IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 15, No. 2, April 2026, pp. 1931~1946
ISSN: 2252-8938, DOI: 10.11591/ijai.v15.i2.pp1931-1946

Hybrid recommender for computer aided design software

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Article Info

Article history:

Received May 14, 2025
Revised Jan 6, 2026
Accepted Jan 22, 2026

Keywords:

Analytic hierarchy process
Collaborative filtering
Computer-aided design
Content-based filtering
Hybrid filtering
K-nearest neighbors

ABSTRACT

Choosing the right computer-aided design (CAD) software is a complex task due to the wide variety of available options. Using user opinions and reviews may not be sufficient, which highlighting the need for a decision support system. In this paper, we develop and evaluate a hybrid recommendation program (HRP) for CAD software written in the Python programming language, combining collaborative filtering (CF) and content-based filtering (CBF) using k-nearest neighbors (KNN). CF uses user ratings to identify similar users, while CBF compares software characteristics to find similar options. In our hybrid approach, we integrate both filtering techniques with KNN to generate personalized recommendations. It will improve the relevance of software options, help users make choices (students, educators, and professionals), and encourage the adoption of tools most appropriate for every profile. We used the analytic hierarchy process (AHP) method to choose the criteria for our recommendation program. We tested the HRP on a simulated CAD dataset and found that it made recommendations much more accurately than using CF and CBF separately. Evaluation metrics like precision (0.81), recall (0.95), and F1-score (0.87) show that this hybrid approach works, making it a more reliable tool for helping people choose CAD software.

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1. INTRODUCTION

Computer-aided techniques, such as computer-aided design (CAD), computer-aided manufacturing (CAM), computer-aided engineering (CAE), and product lifecycle management (PLM), play a crucial role in the creation of new products [1]. They significantly decrease the time required to launch a new version of a product into the market. Conducting tests on virtual prototypes accelerates the introduction of the final version into the market. Consequently, this results in reduced expenses [2]. CAD is a crucial tool for teaching graphic engineering. It allows users to create more precise and realistic models and drawings, and to make modifications easily and efficiently. CAD is used for the creation of precise and intricate drawings necessary for the manufacturing of items.

On every day of their lives, almost everyone faces the paradox of choice [3]. As a result, users need recommender system (RS) to make better decisions when faced with this range of information and products [4]. The advancement in information technology has resulted in the creation of new commercial portals and comprehensive product information. A RS assists users who are faced with a large number of options and are unable to make well-informed decisions. These systems propose attractive goods and services to help users make their selections. The use of RS in literature has increased significantly. They have been widely developed and implemented in various fields such as education [5]–[7], e-commerce [8], streaming movies [9], music [10], social networking [11], books [12], food [13], and health [14].

Currently, RS suggest goods or things to consumers by analyzing their interests and behaviors in many fields. According to Verbert *et al.* [15], RS can be divided into three categories: collaborative filtering (CF), content-based filtering (CBF), and hybrid filtering. But there are other types, which have been dealt with by [16]. For CF, the first article was presented in the mid-90s [17]. Malone *et al.* [18] proposed two categories of information filtering. The first category is cognitive filtering, currently known as CBF. The second category is social filtering; known CF. CF is based on similarity between users. An analysis of the user's past behavior is conducted to determine the connections between user and things of interest. This analysis is used to recommend an item based on preferences of other users who have similar interests [19].

CF suffers from several problems, such as data sparsity, cold start problems, scalability, and synonymy [20]. When it comes to CBF, it is based on user behavior. If a user likes a product, we recommend a similar one. This method is widely used in many fields where product evaluation is an important aspect of this technique [21]. Another type of recommendation system, which is demographic filtering. This type of system suggests products to customers according to their demographic profile. The advantage of this demographic approach is that customer assessments are generally not required for styling, which is desirable in collaborative, content-based approaches [22]. Similarly, knowledge-based systems suggest products based on certain domain knowledge about how particular product attributes meet customer requirements and preferences and, ultimately, how the customer uses the products [10]. In addition, community-based suggests that customers are more interested in recommendations from their friends than from related but anonymous users [23]. Besides these adapted methods, other recommendation methods, such as hybrid methodologies, exist in the literature [24].

Previous methods suffer from the cold start problem, sparsity, and scalability [25], [26]. It is due to the lack of information on user preferences, which is necessary for the system to develop a model based on the user's interests [27]. When it comes to new items or products with low user ratings, sparsity affects the recommendation algorithm [28]. This major problem limits the usefulness of CF [29]. The algorithms necessitate calculations that increase with the number of customers and products. A classic web-based recommendation system, using current algorithms, may encounter significant scalability problems due to the large number of customers and products it serves [30]. Music and film RS encounter this problem [10]. In addition to these three problems, we also find synonymy, a phenomenon that occurs when several identical or extremely similar objects or concepts have distinct names or entries. The majority of RS do not have the capacity to discover this hidden link, so they treat these products differently [20]. Hybrid filtering is defined as a combination of CF and CBF. The method is constructed by merging pre-existing techniques in order to take advantage of their respective advantages while minimizing their disadvantages [31]. The use of RS in literature has increased significantly.

