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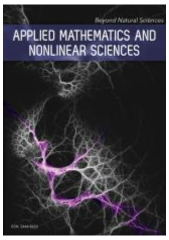


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# Research on the Design of Intelligent Recommendation System for Civic and Political Education Content and the Effectiveness Assessment of Students' Acceptance

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## Abstract

The article improves the traditional collaborative filtering algorithm, integrates it with the content-based recommendation algorithm, proposes the recommendation algorithm based on the mixture of collaborative filtering and content, and serves as the operation logic for designing the intelligent recommendation system of educational content for Civics class. Model variables are determined using structural equation modeling and relevant hypotheses are presented to construct a model of factors that influence student acceptance of the Civics Intelligent Recommendation System, followed by empirical analysis. The mean values of expectation performance, effort performance, social influence, convenience conditions, self-efficacy, perceived pleasantness, and willingness to use are 3.48, 2.70, 3.61, 2.36, 3.77, 3.84, and 3.73, respectively. Students' use of the Civic Intelligent Recommendation System is greatly influenced by their perception of pleasantness and self-efficacy. The questionnaire has good reliability and validity in general. The initial model has valid hypotheses H1, H2, H6, H7, H8, H9, H10, and H11. In the analysis of variance, there were significant differences between genders only in performance expectations (0.000) and perceived pleasantness (0.016). Significant differences existed across grades in terms of performance expectations (0.018) and social influence (0.000). The measurement dimension of willingness to use had a moderating effect across majors. Hypotheses H12 and H13 are partially valid, but H14 is valid.

**Keywords:** Structural equation modeling; Intelligent recommendation algorithm; Student acceptance; Willingness to use.
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## 1 Introduction

The exploration and practice of intelligent teaching of Civics and Politics class in colleges and universities is not only the innovation of technology application, but also the embodiment of the innovation of education concept and teaching mode [1-2]. Intelligent teaching of Civics and Political Science refers to a teaching mode in which Civics teachers make full use of artificial intelligence, big data, cloud computing and other information technologies to transform teaching concepts, teaching mechanisms and teaching methods, deeply integrate Civics and information technologies, and improve the teaching effect and quality of Civics and Political Science [3-6].

The design of the Big Data-based Civic Education Content Intelligent Recommendation System aims to analyze students' learning data, recommend suitable learning resources for them, and improve their learning effect and interest [7-8]. The system needs to adopt the following key technologies: 1. Data collection and analysis: The system will collect students' learning data, including learning time, learning duration, learning content and so on, and through the data analysis technology, the students' learning behavior will be mined and analyzed [9-11]. 2. User profile modeling: by analyzing students' learning data, the system will establish students' user profiles, mastering their characteristics, subject preferences, learning habits, etc. 3. Content recommendation algorithm: the system will analyze the students' user-profiles and the attributes of the course resources, use the recommendation algorithm to recommend suitable learning resources for the students and make real-time adjustments and optimization based on the feedback of their learning [12-15]. By recommending suitable learning resources for students through the intelligent recommendation system, the system provides students with a personalized learning experience and helps them to better learn the Civics course [16-17].

Since there are fewer studies related to intelligent recommendation systems for educational content in Civics and Political Science courses, this paper will discuss the research related to intelligent recommendation of educational content. Literature [18] states that educational recommender systems have an important role in the learning process of students, so it is important to ensure the relevance of recommended educational resources. The aim is to analyze the working conditions of educational recommender systems in order to obtain the correlation between requirements and recommendations and to provide reference value for future research. Literature [19] emphasized the importance of educational recommender systems, stating that, with the assistance of recommender systems, students are able to access more learning resources. A recommendation method for educational resources with personalization was proposed and quality assessment was added to it so that the quality of the recommended resources could be assessed. Literature [20] proposes an intelligent recommendation method for e-learning personalization, which is used to identify the e-learner's learning habits, preferences, content, etc., and intelligently recommends personalized learning resources to the e-learner, which is conducive to improving the learner's learning effect. Literature [21] indicates that intelligent recommender systems have been widely used in the fields of services, e-commerce, and social platforms, and their role in the field of education is becoming obvious. Big data recommender systems are used in education and recommend relevant elective courses to students based on their performance. Its research results have reference value for universities, students and other subjects. Literature [22] suggests that students' emotions can have a greater impact on the teaching and learning process, so changing students' emotions is important for the learning environment. Through technology fusion in order to recognize the lack of complex work, technology fusion can improve the recommendation results of emotional recommender systems, thus creating a good educational environment. Literature [23] illustrates that recommender systems are implemented with the support of technologies such as artificial intelligence to recommend educational resources with personalization for users. A machine learning-based scheme is proposed to identify users' needs, characteristics, etc., so as to discover their personalized interests, but in this process, the recommender system also reveals shortcomings. Literature [24] analyzes the structure of the educational recommender system, based on which it introduces the methods of content recommendation, filtering recommendation, and hybrid recommendation, as well as the advantages and disadvantages of various recommendation methods, and discusses the direction of development of educational recommender system.

The article improves the collaborative filtering recommendation algorithm and mixes it with the content-based recommendation algorithm, and it will be used as the underlying logic of the intelligent recommendation system for the educational content of the Civics and Political Science course, according to which the system architecture and functions are designed. Subsequently, structural equation modeling is used to construct a model of factors influencing students' acceptance of the Civics Intelligent Recommendation System, and corresponding hypotheses are proposed after determining the model variables. The student's acceptance (willingness to use) of the Civic Intelligence Recommendation System is empirically analyzed, and the variables affecting their acceptance are preliminarily analyzed through the descriptive statistics of the questionnaire data. To test some of the proposed hypotheses, the constructed SEM model is revised and tested. Finally, the differences between gender, grade, and major on each variable are analyzed.

## 2 Design of Intelligent Recommendation System for Civics Education Content

### 2.1 Recommendation Algorithm Based on Collaborative Filtering and Content Blending

#### 2.1.1 Improvement of Collaborative Filtering Based Recommendation Algorithm

The method of penalizing popular items or contents is used to improve the complexity of similarity calculations, thus improving similarity calculations. On this basis, the time factor is incorporated into the collaborative filtering recommendation algorithm, and the effectiveness of the improved recommendation algorithm is verified [25].

Figure 1 illustrates the flow of the collaborative filtering recommendation algorithm that incorporates the time factor.

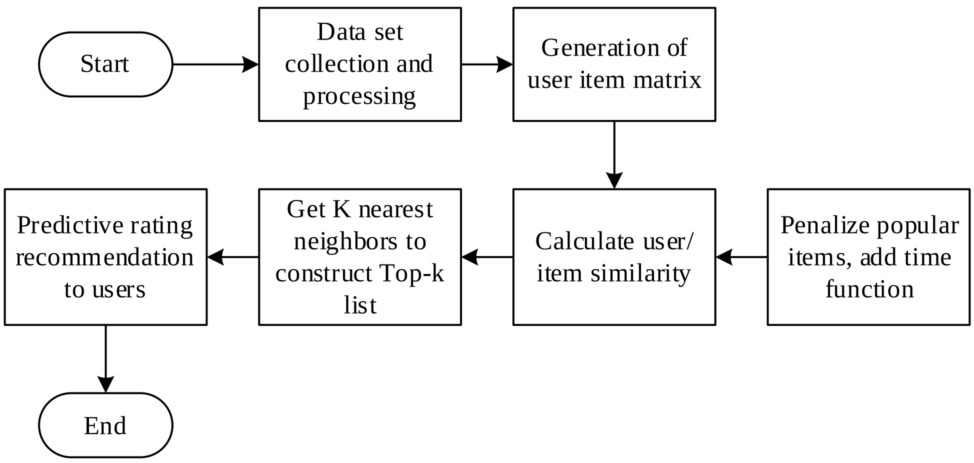


**Figure 1.** Process of collaborative filtering recommendation algorithm integrated with time factor

The collaborative filtering recommendation algorithms that incorporate the time factor are referred to as the two recommendation algorithms based on user (T-UserCF) and item or content (T-ItemCF), respectively. The computational methods of the two recommendation algorithms are as follows:

1) T-UserCF algorithm

(1) Similarity calculation of T-UserCF algorithm

Here the cosine similarity is used to calculate, the formula is shown in (1):

$$W_{uv}=\frac{|N(u)\cap N(v)|}{\sqrt{|N(u)||N(v)|}} \tag{1}$$

Where $N(u)$ and $N(v)$ denote the set of items or contents for which users $u$ and $v$ have generated behavior.

