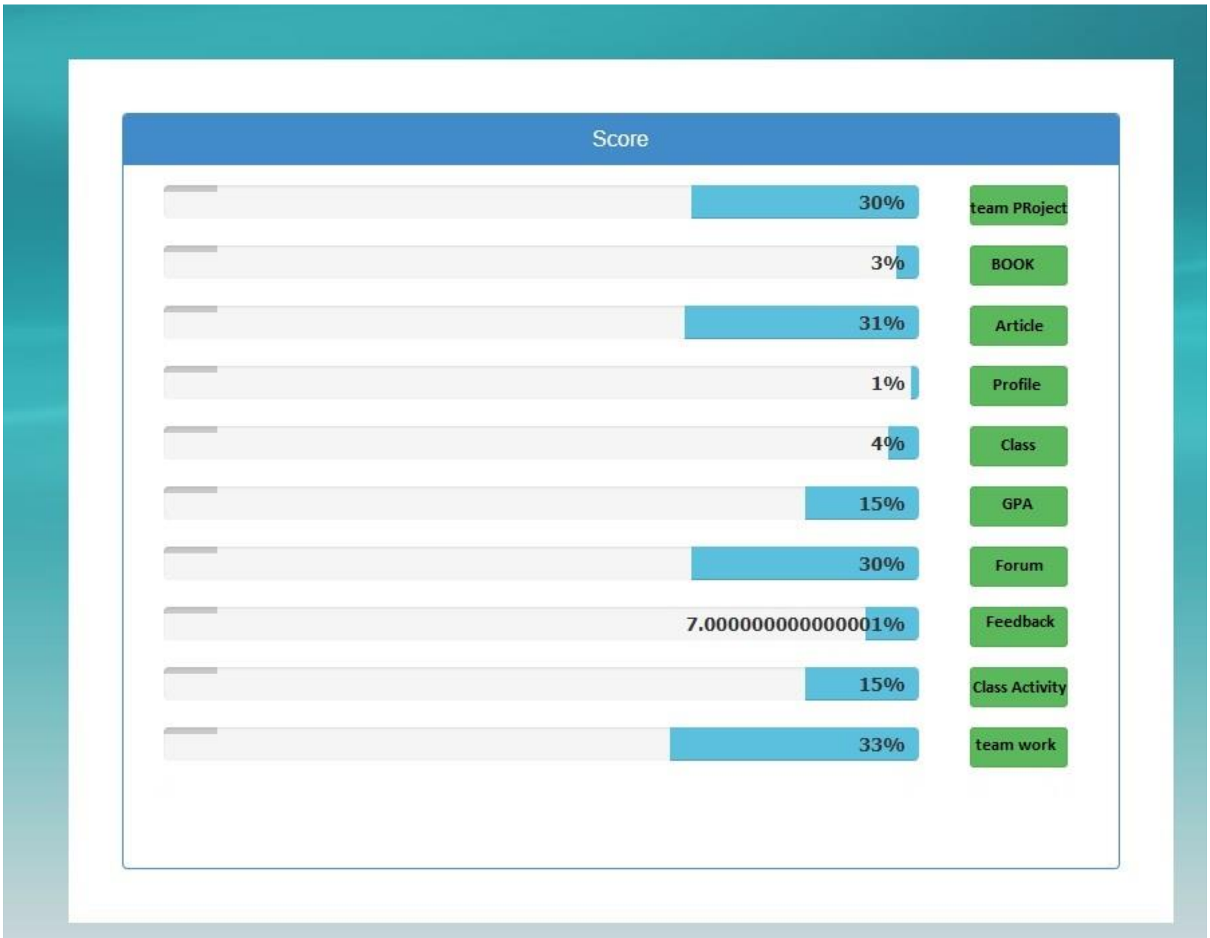

Fig. 8 Score

The game elements should be defined for the specific goals of the project (Ansar & George, 2022). Here, the target is to improve data science education processes. Designing elements aim to simplify and solve the challenges of data science learning. These challenges could be from purely theoretical training, scientific projects, team cooperation in data science projects, and the dispersion areas, such as gamification elements are considered for these problems. In Table 2, the following solutions and facilities are used to solve the challenges of data science learning processes.

Table 2 Solutions and facilities

Challenges	Site Facilities	**Used Elements**
Theory of learning	The possibility of defining the project and also participating in the challenges designed by the professors	Scores for challenges Definition of challenges
Lack of teamwork	Ability to participate in team projects and view and record comments and suggestions	Scores related to team project registration

		Scores for participating in a team project Scores related to polls Chat rooms
Dispersion of subjects	Creating different contents (articles, posts, educational videos) in different various of data science	Scores for reading each section

A view related to the contents of the site is pictured in Fig. 9.

