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Artificial intelligence to predict university master's program recommendations

Inteligencia artificial para predecir la recomendación de un máster universitario

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ABSTRACT

The satisfaction of a student in a master's program can be influenced by factors such as program quality, learning opportunities, guidance and support received, infrastructure and resources available, outcomes, and employability. In this study, impressions of students from the Master's in Financial Counseling and Planning at Universidad Rey Juan Carlos were collected through a survey. These responses were used to train various artificial intelligence models with the aim of predicting whether the master's program would be recommended. The result of retrospective validation shows an accuracy of over 80% in all cases, leading us to conclude that artificial intelligence is a valid tool for this objective. This investigation contributes to understanding the efficacy of AI in predicting student recommendations for master's programs. It highlights the potential of AI models to inform program enhancements and optimize student experiences, while also emphasizing the need for robust research methodologies and considerations of student satisfaction factors

Keywords. university master's program, student satisfaction, artificial intelligence, ai, machine learning, supervised learning

RESUMEN

La satisfacción de un alumno en un máster puede estar influenciada por factores como la calidad del programa, las oportunidades de aprendizaje, la orientación y apoyo recibido, la infraestructura y recursos disponibles, los resultados y la empleabilidad. En este estudio se han recopilado, a través de una encuesta, las impresiones de alumnos del Máster en Asesoramiento y Planificación Financiera de la Universidad Rey Juan Carlos. Esas respuestas se han utilizado para entrenar diversos modelos de inteligencia artificial con el objetivo de predecir si se recomendara el máster o no. El resultado de la validación retrospectiva ofrece una precisión superior al80% en todos los casos por lo que debemos concluir que la inteligencia artificial es una herramienta válida para este objetivo. Esta investigación contribuye a comprender la eficacia de la inteligencia artificial en predecir recomendaciones de estudiantes para programas de maestría. Destaca el potencial de los modelos de inteligencia artificial para informar mejoras en los programas y optimizar las experiencias estudiantiles, al mismo tiempo que enfatiza la necesidad de metodologías de investigación sólidas y consideraciones de factores de satisfacción estudiantil.

Palabras clave. master universitario, satisfacción del alumno, inteligencia artificial, ia, machine learning, aprendizaje supervisado

INTRODUCTION

Student satisfaction in a master's program can be influenced by a variety of factors (Delgado-Alemany, et al., 2020; Nápoles-Nápoles, et al. 2016). While priorities and preferences may vary from one student to another, there are common factors that tend to be significant for student satisfaction in a master's program. Factors such as program quality, learning opportunities, guidance and support, interaction and collaboration, infrastructure and resources, flexibility and balance, as well as outcomes and employability, collectively contribute to student satisfaction in university master's programs. Understanding and addressing these factors are essential for institutions aiming to deliver high-quality education and enhance student experiences.

The quality of a master's program is a critical determinant of student satisfaction. It encompasses several key aspects, including the academic institution's reputation and accreditation, the caliber and experience of faculty members, the curriculum design, and the relevance of courses offered. Students seek programs that provide them with a solid education and adequately prepare them for their professional goals.

Learning opportunities play a pivotal role in student satisfaction within a master's program. Students seek programs that offer meaningful learning experiences, which may include practical projects, internships, teamwork opportunities, interaction with industry professionals, and access to up-to-date research resources or laboratories. The richness of these learning opportunities directly correlates with student satisfaction levels.

Guidance and support from the academic institution are fundamental for student satisfaction and motivation (Villena-Martínez, et al. 2023). Academic advising, tutoring services, student support programs, career guidance, and assistance in job searching are valued resources that contribute to students feeling supported and empowered in their educational and professional endeavors. Having these resources available enhances the overall satisfaction of students.

Interactions and collaborations with peers and faculty members significantly impact student satisfaction. Engaging in discussions, collaborative projects, and extracurricular activities fosters a sense of community and enriches the educational experience. Master's programs that actively promote interaction and collaboration among students tend to be more satisfying overall.

