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PAPER

Utilizing Machine Learning Techniques to Predict University Students' Digital Competence

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ABSTRACT

Given the importance of possessing the digital competence (DC) required by the technological age, whether for teachers or students and even communities and governments, educational institutions in most countries have sought to benefit from modern technologies brought about by the technological revolution in developing learning and teaching and using modern technologies in providing educational services to learners. Since university students will have the doors to work opened in all fields, the research aims to know their level of DC in artificial intelligence (AI) applications and systems utilizing machine learning (ML) techniques. The descriptive approach was used, as the research community consisted of students from the University of Baghdad in its colleges with scientific and human specializations. To measure the level of DC, a questionnaire was applied as a data collection tool to a sample of 400 male and female students, distributed based on gender and academic specialization. The results showed that the sample students did not have high DC. Their possession of DC related to AI applications and systems was to a moderate degree. The results indicated that there were differences in the responses of the study sample members due to the gender variable and the specialization variable, in favor of the female students with scientific specialization.

KEYWORDS

digital competence (DC), artificial intelligence (AI), digital education, university, students, machine learning (ML), support vector classifier (SVC), Gaussian Naïve Bayes (GNB)

1 INTRODUCTION

Universities are educational institutions that use digital educational technologies in teaching, learning, and research methods and in all university functions. Whereas modern technology and artificial intelligence (AI) play a major role in improving students' access to education. AI and technology have affected professors and students alike. Teaching bodies have acquired new teaching skills thanks to modern technologies such as digital tablets, laptops, and computers. As for the students, they have become proficient in using AI applications in their educational programs, which has

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contributed to raising their abilities to deal effectively with this advanced type of technology and pushing them towards a successful life [1].

Smart applications based on AI are expected to be more present and important in imparting education for demands that come in a general or evaluative form; they provide feedback and help make appropriate academic decisions. AI applications can also be used in virtual environments for some courses in which the teacher cannot master the topics simulated in reality. Virtual learning environments may contribute to developing the education system because they depend on applied vocational programs in which the teacher cannot transfer students to all factories, private training centers, or environments suitable for the learner [2, 3].

Addressing one of the topics of great interest to educational decision-makers, ministries, and educational institutions in countries around the world, which is the topic of digital competencies of AI. The connection of AI with many life skills is necessary for university students. The necessity of possessing digital competence (DC) is one of the most important requirements necessary to confront the developments and changes of the time. The study is a response to the recommendation of many studies on the need to pay attention to digital orientation and the developments associated with it. A study can benefit planners and developers of educational curricula and programs at the university stage by including what helps in developing the DC of AI among university students [4].

The contribution and importance of research lie at theoretical and applied levels. Theoretical significance comes from the absence of studies measuring DC related to AI among Iraqi university students. This gap emphasizes the need for empirical research to understand how students engage with AI technologies.

On an applied level, the study evaluates the DC of Baghdad University students in AI applications. The research aims to determine students' readiness for a technology-driven future, informing educational policies and curriculum development.

The objective limits of the research were the extent of the possession of DC of AI in its three axes. The study sample was determined from students of scientific and humanities colleges/University of Baghdad. As for the spatial and temporal scope, it was the College of Education and the College of Arts at the University of Baghdad during the academic year 2024–2025.

2 LITERATURE REVIEW

2.1 Digital competence

Modern societies live in a digital age that requires educational institutions to adapt to rapid technological changes. DC plays a major role in enhancing learning and enabling students to keep pace with the demands of a knowledge-based society. Possessing a DC is a major requirement for working on positive change in academic performance. It is a stage of transformation and transition of education to a sophisticated method through educational technology. It is one of the evaluation criteria for any academic institution or otherwise, and it has even gone beyond that to become a basic criterion for evaluating individuals and a means for self-assessment and institutional development [5].

The interest in employing technology in university education has become a priority topic that requires a review of the entire educational system and all the university's various activities and services. In this way, DC has become the center of digital transformation that seeks to develop the components of the teaching and learning process within the university, which includes students, faculty members, academic programs, administration, financing, and student assessment in conjunction with the rise of AI [6].

It's one of the requirements of digital transformation, and they are skills that depend on the use of computers and the use of the Internet. They are characterized by comprehensiveness, interactivity, complementarity, diversity, flexibility, and continuous updating. They save time, improve quality, and reduce cost, and they reach the learner from anywhere and at any time to hone their skills and develop them through cooperation and participation made possible by Internet tools and services [7, 8].

The possession of skills, experience, and practical ability is essential when using modern technology. It requires information culture, media culture, and information and communications technology culture. This reflects the effective and positive use of digital technologies, managing and editing digital information, and engaging with information on the Internet and network communications [9].

Digital competence is one of the eight core competencies of a lifelong learner. As well as communication proficiency in foreign languages, mathematical proficiency, and basic competencies in the field of natural sciences and technology, learning capacity, and social and civic competencies—the level of DC of people is greatly related to their academic and research competence [10].