(2) Penalization of Hot Items or Content

The method of penalizing popular items or content has some effect on the computed similarity of very popular items or content. In order to more accurately measure the degree of interest similarity between users, weights are applied to penalize hot items or contents to reduce their impact on the interest similarity calculation. As shown in equation (2):

$$W_{uv}=\frac{\sum_{i\in N(u\cap N(v)}\frac{1}{1g\left(1+N(i)\right)}}{\sqrt{|N(u)\cup N(v)|}} \tag{2}$$

Where the inverse of the numerator is the popular item or content in the common interest list of user $u$ and user $v$ that has been penalized. Where $N(i)$ is the set of users who have behaved towards item or content $i$.

(3) Introducing a time decay function

A higher weight is given to recent user behaviors by introducing a time decay function to better reflect the user's current interests.

In Equation (2), although the influence of popular items or content is reduced, a time decay function needs to be introduced to calculate the similarity of users in order to better reflect their current interest preferences. The formula is shown in (3):

$$W_{UV}=\frac{\sum\limits_{i\in N(u)\cap N(v)}\frac{1}{1g\left(1+N(i)\right)}f\left(|t_{ui}-t_{vi}|\right)}{\sqrt{|N(u)\cup N(v)|}} \tag{3}$$

Where $f\left(|t_{ui}-t_{vi}|\right)$ is the time decay function of the form shown in (4):

$$f\left(|t_{ui}-t_{vi}|\right)=\frac{1}{1+\alpha|t_{ui}-t_{vi}|} \tag{4}$$

Where, $\alpha$ is the time decay factor, $t_{ui}$ denotes the time when the user $u$ has behaved towards the item or content $i$ and $t_{vi}$ denotes the time when the user $v$ has behaved towards the item or content $i$.

A time decay function $f\left(\left|t_0 - t_{vi}\right|\right)$ is to be added to the user's rating to more realistically calculate the degree of user $u$ preference for the item or content $i$, as shown in the formula (5):

$$r_{ui} = \frac{\sum_{i \in N(u) \cap N(v)} \frac{1}{1g\left(1 + N(i)\right)} f\left(\left|t_{ui} - t_{vi}\right|\right)}{\sqrt{\left|N(u) \cup N(v)\right|}} \times r_{ni} \times f\left(\left|t_0 - t_{vi}\right|\right) \tag{5}$$

Where the expression for $f\left(\left|t_0 - t_{vi}\right|\right)$ is shown below:

$$f\left(\left|t_0 - t_{vi}\right|\right) = \frac{1}{1 + \beta\left(t_0 - t_{vi}\right)} \tag{6}$$

Where $t_0$ denotes the current time and $t_{vi}$ denotes the time of behavior generated by user $v$ on item or content $i$.

2) T-ItemCF algorithm

(1) Calculation of similarity of T-ItemCF algorithm

The similarity calculation formula is shown in (7):

$$W_{ij} = \frac{\left|N(i) \cap N(j)\right|}{\sqrt{\left|N(i)\right|\left|N(j)\right|}} \tag{7}$$

Where $N(i)$ and $N(j)$ denote the set of users, who have interacted with items or content $i$ and $j$, generating behavior.

(2) Penalty for user activity

When calculating the item or content similarity, the weight of active users on the similarity calculation needs to be appropriately reduced. The calculation formula is shown in (8):

$$W_{ij} = \frac{\sum_{u \in N(inN(j)} \frac{1}{1g\left(1 + N(u)\right)}}{\sqrt{\left|N(i) \cup N(j)\right|}} \tag{8}$$

Where $N(u)$ denotes the set of rated items of user $u$.

(3) Introduce a time decay function

When calculating the similarity between items or contents, the time interval between behaviors needs to be considered. Therefore, a time decay function can be introduced into the original formula (8), and the formula is shown in (9):

$$W_{ij}=\frac{\sum_{ueN(i)\cap N(j)}\frac{1}{1g\left(1+N(u)\right)}f\left(\left|t_{ui}-t_{uj}\right|\right)}{\sqrt{\left|N(i)\cup N(j)\right|}} \tag{9}$$

Where $f\left(\left|t_{ui}-t_{uj}\right|\right)$ is the time decay function of the form shown below.

$$f\left(\left|t_{ui}-t_{uj}\right|\right)=\frac{1}{1+\alpha\left|t_{ui}-t_{uj}\right|} \tag{10}$$

Where $t_{ui}$ and $t_{wj}$ denote the time at which the user $u$ has generated behavior towards item or content $i$ and item or content $j$, respectively.

In order to more accurately represent the user’s current preference, a time decay function should be included in the calculation of the user’s rating of the item or content $f\left(\left|t_0-t_{si}\right|\right)$. Calculating the degree of user $u$ ‘s preference for the item or content $j$ can be expressed using the following equation (11):

$$r_{uj}=\frac{\sum_{u\in N(i\cap N(j)}\frac{1}{1g\left(1+N(u)\right)}f\left(\left|t_{ui}-t_{uj}\right|\right)}{\sqrt{\left|N(i)\cup N(j)\right|}}\times r_{ui}\times f\left(\left|t_0-t_{ui}\right|\right) \tag{11}$$

Where the expression for $f\left(\left|t_0-t_{ui}\right|\right)$ is shown below:

$$f\left(\left|t_0-t_{ui}\right|\right)=\frac{1}{1+\beta\left|t_0-t_{ui}\right|} \tag{12}$$

Where $t_0$ indicates the current time.

### 2.1.2 Content-based recommendation algorithms

Content-based recommendation algorithms are able to provide in-depth analysis and understanding of the content of the items, which can accurately match the user’s interests and needs and provide personalized recommendation services [26-27]. The steps of the algorithm are as follows:

1) Feature selection: select a set of features that best represent the item or content from the various attributes of the item or content, and use these features to describe and characterize the properties and attributes of the item or content.

2) Feature extraction: By analyzing the user’s browsing records and behavioral information, the common features in the corresponding item or content features are extracted and edited into a user preference document to reflect the user’s current preferences.

3) Item or content matching: The item or content to be recommended is characterized, and the user preference document is constructed based on the user's past behavior and preferences. Then, the similarity between each item or content to be recommended and the user preference document is calculated so as to select the item or content that is most similar to the user's preference as the candidate set of the recommendation list. Finally, the user is presented with the recommendation result, which is the final item or content from the candidate set.

Following the above algorithmic steps, the TF-IDF (Word Frequency-Inverse Document Frequency) method will be used to generate content-based recommendations.

The TF-IDF method will be combined with the user's historical preferences to provide a more accurate assessment of their preference for an item or content. Firstly, the word frequency is calculated, and the word frequency calculation is shown in Equation (13):

$$TF_{i,j} = \frac{f_{i,j}}{\sum_{z \in j} f_{z,j}} \tag{13}$$

Where $f_{i,j}$ denotes the number of times feature word $i$ appears in item or content $j$, and $\sum_{z \in j} f_{z,j}$ is the sum of the number of times all words appear in item or content $j$. Next, the anti-document frequency is calculated, which is shown in Equation (14):

$$IDF_i = \log \frac{N}{n_i} \tag{14}$$

Where $N$ refers to the number of all items or contents, and $n_i$ indicates the number of items in which the feature word $i$ appears in $N$ items or contents. According to Equation (13) and Equation (14), the weight of each feature word in each item or content can be calculated, and the corresponding formula is shown in (15):

$$W_{i,j} = TF_{i,j} \times IDF_i = \frac{f_{i,j}}{\sum_{i \in j} f_{z,j}} \times \log \frac{N}{n_i} \tag{15}$$

Finally, the cosine similarity is used to calculate the degree of user preference for the item or content, as shown in the formula in (16):

$$P_{CB}(u, j) = \cos\left(\vec{d_u}, \vec{d_j}\right) = \frac{\sum_{i=1}^{k} W_{i,u} W_{i,j}}{\sqrt{\sum_{i=1}^{k} W_{i,u}}^{2} \sqrt{\sum_{i=1}^{k} W_{i,j}}^{2}} \tag{16}$$

Where $\vec{d_u} = \left(w_{1,u}, w_{2,u} \cdots, w_{k,u}\right)$, $\vec{d_j} = \left(w_{1,j}, w_{2,j} \cdots, w_{k,j}\right)$ are $k$-dimensional vectors denoting user $u$'s preference document and item or content document $j$, respectively, and $P_{CB}(u, j)$ denotes user $u$'s preference degree for item or content $j$.