Known as the supervised machine-learning algorithm, the k-nearest neighbor (KNN) method learns a specific function that will provide an appropriate output [32]. The use of KNN in RS is beneficial in e-commerce, social media, and healthcare, and it is a valuable tool for producing accurate and customized recommendations [33]. Used alone, traditional techniques that include CBF and CF have limitations. The variety of CAD software options presents a challenge for people in finding software that corresponds to their specific needs. Additionally, there is an absence of programs that suggest recommendations based on user-defined criteria in the context of CAD and engineering.

The aim of our present research is to create and evaluate a hybrid recommendation program (HRP) that uses hybrid filtering to recommend CAD software, which combines the capabilities of CF and CBF, utilizing the KNN algorithm, a simple but efficient method for identifying similarities [34]. Combining the best features of CBF, CF, and KNN produces accurate and personalized suggestions. In order to execute this particular program, it is important to own a database that encompasses comprehensive details on the many software packages accessible within the CAD domain. While we can cite a wide range of them, our work will focus on the most relevant ones. For this purpose, we propose the following most widely used software: Catia, SolidWorks, SolidEdge, AutoCad, and TopSolid. Data pertaining to each of software packages examined will be gathered via a questionnaire [35], which will be distributed among people who are involved in field of CAD.

The structure of the article is as follows: firstly, the section on the state of the art, in which we review the recommendation methods used in different fields, discussing their advantages and limitations, and the methods for evaluating recommendation systems. Secondly, section 3 details the proposed HRP and describes the selection of important criteria for CAD software using the analytic hierarchy process (AHP). Thirdly, section 4 presents the evaluation measures used to assess the performance of the HRP. It also discusses the results obtained and their implications for the accuracy and reliability of the proposed recommender program. Finally, section 5 summarizes the main results of the research. It also suggests future directions for research.

2. RELATED WORKS

2.1. Recommendation methods used in various fields

Different systems employed a variety of techniques. Table 1 shows the various recommendation methods and adapted evaluation models. It is evident that no specific recommendation model exists for any desired domain.

Table 1. Summary of recommendation methods and appropriate evaluation models

Reference	Used approach	Evaluation method	Application domain
[25]	CF Content-based approach	Accuracy, precision, recall, F1-score	Books
[27]	Hybrid filtering approach KNN	Mean absolute error (MAE), precision	
[31]	CF Content-based approach Self-organizing map Neural network technique	Root mean squared error (RMSE), precision, recall	
[9]	Deep artificial neural networks	RMSE	
[11]	Hybrid filtering approach Social filtering Semantic filtering	Accuracy, precision, recall, F1-score	Social networking
[12]	Hybrid filtering approach Matrix factorization	MAE Location- and reputation-aware matrix factorization (LRMF)	Books
[36]	Reinforcement learning technique	Hit ratio, predictive ability, click reduction	Web
[37]	CF KNN	K-tail, recall	Software commands
[38]	Implicit rating-based collaborative filtering Sequential pattern analysis	F1-score, precision, recall	E-commerce
[39]	Time correlation coefficient K-means with cuckoo search	Recall, precision, F-measure, mean average precision (MAP), MAE	Internet of things
[40]	Hybrid filtering approach	Precision, recall, F1-score, area under the curve (AUC), normalized discounted cumulative gain (NDCG)	Food
[41]	Hybrid filtering approach		Laptops
[42]	Hybrid filtering approach	RMSE, precision, recall, F1-score	Movies
[43]	Convolutional neural networks Deep-learning technology Multimodal data analysis	Train/test, RMSE	Movies
[44]	AHP		CAD software
[45]	Hybrid filtering approach	Accuracy, precision, recall, F1-score	Movies

2.2. Graph of the most used approaches in recommender systems

The following pie chart (Figure 1) shows the use of different recommendation models. It shows that hybrid filtering is the most widely used of the other models, with a percentage of 32%, while CF and neural networks are in 2nd place, with a percentage of 12% each. The other methods distribute the remaining percentage.

2.3. Methods used for evaluation

Figure 2 illustrates the diverse range of evaluation metrics employed in the assessment of recommendation models, revealing a clear dominance of classification-based measures over alternative approaches. Among these metrics, precision, recall, and F1-score stand out as the most widely adopted, collectively accounting for 54% of all evaluation techniques used across the reviewed studies, which underscores the research community's strong preference for measuring the accuracy and completeness of recommended items. This prevalence can be attributed to the straightforward interpretability of these three metrics, as they directly capture how well a model identifies relevant items (precision), how thoroughly it retrieves all relevant items (recall), and how effectively it balances both concerns (F1-score), making them natural choices for researchers seeking clear and comparable performance benchmarks.