Fig. 9 Site Contents

Table 1 Game elements

Row	Game Element	Type	Description
1	Points	normal	Points presence and absence
			Solve the exercise
		Class points	class activity
			Midterm grade
			End of semester grade
			Register questions and answers in the discussion forum
		Network activities	Record data science experiences
2	Badges Designed badges and) (medals		Registration and participation in a team project
			Book
			Article
			Computer skills
		Research points	Invention
			GPA
			Research projects
			Profile (educational records, educational records)
		Total points	Sum of all points
		normal	All students
		Top of the class	Highest class scores in each class
3	Levels	Elite levels	Most points in research points
		At the level of the entire network	Sum of all points
4	Progress	normal	Show the progress of points in the system
		normal	1st, 2nd and 3rd grade
5	Leaderboard		Rank 1, 2 and 3 elite
			Rank 1, 2 and 3 overall
6	Challenge	normal	Challenges created by professors in each of the 9 data science learning areas
7	Avator	normal	Ability to upload avatar
		normal	Commenting on game elements
8	Feedback		Commenting on the content used
			Registered projects
9	Rewards	normal	Rewards based on points received and in an innovative way
10	Forum	normal	Forums for data science
11	Record data science experiences	normal	Points to record data science experiences and knowledge sharing
12	Doing team work and team projects	normal	To encourage people for teamwork in data science (Creation of teams)
			Registering a team work, participating in a team work,) (registering comments in the team work
13	Educational contents uploaded by) (professors	normal	Post related to data science، Articles، Video

As mentioned in Table 4, a total of 36 game elements have been designed for this educational environment, and the goal is to suggest appropriate elements to members through personalization.

Table 2 Total number of game elements without content provided

Name	Number
Class activity	5
Network activity points	13
Research points	12
Resume Completion	6
Sum of all elements	36

4. Implemented Recommender System (explanation of the algorithm used for personalization)

For personalizing the designed system recommender algorithms were used. Various data and many logs were collected from the system and the logs were used to generate the user * item table. The considered model offers two recommendations to users:

1) Personalization and assigning suitable content to each user
2) Appropriate gamified elements in the system for each user

In Fig. 10 a top view of the proposed model for personal gamification is shown.

4-1 Data Collection

Recommender systems need specific feedback to make recommendations. That is why they need information about past user behavior, other people's behavior, or domain content information or feedback to generate predictions. There are three main ways to gather information for a recommender system. Explicit feedback is the most useful method for collecting information because the data is received directly from the user and the participation of users is needed in this part. For this purpose, points have been considered to encourage users to enter information. The system is designed in such a way that it has used direct survey for the contents and also for the elements and facilities of the site which can be very useful in increasing the quality as well as volume of the collected data. The figure below shows an example of this survey. The Likert scale has been used for direct scientific opinion.

Implicit feedback is another way to receive information for recommender systems. Unlike explicit feedback, no user participation is required to collect implicit feedback and the desired data can be extracted based on the observation of users' behavior. Data and site logs can also be used for the input of recommender algorithms (Lin et al., 2023). For example, the data of click flow or the time spent on a web page can be used for implicit data. A large set of data from gamification systems can be extracted for analysis. In this study, many logs of students and their behavior with the system were used for recommender systems, which is the input for calculating implicit calculations. On top of this, a combined method was used to receive feedback and fill the user*item table. Recommender systems deal with two entities - users and items, where each user assigns a rating to an item or product.