### 2.1.3 Hybrid-based recommendation algorithms

1) Hybrid recommendation strategy

In this paper, a weighted hybrid approach is used, which combines the improved user-based collaborative filtering recommendation algorithm and the content-based recommendation algorithm, and the formula of the weighting method is shown in (17):

$$P = \alpha P_{ucf} + (1-\alpha) P_{CB} \tag{17}$$

Wherein, $\alpha$ denotes a rating prediction weight based on user synergy, and $(1-\alpha)$ denotes a rating prediction weight based on content. According to the above description, by reasonably adjusting the size of each weight to obtain better results.

2) Hybrid recommendation process

In this paper, a new integration model is proposed that fuses user behavior relevance information from the collaborative filtering algorithm with item content relevance information from the content-based recommendation algorithm. Figure 2 depicts the hybrid recommendation process.

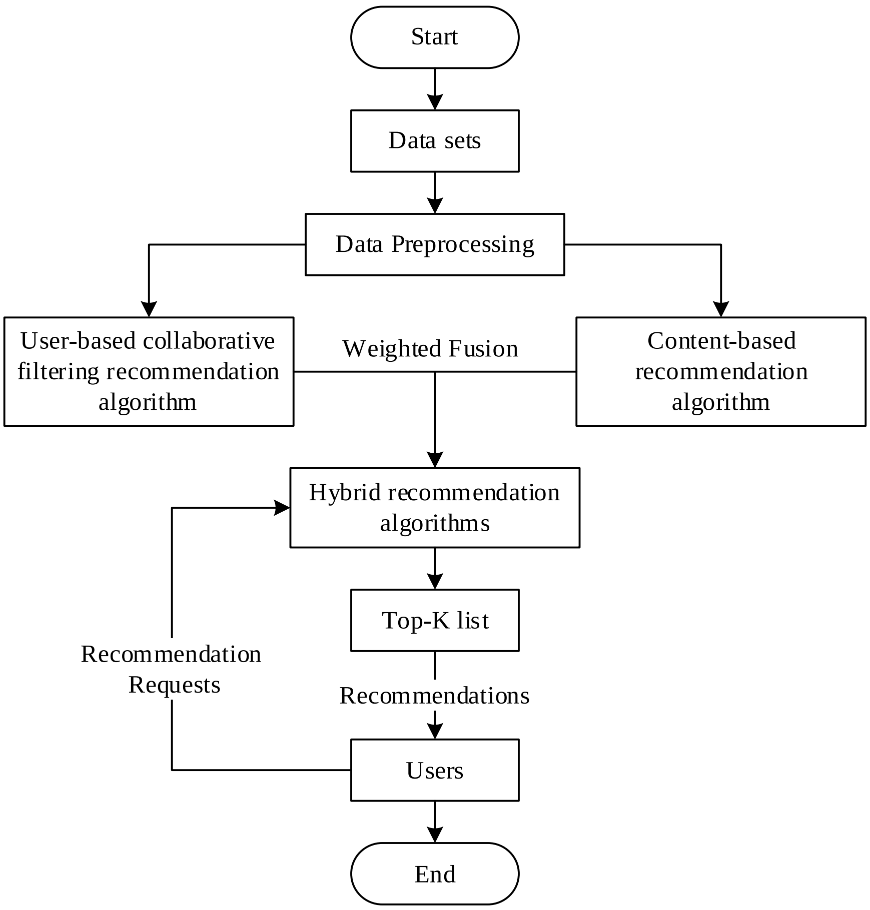


**Figure 2.** Mixed recommendation process

## 2.2 Civic Education Content Intelligent Recommendation System Architecture Design

### 2.2.1 Architecture Design Goals and Constraints

1) Architecture Design Objectives

Through reasonable architecture design to give a user operation that is simple, high stability, high scalability, and good reusability of components, the language version can be extended using object-oriented analysis and the design of an intelligent recommendation system.

2) Key function constraints

The key functions of the intelligent recommendation system include today's recommendations, popular videos, popular courses, and other 7 major aspects. To achieve intelligent recommendations, all sectors of the system, user behavior, and key functions must have relevant constraints. The key constraints for the function are shown in Figure 3.

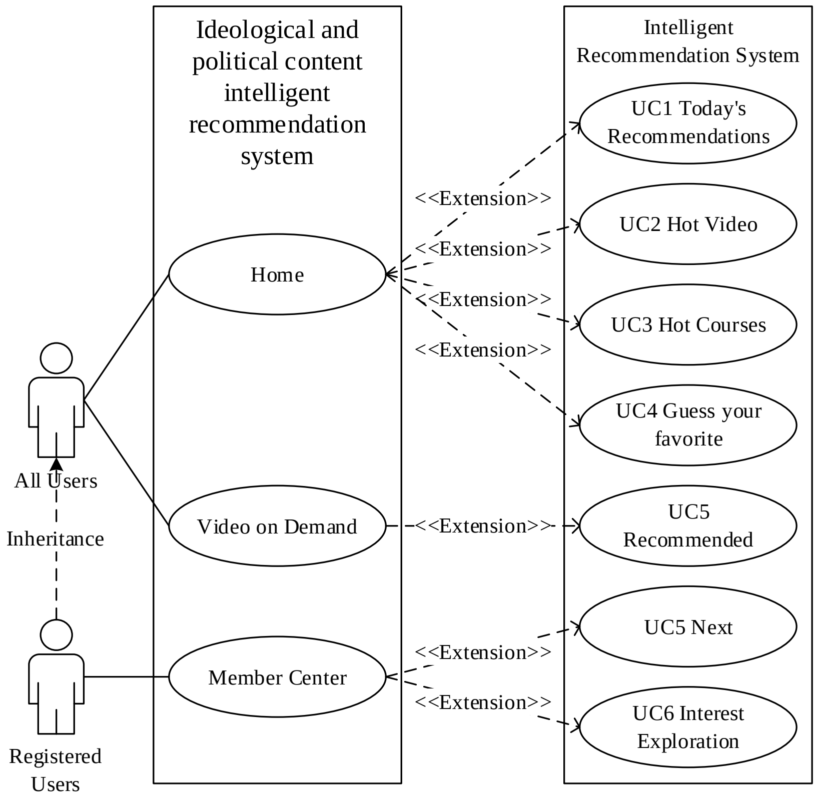


**Figure 3.** Key function constraint

### 2.2.2 Scene description

Intelligent recommendation systems are capable of providing recommendation services to both anonymous and registered users. There are three application points in the university video-on-demand platform, namely: home page, video-on-demand page and member center. The intelligent recommendation system can be started and stopped at any time, and the VOD platform hides the relevant display area after the recommendation is stopped.

### 2.2.3 Overall system architecture

The overall architecture of the system includes an information management console, a user center, and intelligent recommendations, where all user behaviors and interests are recommended through a distributed core database.

### 2.2.4 System logical architecture

To meet the requirements of performance, data capacity, user experience, and more, the recommendation system is designed with a multi-tier system architecture that takes into account the information processing environment and the size of the data set. The architecture provides a unified configuration system to manage each recommendation module and provide interface support for upper-layer application scenarios. The architecture provides a unified configuration system to manage each recommendation module to provide interface support for the upper-layer application scenarios and, at the same time, provides high-performance distributed storage in the bottom layer, thus providing ABTest support and dynamic adjustment of recommendation strategies. Figure 4 illustrates the overall architecture of the intelligent recommendation system.

