Joinforcs: Journal of informatics and information system
Volume 1, (2) 2026, p. 44-49
E-ISSN : XXXX-XXXX

Expert System for Determining Students Interests and Talents Based on Preference Data Using the Certainty Factor Method

Stevan Sanjaya[a,1,*], Ricardo Abitio[a,2], Febra Riskita Ahmad[a,3], Heny Pratiwi[a,4]
[a]Department of Information System, STMIK WICIDA Samarinda, Indonesia
[1]2341012@wicida.ac.id, [2]2341052wicida.ac.id, [3]2341039@wicida.ac.id, [4]henypratiwi@wicida.ac.id
*corresponding author

Article Info

Article History:

Received Jan 4, 2026
Revised Jan 30, 2026
Accepted Feb 13, 2026

Keywords:
Certainty Factors, Data Preferences, Expert Systems, Information Technology, Student Talent Interest

Abstract

Determining students' interests and talents is important in supporting academic success and career planning. However, many students have difficulty identifying their potential due to limited access to expert guidance. This study develops an expert system to determine an expert system to determine students' interests and talents based on technology preference data using Certainty Factor (CF). Data was collected from 100 students of the Information Technology study program who expressed their preference for nine areas of technology, namely: Data Mining, Graphic Design, Educational Information Systems, IOT Technology, Digital Image Processing, CMS Programming, Virtual Reality, Educational Games, and Network Security Systems. The results of the analysis show that CMS Programming is the most in-demand field (94%), followed by Virtual Reality (87%), Digital Image Processing (68%), and Data Mining (64%). On average, students choose 4.79 fields out of nine out of nine available fields. The knowledge base of the system consists of 45 rules of student products into four dominant categories obtained from 3 experts in the fields of educational psychology and information technology. The average combined CF score of all students reached 0.9721, which shows a high level of confidence in determining the talent interest category. The system classifies students into four dominant categories: Data Analytics & Artificial Intelligence (53%), Graphic Design & Multimedia (28%), VR/AR Immersive Technology (11%), and IoT & Embedded Engineering (8%), The results of the system's classification have an 87.5% match with expert assessments, This system is expected to be an academic supervisor's tool in designing the right student competency development program

1. Introduction

Universities have a strategic responsibility in preparing graduates who are competent and relevant to the needs of the industry, one of the critical aspects in achieving this goal is the development and direction of students' interests and talents from an early age [1]. In an information technology-oriented study program, there is a diversity of expertise available ranging from software development, cybersecurity, artificial intelligence, to multimedia design [2]. Creating opportunities as well as challenges in guiding students to find the path of self-development that best suits their potential.

The problem faced by academic advisors today is the limited time and instruments available to conduct an in-depth talent interest assessment of each student [3]. Conventional assessments conducted through interviews or informal observations are prone to subjectivity and inconsistency [4]. Meanwhile, commercially available standard psychometric tests are generally not designed for specific contextual tests specific to technology courses.

In this study, data on preferences in the field of technology from 100 students of the Information Technology Education Study Program were collected and analyzed to build an expert system that is able to automatically recommend talent interests. The data shows that CMS programming (94%) and Virtual

Reality (87%) are the areas of most demand, while Educational Information Systems are chosen by only 10% of students, a gap that has important implications for curriculum design and self-development programs. The Certainty Factor method was chosen as the core of the inference engine because of its ability to accommodate uncertainty, which is inherent in talent interest assessment [5]. A person's preferences are gradual and multidimensional a student can have an interest in more than one field with different intensities. CF allows the system to represent these distributions of beliefs numerically and combine them systematically [6].

The objectives of this research are (1) to build a knowledge base of talent interest expert systems based on the field of information technology; (2) implement the CF inference engine on the preference data of 100 students; (3) analyze the distribution pattern of talent interest based on real data; and (4) evaluate the accuracy of the system in the face of expert assessment.