2.2 Artificial intelligence

Artificial intelligence is known as the scientific and technological field that includes methods, theories, and techniques that aim to create machines capable of simulating intelligence. It is a general branch of computing that aims to make computers think, create machines that have minds, perform functions that require intelligence, and mimic the intelligent behavior of humans [11, 12].

Machine learning (ML) is part of AI, focusing on creating algorithms that help computers learn and improve through experience. It plays a crucial role in various applications such as enhanced identification [13], clustering [14], security [15], detection [16], and pattern recognition [17].

Natural language processing (NLP) is a key AI area dealing with computer-human language interaction. It allows machines to understand, interpret, and generate human language, advancing chatbots, language translation, and sentiment analysis [18].

Robotics merges AI and engineering to create robots that can work independently. Applications include industrial automation, healthcare, and hazardous environment exploration [19, 20].

3 MATERIALS AND METHODS

The procedures carried out by the researchers, which are related to defining the community, selecting its sample, selecting and applying research tools, and the statistical methods used, were as follows:

1. **The descriptive method:** It was used as the most appropriate approach in terms of the objectives and questions that it seeks to answer, i.e., employing it to reveal the extent to which University of Baghdad students possess digital competence.
2. **Determining the research community and selecting its sample:** A sample was randomly selected from the University of Baghdad, consisting of 400 male

and female students. It amounted to 400 male and female students distributed according to gender to 155 males and 245 females, and according to specialization to 232 scientific specialization and 168 humanities. Their opinions were collected through electronic questionnaires, numbering 400, valid for analysis. The response from the students was completed by filling out the questionnaires, as the number of completed questionnaires prepared for analysis became 400 questionnaires representing a sample of the current research. As [21] indicated, the size of the sample is related to the number of items on the scale, and the size should range from (5–10) times the number of items. The questionnaire was prepared and divided into two main parts as follows: The first section is concerned with collecting data and personal information for the research sample individuals, which includes sex and college, where the classification is sex in two categories: male and female and college in two categories: scientific and humanities. Table 1 shows that.

Table 1. The details of the research sample

Population Statistical	Sample/Specialization	N	R	Sample/Gender	No.	%
University of Baghdad	Scientific	232	58%	M	155	38.75%
	Human	168	42%	F	245	61.25%
Sum	400		100%	400		100%

3. **Tool of research:** To achieve the objective of the research, researchers adopted the DC questionnaire aimed to collect the answers and estimates of the sample members for a group of items 30 phrases assigned 30 phrases distributed over three axes to measure DC for AI. The questionnaire was prepared by [22] and divided into three axes as follows:

The 1st axis is the DC related to AI applications and systems axis with its phrases consisting of 10 phrases.

The 2nd axis is the axis of DC related to skills required for AI, with its phrases consisting of 10 phrases. The 3rd axis is the axis of proposed ways to enhance DC for AI, which consists of 10 phrases. Researchers used an electronic scale questionnaire to collect the required data and identify the level of DC distributed to the sample via an electronic link, which consists of 30 items. By using the five-point Likert scale to determine the responses of the research sample, as it is the common method in analyzing the answers because it provides a visual estimate of the number of closed questions. Where the Likert scale scores ranged between 1 and 5 (strongly disagree, disagree, neutral, agree, strongly agree), the value 5 means "strongly agree" and 1 means "strongly disagree." The five-point Likert scale and its reversal, where the inverse criterion was adopted to evaluate the negative paragraphs, where the grading was reversed. As shown in Table 2.

Table 2. Five-point Likert scale

Category Range	Evaluation	Evaluation of Negative Items
5	Strongly Agree	Strongly Disagree
4	Ok	Disagree
3	Neutral	Neutral
2	Disagree	Ok
1	Strongly Disagree	Strongly Agree

To answer the 1st goal: To what extent do University of Baghdad students possess DC related to AI and its systems?

In light of the statistical distribution according to the relative weight and level of agreement with the statement and rank, the reality of students' possession of DC related to AI applications and systems came at a medium level, and the percentage came to 65.85. Also, Table 3 shows the details.

Table 3. University of Baghdad students possess DC related to AI applications and systems

N	Mean	SD	V	HM	DF	Ct-Test	Tt-Test	Significance Level
400	96.995	24.929	621.465	90	403	5.611	1.96	0.05

From observing Table 3 and comparing the arithmetic mean of the scores obtained by the sample students on the digital proficiency test with the hypothetical mean, which was higher, the differences are in favor of the arithmetic mean. That is, the sample students have digital proficiency. It is also noted that the calculated "t" value (5.611) is greater than the tabular "t" value (1.96), meaning that there is a statistically significant difference at the significance level (0.05) between the actual average performance of the students and their hypothetical average performance on the digital proficiency scale, which supports the conclusion above, that is, the sample students have digital proficiency.