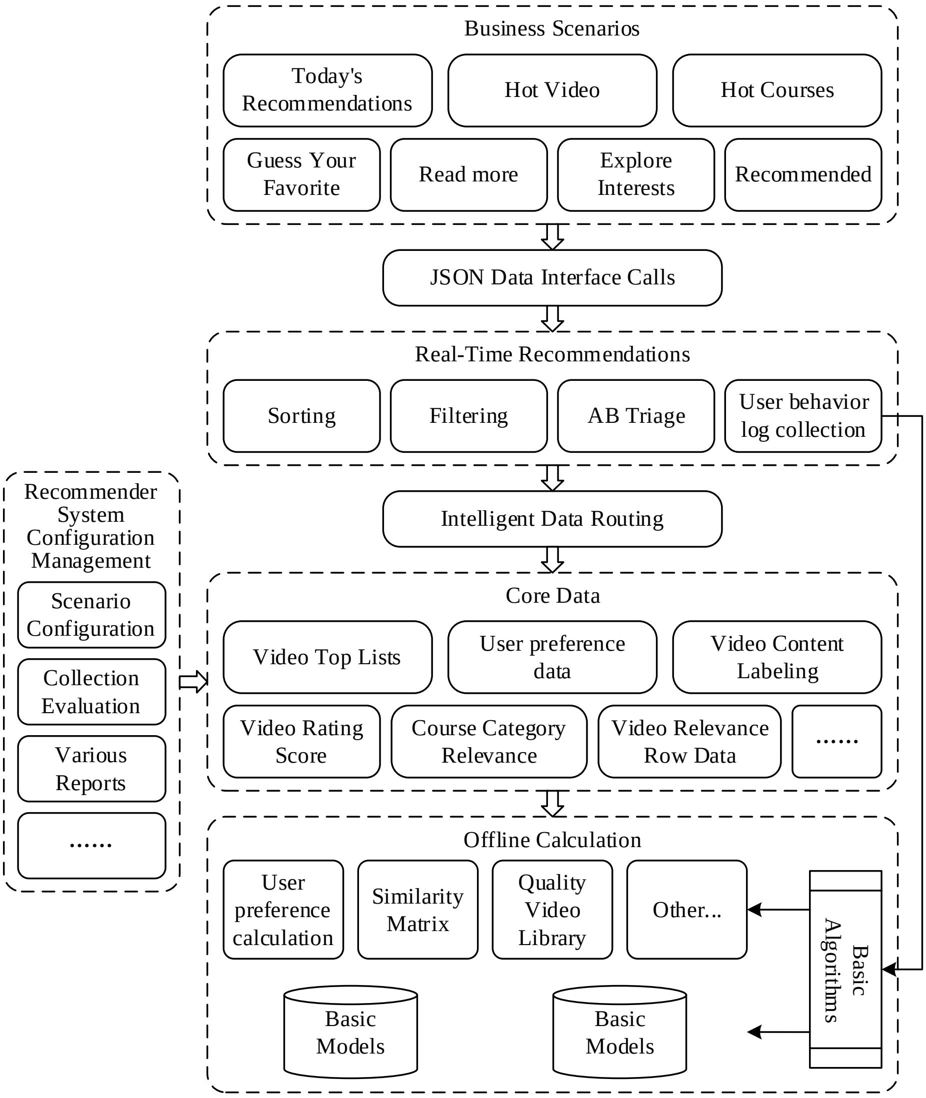


**Figure 4.** The overall architectural design of the intelligent recommendation system

Logically, the whole intelligent recommendation system is designed as a four-layer logical structure, and there is another platform for managing and controlling the application strategies of the recommendation system.

### 2.2.5 System technical architecture

After determining the logical architecture of the intelligent recommender system, the basic technical architecture of the intelligent recommender system is refined and determined.

In the following, the different components of the technical architecture of the intelligent recommendation system and their roles will be elaborated one by one according to the data flow process of the recommendation system:

1) User behavior data acquisition subsystem

   In the offline computing layer, it mainly performs offline data computation on the basic business data and user behavior records of the university video on-demand platform. To facilitate the extraction of the relevant basic model data required by the quasi-real-time recommendation computing engine from the mixed information according to the established model. This article does not provide a detailed explanation of the system database of the on-demand platform for college video open courses, but the technical implementation architecture for recording user behavior data is highlighted.

   Since user behavior data is generated with every operation of the user, the amount of data is very large. To effectively deal with this large data, we need to implement the more mature Hadoop technology architecture. First of all, the user behavior analysis record collector (JS script) has been added to all pages of the university's video open class on-demand platform. The punched log server cluster will receive these user operation data from the client through the GET method for Web requests. At this time, the Web server will record the current request data. Then, the pre-written scripts are executed at regular intervals of half an hour using RocketMQ messaging middleware. The log data will be transmitted to the Hadoop server cluster and stored in the HBase cluster using the Load method.

2) Offline Data Computation Engine

   The offline data computing engine will regularly (every half hour) summarize, organize and analyze the user behavior data from HBase through the summary calculation based on Hsq1, and store the processed user behavior base model data into MySqI cluster for the higher quasi-real-time data computing engine to call. The user behavior model data and the basic business database of the university video open class on-demand platform can be stored in a library or stored in a separate server node. However, considering the possibility of increased data volumes in the future, the two libraries are actually separated during the initial implementation.

3) Quasi-real-time recommendation computing engine

   From the viewpoint of the current demand for intelligent recommendation of college video open course on-demand platforms, the real-time recommendation of real-time requirements is not very high to the millisecond level. Our system recommendation engine's performance is currently set at the second level. Even so, due to the existing hardware cost, the time interval for offline data computation cannot meet the requirements. For this reason, we have designed a quasi-real-time recommendation engine.

The quasi-real-time recommendation engine will calculate the pre-recommendation based on the current user's personalized data from the open video class on-demand system database and the user's behavioral model data from the MySQL cluster after preliminary processing. The pre-recommendation results will be stored in the upper level of the recommendation core database MySQL cluster, allowing the recommendation service interface to directly call and provide feedback to different business applications.

# 3 Modeling of factors influencing the acceptance of Civic Intelligence Recommender System

## 3.1 Determination of model variables

### 3.1.1 Core variable extraction

1) Performance Expectation (PE)

"Performance Expectation (PE)" refers to an individual's cognitive belief that the use of technology can help them improve their job performance, a definition derived from perceived usefulness in the Technology Acceptance Model (TAM) model. In the context of this study, performance expectancy specifically refers to the belief that an intelligent recommendation system for educational content in the Civics and Political Science classes can help improve the efficiency and effectiveness of their learning and future teaching. The study shows that performance expectations have a direct influence on behavioral intention to use technology, and they are also the most stable and important influence factor.

2) Effort Expectation (EE)

"Effort Expectation (EE)" refers to the individual's perceived ease of using information technology, a definition derived from the perceived ease of use in the Technology Acceptance Model (TAM) model. In the context of this study, effort expectation specifically refers to the degree of perceived ease and the degree of willingness of students to make efforts to do so in the process of using the intelligent recommendation system for educational content in the Civics and Political Science class, and a number of studies have shown that effort expectation affects performance expectation.

3) Social Influence (SI)

"Social Influence (SI)" refers to the impact on individuals of the degree of recognition of this information technology by people who are important to them. In the context of this study, social influence is interpreted as the degree to which important people in the student's intended academic life (classmates, friends, and teachers) influence their use of the Intelligent Recommender System for Civics Education Content.

4) Facilitating Conditions (FC)

"Facilitating Conditions (FC)" refers to the extent to which individuals believe that external organizational and technological systems support the use of new information technologies. In the context of this study, facilitating conditions refer to students' perceptions of the degree of completeness of the convenience and various technical support conditions required for the smooth use of the Civics Education Content Intelligent Recommendation System, an information technology.

5) Self-efficacy (SE)

"Self-efficacy (SE)" refers to an individual's assessment of their efficiency or ability in accomplishing a specific task and their degree of self-confidence. Bandura's research shows that individuals who believe that they are capable of achieving their goals and putting in efforts to solve problems, when there is a certain sense of self-efficacy, tend to be enthusiastic about new things, show great interest, actively put them into action, believe that they are able to successfully carry out their goals and achieve better results, and utilize various cognitive strategies of their own to achieve their goals.

6) Perceived Pleasure (PP)

The degree of pleasant playfulness that an individual feels internally while engaging in an activity or work is called perceived pleasantness. The heart expects pleasantness as a motivational expectation. When a person is satisfied with perceived pleasure, their attitude is likely to have a positive impact, resulting in a radiation effect, which in turn positively affects their willingness to use.