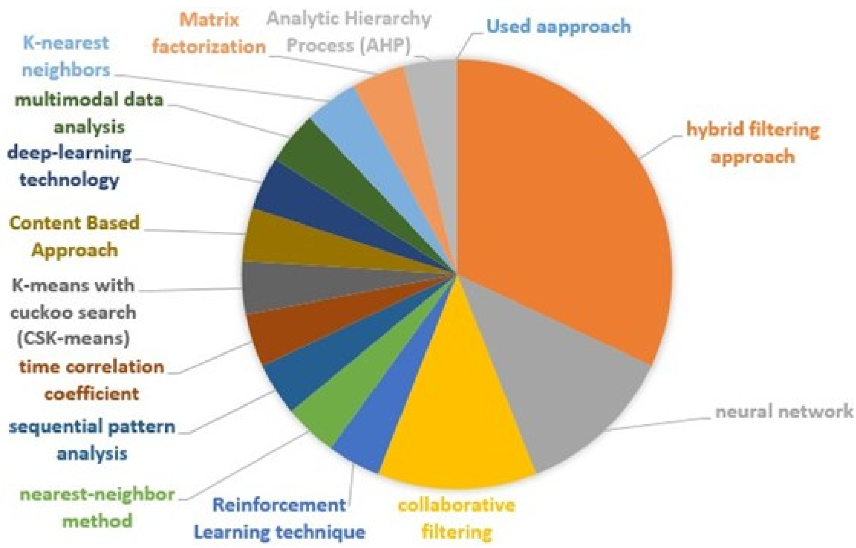

Figure 1. The most frequently used recommendation methods

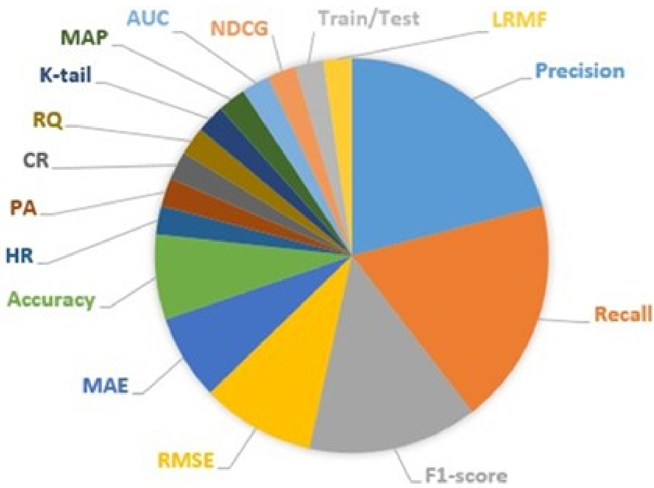

Figure 2. The most frequently used evaluation

3. METHOD
3.1. Flowchart of the proposed model
For our proposed recommendation program, we will opt for a hybrid approach that combines CF, CBF, and KNN. This program, which we will call HRP (Figure 3), combines the advantages of the two traditional approaches to suggest more relevant recommendations for users. Figure 3 shows the flowchart of the proposed model.

3.2. Data collection
First, we will use an open-ended questionnaire to generate the database for our program. The questionnaire first looks at the profile of respondents, gathering information on their age, level of education, profession, and sector of activity. They then share their experience with a specific CAD software; including how long they have been using it. The questionnaire also examines the criteria that influence the choice of software, such as its efficiency, visual aspects, simulation, and modelling capabilities. Technical specifications are also addressed, including system requirements, multilingual support, costs, updates, data security, and integration with other software. Finally, the questionnaire analyses the reputation of each CAD software, the quality of technical support, the training offered, and ease of use. We have sent this questionnaire to people who have a direct affiliation with the

mechanical engineering and design industry like educators, engineers, students. The dataset was cleaned by checking missing values and duplicate values using the Python function. Four attributes were used in our dataset, which are: i) user id, ii) preferred software, iii) rating of each criteria, and iv) user rating.