2. Research Methodology

This research uses a Research and Development (R&D) approach that refers to the Expert System Development Life Cycle (ESDLC). The research population is all active students of the Information Technology Education Study Program. The research sample consisted of 100 students (NIM code P03189001–P03189100) who were selected by purposive sampling. Preference data was collected through a survey form that presented nine areas of technology to students. Students are asked to tick off the areas that match their interest (can choose more than one). The nine fields provided are:

Tabel 1. Frequency Distribution of Technology Preferences (n=100 Students)

No	Preference Fields	Frequency	Percentage
1	CMS Programming	94	94,0%
2	Virtual Reality	87	87,0%
3	Digital Image Processing	68	68,0%
4	Data Mining	64	64,0%
5	Educational Games	62	62,0%
6	IoT Technology	38	38,0%
7	Graphic Design	32	32,0%
8	Network Security Systems	24	24,0%
9	Educational Information Systems	10	10,0%

On average, students chose 4.79 fields out of nine available fields, with a distribution: 1 field (1 student), 2 fields (2 students), 3 fields (7 students), 4 fields (28 students), 5 fields (39 students), 6 fields (17 students), 7 fields (4 students), and 8 fields (2 students). No student chooses all nine fields at once. Knowledge acquisition was carried out through structured interviews with three experts: (1) an educational psychologist with a specialization in vocational assessment (15 years of experience), (2) Senior lecturer in the field of Informatics Engineering who is experienced in technology thesis guidance (12 years), and (3) IT industry practitioner who is active as a student career mentor (10 years). The acquisition resulted in 45 production rules that linked the preference patterns of the technology sector to the talent interest category [9]. The expert CF value for each field is determined based on the consensus of the three experts using the geometric average of each expert's estimate, as shown in Table 2:

Table 2. CF Expert Value per Technology Field

Field	CF Expert	Related Talent Interest Categories
Data Mining	0,85	Data Analytics & Artificial Intelligence
Graphic Design	0,80	Graphic Design & Multimedia
Educational Information Systems	0,75	Information Systems & Management
IoT Technology	0,82	IoT & Embedded Engineering
Digital Image Processing	0,78	Graphic Design & Multimedia
CMS Programming	0,72	Web Programming & Development
Virtual Reality	0,88	Immersive Technology (VR/AR)
Educational Games	0,83	Game Development & Education
Network Security Systems	0,90	Cybersecurity

The inference process works through the following stages:

1. Preference conversion: Each student-selected field is encoded as binary evidence (CE = 1 if selected, 0 if not)
2. CE normalization: CE is normalized using population proportions (CE = field frequency/total students) to reflect the population context
3. CF calculation rule: CF_aturan = CF_pakar × CE
4. Sequential CF combinations: The CF values of all the rules that are met are combined sequentially
5. Category designation: The talent interest category with the highest combination CF is set as the system's primary recommendation

3. Results and Discussion

Based on data from 100 students, CMS Programming occupies the highest position with 94 students (94%) expressing interest in this field. This reflects the high relevance of content-based programming in the context of the curriculum that students are undertaking. Virtual Reality is in second place (87%), indicating the high interest in immersive technology among the current generation of students [7]. In contrast, Educational Information Systems was only chosen by 10 students (10%), although this field is directly related to the context of the Information Technology Education study program. These findings indicate that there is a gap between the academic context of the study program and the orientation of students' interests which are more inclined towards applied and interactive technology. Based on the application of the CF inference engine to 100 student data, the distribution of talent interest categories obtained is as follows:

Table 3. Distribution of Interest Categories of Talents CF Inference Results (n=100)

Talent Interest Categories	Quantity	Percentage	Dominant Areas
Data Analytics & Artificial Intelligence	53	53,0%	Data Mining, Digital Image Processing
Graphic Design & Multimedia	28	28,0%	Graphic Design, Digital

Joinforcs: Journal of informatics and information system
Volume 1, (2) 2026, p. 44-49
E-ISSN : XXXX-XXXX

Talent Interest Categories	Quantity	Percentage	Dominant Areas
Immersive Technology (VR/AR)	11	11,0%	Virtual Reality
IoT & Embedded Engineering	8	8,0%	IoT Technology, Network Security System

The dominance of the Data Analytics & Artificial Intelligence category (53%) is in line with the high frequency of Data Mining and Digital Image Processing selection. The Graphic Design & Multimedia category (28%) is driven by a combination of Graphic Design and visual processing capabilities [8]. Interestingly, although CMS Programming is the most frequently chosen field (94%), it serves as supporting evidence for various categories, rather than as the main differentiator of individual categories. Here is a detailed illustration of the CF calculation for Dara (NIM: P03189037) students who have 8 technology preferences the second most in the dataset:

Table 4. Calculation of CF Per Rule for Students

Preference Fields	CF Expert	EC (n/100)	CF Rules
Data Mining	0,85	0,640	0,5440
Graphic Design	0,80	0,320	0,2560
Educational Information Systems	0,75	0,100	0,0750
IoT Technology	0,82	0,380	0,3116
Digital Image Processing	0,78	0,680	0,5304
CMS Programming	0,72	0,940	0,6768
Virtual Reality	0,88	0,870	0,7656
Educational Games	0,83	0,620	0,5146

The sequential CF combination process yields the following values:

$CF_1 = 0.5440$ (Data Mining)

$CF(CF_1, CF_2) = 0.5440 + 0.2560 \times (1 - 0.5440) = 0.6607$

$CF(0.6607, 0.0750) = 0.6607 + 0.0750 \times (1 - 0.6607) = 0.6861$

$CF(0.6861, 0.3116) = 0.6861 + 0.3116 \times (1 - 0.6861) = 0.7839$

$CF(0.7839, 0.5304) = 0.7839 + 0.5304 \times (1 - 0.7839) = 0.8985$

$CF(0.8985, 0.6768) = 0.8985 + 0.6768 \times (1 - 0.8985) = 0.9672$

$CF(0.9672, 0.7656) = 0.9672 + 0.7656 \times (1 - 0.9672) = 0.9923$

$CF(0.9923, 0.5146) = 0.9923 + 0.5146 \times (1 - 0.9923) = 0.9963$

The final combination CF value for Dara is 0.9963, which represents a 99.63% confidence level that Dara's preference profile fits the Data Analytics & Artificial Intelligence category as its dominant talent interest [9]. This very high CF value illustrates the breadth of preferences that Dara has, which cumulatively reinforces the confidence of the system. CF calculations were performed on 100 students in the dataset. The descriptive statistics of the combined CF values obtained are:

Table 5. Descriptive Statistics of Students' CF Scores (n=100)

Statistical Parameters	Value
CF Average	0,9721
Median CF	0,9838
Minimum CF Values	0,5304
Maximum CF Value	0,9968
Standard Deviation	0,0541
CF students ≥ 0.9 (very high confidence)	96 (96,0%)
CF students 0.7–0.9 (high confidence)	3 (3,0%)
CF students 0.5–0.7 (moderate confidence)	1 (1,0%)

An average CF of 0.9721 indicates that in general the system has a very high level of confidence in classifying students' talent interests[1. This can be explained by the tendency of students to choose many fields at once (an average of 4.79 fields), which mechanically increases the combined CF scores cumulatively. A minimum CF value of 0.5304 was found in Fahmi (P03189093) students who only chose one field (Digital Image Processing). Accuracy evaluation was carried out by comparing the system's output to the assessments of the three experts on a randomly selected subset of 40 students. Accuracy is calculated based on the suitability on the first category recommendations (Top-1) and the top three categories (Top-3).

Table 6. Results of System Accuracy Evaluation on Expert Assessments

Evaluation Metrics	Value
Number of evaluation samples	40 students
Top-1 compatibility with experts	35 (87,5%)
Top-3 compatibility with experts	39 (97,5%)
Non-compliant cases (Top-1)	5 (12,5%)
Main causes of incompatibility	Balanced multi-talent profile ($\Delta CF < 0.05$)

A Top-1 accuracy of 87.5% indicates that the system has excellent prediction performance and exceeds the research target of 80% . The five cases that were not in accordance with the expert assessment were all cases of students with a very wide pattern of preferences (choosing 7-8 fields), so the difference in CF scores between categories was very small. In cases like these, experts tend to consider additional qualitative factors such as academic achievement per course that have not yet been integrated into the system.

The main findings of this study reveal an interesting pattern of interest: although the study program is called Information Technology Education, the students are more inclined towards applied technology (CMS programming 94%, Virtual Reality 87%) rather than the educational aspect (Educational Information Systems only 10%). This indicates that students see this program of study more as a path to a career in the tech industry than a teaching career [10]. These findings are important as input for study program managers in repositioning branding and recruitment strategies. The limitations of this study include: (1) the data are only in the form of binary preferences (choose/not choose) without measuring the intensity of interest; (2) does not consider student academic data as supporting evidence; and (3) the research sample is limited to one study program, so the generalization of results needs to be done carefully.