The percentage of students' possession of DC related to AI was medium, which is attributed to the multiplicity of AI applications and students' reliance on unreliable sources to learn about them and support their competence, as well as the scarcity and lack of specialized programs within the university that work to raise students' knowledge in the field of AI, as well as the lack of qualification of faculty members to possess the required competencies to transfer DC related to AI to their students. In addition to all of the above, there is a lack of organized guidance, support, infrastructure, tools, and equipment necessary to teach AI and develop its competence among students. Therefore, studies have recommended the necessity of providing the necessary components for teachers, including [23] the necessity of spreading digital culture in schools, universities, and society in general in order to empower students and academics digitally.

To answer the 2nd goal: What is the level of DC of AI among university students, each according to their scientific or human specialization?

4. **The proposed model:** The proposed model aims to predict university students' DC of AI using two ML techniques: the support vector classifier (SVC), a well-established machine learning technique for classification tasks, and the Gaussian Naïve Bayes (GNB). GNB is a powerful algorithm for classification, applying Bayes' theorem with the independence assumption between features. Naïve Bayes models, also known as simple Bayes or independent Bayes, apply Bayes' theorem in the classifier's decision rule. The classifier uses Bayes' theorem in practice, bringing its power to ML [24, 25]. The model consists of four stages: data collection, preprocessing, feature construction, and classification.
   a) **Data collection:** Data were collected through a survey administered to undergraduate students in stages 1–4 at the University of Baghdad, encompassing both human and scientific specialists. The questionnaire comprised 30 questions, with DC queries divided into three subgroups of ten questions each. Respondents rated their experiences using a Likert scale ranging from 1 to 5.

The survey was distributed via Google Classroom, yielding responses from 400 students, predominantly females from scientific disciplines. Figures 1 and 2 show the histograms of sex and specialty.

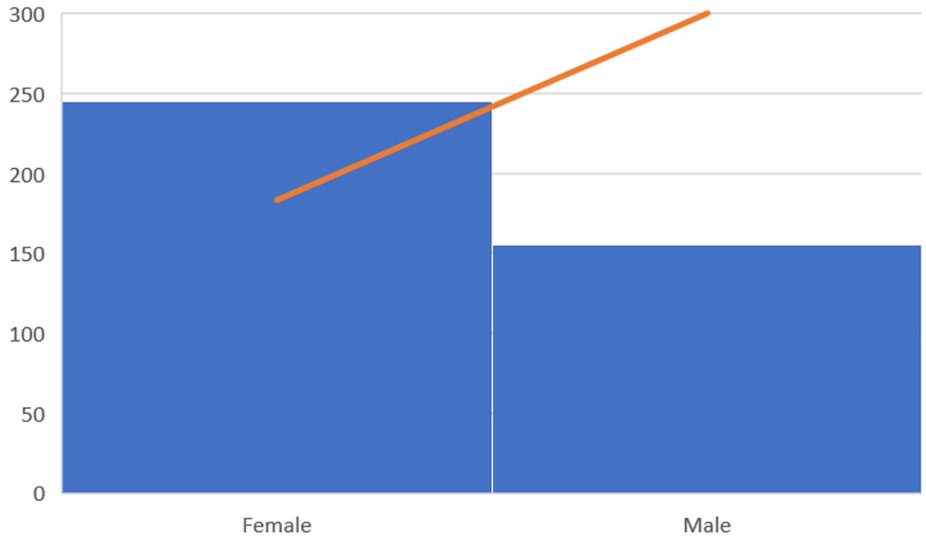

Fig. 1. The histogram of males and females in the DC dataset

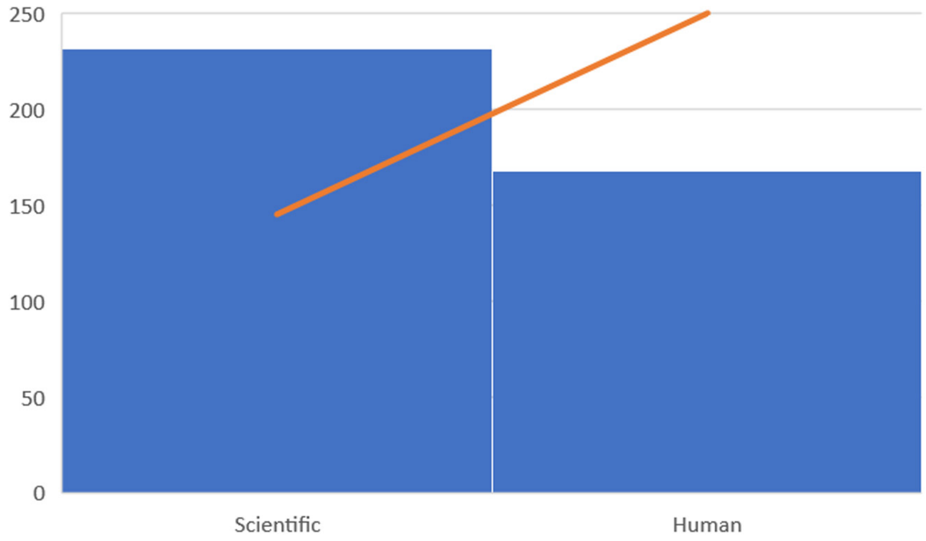

Fig. 2. The histogram of specialists in the DC dataset

b) **The pre-processing stage:** Preprocessing is crucial in the ML pipeline to prepare data for model building and training. It ensures the quality and accuracy of the prediction process.