7) Intention to use (UI)

"Willingness to use (UI)" is the likelihood of influencing an individual's decision on whether to adopt certain future behaviors or whether the individual will adopt specific behaviors, and a number of studies have shown that there is a correlation between willingness to act and specific behaviors, and that willingness to act is a direct determinant of actual behaviors. In this study, willingness to use is defined as the degree of students' readiness to utilize the intelligent recommendation system in the Civics and Political Science class.

### 3.1.2 Selection of moderating variables

The original model of UTAUT2 theory covers three inherent moderating variables: age, gender, and experience. These moderating variables affect different model paths, respectively. Regarding the selection of the moderating variables in this study, this study follows the gender selection in the original model and adds the moderating variables grade and major.

## 3.2 Model Construction and Research Assumptions

### 3.2.1 Modeling

The UTAUT2 model repaired in this study was divided into four parts.

Independent variables: performance expectation (PE), effort expectation (EE), self-efficacy (SE), social influence (SI), facilitation (FC), and perceived pleasantness (PP).

Dependent variable: intention to use (UI).

Moderating variables: gender, grade level, and major.

### 3.2.2 Research hypotheses

H1: Performance expectation has a significant positive effect on students' willingness to use the Civic Intelligence recommender system (PE→UI).

H2: Effort expectation has a significant positive effect on students' willingness to use the Civic Intelligence recommender system (EE→UI).

H3: Social influence has a significant positive effect on students' willingness to use the Civic Intelligence recommender system (SI→UI).

H4: Convenience has a significant positive effect on students' willingness to use the Civic Intelligence recommender system (FC→UI).

H5: Self-efficacy has a significant positive effect on students' willingness to use the Civic Intelligence recommender system (SE→UI).

H6: Perceived pleasantness has a significant positive effect on students' willingness to use the Civic Intelligence recommender system (PP→UI).

H7: Convenience has a significant positive effect on students' effort expectation to use the Civic Intelligence recommender system (FC→EE).

H8: Self-efficacy has a significant positive effect on students' effort expectation of using the Civic Intelligence recommender system (SE→EE).

H9: Social influence has a significant positive effect on students' performance expectations of using the Civic Intelligence recommender system (SI→PE).

H10: Perceived pleasantness has a significant positive effect on students' social influence in using the Civic Intelligence recommender system (PP→SI).

H11: Self-efficacy has a significant positive effect on students' perceived pleasantness of using the Civic Intelligence recommender system (SE→PP).

H12: There is a difference in the acceptance of the Civic Intelligence Recommendation System among students of different genders.

H13: There is a difference in the acceptance of the Civic Intelligence Recommender System among students of different grades.

H14: There is a difference in the acceptance of the Civic Intelligence Recommendation System among students of different majors.

## 4 Empirical Analysis of the Acceptance of Civic Intelligence Recommender System

The author designed the student questionnaire that was designed by the Civics Course Content Intelligent Recommendation System and distributed it to students of 10 colleges and universities in S city. The study gave away 1000 questionnaires and found 824 that were valid.

## 4.1 Descriptive statistical analysis

### 4.1.1 Sample characterization

The main characteristics of college students covered in the questionnaire were gender, grade level (lower and upper), major, and IT proficiency. The descriptive statistics of the sample are shown in Table 1. The analysis of Table 1 shows that out of the 824 valid questionnaires recovered from the formal survey, 398 (48.30%) were male students, while 426 (51.70%) were female students. The distribution percentages for the grades (lower and upper grades) were 44.66% and 55.34%, respectively. In the distribution of the surveyed students' IT proficiency, the levels of novice, competent and proficient were 21.36%, 70.87% and 7.77%, respectively. In terms of the distribution of majors of the surveyed students, 48.06% of the students in science and technology and 51.94% of the students in literature and history.

**Table 1.** Sample descriptive statistical results

| Student feature | Option | Total frequency | Frequency | Percentage |
|---|---|---|---|---|
| Gender | Male | 824 | 398 | 48.30% |
| | Female | | 426 | 51.70% |
| Grade | Junior | 824 | 368 | 44.66% |
| | Senior | | 456 | 55.34% |
| Discipline | Science & engineering | 824 | 396 | 48.06% |
| | Literature & history | | 428 | 51.94% |
| Information technology proficiency | Novice | 824 | 176 | 21.36% |
| | Competent | | 584 | 70.87% |
| | Proficient | | 64 | 7.77% |

### 4.1.2 Descriptive statistical analysis of core variables

In order to test whether the distribution of the formal sample data conforms to the characteristics necessary for a normal distribution, this study launched a multivariate normal analysis of numerous detection quantities, including mean, standard error, skewness, and kurtosis for the cause and effect variables involved in the initial model. Relevant studies have shown that when the absolute value of the kurtosis value of a detected variable is less than 8, and the absolute value of the skewness value is less than 3, it indicates that the detected data conforms to a normal distribution.1 The results of the statistical analyses of the latent variables (the measured dimensions in the model) are shown in Table 2, which shows that the data of the formal sample of the present study satisfy the relevant characteristics of a normal distribution. Most of the latent variables correspond to means higher than 3. Among them, the mean value of perceived pleasantness is as high as 3.84, and the mean value of self-efficacy also reaches 3.77. It indicates that among the factors affecting students' use of the Civic Intelligence Recommendation System, perceived pleasantness and self-efficacy have the greatest influence, i.e., the student's curiosity and interestingness about the Civic Intelligence Recommendation System or their willingness to try out the new technology or educational and teaching concepts are the main reason. Comparing the mean values of the variables, it can be seen that convenience (2.36) and effort expectation (2.70) have the lowest mean values, indicating that the Civics Intelligent Recommendation System designed by the students' school is still insufficient.

**Table 2.** Descriptive statistics of variables

| Core variable | Item | Item mean | Variable mean | Skewness | | Kurtosis | |
|---|---|---|---|---|---|---|---|
| | | | | Value | SD | Value | SD |
| Performance expectation | PE-1 | 3.70 | 3.48 | -1.215 | 0.103 | 2.712 | 0.205 |
| | PE-2 | 3.42 | | -0.452 | 0.103 | 0.306 | 0.205 |
| | PE-3 | 3.14 | | -0.118 | 0.103 | -0.204 | 0.205 |
| | PE-4 | 3.67 | | -0.917 | 0.103 | 1.624 | 0.205 |
| Effort expectation | EE-1 | 2.70 | 2.70 | 0.415 | 0.103 | 0.112 | 0.205 |
| | EE-2 | 2.65 | | 0.562 | 0.103 | 0.127 | 0.205 |
| | EE-3 | 2.62 | | 0.473 | 0.103 | -0.208 | 0.205 |
| | EE-4 | 2.82 | | 0.384 | 0.103 | -0.613 | 0.205 |
| Social influence | SI-1 | 3.56 | 3.61 | -0.728 | 0.103 | 0.911 | 0.205 |
| | SI-2 | 3.64 | | -0.802 | 0.103 | 1.238 | 0.205 |
| | SI-3 | 3.63 | | -0.624 | 0.103 | 0.852 | 0.205 |
| Facilitation condition | FC-1 | 2.34 | 2.36 | 0.894 | 0.103 | 2.241 | 0.205 |
| | FC-2 | 2.32 | | 0.516 | 0.103 | 0.822 | 0.205 |
| | FC-3 | 2.41 | | 0.578 | 0.103 | 0.736 | 0.205 |
| Self-efficacy | SE-1 | 3.74 | 3.77 | -0.568 | 0.103 | 0.916 | 0.205 |
| | SE-2 | 3.65 | | -0.564 | 0.103 | 0.824 | 0.205 |
| | SE-3 | 3.92 | | -0.904 | 0.103 | 3.485 | 0.205 |
| Perceived pleasure | PP-1 | 3.83 | 3.84 | -0.948 | 0.103 | 2.536 | 0.205 |
| | PP-2 | 3.85 | | -0.826 | 0.103 | 2.473 | 0.205 |
| | PP-3 | 3.84 | | -0.630 | 0.103 | 1.712 | 0.205 |
| Use intention | UI-1 | 3.67 | 3.73 | -0.627 | 0.103 | 1.254 | 0.205 |
| | UI-2 | 3.66 | | -0.446 | 0.103 | 1.023 | 0.205 |
| | UI-3 | 3.76 | | -0.768 | 0.103 | 2.015 | 0.205 |
| | UI-4 | 3.75 | | -0.423 | 0.103 | 1.106 | 0.205 |
| | UI-5 | 3.82 | | -0.562 | 0.103 | 1.328 | 0.205 |

## 4.2 Measurement model reliability test

In order to verify whether the acceptance model of the Civic Intelligent Recommender System is accurate and reasonable or not, the reliability and validity indexes of the measurement model should be analyzed first to determine the usefulness and reliability of the formal sample data before testing the SEM.