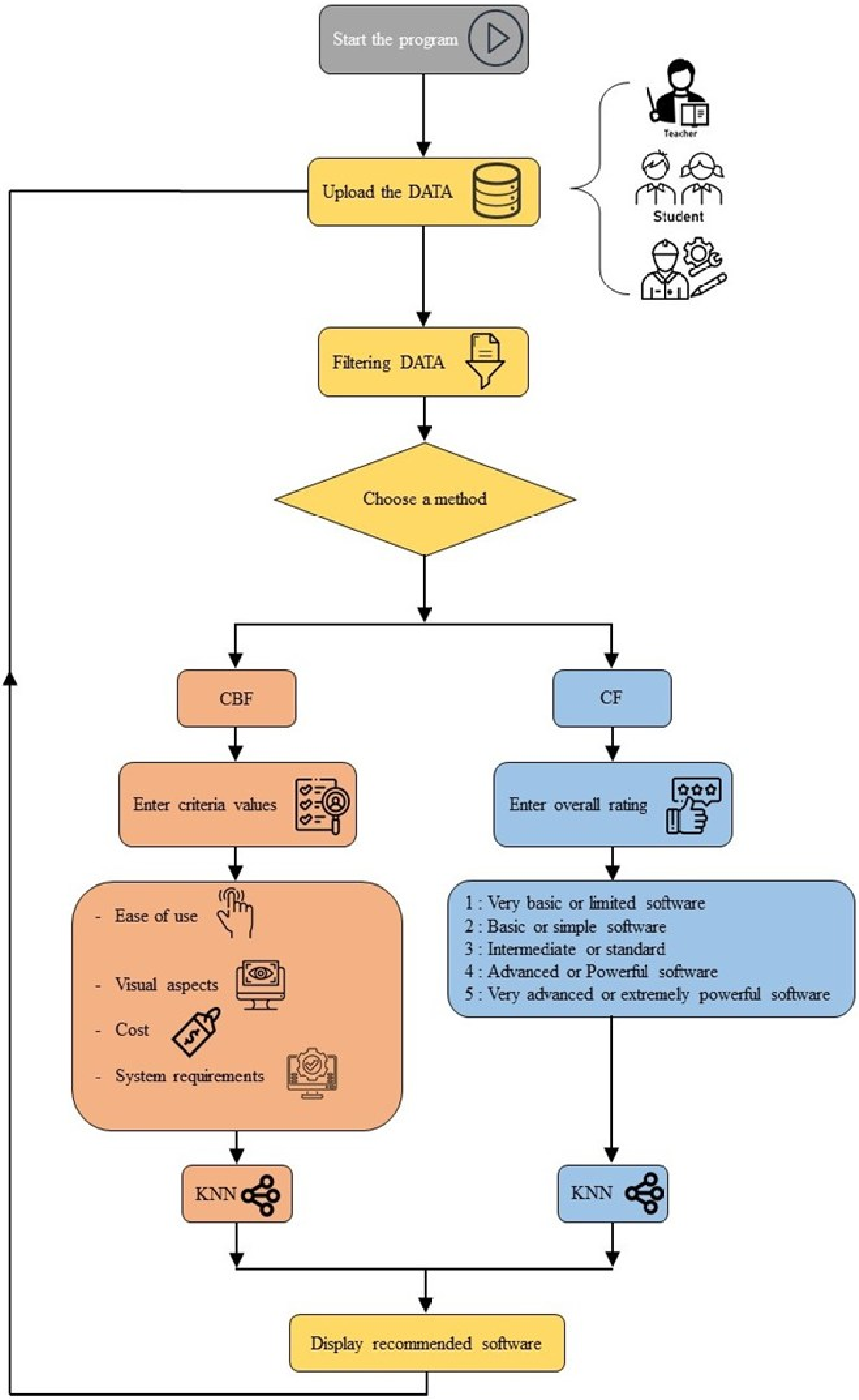

Figure 3. Steps of the proposed model

3.3. Selection of the most important criteria for the selection of a CAD software based on the questionnaire

The process of making decisions gives rise to significant industrial and economic concerns that have a direct impact on the management and competitiveness of companies [46]. Different types of multi-criteria decision-making (MCDM) methods are being utilized, including AHP, analytic network process (ANP), technique for order preference by similarity to ideal solution (TOPSIS), multi-criteria optimization and compromise solution (*višekriterijumska optimizacija I kompromisno rešenje* (VIKOR)), decision making trial and evaluation laboratory (DEMATEL), simple additive weighting (SAW), preference ranking organization method for enrichment evaluation (PROMETHEE), and elimination and choice translating reality (ELECTRE), along with their variants [47]. For our case, we will use the questionnaire and the AHP method, developed by [48]. It is used to select the criteria, their weights and to evaluate the alternatives [44]. This method is based on six steps, as shown in Figure 4.

Figure 4. AHP method steps

3.2.1. Hierarchy definition

The aim of this step is to define the main objective of the analysis, select the selection criteria, and identify the proposed solutions. During this stage, the state of the art and expert opinion are used to identify a specific set of criteria. The various research studies specified several criteria for choosing simulation software. The various research studies specified several criteria for choosing simulation software. For Banks [49], precision and detail, powerful capabilities, fastest speed, demonstration of the problem solution, opinions from companies with similar applications, and participation in user group meetings are key factors to consider when purchasing simulation software. Other factors, such as modeling support, general characteristics, visual aspects, efficiency, testability, input/output, physical elements, user support, performance, financial technical characteristics, scheduling characteristics, general manufacturing, modeling characteristics, statistical means, experimentation means, software compatibility, and coding aspects, have been added [50]. Tricot *et al.* [51] presented utility, usability, and acceptability as criteria for evaluating simulation software.