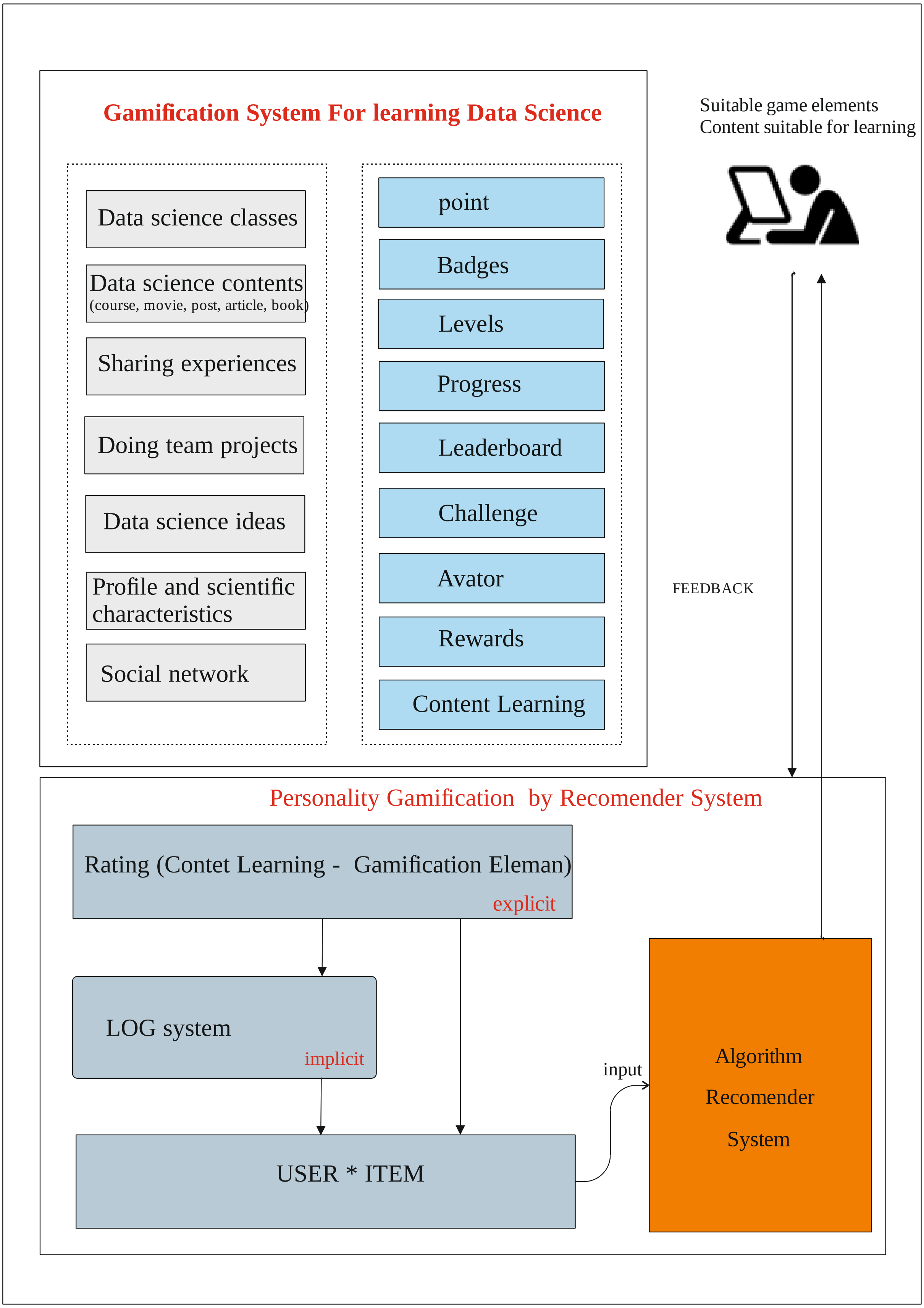

Fig. 10. A top view of the proposed model for personal gamification

4-2 User * Item Table Favorites

An important matrix named User*item is used in recommender system algorithms. The format of this data is better to be in the form of user, item, and the user's interest in the desired item. In this study, the item is the person's interest in the game element or content. First, direct feedback is employed for each user, and if the user does not want to fill in the explicit feedback, implicit feedback is used. For this purpose, SQL queries are used. According to the following algorithm (Fig 11), the queries are written. The output of these commands is the user*item table, which is used for recommender systems. Due to the USER*Item algorithm, user interests are created between 1 and 5 and stored in the SQL Server table.