### 4.2.1 Reliability Tests for Measurement Models

The Cronbach α index was used to measure the reliability of each measurement question item involved in the formal research questionnaire for the judgment criteria of the Cronbach α coefficient. When the Cronbach α value is higher than 0.5, it means that the reliability of the measurement model is in the acceptable range, and when the Cronbach α value is higher than 0.7, it means that the measurement model has a good level of reliability. The results of the reliability test of the measurement model are shown in Table 3.

From Table 3, it can be seen that the Cronbach α coefficient value of each measurement item in the questionnaire is above 0.7. From the comparison of Cronbach α values, the Cronbach α value of perceived pleasantness is as high as 0.948, which means that perceived pleasantness plays the greatest role effect in influencing the influence of students' willingness to use the Civic Intelligence Recommender System. The overall reliability of the formal research questionnaire also reached 0.871, and the measurement model (formal questionnaire) has good reliability in general.

**Table 3.** Cronbach α of variables

| Core variable | Item | Total correlation | Cronbach α |
|---|---|---|---|
| PE | PE-1 | 0.526 | 0.792 |
| | PE-2 | 0.683 | |
| | PE-3 | 0.592 | |
| | PE-4 | 0.662 | |
| EE | EE-1 | 0.602 | 0.796 |
| | EE-2 | 0.650 | |
| | EE-3 | 0.608 | |
| | EE-4 | 0.653 | |
| SI | SI-1 | 0.864 | 0.925 |
| | SI-2 | 0.872 | |
| | SI-3 | 0.773 | |
| FC | FC-1 | 0.603 | 0.768 |
| | FC-2 | 0.631 | |
| | FC-3 | 0.538 | |
| SE | SE-1 | 0.745 | 0.826 |
| | SE-2 | 0.656 | |
| | SE-3 | 0.634 | |
| PP | PP-1 | 0.906 | 0.948 |
| | PP-2 | 0.911 | |
| | PP-3 | 0.857 | |
| UI | UI-1 | 0.844 | 0.956 |
| | UI-2 | 0.879 | |
| | UI-3 | 0.898 | |
| | UI-4 | 0.857 | |
| | UI-5 | 0.833 | |
| Overall reliability of questionnaire | | | 0.871 |

### 4.2.2 Validity Tests of Measurement Models

The construct validity of formal research data (also called questionnaire structure) can be determined with the help of factor analysis, using principal component analysis to find out the KMO and Bartlett values. Usually, the KMO value is higher than 0.6, and Bartlett's test value has a differential effect (Sig.<0.05) as the judgment criteria, and the specific test results are shown in Table 4.

As can be seen from Table 4, the KMO value of the formal questionnaire is 0.958, which is a high level. Meanwhile, Bartlett's chi-square value is 12065.263, the df value is 600, and the significance is Sig. The value is less than 0.05, which indicates that the measurement model (formal questionnaire) has good validity in general.

**Table 4.** KMO and Bartlett test results

| | | Formal questionnaire | Prediction questionnaire |
|---|---|---|---|
| KMO sampling appropriate quantity | | 0.958 | 0.796 |
| Bartlett's spherical test | Approximate cabal distribution | 12065.263 | 1756.543 |
| | df | 600 | 105 |
| | Sig. | 0.000 | 0.000 |

## 4.3 Structural equation modeling

The author found that four indicators did not meet the fit criteria through the fit test, so the SME1 model did not match well with the sample data, and the initial model could not be effectively supported, so it was necessary to amend the SME1 model.

A comparison of the fitness of the amended SEM2 and the initial model SEM1 is shown in Table 5. From the comparison of the fitness parameters of SEM1 and SEM2 in Table 5, it can be seen that the overall fitness index value of SEM2 has greatly improved after correction. The overall index basically meets the fitness standard value, so the modified model SEM2 and the sample data again fit and do not need to be corrected.

**Table 5.** SEM2 and SEM1 match condition contrast

| | Fitness indicator | Fitness standard or threshold | SEM1 | SEM2 | Fitness (Yes or no) |
|---|---|---|---|---|---|
| Absolute fitness indicator | CMIN/DF chi-square | <3 | 3.875 | 2.695 | Yes |
| | RMR | <0.08 | 0.042 | 0.028 | Yes |
| | RMSEA | <0.1 | 0.075 | 0.051 | Yes |
| | GFI | >0.90 | 0.882 | 0.918 | Yes |
| | AGFI | >0.90 | 0.843 | 0.893 | Yes |
| Value-added fitness indicator | NFI | >0.90, the closer the value is to 1, the better the model fitness. | 0.914 | 0.943 | Yes |
| | RFI | | 0.892 | 0.936 | Yes |
| | IFI | | 0.946 | 0.964 | Yes |
| | TLI | | 0.927 | 0.958 | Yes |
| | CFI | | 0.936 | 0.967 | Yes |

The estimation of each path coefficient in SEM2 is shown in Table 6. From the significance and path coefficients among the latent variables in SEM2, it can be seen that "PE→UI", "EE→UI", "PP→UI", "PP→UI "FC→EE", 'SE→EE', 'SI→PE', 'SE→PP'. "PP→SI" are significant, and the path coefficients are greater than 0, indicating that the dependent variable (right side of the arrow) has a positive influence on the independent variable (left side of the arrow), and these eight paths correspond to the original hypothesized relationships H1, H2, H6, H7, H8, H9, H10, and H11 proposed in the constructed initial model. It shows that the research hypothesized relationships H1, H2, H6, H7, H8, H9, H10, H11 in the initial model are proven accordingly.

**Table 6.** SEM2 path coefficient estimation

| | β | S.E. | C.R. | P | Sig. |
|---|---|---|---|---|---|
| PP←SE | 0.932 | 0.054 | 22.163 | *** | Significant |
| SI←PP | 0.748 | 0.045 | 18.541 | *** | Significant |
| PE←SI | 0.752 | 0.050 | 14.631 | *** | Significant |
| EE←SE | 0.926 | 0.552 | 2.652 | 0.028 | Significant |
| EE←FC | 0.937 | 0.681 | 2.608 | 0.029 | Significant |
| UI←PE | 0.121 | 0.037 | 4.066 | *** | Significant |
| UI←PP | 0.857 | 0.045 | 22.453 | *** | Significant |
| UI←EE | 0.109 | 0.026 | 4.672 | *** | Significant |
| PE1←PE | 0.682 | | | | |
| PE2←PE | 0.678 | 0.085 | 14.226 | *** | Significant |
| PE3←PE | 0.576 | 0.089 | 12.232 | *** | Significant |
| PE4←PE | 0.820 | 0.082 | 15.678 | *** | Significant |
| SI3←SI | 0.823 | | | | Significant |
| SI2←SI | 0.926 | 0.046 | 27.652 | *** | Significant |
| SI1←SI | 0.918 | 0.048 | 26.879 | *** | Significant |
| EE4←EE | 0.725 | | | | |
| EE3←EE | 0.668 | 0.071 | 14.622 | *** | Significant |
| EE2←EE | 0.759 | 0.072 | 15.285 | *** | Significant |
| EE1←EE | 0.706 | 0.065 | 15.065 | *** | Significant |
| FC3←FC | 0.574 | | | | |
| FC2←FC | 0.697 | 0.112 | 13.558 | *** | Significant |
| FC1←FC | 0.843 | 0.106 | 14.689 | *** | Significant |
| SE3←SE | 0.807 | | | | |
| SE2←SE | 0.662 | 0.066 | 16.945 | *** | Significant |
| SE1←SE | 0.764 | 0.059 | 19.812 | *** | Significant |
| PP1←PP | 0.896 | | | | |
| PP2←PP | 0.893 | 0.026 | 43.851 | *** | Significant |
| PP3←PP | 0.914 | 0.033 | 32.450 | *** | Significant |
| UI1←UI | 0.857 | | | | |
| UI2←UI | 0.906 | 0.040 | 30.841 | *** | Significant |
| UI3←UI | 0.924 | 0.038 | 31.458 | *** | Significant |
| UI4←UI | 0.861 | 0.038 | 27.845 | *** | Significant |
| UI5←UI | 0.894 | 0.041 | 29.585 | *** | Significant |

## 4.4 Analysis of variances

The three moderating variables set in the initial model of the factors influencing the acceptance of the Civic Intelligence Recommender System by college students are gender, grade level, and major. In order to explore whether these three moderating variables would have a significant effect on the independent variables: performance expectation, effort expectation, social influence, convenience, self-efficacy, and perceived pleasantness at different levels. The analysis of moderator variables was conducted using independent samples t-tests when the grouping of analyzed moderator variables was less than three.