By classifying them into seven categories, Vuksic *et al.* [52] was able to propose further criteria: model development, simulation, animation, integration with other tools, analysis of results, optimization, testing, and efficiency. However, Verma *et al.* [53] presented a theoretical framework consisting of four categories of criteria for evaluating simulation software. The main categories are:

i) Hardware and software considerations: coding aspects, software compatibility, and user support;
ii) Modelling capabilities: general features, modelling assistance;
iii) Simulation capabilities: visual aspects, efficiency, testability, experimentation facilities, and statistical facilities;
iv) Input/output issues: input and output capabilities, analysis capabilities.

Finally, Cafasso *et al.* [54] based on previous research, has been able to develop another theoretical framework that will enable companies to choose the most appropriate manufacturing simulation software. This framework is based on two distinct multi-criteria approaches: the AHP combined with benefit-opportunity-cost-risk (BOCR) analysis, and the best-worst-method (BWM). Cafasso *et al.* [54] has also added other criteria to the existing ones, such as data security, supported languages, availability of tutorials, updates, supplier reputation, and longevity. The selection criteria in our situation will be grouped into four families: i) user criteria and company reputation (C1), ii) criteria for modeling and simulation capabilities (C2), iii) criteria for input/output issues (C3), and iv) hardware and software criteria (C4). For each group of criteria, there are several sub-criteria, as shown in Table 2. After selecting the criteria, the next question to ask is: which of those factors has the most importance in selecting CAD software?

3.2.2. Pairwise comparisons

This is an essential step in the AHP method, as it establishes the foundational framework upon which all subsequent priority calculations and decision-making outcomes are built. During this step, participants must first prioritize their main criteria by evaluating them in pairs according to their relative importance, using a structured scale that quantifies the degree to which one criterion is favored over another based on expert judgment and domain knowledge. This process of systematic pairwise evaluation generates a comparison matrix that captures all possible inter-criteria relationships, ensuring that the final weight assignments are derived not from arbitrary rankings but from consistent, mathematically grounded assessments that reflect the collective reasoning of the decision-makers involved.

Table 2. Criteria and sub-criteria

Criteria	Sub-criteria	ID
User criteria and company reputation (C1)	Ease of use	C_{11}
Criteria for modeling and simulation capabilities (C2)	Modeling efficiency (capacity and quality)	C_{21}
	Visual aspects (graphic display and animation)	C_{22}
Criteria for input/output issues (C3)	Coding aspects (programming, access to source code)	C_{31}
	Effectiveness of data and results analysis	C_{32}
Hardware and software criteria (C4)	Cost	C_{41}
	Software speed	C_{42}
	Field of use	C_{43}
	System requirements	C_{44}

3.2.3. The importance of each criterion according to the participants who completed the questionnaire

To select the most appropriate criteria for choosing CAD software, a questionnaire was shared with 97 people who work in the CAD field or in another CAD-related field. Based on the questionnaire, we found that 72 people have experience of 3 years or more. We asked this group of experts to give a score between 1 and 9 using the following scale shown in the Table 3 [55] according to the importance of the criteria based on their experience. These notes enabled us to calculate the concordance coefficient W, described by [56] to determine the degree of agreement between the experts' estimates.

Table 3. Scale for pairwise comparisons

Scale	Description
1	Equal importance
3	Moderate importance
5	Essential importance
7	Very strong importance
9	Extreme importance
2, 4, 6, and 8	Intermediate values

The concordance coefficient, W, is calculated using (1).

$$W = \frac{12 \times S}{r^2 \times m(m^2 - 1)} \quad (1)$$

Here r is the number of experts, m is the number of attributes, and S is the deviation of the sum of the criteria ranks from the overall mean of the ranks, the sum of squares. S is associated with the sum rankings of specific criteria obtained from all experts, as shown in (2).

$$e_i = \sum_{j=1}^{r} e_{ij} (i = 1, \dots, m) \quad (2)$$

We also have to calculate the general mean by (3).

$$\overline{e} = \frac{\sum_{j=1}^{r} e_i}{m} \quad (3)$$

In our case, $\overline{e} = \frac{6441}{16} = 408$. In addition, for S, it is calculated by (4).

$$S = \sum_{i=1}^{m} (e_i - \overline{e})^2 \quad (4)$$

Then the concordance coefficient $W = 0.81$. We can confirm that in our case, we have a strong agreement between the experts. The strength of the concordance can be read in Table 4.