The pre-processing stage involved three key steps:

1. Handling null values by replacing them with the mode of the respective features.
2. Encoding categorical data (e.g., sex and specialist) into numeric values.
3. Removing non-essential features such as timestamps to simplify the dataset and prevent overfitting.

The class label for binary classification was determined based on a threshold of 90. The dataset ultimately contained 400 records: 236 instances classified as 'existing,' and 164 as 'not existing', as shown in Figure 3. The dataset was split into training (75%) and testing (25%) sets.

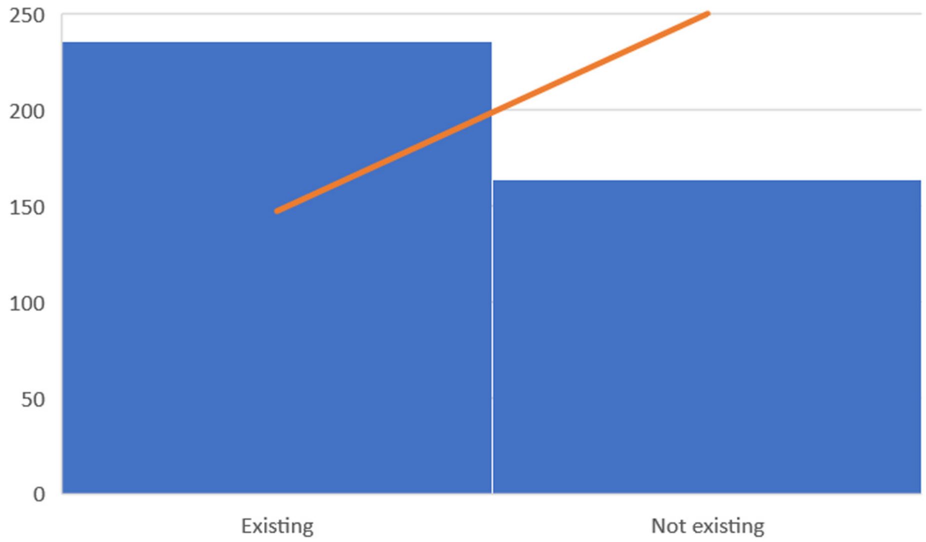

Fig. 3. The histogram of class labels in the DC dataset

c) **Feature construction stage:** The diverse nature of features poses a challenge in achieving higher prediction accuracy. Implement feature selection to extract key features before applying a ML model, reducing irrelevant variables, costs, and overfitting. Selecting only significant features is crucial for successful predictions [26, 27]. There were 30 features in the dataset. Using the questionnaires indicated in the previous section, the students filled out these features. The features fall into three groups:
   1. Feature 1–Feature 10: DC related to AI applications and systems. These features focus on the student's abilities to use and interact with AI systems and applications, such as handling information, speech recognition, AI-based learning systems, etc. The skills involve both understanding and applying AI technologies directly.
   2. Feature 11–Feature 20: DC related to the skills required for AI. These features describe the digital skills needed to effectively interact with AI tools and applications, including the ability to design websites, work with augmented reality, and utilize AI for self-learning.
   3. Feature 21–Feature 30: Proposed ways to enhance DC for AI. These features focus on institutional strategies to improve students' DC, such as faculty training, curriculum updates, and infrastructure provision.

   The score of each feature ranges from one to five. Pearson's correlation was utilized to analyze relationships between features, identifying significant correlations that inform feature dependency. A positive correlation means an increase in one feature causes an increase in the correlated feature, as shown in Figure 4. Multiple features are correlated. Table 4 summarizes the strongest correlations within defined groups.