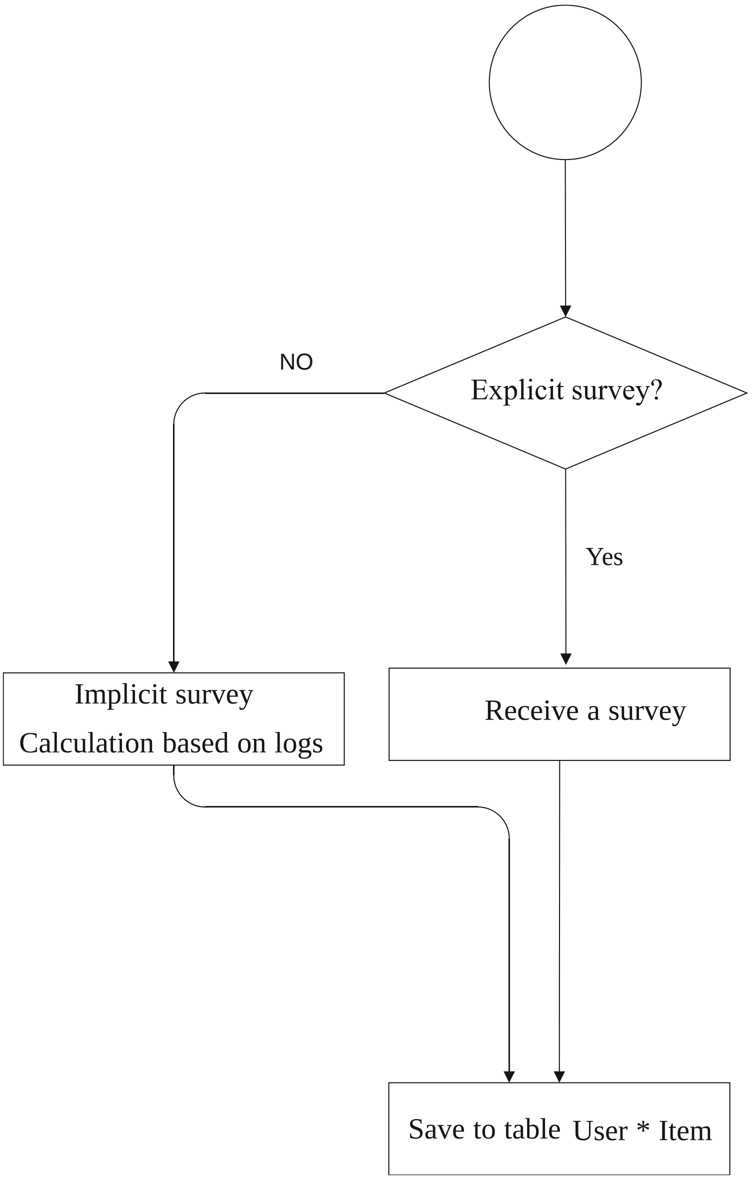

Fig. 11: Flowchart

After designing the learning environment in for data science and game elements, recommendation algorithms were used for personal gamification. Many game content and elements were designed in the system, to use personal gamification systems by utilizing recommender algorithms to provide suitable content and elements to each user. In the step of data collection and pre-processing, a hybrid algorithm was used to fill the user*Item table. In case of user not employing survey in each content and element (explicit survey), his favorite items will be selected based on logs (implicit survey). By this method, a suitable dataset with desired quality for the recommender system will be prepared.

To enable recommender systems to suggest items that are useful to a particular user, it can be essential to understand the user and his or her interactions with the system. These interactions typically manifest themselves as explicit and implicit user feedback that provides the key indicators for modeling users' preferences for items and essential information for personalizing recommendations. The use of explicit and implicit user feedback in recommender systems as key mechanisms for modeling user preferences in items [Yifan Hu, Yehuda Koren, and Chris Volinsky. 2008].

The total number of records in this table, which is collected from the recommender system, is 50194 records. The number of explicit records is 30120, and users expressed their opinions after viewing the items and elements, and entered their polls explicitly, while 20074 records were collected implicitly.

4-3 Implicit algorithms formula

Explicit feedback is likely the most accurate input for the recommender system because it is pure information provided by the user about their preference for certain content. [Qian Zhao 2018]

In the proposed system, the priority is with explicit survey. If the user does not use explicit, the game element data and content will implicitly be calculated by using the equations (1) to (3).

4-4 The implicit survey calculation for game and content elements (between 1 and 5)

1- First priority is with the explicit survey that is asked in every part of the system.
2- n case of not using the survey: calculation and checking the logs will be according to the following formula:

Elements:

$$\text{Points of each element} = \frac{\text{points scored in each element}}{\text{total points}} \qquad (1)$$

$$\text{Implicit survey} = \text{Percentage calculation of points of each element} \times 5 \qquad (2)$$

Content:

$$\text{Score of each content} = \frac{\text{number of observations, searches of each content}}{\text{total observations}} \qquad (3)$$

Some of the SQL commands were used to fill the User*Item table information and enter direct polls for the content. If direct polls are not utilized, poll data will be calculated and filled by implicit logs:

4-5 Descriptions of the participants

680 students registered into the system and received its facilities. They were divided into 8 different classes. After three months of interacting and using the system, according to the collected logs and comments, the personal gamification algorithm model was implemented by

machine algorithms, and suggestions related to the elements and content were presented to the students on the website. Figs 12 and 13 show the demographics of the contributors.