### 4.4.1 Analysis of Differences by Gender across Variables

The descriptive statistics of students of different genders on each measurement variable were analyzed, as shown in Table 7. In order to find out the differences between students of different genders on each measurement variable, this study used an independent samples t-test to analyze the differences between men and women on each measurement variable, and the results of the independent samples t-test for gender variables are shown in Table 8.

As shown in Table 8, different genders reach significant levels in two measurement dimensions of Performance Expectation (PE) and Perceived Pleasure (PP), indicating that there are significant differences between genders in Performance Expectation and Perceived Pleasure with moderating effect, and there is no significant difference in the other five dimensions. According to Table 7, it can be seen that male students scored slightly higher on the mean performance expectations and willingness to use than female students. The male group has a significantly higher level of convenience and perceived pleasantness than the female group. This indicates that male students in higher education have significantly higher performance expectations (3.8608) and perceived pleasantness (3.8562) than female students (3.6966, 3.6598) in using the Civic Intelligence Recommender System. The Civic Intelligence Recommendation System’s performance expectation and perceived pleasantness are influenced by the gender variable. Hypothesis H12 is applicable to both performance expectation (PE) and perceived pleasantness (PP).

**Table 7.** Descriptive analysis of gender in each measurement variable

| | Gender | Number | Mean | SD | SE mean |
|---|---|---|---|---|---|
| PE | Male | 398 | 3.8608 | 0.6203 | 0.0369 |
| | Female | 426 | 3.6966 | 0.6811 | 0.0385 |
| EE | Male | 398 | 4.0791 | 0.6014 | 0.0366 |
| | Female | 426 | 3.9415 | 0.6534 | 0.0387 |
| SI | Male | 398 | 4.1296 | 0.6023 | 0.0358 |
| | Female | 426 | 4.0746 | 0.5845 | 0.0359 |
| FC | Male | 398 | 4.2688 | 0.5768 | 0.0351 |
| | Female | 426 | 4.1716 | 0.5425 | 0.0335 |
| SE | Male | 398 | 3.9555 | 0.6333 | 0.0356 |
| | Female | 426 | 3.8872 | 0.6525 | 0.0362 |
| PP | Male | 398 | 3.8562 | 0.6397 | 0.0322 |
| | Female | 426 | 3.6598 | 0.6897 | 0.0338 |
| UI | Male | 398 | 4.0605 | 0.6344 | 0.0338 |
| | Female | 426 | 3.9032 | 0.7169 | 0.0368 |

**Table 8.** Independent sample t test results of gender variable

| | | Variance equation Levene test | | Mean equivalent t test | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | F | Sig | t | df | Sig. (2-tailed) | MD | SED | 95% difference confidence interval | |
| | | | | | | | | | Lower | Upper |
| PE | Assuming equal variance | 2.105 | 0.162 | 3.623 | 822 | 0.000 | 0.164 | 0.048 | 0.076 | 0.272 |
| | Unassuming equal variance | | | 3.625 | 820.785 | 0.000 | 0.164 | 0.047 | 0.077 | 0.271 |
| EE | Assuming equal variance | 0.031 | 0.879 | 1.594 | 822 | 0.116 | 0.138 | 0.046 | -0.017 | 0.184 |
| | Unassuming equal variance | | | 1.597 | 821.584 | 0.116 | 0.138 | 0.045 | -0.016 | 0.183 |
| SI | Assuming equal variance | 0.000 | 0.998 | 0.985 | 822 | 0.332 | 0.055 | 0.043 | -0.045 | 0.145 |
| | Unassuming equal variance | | | 0.988 | 821.654 | 0.331 | 0.055 | 0.042 | -0.044 | 0.144 |
| FC | Assuming equal variance | 1.643 | 0.218 | 1.024 | 822 | 0.314 | 0.097 | 0.040 | -0.039 | 0.121 |
| | Unassuming equal variance | | | 1.022 | 815.332 | 0.314 | 0.097 | 0.039 | -0.040 | 0.120 |
| SE | Assuming equal variance | 0.072 | 0.805 | 0.483 | 822 | 0.635 | 0.068 | 0.047 | -0.067 | 0.162 |
| | Unassuming equal variance | | | 0.483 | 821.845 | 0.635 | 0.068 | 0.046 | -0.066 | 0.161 |
| PP | Assuming equal variance | 0.359 | 0.567 | 2.458 | 822 | 0.016 | 0.196 | 0.050 | 0.025 | 0.223 |
| | Unassuming equal variance | | | 0.463 | 821.596 | 0.016 | 0.196 | 0.049 | 0.026 | 0.222 |
| UI | Assuming equal variance | 4.978 | 0.032 | 1.406 | 822 | 0.168 | 0.157 | 0.055 | -0.031 | 0.185 |
| | Unassuming equal variance | | | 1.411 | 819.743 | 0.167 | 0.157 | 0.054 | -0.030 | 0.184 |

### 4.4.2 Analysis of differences between grade levels on each variable

In order to explore the status of differences in each of the measured variables among students in different grades (lower and upper grades), this study used the same methodology as the analysis of differences in the gender variable to analyze the differences in each of the measured variables across grades. Table 9 displays the analysis results, and Table 10 displays the independent samples t-test results for the grade level variables.

As can be seen from Table 10, different grades reached significant levels on the two measurement dimensions of Performance Expectation (PE) and Social Influence (SS), indicating that there are significant differences in Performance Expectation and Social Influence in different grades with moderating effects. Table 9 shows that the higher grade level group had a significantly higher performance expectation (3.7541) and social influence (4.2661) than the lower grade level group (3.6504, 4.0173). This indicates that the grade level variable has a moderating effect on the performance expectation and social impact of the Civic Intelligence Recommender System. Hypothesis H13 holds true for performance expectations (PE) and social influence (SI).

**Table 9.** Descriptive analysis of grade in each measurement variable

| | Grade | Number | Mean | SD | SE mean |
|---|---|---|---|---|---|
| PE | Junior | 368 | 3.6504 | 0.6245 | 0.0386 |
| | Senior | 456 | 3.7541 | 0.6377 | 0.0385 |
| EE | Junior | 368 | 3.7813 | 0.6524 | 0.0402 |
| | Senior | 456 | 3.8697 | 0.6358 | 0.0378 |
| SI | Junior | 368 | 4.0173 | 0.6015 | 0.0362 |
| | Senior | 456 | 4.2661 | 0.6135 | 0.0351 |
| FC | Junior | 368 | 3.9847 | 0.5584 | 0.0347 |
| | Senior | 456 | 3.9895 | 0.5648 | 0.0335 |
| SE | Junior | 368 | 3.6668 | 0.6453 | 0.0396 |
| | Senior | 456 | 3.7412 | 0.6328 | 0.0374 |
| PP | Junior | 368 | 3.7327 | 0.6539 | 0.0384 |
| | Senior | 456 | 3.7757 | 0.6873 | 0.0395 |
| UI | Junior | 368 | 4.0696 | 0.7526 | 0.0445 |
| | Senior | 456 | 4.1129 | 0.7344 | 0.0412 |