After calculating the concordance coefficient, our next step is to determine the weight of each sub-criterion listed in Table 2. This will help us to determine what the most significant ones are. In order to do this, it is necessary to calculate the mean score for each sub-criterion using (5). Table 5 shows the rating score for each sub-criteria.

$$Rating = \frac{Sum\ of\ the\ expert's\ scores\ for\ a\ single\ sub-criterion}{Number\ of\ experts} \quad (5)$$

Table 4. Strength of the correlation

Variation of W	Interpretation
0	No agreement
0.1	Weak agreement
0.3	Moderate agreement
0.6	Strong agreement
1	Perfect agreement

Table 5. Rating score for each sub-criteria

Criteria	Sub-criteria	ID	Rating
User criteria and company reputation (C1)	Ease of use	C_{11}	9
Criteria for modeling and simulation capabilities (C2)	Modeling efficiency (capacity and quality)	C_{21}	5
	Visual aspects (graphic display and animation)	C_{22}	6
Criteria for input/output issues (C3)	Coding aspects (programming, access to source code)	C_{31}	3
	Effectiveness of data and results analysis	C_{32}	4
Hardware and software criteria (C4)	Cost	C_{41}	8
	Software speed	C_{42}	1
	Field of use	C_{43}	2
	System requirements	C_{44}	7

3.2.4. Pairwise comparison matrix and relative weight calculation

Table 6 presents the relative importance of the nine sub-criteria through pairwise comparisons, providing a systematic evaluation of how each criterion weighs against the others in determining its overall significance within the decision-making framework. The comparison matrix reveals that sub-criterion C_{11} holds the highest relative weight at 0.2544, followed by C_{41} at 0.2063 and C_{44} at 0.1616, indicating that these three factors exert the greatest influence on the overall evaluation process compared to the remaining criteria. In contrast, sub-criteria such as C_{42} and C_{43} carry notably lower weights of 0.0255 and 0.0315 respectively, suggesting that while they contribute to the assessment, their impact on the final recommendation outcome is considerably less pronounced than that of the dominant criteria.

Table 6. Pairwise comparison matrix with calculation of relative weight of the criteria

Sub-criteria	C_{11}	C_{21}	C_{22}	C_{31}	C_{32}	C_{41}	C_{42}	C_{43}	C_{44}	Average rating	Weight
C_{11}	**1**	4	3	6	5	1	8	7	2	4.111	0.2544
C_{21}	0.25	**1**	1	2	1	0.33	4	3	0.5	1.453	0.0899
C_{22}	0.33	1	**1**	3	2	0.5	5	4	1	1.981	0.1226
C_{31}	0.16	0.5	0.33	**1**	1	0.2	2	1	0.25	0.716	0.0443
C_{32}	0.2	1	0.5	1	**1**	0.25	3	2	0.33	1.031	0.0638
C_{41}	1	3	2	5	4	**1**	7	6	1	3.333	0.2063
C_{42}	0.125	0.25	0.2	0.5	0.33	0.142	**1**	1	0.166	0.413	0.0255
C_{43}	0.142	0.33	0.25	1	0.5	0.166	1	**1**	0.2	0.51	0.0315
C_{44}	0.5	2	1	4	3	1	6	5	**1**	2.611	0.1616

3.2.5. Aggregation and analysis of results

Table 7 represents the weight of the nine sub-criteria used in the selection of computer aided design (CAD) software. The weight is used to rank each sub-criteria. With a placement of 25.44%, the criterion of ease of use (C_{11}) signifies its greatest importance. This indicates that the intended audience places a high value on software that is easy to use. The categories of Cost (C_{41}) and system needs (C_{44}) have considerable importance, accounting for 20.63% and 16.16% of the total weightage, respectively. This emphasizes the significance of taking into account the software's capabilities in a certain sector of usage while also ensuring that it operates efficiently on the available hardware, as specified by the system requirements. The visual aspects (C_{22}) and modeling efficiency (C_{21}) have a moderate level of importance, accounting for 12.26% and 8.99%, respectively. This means that while visual representation and modeling skills are required, they are not the highest requirements. The relative weights for the data and results analysis (C_{32}) and coding aspects (C_{31}) are rather low, at 6.38% and 4.43%, respectively. Consequently, the importance of data analysis and coding characteristics is diminished in this specific selection procedure. The weights assigned to the field of use (C_{43}) and software speed (C_{42}) are the lowest, with values of 3.15% and 2.55%, respectively. Cost and speed should be taken into account, but they are not the main determining variables. In our case, we will choose the top four criteria for selecting CAD software, which are ease of use, visual aspects (graphic display and animation), cost, and system requirements.

Table 7. Ranking criteria by weight

Sub-criteria	Weight	Percentage	Rank
Ease of use C_{11}	0.2544	25.44	1
Cost C_{41}	0.2063	20.6283	2
System requirements C_{44}	0.1616	16.1588	3
Visual aspects (graphic display and animation) C_{22}	0,1226	12.2601	4
Modeling efficiency (capacity and quality) C_{21}	0.0899	8.9939	5
Effectiveness of data and results analysis C_{32}	0.0638	6.3810	6
Coding aspects (programming, access to source code) C_{31}	0.0443	4.4282	7
Field of use C_{43}	0.0315	3,1547	8
Software speed C_{42}	0.0255	2.5531	9

3.4. List of software used in this experiment

Our model will use five mechanical engineering and design software packages. The software selected are Catia, SolidWorks, SolidEdge, AutoCad, and TopSolid. The choice of these software packages is based on their reputation, their advanced features, and their relevance to different areas of engineering and CAD.