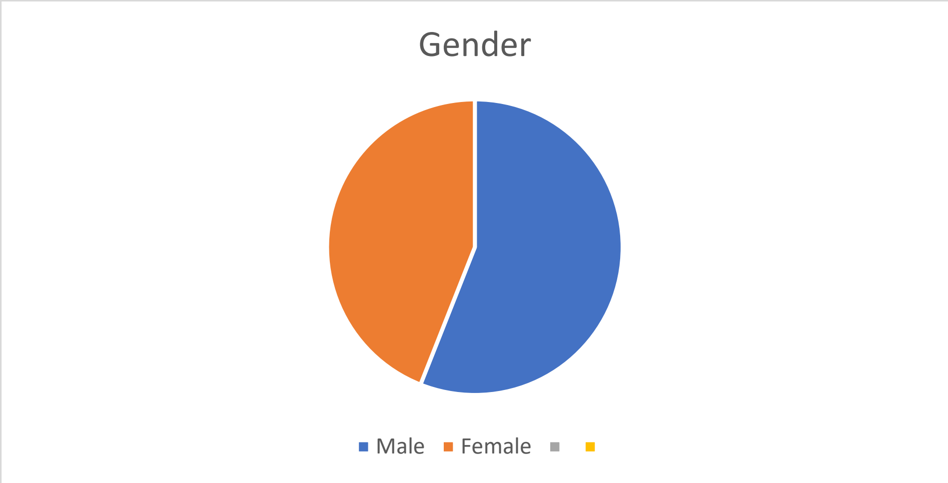

Fig. 12: Number of men and women participants

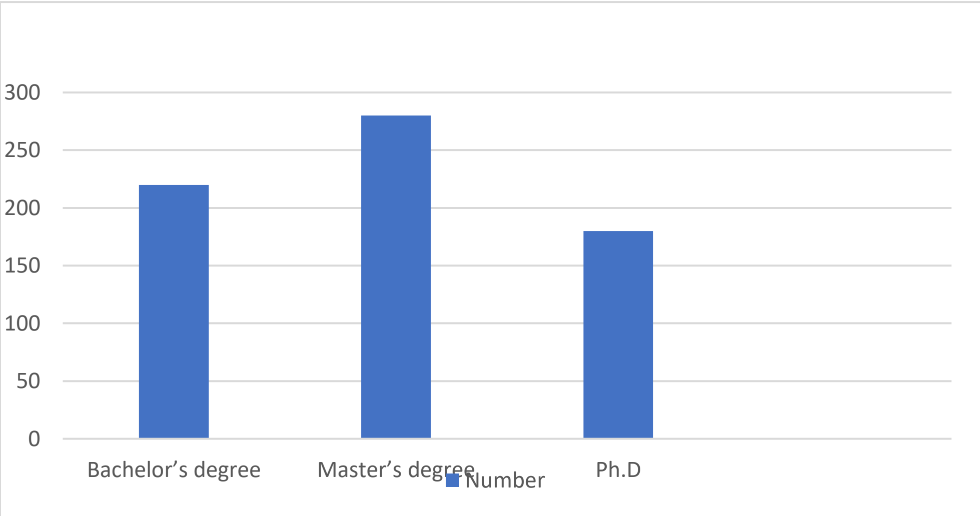

Fig. 13: Number of participants based on degree of education

5. Comparison of evaluation algorithms and operations

Recommender systems are suitable tools to filter information and guide users. The main goal of these systems is to reduce the effort and time needed to search for information and provide proper suggestions to users. Recommender systems have been used in various fields (Lin et al., 2023). One of them is gamification. In a study, a model using recommender system algorithms has been proposed, but the implementation has not been done yet. This is the first study that used recommender algorithms for personalization.

One of the problems of recommender systems is the problem of the sparsity of the user*item matrix. Generally, users have less desire to rate items. In our paper, gamification was used to solve the problem and users are also given points for giving feedback and points to the elements and items. Furthermore, the hybrid method mentioned in Table 1 was used to fill and improve the data of this table and the problem of sparsity.

Recommender systems are divided into three different categories: based on content, collaborative, and hybrid. The efficiency of a recommender system depends on the algorithm and its type (Pereira et al., 2023). The type of data in the system is significant in choosing recommender systems. In content-based systems, item specifications need to be gathered. Because of this, the content-based algorithm was not selected for this model. Collaborative approaches use the criterion of similarity between users. In our algorithm, the collected data and the nature of the dataset are established on item-based collaborative algorithms.

In this research, Python programming language was used to implement the recommender system. A library named Surprise was used to build the model. Different algorithms were used to implement the model. 12 algorithms were tested and selected to choose the best model. Various performance evaluation criteria were used for the accuracy and analysis of recommender systems. Generally, performance evaluation criteria were employed to analyze different recommenders. In most studies, Recall, MAE, and RMSE criteria were used. We used RMSE and MAE criteria to compare algorithms (similar to Amalnick et al., 2020; Azizi et al., 2023; Bastan et al., 2024; Fkih, 2022; Gharoun et al., 2019; Ghasemkhani et al., 2020; Ghazizadeh et al., 2025; Ghazizadeh et al., 2022; Mehdizadeh-Somarin et al., 2022; Pourbasir et al., 2024; Torabzadeh et al., 2022; Yazdanparast et al., 2018). In addition, the cross-validation method is also used for validation with parameter three.