The availability of resources such as well-equipped libraries, updated laboratories, modern technology, and access to academic databases also influences student satisfaction. A robust infrastructure and adequate resources facilitate learning and enhance the overall master's experience for students.

Flexibility in class schedules, elective course options, and the ability to balance the master's program with personal or professional responsibilities are important considerations for student satisfaction. Programs that offer flexible options enable students to find a balance between their various obligations, leading to increased satisfaction levels.

Furthermore, the outcomes of the master's program and the employability of graduates are significant factors influencing student satisfaction. Students seek programs with a proven track record of successful graduate employment and that equip them with relevant skills and knowledge for the job market. Programs that demonstrate strong outcomes and high employability rates contribute positively to student satisfaction (Pérez Padilla, 2015).

It is important to note that these factors may vary according to the individual needs and expectations of each student (González Zamora & Sanchís Pedregosa, 2014). What may be important to one student may not be as crucial to another. Therefore, it is advisable for students to research and carefully evaluate the master's programs they are considering ensuring they align with their goals and personal preferences (Díez de Castro, 2020; Cruz-Suárez et al., 2022).

The aim of this research is to utilize artificial intelligence to generate a model capable of predicting whether a student will recommend a master's program or not. This research offers significant scientific contributions. Initially, it extends the utilization of artificial intelligence techniques into educational domains, fostering progress in predictive modeling methodologies. Subsequently, it enriches comprehension regarding the determinants shaping student contentment program endorsement and loyalty (Cachón-Rodríguez & Prado-Román, 2020), thereby guiding program enhancement and evaluation strategies. Additionally, the framework bears practical implications for academic institutions by facilitating tailored interventions and resource distribution to elevate student satisfaction and retention rates. Furthermore, this inquiry contributes to broader conversations surrounding educational quality assessment and predictive analytics within higher education, stimulating further inquiry and innovation. In essence, the establishment of such a framework represents a significant stride towards refining educational outcomes and fostering student achievement within master's programs.

HYPOTHESIS AND METHODOLOGY

In this study, we will analyze whether artificial intelligence (AI) is capable of predicting whether a student will recommend a master's program. AI can be an advantageous choice when it comes to analyzing complex data, identifying subtle patterns, and making more precise predictions about student satisfaction in a university master's program (Gómez-Martínez, Medrano-García, & Aznar-Sánchez, 2023).

Utilizing artificial intelligence (AI) for prognosticating the contentment quotient of a university master's curriculum confers manifold benefits vis-à-vis traditional statistical methodologies. AI demonstrates prowess in managing intricate and non-linear datasets, a salient feature particularly advantageous when scrutinizing the contentment index of master's programs replete with myriad interrelated variables that defy adherence to linear statistical paradigms. Furthermore, AI's acumen in discerning nuanced patterns and correlations, which may elude orthodox statistical techniques, enriches our comprehension of the intricate factors underpinning student contentment.

Moreover, AI architectures, exemplified by machine learning algorithms, exhibit adaptative learning prowess, facilitating continual refinement of accuracy with heightened exposure to data germane to the master's program milieu. This adaptability, conjoined with AI's versatile and scalable nature, catering to diverse datasets and extensive sample sizes, engenders more refined prognoses pertaining to student contentment. These prognostic revelations serve as pivotal tools in delineating domains within the master's program necessitating amelioration or adjustments to optimize holistic student experiences and program efficacy.

The hypothesis to be validated is:

H0: Artificial intelligence is a valid tool for predicting the recommendations that a student will make regarding a university master's program.

Considering that the student may recommend the master's program (the target variable of the model is dichotomous, yes/no), we will validate H0 if the trained artificial intelligence model has an accuracy greater than 50% (El Naqa & Murphy, 2015).

Data analysis and variables

The data to create the training dataset were collected through a survey requested from students and graduates of the master program in financial counseling and planning of Rey Juan Carlos university. This master is typically designed to provide students with the knowledge and skills necessary to work in the field of personalized financial planning and management. These programs are often geared towards professionals seeking to advance their careers in financial advising, personal banking, wealth management, insurance, or related areas.