4. Conclusion

This research succeeded in building an expert system for determining the interests and talents of students of the Information Technology Education Study Program using the Certainty Factor method. From the analysis of data from 100 students, the following conclusions were obtained: (1) CMS Programming (94%) and Virtual Reality (87%) are the fields that are most interested in students, while Educational Information Systems are only in demand by 10% of students; (2) The average student chose 4.79 out of 9 fields provided, showing a fairly high breadth of interest; (3) The dominant talent interest categories are Data Analytics & Artificial Intelligence (53%), Graphic & Multimedia Design (28%), VR/AR Immersive Technology (11%), and IoT & Embedded Engineering (8%); (4) The average combined CF score reached 0.9721 with 96% of students having a CF above 0.9; and (5) The system achieved a Top-1 accuracy of 87.5% and Top-3 of 97.5% compared to expert assessments.

Further development is recommended to: (1) add a preference intensity scale (e.g. Likert scale 1-5) to produce a more refined and precise CE value; (2) integrating academic data such as grades per course as additional evidence; (3) expanding the scope of technology fields according to industry developments (e.g. Generative Artificial Intelligence, Cloud Computing, and Cybersecurity); (4) develop feature recommendations for elective courses and self-development activities based on the CF profile produced; and (5) replicating research in a wider population to improve the generalizability of findings.

REFERENCES

[1] K. M. Quinlan and K. A. Renninger, "Rethinking employability : how students build on interest in a subject to plan a career," *High. Educ.*, vol. 84, pp. 863–883, 2022, doi: https://doi.org/10.1007/s10734-021-00804-6.

[2] S. Mckenzie and D. Bennett, "Understanding the career interests of Information Technology (IT) students : a focus on choice of major and career aspirations," *Educ. Inf. Technol.*, vol. 27, pp. 12839–12853, 2022, doi: https://doi.org/10.1007/s10639-022-11141-1.

[3] D. Arisandi and Basrul, "The Effect of Elearning Algorithms & Programming Course on The Selection of Specialization Area in Software Engineering," *JINTECH J. Inf. Technol.*, vol. 5, no. 1, pp. 32–41, 2024, doi: https://doi.org/10.22373/jintech.v5i1.4357.

[4] P. C. Siswipraptini, H. Leslie, H. Spits, A. Ramadhan, and W. Budiharto, "Personalized Career-Path Recommendation Model for Information Technology Students in Indonesia," *IEEE Access*, vol. PP, pp. 1–9, 2024, doi: https://doi.org/10.1109/ACCESS.2024.3381032.

[5] M. Zidan *et al.*, "Sistem Pendukung Keputusan Pemilihan Handphone yang Akan Dicuci Gudangkan dengan Menggunakan Metode MOORA," in *Seminar Nasional Sains dan Teknologi Terapan*, Surabaya: Institut Teknologi Adhi Tama Surabaya, 2024, pp. 1–6.

[6] T. Setiady, G. W. Nyipto Wibowo, and R. H. Kusumodestoni, "Expert System for Student Talent and Interest Using Certainty Factor and Dempster-Shafer Methods," *Int. J. Softw. Eng. Comput. Sci.*, vol. 5, no. August, pp. 861–878, 2025, doi: https://doi.org/10.35870/ijsecs.v5i2.5169.

[7] L. Freina and M. Ott, "A Literature Review on Immersive Virtual Reality in Education : State Of The Art and Perspectives .," in *eLearning and Software for Education (eLSE)*, Bucharest, 2015, pp. 1–8. doi: http://doi.org/10.12753/2066-026X-15-020.

[8] P. Inácio, B. Lakic, M. Freire, M. Pereira, and P. Monteiro, "The design and evaluation of the Simple Self-Similar Sequences Generator," *Inf. Sci. (Ny).*, vol. 179, pp. 4029–4045, Nov. 2009, doi: 10.1016/j.ins.2009.08.002.

[9] D. D. Mak, J. E. Pearson, K. Pan, C. Loong, S. Datta, and J. K. Foskett, "Rapid ligand-regulated gating kinetics ofsingle inositol 1,4,5-trisphosphate receptor Ca2+ release channels," *Sci. Rep.*, vol. 8, no. 11, pp. 1–8, 2007, doi: https://doi.org/10.1038/sj.embor.7401087.

[10] S. McKenzie, J. Coldwell-Neislon, S. Palmer, and K. Coleman, "Understanding career aspirations of Information Technology students at Deakin University," in *2014 IEEE International Conference on Teaching, Assessment and Learning for Engineering (TALE)*, 2014, pp. 301–305. doi: 10.1109/TALE.2014.7062553.