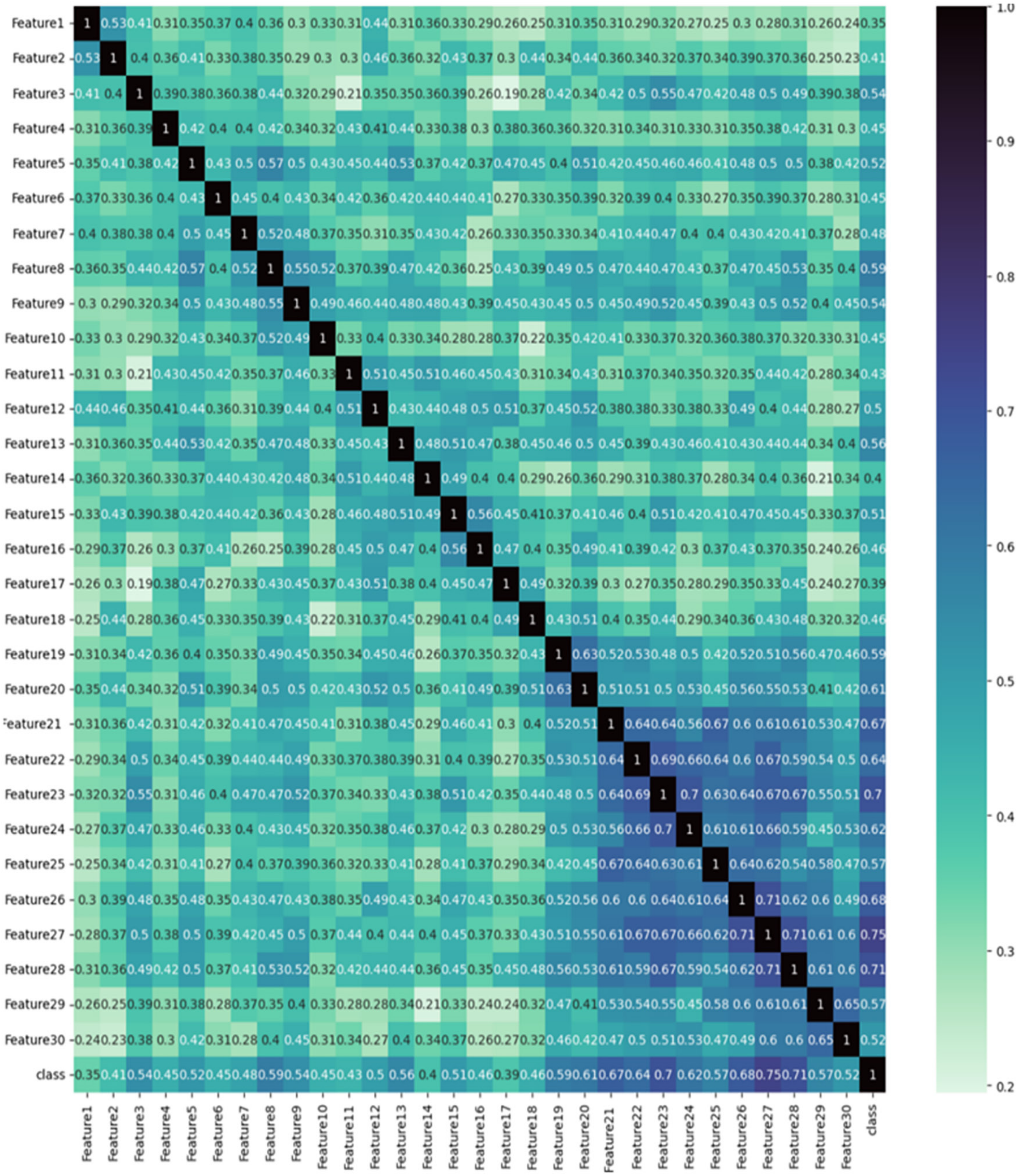

Fig. 4. The Pearson correlation between features

Table 4. Correlation analysis of DC features in AI applications and skills

Group	Feature Pair	Correlation Coefficient	Key Insights
Group 1: DC Related to AI Applications and Systems	Feature 1–Feature 2	0.53	Foundational AI tasks (transferring expertise, inference) are closely related.
	Feature 5–Feature 7	0.5	NLP skills connect with pattern recognition, showcasing the interplay of advanced AI abilities.
	Feature 5–Feature 8	0.57	NLP links with image and shape recognition, emphasizing its central role in AI applications.
	Feature 5–Feature 9	0.5	NLP supports knowledge extraction for intelligent learning systems.
	Feature 8–Feature 9	0.55	Pattern recognition ties closely to knowledge extraction, reflecting shared skill foundations.
	Feature 8–Feature 10	0.52	Recognizing patterns is tied to representing information symbolically.
Group 2: DC Related to AI Skills	Feature 11–Feature 12	0.51	General digital navigation aids in website design skills.
	Feature 12–Feature 16	0.5	Website design connects with robot interaction skills.
	Feature 12–Feature 17	0.51	Proficiency in design overlaps with predictive analytics.
	Feature 13–Feature 15	0.51	AR-based learning correlates with troubleshooting skills.
	Feature 15–Feature 16	0.56	Technical problem-solving is critical for robot interaction.
	Feature 18–Feature 20	0.51	Self-learning aligns with using AI to save effort and time.
Group 3: Enhancing DC for AI	Feature 21–Feature 25	0.67	Faculty training links strongly with curriculum updates and e-course expansion.
	Feature 22–Feature 24	0.66	Curriculum updates promote positive AI attitudes among students.
	Feature 23–Feature 28	0.67	Infrastructure provision connects with expert consultations for skill-building.
	Feature 26–Feature 27	0.71	Practical exposure is critical for solidifying theoretical skills (e.g., website design).
Cross-Group Correlations	Feature 5–Feature 13	0.53	NLP skills align with immersive AR learning applications.
	Feature 9–Feature 20	0.5	Data inference skills align with using AI for time and effort-saving tasks.
	Feature 3–Feature 23	0.55	Speech recognition links to the role of infrastructure for enabling AI tasks.
	Feature 8–Feature 28	0.53	Pattern recognition benefits from external expertise in AI.
	Feature 19–Feature 28	0.56	Collaboration with experts enhances AI-related task delegation.