In our method, after analysis of data and pre-processing, different algorithms were used to create the model, and these algorithms were evaluated with the RMSE and MSE. In the table below, these algorithms and their evaluation criteria are listed in Table 5.

Table 3: Algorithms used and criteria used in this model

Algorithm	test_RMSE	test_MAE	fit_time	test_time
BaselineOnly	1.393405	1.200658	0.010736	0.015778
SVD	1.421636	1.219849	0.936156	0.038880
SVDpp	1.433767	1.225453	2.414531	0.150667
KNNBasic	1482301	1252259	0.008224	0.075149
KNNBaseline	1.494499	1.263488	0.016190	0.135152
KNNWithMeans	1.500390	1.271461	0.014724	0.083242
KNNWithZScore	1.512120	1.273587	0.024417	0.095742
CoClustering	1.539109	1.295320	0.132702	0.015487
SlopeOne	1.588915	1.303252	0.014446	0.061850
NMF	1.643072	1.356468	0.417466	0.017906
MormalPredictor	1.838830	1.498433	0.008260	0.021943

The SVD algorithm result the least error and the best answer in the evaluation criteria, so the selected algorithm according to the table was considered to build the SVD algorithm model.

SVD is a basic mathematical method in data mining. SVD is usually calculated by batch, and the time complexity is O(m2n+n3) (m, n are the row size and column size of a matrix, respectively), meaning that all data must be processed immediately. Therefore, it is not feasible for very large dataset.

SVD is a matrix factorization technique commonly used for producing low-rank approximations. Given a matrix A ∈ Rm×n with rank(A) = r, the Singular Value Decomposition of A is defined as the following: A = USV T , (2) where U ∈ Rm×m, V ∈ Rn×n and S ∈ Rm×n. The matrices U, V are orthogonal, with their columns being the eigenvectors of A AT and AT A, respectively. The middle matrix S is a diagonal matrix with r nonzero elements, which are the singular values of A. Therefore, the effective dimensions of these three matrices U, S and

V are $m \times r$, $r \times r$ and $n \times r$, respectively. The initial diagonal r elements ($\sigma 1, \sigma 2, ..., \sigma r$) of S have the property that $\sigma 1 \geq \sigma 2 \geq ... \geq \sigma r > 0$ [Xun Zhou 2015]

Singular Value Decomposition (SVD), a classical method from linear algebra is getting popular in the field of data science and machine learning. This popularity is because of its application in developing recommender systems. the algorithm gives the best results in small datasets

In addition, for better improvement of this algorithm and better setting of hyper-parameters, grid search was employed. After checking the following parameters were considered for this algorithm:

{'n_epochs': 10, 'lr_all': 0.002, 'reg_all': 0.02}

There are many methods for evaluating TOP-N recommendations. However, selecting the proper method for each system and designing a suitable evaluation criterion according to the created algorithms are important. The three criteria were used to evaluate Top-n of this system as novelty=40, coverage= =0.8, and hit rate=0.03.

5-1 Model evaluation

After creating the model, different game elements and contents were suggested to the users based on the generated model and users could see their suggestions on one page and also refer to the content.

There are different classifications of recommender system evaluation methods. Some researchers distinguish between offline and online evaluations [Zheng et al. 2010]. Most recommender systems are evaluated with offline evaluations, although offline evaluations are subject to strong criticism. offline evaluations could sometimes not predict recommender effectiveness in online evaluations and user studies.

In an online RS evaluation, a live service is used to generate real-time recommendations for genuine users, and their reaction to those items is measured perhaps via explicit pop-up surveys asking for ratings of the items offered or perhaps by implicit signals such as selection clicks Dacrema MF, Cremonesi P, Jannach D 2019]

The following metrics were used to check and perform the personal gamification system using recommender algorithms on machine learning.

- Check usage of the item and content suggested by the user.
- Direct survey on the website about the suggestions provided*?*
- The performance of grades obtained in classroom subjects before and after using the gamified system?

After two months of students using the gamification system, the following functions were achieved are listed in Table 6.

Table 4: Functions

The number of items suggested to users	Number of items used
1100	620

The level of user satisfaction in the survey of the suggestions is provided in Table 7.

In Table 7, we used a direct survey for the level of user satisfaction in using the recommender system. This evaluation criterion is the best method for evaluating recommender systems. Because the user's comments are directly used to evaluate the system**.** In this study, we implemented a direct survey in the system**.** Users expressed their satisfaction after working with the gamification system.