The questionnaire collected the following information:

- Timestamp
- Age
- Gender
- Origin
- City of origin
- Professional situation before starting the master's program
- Have you completed the master's program?
- In what year did you enroll in the master's program?
- In what modality did you enroll?
- The master's program is well organized
- The number of students in the group has been adequate
- The contents of the master's program have met my training needs
- I observe an adequate combination of theory and practice
- The duration of the course is adequate
- The course schedule is appropriate
- The way the master's program is taught has facilitated learning
- The teachers are knowledgeable about the topics taught in depth
- The teachers have pedagogical capacity
- The teachers encourage the exchange of opinions
- The study material is understandable and adequate
- Didactic means are up-to-date
- The classroom has been appropriate for teaching and/or technical means (virtual classroom) have been adequate
- Evaluation tests allow to know the level reached
- The course allows me to obtain an accreditation that recognizes my qualification
- The master's program will help me progress professionally
- The master's program has favored my personal development
- Overall satisfaction level

And the target variable of the study:

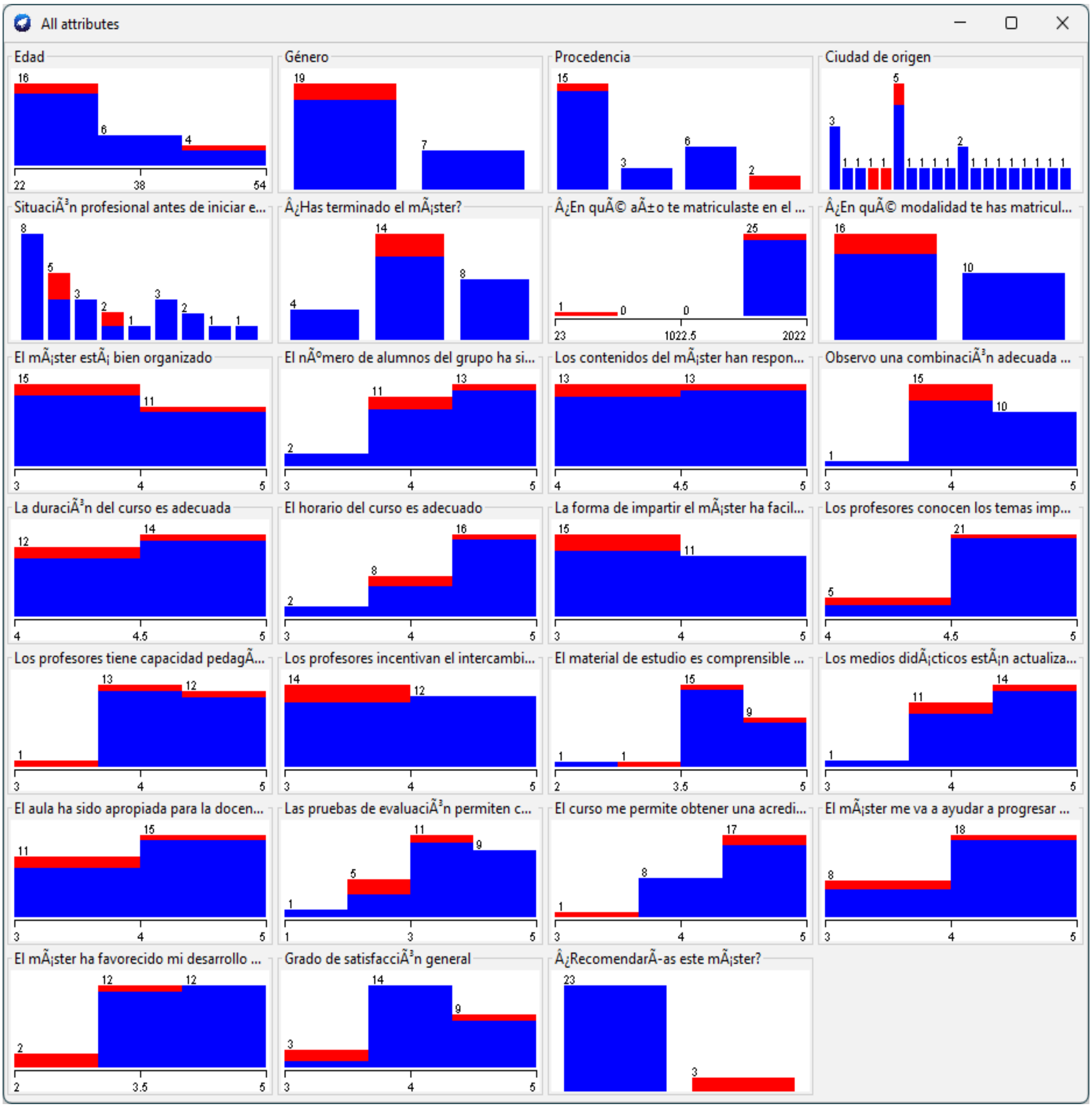
- Would you recommend this master's program?