Figure 5 shows the correlation coefficient of feature pairs.

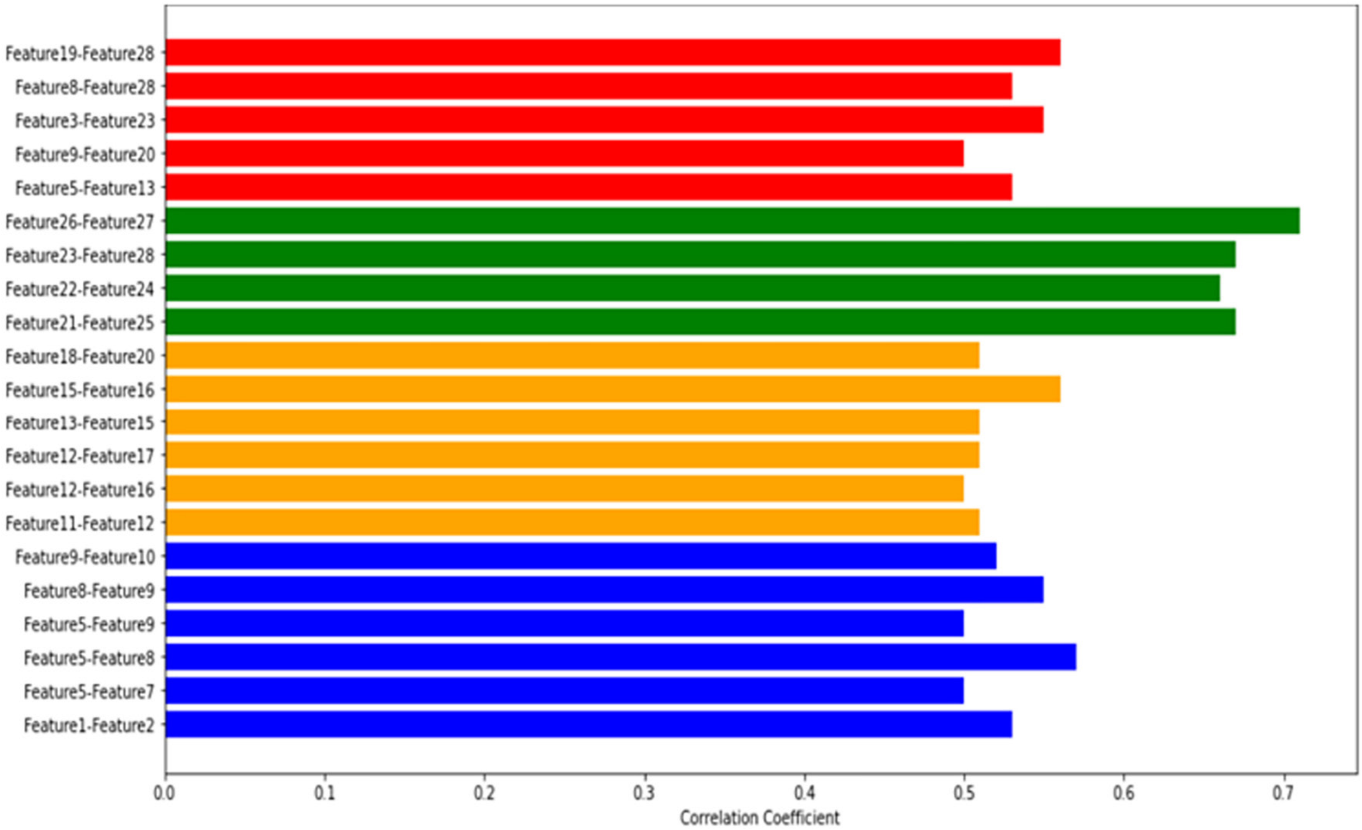

Fig. 5. Correlation coefficients of feature pairs

The most important features that are related to the class with their correlation values (greater than or equal to 0.5) and names appear in Table 5. These 18 features were selected from the original 30 features to be used for the prediction stage.

Table 5. The most important features used

Feature	Feature in English	Correlation Coefficient
Feature 3	I pay attention to the reflections of life changes on my future.	0.541853
Feature 5	I strive to seize opportunities that achieve my goals.	0.516412
Feature 8	I anticipate the future to develop myself in the long term.	0.588452
Feature 9	I commit to completing my tasks within the available time.	0.53571
Feature 13	I identify the time and place where the problem occurred.	0.55859
Feature 15	I compare the proposed alternatives and the availability of the necessary resources for them.	0.511253
Feature 19	I compare the proposed alternatives and their suitability for the time needed to solve the problem.	0.594067
Feature 20	I choose the appropriate alternative after ranking the alternatives based on their advantages and disadvantages.	0.605725
Feature 21	I compare the results of each alternative with the goals I seek to achieve.	0.672662
Feature 22	I plan to reduce the impact of certain problems on my future.	0.635143

(Continued)