3.5. Description of the proposed program

Once the most important criteria have been determined, each criterion is assigned an evaluation as shown in Table 8. The program, which is written in the Python programming language, starts by asking the user to choose a method for software recommendation. The user has to give both criteria values in the first method or an overall rating in the second method (Figure 5).

Table 8. Values associated with each evaluation

Sub-criteria	Evaluation	Value
Ease of use	Very difficult	1
	Difficult	2
	Medium	3
	Easy	4
	Very easy	5
Visual aspects (graphic display and animation)	Very low	1
	Low	2
	Medium	3
	High	4
	Very high	5
Cost	Very expensive	1
	Expensive	2
	Inexpensive	3
System requirements	Maximum configuration	1
	Medium configuration	2
	Minimum configuration	3

Figure 5. The program asks the user to choose a method of recommendation

The program asks the user to choose a method of recommendation. If the user chooses the first method, the program requests input on the following criteria: ease of use, visual aspects, cost, and system requirements (Figure 6). The program then uses CBF to recommend software. The recommended software is then displayed to the user (Figure 7). The program uses the KNN method to identify similar software based on the criteria entered.

```
# Run the programme
if __name__ == "__main__":
    main()

Choose a recommendation method :
1. Enter criteria values (Ease of use, Visual aspects, cost, System requirements)
2. Enter a rating
Your choice (1 ou 2) : 1
Please enter your preferences for the following criteria :
Ease of use (1-5) : 2
Visual aspects (1-5) : 2
cost (1-3) : 2
System requirements (1-3) : 2
```

Figure 6. The user enters their preferences for each criterion

```
# Run the programme
if __name__ == "__main__":
    main()

Choose a recommendation method :
1. Enter criteria values (Ease of use, Visual aspects, cost, System requirements)
2. Enter a rating
Your choice (1 ou 2) : 1
Please enter your preferences for the following criteria :
Ease of use (1-5) : 2
Visual aspects (1-5) : 2
cost (1-3) : 2
System requirements (1-3) : 2

The recommended CAD software is : SolidWorks
```

Figure 7. The program displays the most suitable CAD software based on software criteria

If the user chooses the second method, the program asks for an overall evaluation in the form of a user rating (Figure 8), offering a simplified yet effective alternative to the detailed criteria-based assessment approach. In this method, instead of evaluating individual criteria such as ease of use, visual aspects, cost, and system requirements separately, the user is asked to provide a single holistic rating on a scale from 1 to 5, which captures their general perception of the software's overall quality and suitability in one consolidated score. This rating is then mapped against the classification scale presented in Table 9, which organizes software into five distinct levels ranging from the most basic to the most advanced, thereby enabling the recommendation system to categorize and rank software options based on the user's expressed level of satisfaction or expectation.

```
# Run the programme
if __name__ == "__main__":
    main()

Choose a recommendation method :
1. Enter criteria values (Ease of use, Visual aspects, cost, System requirements)
2. Enter a rating
Your choice (1 ou 2) : 2
Please enter a rating :
rating (1-5) :
```

Figure 8. The program asks the user to enter a rating

Table 9. Rating scale for evaluating the software

Scale	Description
1	Very basic or limited software
2	Basic or simple software
3	Intermediate or standard
4	Advanced or Powerful software
5	Very advanced or extremely powerful software

```
# Run the programme
if __name__ == "__main__":
    main()

Choose a recommendation method :
1. Enter criteria values (Ease of use, Visual aspects, cost, System requirements)
2. Enter a rating
Your choice (1 ou 2) : 2
Please enter a rating :
rating (1-5) : 3

The recommended CAD software is : Topsolid
```

Figure 9. The program displays the most suitable CAD software based on user ratings

```
# Run the program
if __name__ == "__main__":
    main()

Choose a recommendation method :
1. Enter criteria values (Ease of use, Visual aspects, Cost, System requirements)
2. Please enter a rating
Your choice (1 ou 2) : 1
VEnter criteria values (Ease of use, Visual aspects, Cost, System requirements) :
Ease of use (1-5) : 3
Visual aspects (1-5) : 2
Cost (1-3) : 2
System requirements (1-3) : 1

The recommended CAD software is : SolidWorks

The recommended software is : SolidWorks
Please rate this software on the following scale :
1: Very dissatisfied, 2: Dissatisfied, 3: Neutral, 4: Satisfied, 5: Very satisfied
Rating score (1-5) : 3

Thank you for your feedback.
```

Figure 10. The program asks the user who has used the CBF to evaluate the proposed software