Through Weka, various models will be trained using diverse algorithms and retrospectively validated using 10-fold cross-validation (Zhou, 2021). Weka, an open-source software, encompasses a plethora of machine learning algorithms tailored for data mining tasks. It comprises tools for data preparation, classification, regression, clustering, association rule mining, and data visualization.

RESULTS

A total of 26 valid surveys have been compiled, and their attributes are presented in Figure 1.

Figure 1. Statistics of Compiled Surveys



The histograms depicted in Figure 1 align with the characteristics of a university master's program where the students or respondents are predominantly young, with most having completed or are in the process of completing the master's program. There is also diversity in both the origin and the professional situation prior to the studies.

Regarding the predictors of the AI model concerning the perception of students about the master's program, it is notable that the respondents generally rate the program highly, with almost all questions receiving a rating of 4 or 5 out of 5. They are satisfied with the organization of the course (both in terms of duration and schedule), as well as with the capabilities of the instructors and the materials used. Furthermore, there is a general optimism among the respondents about prosperous career prospects due to this education. All these factors culminate in a majority of recommendations. Now, we will see if the AI model has the capacity to identify this optimism or pessimism.

The trained model and the cross-validation according to the J48 decision tree algorithm are outlined in Table 1.

Table 1. J48 Algorithm Output

```
=== Run information ===

Scheme:       weka.classifiers.trees.J48 -C 0.25 -M 2
Relation:     Encuesta Valoración Master en Asesoramiento y Planificación Financiera (MAPF)
(respuestas) - Respuestas de formulario 1
Instances:    26
Attributes:   27
Test mode:    10-fold cross-validation

=== Classifier model (full training set) ===

J48 pruned tree
------------------

El mÃ¡ster ha favorecido mi desarrollo personal <= 3: No (2.0)
El mÃ¡ster ha favorecido mi desarrollo personal > 3: Si (24.0/1.0)

Number of Leaves  :   2

Size of the tree :    3


Time taken to build model: 0.01 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances          22               84.6154 %
Incorrectly Classified Instances         4               15.3846 %
Kappa statistic                         -0.0612
Mean absolute error                      0.1892
Root mean squared error                  0.3789
Relative absolute error                 81.5568 %
Root relative squared error            114.8524 %
Total Number of Instances               26

=== Detailed Accuracy By Class ===

TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
0,957    1,000    0,880      0,957    0,917      -0,072   0,594     0,895     Si
0,000    0,043    0,000      0,000    0,000      -0,072   0,594     0,229     No
Weighted Avg.    0,846    0,890    0,778      0,846    0,811      -0,072   0,594     0,818

=== Confusion Matrix ===

  a  b   <-- classified as
 22  1 |  a = Si
  3  0 |  b = No
```

The trained model and the cross-validation according to the Bayesian Network algorithm are presented in Table 2.