Table 5. The most important features used *(Continued)*

Feature	Feature in English	Correlation Coefficient
Feature 23	I identify my mistakes to avoid repeating them in the future.	0.702714
Feature 24	I consider all variables that affect my future.	0.615826
Feature 25	I enjoy exchanging experiences with my colleagues.	0.57473
Feature 26	I gather information from its sources before making decisions.	0.68389
Feature 27	I am cautious about problems with long-term effects.	0.747263
Feature 28	I have extensive relationships within the university.	0.70905
Feature 29	I understand the relationships between university departments.	0.565193
Feature 30	I possess the ability to persuade and guide others.	0.515601

The selected features were then standardized by computing the standard deviation for each feature. This is an essential preprocessing step in many ML tasks, since it ensures:

- Equal weighting of features ensures fair contribution to distance calculations in algorithms.
- Optimization algorithms converge faster with standardized features.
- Model performance improves with standardized features for distance-based models.
- Interpretability is enhanced when features are standardized.
- Standardization ensures compatibility across different data sources.
- Handling different units of measurement becomes easier with standardization.

All the above means standardizing features enhances model training by ensuring equal contribution, improving convergence rates, and enhancing predictive performance and interpretability. It is a critical step in data preparation for effective analysis and modeling.

d) **Classification and evaluation methods:** As mentioned earlier, the feature vector was created from questionnaire responses with 18 features (the most important features). SVM and GNB from ML were recommended for classifying the vector. Dataset split into 75% training and 25% testing sets to evaluate model performance. The dataset had 400 instances.

The proposed work is evaluated using precision, recall, F1-score, support, accuracy, specificity, and AUROC. Using different evaluation metrics is important to ensure that the proposed work effectively addresses its objectives. Accuracy measures correctness, precision, and recall to show effectiveness in identifying positive cases. Trade-offs between false positives and false negatives are understood through precision and recall. The F1 score balances precision and recall. Specificity measures the true negative rate. AUROC evaluates a model's ability to distinguish between classes. Metrics support decision-making on model selection. Standardized metrics enable consistent comparisons. Analysis of metrics can highlight areas for improvement.

4 RESULTS AND DISCUSSION

1. ***The result of classifying selected features vsing SVC:*** In this section, the results of classification using SVC for the selected 18 important features appear

in Table 6, while Figure 6 shows the confusion matrix for the tested data. Figure 7 shows the AUROC.

Table 6. Performance evaluation report for SVC

Metric	Class 0	Class 1	Accuracy	Macro Avg.	Weight Avg.
Precision	0.9487	0.9836	0.97	0.9662	0.9703
Recall	0.9737	0.9677		0.9707	0.97
F1-Score	0.961	0.9756		0.9683	0.9701
Support	38	62	100	100	100
Overall Accuracy			0.97		
Specificity					0.9737
AUROC					0.9983

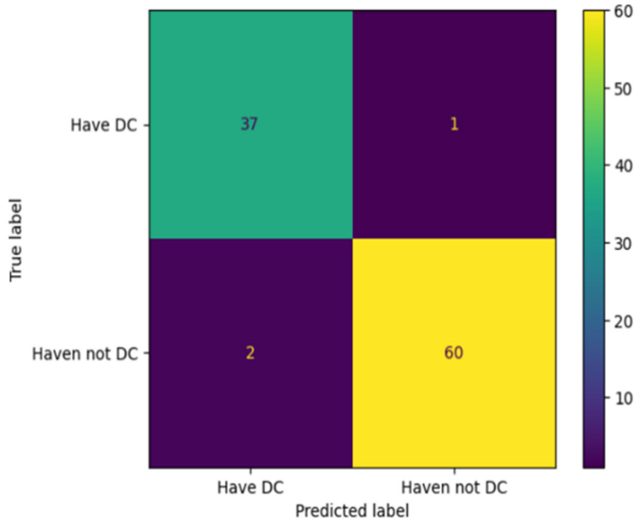

Fig. 6. Confusion matrix for the tested data using SVC

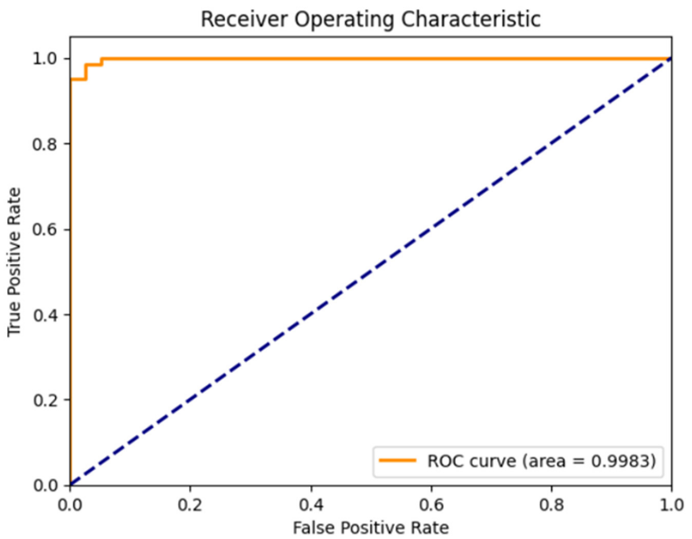

Fig. 7. The AUROC curve using SVC

2. ***The result of classifying selected features using GNB:*** The results of classification using GNB for the selected 18 important features appear in Table 7, while Figure 8 shows the confusion matrix for the tested data. Figure 9 shows the AUROC.