45 percent of users were satisfied with working with the system**.** After the recommender system provides its suggestions to the users**.** Users were again asked to participate in the survey, and the number of satisfied users increased to 55%**.** And this increase in criteria shows users' satisfaction with the recommender system**.** This criterion is an online evaluation criterion in recommender systems, which is summarized in this table. Table 8 shows the average scores obtained before and after the gamification system.

Table 5: Level of user satisfaction

The level of satisfaction after offering suggestions	The level of satisfaction before submitting proposals
55%	45%

Table 6: Average scores

Average scores obtained after personal gamification	Average scores before personalization
17	16

5-3 Statistical population and research sample

The statistical population of this research is 680 users of the personal gamification model platform in data science learning. The statistical sample of the research is randomly selected. For this purpose, according to Morgan's table, the number of statistical samples for the population of 680 people was considered to be about 80 people.

An anonymous questionnaire with four questions in the form of a five-point Likert scale was designed to evaluate the effectiveness of personal gamification on data science learning in the platform environment. For this purpose, the number 5 was considered as very high, 4 high, 3 medium, 2 low and 1 for very low. Table 9 categorized mentioned scaled. The questionnaire is as follows:

- To what extent has gamification had an impact on (longer) use of the platform?
- To what extent have the offers presented on the platform been expected by you?
- To what extent were the suggestions presented interesting to you?
- To what extent has the learning path of the courses made the learning curve easier for you?

Table 7 : Five-state Likert scale

Very Low	Low	Medium	High	Very High
1	2	3	4	5

5-4 Statistical hypothesis evaluation

In this section, in order to investigate the effect of the gamification process on attracting the audience, a t-test was used. The statistical hypotheses are as follows:

- Hypothesis (H0): Recommender Systems for Personalized Gamification has no effect on audience attraction.
- Hypothesis (H1): Recommender Systems for Personalized Gamification has had an impact on the level of audience attraction.

The results of the one-sample t-test in Table 10 showed. If the p-value is less than 0.05, it can be claimed that the recommender system is effective at a significance level of $\alpha = 0.05$ (Aghakarimi et al., 2023; Azadeh et al., 2016; Azizi et al., 2021; Babajani et al., 2019; Eskandari et al., 2022; Esteghamat et al., 2024; Gharoun et al., 2021; Ghasemkhani et al., 2023; Habibifar et al., 2019; Hamid et al., 2019; Hamid et al., 2019; Hamid et al., 2023; Hamid et al., 2020; Heidari et al., 2024; Samieinasab et al., 2022; Taghipour et al., 2023). Since the value of the test statistic is less than 0.05 ($T=4.872$, P-Value <0.05), the null hypothesis is rejected.

Therefore, it can be said with a probability of 95% that the use of gamification was effective in attracting the audience.

Table 8: One-sample t-test results

T	P-Value	Average
4.872	0.000	4.15

One of the methods of checking the performance of recommender systems is to use the A/B test method. However, it is a complicated method because it must be implemented and measured in the system. For this purpose, users in the system were divided into two groups, and a designed gamification system was employed. A number of 340 users were offered content suggestions and elements created by the model, while 340 of the students did not receive any offered. After using the system and through the collected logs from the system and students' performance, the following results were obtained:

Table 9 :Results achieved by A/B test

Criterion	Control group	Experiment group
Average number of studies done by users	14	9
Average points earned in challenges	32	29

The results show that the people who were given suggestions performed better in different forms and the recommender system in the personal gamification was able to improve the learning performance of individuals.

6. Final result and suggestion

The main question of this research is whether personal gamification using recommender systems can improve the efficiency of these systems or not. For this purpose, 680 students joined this system and also used the system's facilities. The gamification system was divided into 8 classes. After three months of interacting with the system, according to the collected logs and also the comments of the personalized gamification algorithm model, it was implemented by the machine algorithms, and the suggestions related to the game items and elements were presented to the users. The best algorithm in this environment was SVD which was selected according to RMSE and MAE criteria. The proposed model was checked with performance and criteria and was approved by the users according to the reviews. After the investigations and statistical tests (T-test) and A/B test, this model was able to have a positive effect on students' learning and performance in this field.

Our work is a novel personalized gamification design in the field of data science learning, where recommender systems have been used for personalization. During these studies, the problem of cold start of recommender systems, which is one of the challenges of recommender systems, was solved to some extent by using the score of game elements and also by using system logs. Unfortunately, there are few studies related to recommender models in gamification systems, and it is required to be investigated in various other fields as well. Besides, this research represented that recommender algorithms can create personal gamification systems more dynamically than other algorithms. Furthermore, the dataset and the amount of data collected are other issues that should be considered. The limitation of datasets is a serious challenge in machine algorithms because large datasets are a fundamental requirement for gamified platforms based on machine learning, especially recommender systems (Barata et al., 2016)(Barata et al. 2016). Also, more data with more quality can improve the performance of these systems. In this context, gamification can be used to encourage more people to participate and collect more data for the systems. It is also suggested that more precisely, the performance of users should be determined in the long-term cooperation of these systems with users.