**Table 10.** Independent sample t test results of grade variable

| | | Variance equation Levene test | | Mean equivalent t test | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | F | Sig | t | df | Sig. (2-tailed) | MD | SED | 95% difference confidence interval | |
| | | | | | | | | | Lower | Upper |
| PE | Assuming equal variance | 2.596 | 0.184 | 3.680 | 822 | 0.018 | -0.104 | 0.056 | 0.085 | 0.285 |
| | Unassuming equal variance | | | 3.682 | 721.652 | 0.018 | -0.104 | 0.055 | 0.086 | 0.284 |
| EE | Assuming equal variance | 0.085 | 0.889 | 1.845 | 822 | 0.096 | -0.088 | 0.049 | 0.028 | 0.196 |
| | Unassuming equal variance | | | 1.843 | 820.642 | 0.096 | -0.088 | 0.048 | 0.027 | 0.195 |
| SI | Assuming equal variance | 0.000 | 0.993 | 0.996 | 822 | 0.000 | -0.249 | 0.052 | 0.026 | 0.172 |
| | Unassuming equal variance | | | 0.995 | 821.428 | 0.000 | -0.249 | 0.051 | 0.025 | 0.171 |
| FC | Assuming equal variance | 1.845 | 0.234 | 1.025 | 822 | 0.325 | -0.005 | 0.044 | 0.037 | 0.125 |
| | Unassuming equal variance | | | 1.026 | 820.364 | 0.325 | -0.005 | 0.042 | 0.038 | 0.124 |
| SE | Assuming equal variance | 0.095 | 0.814 | 0.526 | 822 | 0.178 | -0.074 | 0.047 | 0.033 | 0.268 |
| | Unassuming equal variance | | | 0.526 | 820.652 | 0.178 | -0.074 | 0.046 | 0.034 | 0.267 |
| PP | Assuming equal variance | 0.462 | 0.583 | 2.584 | 822 | 0.265 | -0.043 | 0.053 | 0.044 | 0.205 |
| | Unassuming equal variance | | | 2.585 | 819.748 | 0.265 | -0.043 | 0.052 | 0.045 | 0.193 |
| UI | Assuming equal variance | 5.045 | 0.036 | 1.549 | 822 | 0.265 | -0.043 | 0.048 | 0.023 | 0.156 |
| | Unassuming equal variance | | | 1.548 | 820.748 | 0.265 | -0.043 | 0.047 | 0.022 | 0.155 |

### 4.4.3 Analysis of differences between professions on each variable

The specialty variable's variance analysis was conducted in the same manner as gender and grade. The results of the descriptive analysis of the major on each measured variable are shown in Table 11, and the results of the independent samples t-test for the major variables are shown in Table 12. Combining Table 11 and Table 12, it can be seen that there is a significant difference between science and engineering students and literature and history students only in their willingness to use UI. The students of literature and history are significantly higher than the students of science and engineering (3.8564) on the willingness to use (3.9762). To sum up, major types have a moderating effect on the measurement dimension of willingness to use. Hypothesis H14 is valid.

**Table 11.** Descriptive analysis of discipline in each measurement variable

| | Discipline | Number | Mean | SD | SE mean |
|---|---|---|---|---|---|
| PE | Science & engineering | 396 | 3.6825 | 0.6245 | 0.0298 |
| | Literature & history | 428 | 3.7356 | 0.6837 | 0.0287 |
| EE | Science & engineering | 396 | 3.9015 | 0.5946 | 0.0343 |
| | Literature & history | 428 | 3.8978 | 0.70503 | 0.0376 |
| SI | Science & engineering | 396 | 4.1628 | 0.5841 | 0.0352 |
| | Literature & history | 428 | 4.1268 | 0.6003 | 0.0335 |
| FC | Science & engineering | 396 | 4.1548 | 0.5625 | 0.0310 |
| | Literature & history | 428 | 4.1672 | 0.5387 | 0.0282 |
| SE | Science & engineering | 396 | 3.8455 | 0.6228 | 0.0345 |
| | Literature & history | 428 | 3.8629 | 0.6826 | 0.0353 |
| PP | Science & engineering | 396 | 3.7463 | 0.6585 | 0.0299 |
| | Literature & history | 428 | 3.7544 | 0.7029 | 0.0310 |
| UI | Science & engineering | 396 | 3.8564 | 0.7234 | 0.0374 |
| | Literature & history | 428 | 3.9762 | 0.7617 | 0.0368 |

**Table 12.** Independent sample t test results of discipline variable

| | | Variance equation Levene test | | Mean equivalent t test | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | F | Sig | t | df | Sig. (2-tailed) | MD | SED | 95% difference confidence interval | |
| | | | | | | | | | Lower | Upper |
| PE | Assuming equal variance | 0.296 | 0.598 | -1.152 | 822 | 0.254 | -0.053 | 0.046 | -0.1542 | 0.045 |
| | Unassuming equal variance | | | -1.153 | 819.264 | 0.254 | -0.053 | 0.045 | -0.1541 | 0.044 |
| EE | Assuming equal variance | 14.255 | 0.000 | 0.214 | 822 | 0.826 | 0.004 | 0.056 | -0.0852 | 0.109 |
| | Unassuming equal variance | | | 0.216 | 820.745 | 0.826 | 0.004 | 0.055 | -0.0853 | 0.108 |
| SI | Assuming equal variance | 0.426 | 0.582 | 0.754 | 822 | 0.415 | 0.036 | 0.052 | -0.056 | 0.145 |
| | Unassuming equal variance | | | 0.755 | 818.348 | 0.415 | 0.036 | 0..051 | -0.055 | 0.144 |
| FC | Assuming equal variance | 0.746 | 0.483 | -0.075 | 822 | 0.926 | -0.012 | 0.048 | -0.087 | 0.078 |
| | Unassuming equal variance | | | -0.075 | 820.482 | 0.926 | -0.012 | 0.047 | -0.086 | 0.079 |
| SE | Assuming equal variance | 4.568 | 0.082 | -0.356 | 822 | 0.725 | -0.017 | 0.041 | -0.105 | 0.095 |
| | Unassuming equal variance | | | -0.358 | 821.565 | 0.725 | -0.017 | 0.042 | -0.104 | 0.096 |
| PP | Assuming equal variance | 2.844 | 0.206 | -0.192 | 822 | 0.836 | -0.008 | 0.053 | -0.115 | 0.082 |
| | Unassuming equal variance | | | -0.192 | 820.716 | 0.836 | -0.008 | 0.052 | -0.114 | 0.083 |
| UI | Assuming equal variance | 0.266 | 0.958 | -2.566 | 822 | 0.022 | -0.120 | 0.046 | -0.256 | -0.018 |
| | Unassuming equal variance | | | -2.568 | 819.386 | 0.022 | -0.120 | 0.047 | -0.255 | -0.019 |

To summarize, hypotheses H1, H2, H6, H7, H8, H9, H10, H11, and H14 hold true, H12 holds true for Performance Expectations (PE), as well as Perceived Pleasurability (PP), and H13 holds true for Performance Expectations (PE), as well as Social Impact (SS).

## 5 Conclusion

In this paper, we first design and build an intelligent recommendation system for the educational content of Civics and Political Science classes, taking the recommendation algorithm based on collaborative filtering and content mixing as the underlying logic and designing the system architecture. Structural equation modeling is used to construct a model of factors influencing student acceptance of the Civics Intelligent Recommendation System, to explore what factors influence students' willingness to use the Civics Intelligent Recommendation System in Civics.

1) Among the core variables, perceived pleasantness and self-efficacy have the highest mean values, respectively 3.84 and 3.77, indicating that perceived pleasantness and self-efficacy have the greatest influence on students' use of the Civic Intelligence Recommendation System.

2) The overall reliability of the questionnaire is 0.871, the KMO value is 0.958, Bartlett's chi-square value is 12065.263, the df value is 600, and the significance Sig. If the value is below

0.05, it means that the measurement model (the formal questionnaire) is reliable and valid in general.

3) The initial model was corrected due to lack of fitness, and after correction, it reached the standard. The initial model's hypotheses H1, H2, H6, H7, H8, H9, H10, and H11 were confirmed based on the path coefficients of SEM2.

4) There is a moderating effect of significant differences across genders only in performance expectations (0.000) as well as perceived pleasantness (0.016). There were significant differences between grade levels in performance expectations (0.018) and social influence (0.000), with moderating effects. There was a moderating effect across majors on the measurement dimension of willingness to use.

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