Table 10. Software experience rating scale

Score	Significance	Description
1	Very dissatisfied	Very bad experience: the software does not meet expectations at all.
2	Dissatisfied	Bad experience: the software has major shortcomings.
3	Neutral	Moderate experience: the software is acceptable, but with limitations.
4	Satisfied	Good experience: the software meets expectations.
5	Very satisfied	Excellent experience: the software exceeds expectations.

```
# Run the program
if __name__ == "__main__":
    main()

Choose a recommendation method :
1. Enter criteria values (Ease of use, Visual aspects, Cost, System requirements)
2. Please enter a rating
Your choice (1 ou 2) : 2
Please enter a rating :
rating (1-5) : 2

The recommended CAD software is : AutoCAD

The recommended software is : AutoCAD
Please enter your ratings for the following criteria :
Ease of use (1-5) : 3
Visual aspects (1-5) : 1
Cost (1-3) : 2
System requirements (1-3) : 3

Thank you for your feedback.
```

Figure 11. The program asks the user who has used the CF to enter the ratings of each criterion of the proposed software

4. RESULTS AND DISCUSSION

Depending on the task, there are various forms of evaluation metrics for RS. Depending on the type of application and the prediction's purpose, rating indicators generally fall into two categories: the rating-based indicator (RBI), which represents a rating score, and the item-based indicator (IBI), which represents a set or list of items [57]. According to Figure 2, the best evaluation tools used in most articles are precision, recall, and F1-score. To evaluate the HRP, we will work with these three statistical accuracy metrics (statistical accuracy metrics evaluate accuracy) [58]–[63], which are defined by the following equations:

i) Precision measures the percentage of relevant recommendations among those made by the system, with (6).

$$Precision = \frac{TP}{TP+FP} \tag{6}$$

ii) The recall measures the percentage of relevant recommendations found by the system out of all possible relevant recommendations, with (7).

$$Recall = \frac{TP}{TP+FN} \tag{7}$$

With:
- True positive (TP): number of times the recommendation model has correctly predicted a CAD program, which in our case is 56;
- False positive (FP): number of times the recommendation model predicted the wrong CAD software, which, in our case, was 13;
- False negative (FN): number of times the recommendation model has not predicted the correct CAD software, which in our case is 3.

iii) The F1-score is the harmonic average of precision and recall. It combines the two metrics to give an overall measure of system performance, with (8).

$$F1 - score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{8}$$

For our recommendation model, we obtained the following results. The precision indicates that when the model makes a positive prediction (i.e., recommends software), it is right 81% of the time. However, the high recall of 0.95 means that the model manages to identify 95% of the cases where it should have made a positive prediction. This indicates that the model is good at detecting positive instances but could make some type II errors (false negatives). Finally, F1-score is a harmonic mean of precision and recall. In our case, a score of 0.87 is excellent, indicating a good balance between the two indicators. This means that the model performs well both in identifying positive instances and in avoiding false positives.

5. CONCLUSION

The RS have grown considerably recently, finding applications in a wide range of fields, including e-commerce, streaming platforms, and social networks. However, in the field of CAD, the absence of a dedicated recommendation program is remarkable. Traditional recommendation approaches still have significant limitations, even though CF and CBF are widely used in many domains. CF, which is based on users' previous ratings, suffers from the problem of data sparsity. In addition, the CF does not take into consideration the technical features of the software, which can result in inappropriate recommendations. On the other hand, CBF, which is based on software features, has difficulty in capturing individual user preferences. This approach recommends software that is similar to that already in use, limiting the discovery of new, possibly suitable options. Faced with these limitations, it is necessary to develop a hybrid program that combines the advantages of CF and CBF to improve both the accuracy and personalization of recommendations. Our paper presents the development and evaluation of a hybrid CAD software recommendation program called HRP, which combines the two methods (CBF and CF) using KNN. In our study, we found an accuracy of 0.81, which means that 81% of the positive predictions made by the model are correct. This indicates that the model makes relatively few false positive predictions. We also obtained a recall of 0.95, meaning that the model detects 95% of positive examples. This is a high score, indicating that the model is very effective in identifying almost all true positives, even at the cost of a slight increase in false positives. Finally, the F1-score was 0.87, which means that our model is able to reliably identify software that meets users' needs (high precision). It is also capable of proposing the majority of relevant software from all those in the database (high recall). At present, HRP is based on a limited set of software packages (Catia, SolidWorks, SolidEdge, AutoCAD, and Topsolid). An initial area for development would be to expand this base by integrating other CAD software. It is working on the basis of data analysis with no real user interface. To improve the user experience and make it easier to use the recommendations, the introduction of an interactive graphical interface would be a major asset.

ACKNOWLEDGMENTS

The authors extend their sincere appreciation to their respective institutions for providing the academic support and research environment necessary to conduct this study.

FUNDING INFORMATION

This work did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
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R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

DATA AVAILABILITY

Derived data supporting the findings of this study are available from the corresponding author, [YZ], upon reasonable request.

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