6. Discussion

In recent years, gamification technology has been used to widely optimize human–computer interactions. On the other hand, the advancement of machine learning approaches results in the expansion of the studies around the prospective potential of combining these two technologies. In this study, we investigated the convergence of gamification and Recommender system in the field of data science learning.

In this study, create and implement a model in personal gamification design in the field of data science learning, which uses recommender systems algorithms for the first time to improve data quality in these algorithms.

As a first step, to evaluate the acceptance and use of recommender system models in personal gamification, initially, A site with game element capabilities was implemented. Also, 170 pieces of educational content in three topics, posts, articles, and books were uploaded by professors in this system. total of 36 game elements have been designed for this educational environment, and the goal is to suggest appropriate elements to members through personalization. In this study, the recommender system gives the following two suggestions to users

For personalizing the designed system recommender algorithms were used.

1) Personalization and assigning suitable content to each user
2) Appropriate gamified elements in the system for each user

In this study, explicit and implicit methods were used for data collection, and the implicit method was preferred. feedback is employed for each user, and if the user does not want to fill in the explicit feedback, implicit feedback is used. For this purpose, SQL queries are used. The result of this method was that the number of data related to the user*Item table increased and the quality of the data improved for machine algorithms.

After analysis of data and pre-processing, different algorithms were used to create the model Different algorithms were used to implement the model.12 algorithms were tested and selected to choose the best model. Various performance evaluation criteria were used for the accuracy and analysis of recommender systems. The SVD algorithm result the least error and the best answer in the evaluation criteria, so the selected algorithm according to the table was considered to build the SVD algorithm model. SVD algorithm can be a good option for small datasets in recommender systems.

There are different classifications of recommender system evaluation methods. In this study, online and offline evaluation methods were used to check the model. RMSE and MSE criteria were used for the offline method. according to these criteria, the SVD algorithm with the least error was selected. In most studies, Recall, MAE, and RMSE criteria were used. After the investigations and statistical tests (T-test) and A/B test, this model was able to have a positive effect on students' learning and performance in this field.

Another method for evaluating recommender systems is the online evaluation method. One of the methods of checking the performance of recommender systems is to use the A/B test method. However, it is a complicated method because it must be implemented and measured in the system.

Two criteria Average number of studies done by users and Average points earned in challenges are used for A/B test the results show that the people who were given suggestions performed better in different forms and the recommender system in the personal gamification was able to improve the learning performance of individuals. There are different methods for evaluating recommender systems, and each of them examines aspects of recommender systems. In this study, different methods were used for evaluation. And the results show that the gamification system along with recommender systems can improve the performance of education

7. Conclusion

There are different ways to implement personal gamification. This study is presented with the aim of evaluating gamification along with recommender models in learning of data science .Different game elements have been designed for data science learning. The quality of the collected data can have a great impact on the implementation of recommender systems. To increase the quality of the data, the gamification system has been used in this study, which can greatly affect the quality of the user*Item table data. Therefore, one of the results of the research is the use of gamification in improving the processes of machine algorithms. Explicit and implicit methods were used to collect feedback. The results show that the use of explicit and implicit methods can create quality data that can be used to increase the accuracy of recommender system models.

After data collection and data pre-processing, different algorithms have been used to build the model. According to the RMSE and MSE criteria, the SVD algorithm had the best results in recommender algorithms and could be used in the personalization of gamification. In this study, the results show that the SVD algorithm can work very well with small datasets and provide higher accuracy. The grid search method was used to determine the hyperparameters of the SVD algorithm. The results in this article show that this method can be very suitable for checking the hyperparameters of models built on small datasets. In this article, online methods are used. and offline were used to evaluate the recommender system along with the modified game model. And the results of this evaluation showed that the learning performance improved by using the designed system. The results showed that the best evaluation method is the A/B test method. In this part, the definition of two grade criteria and the use of elements can be considered a good factor for evaluation.

This paper provides valuable insights for evaluating the performance of gamification along with recommender models. However, certain limitations may affect the creation of gamification along with recommender models. First, this research is exclusively focused on the influencing factors of personal gamification in the field of data science. Future research can investigate the impact of these models on other environments. In addition, the number of records in this dataset greatly affects the accuracy of the models. Therefore, the use of more people and data collection can greatly improve the performance of these models. It is effective and should be considered in future research.

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