Table 7. Performance evaluation report for GNB

Metric	Class 0	Class 1	Accuracy	Macro Avg.	Weight Avg.
Precision	0.8837	1.000	0.95	0.9419	0.9558
Recall	1.000	0.9194		0.9597	0.95
F1-Score	0.9383	0.9580		0.9481	0.9505
Support	38	62	100	100	100
Overall Accuracy			0.95		
Specificity					1.000
AUROC					0.9597

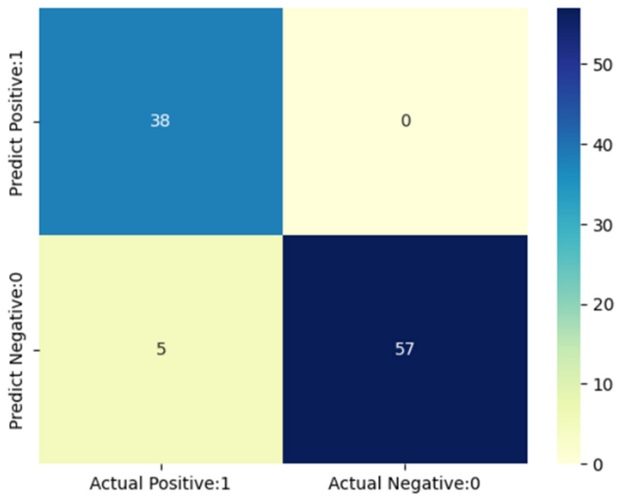

Fig. 8. Confusion matrix for the tested data using GNB

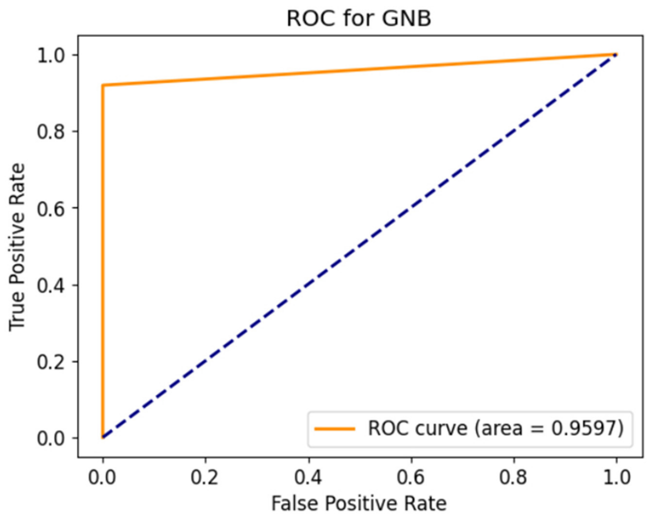

Fig. 9. The AUROC curve using GNB

3. ***Gender distribution by class:*** The distribution of DC among students based on gender and specialization type is summarized in Table 8.

Table 8. Gender distribution

Gender	Specialist	Class = 1 (Has DC)	Class = 0 (Has no DC)
Female	Scientific	103	36
Female	Human	62	44
Male	Scientific	49	44
Male	Human	22	40

5 CONCLUSION

The findings indicate that a considerable gap exists in DC among university students, with only 236 out of the 400 students possessing the necessary skills. It utilized two machine learning techniques (SVC and GNB) to predict the university students' DC. Both of them have proven highly effective with an impressive accuracy rate of 97% for support vector classifier.

Furthermore, the analysis delves into the gender disparities in DC among students. It reveals that female students, particularly those in scientific disciplines, exhibit a higher level of DC compared to their male counterparts. For instance, there are 103 competent females in scientific fields and 62 in human fields, whereas male students show 49 and 22 competent individuals, respectively in these fields. These findings underscore the importance of targeted educational interventions aimed at bridging the digital skills gap, especially in an academic landscape increasingly driven by technology.

The suggested work integrates a comprehensive set of evaluation metrics, which enhances the robustness of the analysis and ensures that the proposed work effectively addresses its objectives. By utilizing precision, recall, F1-score, support, accuracy, specificity, and AUROC, this research not only evaluates the predictive performance of ML techniques but also provides valuable insights that can guide future research and practical applications in assessing DC among university students.

Moving forward, it is crucial for future research to explore specific educational strategies that can effectively address these disparities and enhance digital literacy among all students. Understanding the factors contributing to gender differences in DC will be essential in designing tailored interventions that promote equal opportunities for all students to excel in the digital realm.

Future research can expand the sample size, explore more institutions, and use a broader range of machine-learning techniques to enhance predictive accuracy and generalizability.

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