Table 2. Bayesian Algorithm Output

```
=== Run information ===

Scheme:                                    weka.classifiers.bayes.BayesNet     -D     -Q
weka.classifiers.bayes.net.search.local.K2     --     -P     1     -S     BAYES     -E
weka.classifiers.bayes.net.estimate.SimpleEstimator -- -A 0.5
Relation:    Encuesta Valoración Master en Asesoramiento y Planificación Financiera (MAPF)
(respuestas) - Respuestas de formulario 1
Instances:    26
Attributes:   27
Test mode:    10-fold cross-validation

=== Classifier model (full training set) ===

Bayes Network Classifier
not using ADTree
#attributes=27 #classindex=26
Network structure (nodes followed by parents)
Edad(1): Â¿RecomendarÃas este mÃ¡ster?
Género(2): Â¿RecomendarÃas este mÃ¡ster?
Procedencia(4): Â¿RecomendarÃas este mÃ¡ster?
Ciudad de origen(19): Â¿RecomendarÃas este mÃ¡ster?
SituaciÃ³n profesional antes de iniciar el mÃ¡ster(9): Â¿RecomendarÃas este mÃ¡ster?
Â¿Has terminado el mÃ¡ster?(3): Â¿RecomendarÃas este mÃ¡ster?
Â¿En quÃ© aÃ±o te matriculaste en el mÃ¡ster?(1): Â¿RecomendarÃas este mÃ¡ster?
Â¿En quÃ© modalidad te has matriculado?(2): Â¿RecomendarÃas este mÃ¡ster?
El mÃ¡ster estÃ¡ bien organizado(1): Â¿RecomendarÃas este mÃ¡ster?
El nÃºmero de alumnos del grupo ha sido adecuado(1): Â¿RecomendarÃas este mÃ¡ster?
Los contenidos del mÃ¡ster han respondido a mis necesidades formativas(1): Â¿RecomendarÃas
este mÃ¡ster?
Observo una combinaciÃ³n adecuada de teorÃa y prÃ¡ctica(1): Â¿RecomendarÃas este mÃ¡ster?
La duraciÃ³n del curso es adecuada(1): Â¿RecomendarÃas este mÃ¡ster?
El horario del curso es adecuado(1): Â¿RecomendarÃas este mÃ¡ster?
La forma de impartir el mÃ¡ster ha facilitado el aprendizaje(1): Â¿RecomendarÃas este
mÃ¡ster?
Los profesores conocen los temas impartidos en profundidad(1): Â¿RecomendarÃas este
mÃ¡ster?
Los profesores tiene capacidad pedagÃ³gica(1): Â¿RecomendarÃas este mÃ¡ster?
Los profesores incentivan el intercambio de opiniones(1): Â¿RecomendarÃas este mÃ¡ster?
El material de estudio es comprensible y adecuado(1): Â¿RecomendarÃas este mÃ¡ster?
Los medios didÃ¡cticos estÃ¡n actualizados(1): Â¿RecomendarÃas este mÃ¡ster?
El aula ha sido apropiada para la docencia y/o  los medios tÃ©cnicos (aula virtual) han
sido adecuados(1): Â¿RecomendarÃas este mÃ¡ster?
Las pruebas de evaluaciÃ³n permiten conocer el nivel alcanzado(1): Â¿RecomendarÃas este
mÃ¡ster?
El curso me permite obtener una acreditaciÃ³n que reconoce mi cualificaciÃ³n(1):
Â¿RecomendarÃas este mÃ¡ster?
El mÃ¡ster me va a ayudar a progresar profesionalmente(1): Â¿RecomendarÃas este mÃ¡ster?
El mÃ¡ster ha favorecido mi desarrollo personal(2): Â¿RecomendarÃas este mÃ¡ster?
Grado de satisfacciÃ³n general(1): Â¿RecomendarÃas este mÃ¡ster?
Â¿RecomendarÃas este mÃ¡ster?(2):
LogScore Bayes: -253.9683983276591
LogScore BDeu: -458.14436311897856
LogScore MDL: -418.8719030723382
LogScore ENTROPY: -306.4675725105971
LogScore AIC: -375.4675725105971


Time taken to build model: 0 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances          23               88.4615 %
Incorrectly Classified Instances         3               11.5385 %
Kappa statistic                          0.5063
Mean absolute error                      0.1523
Root mean squared error                  0.2786
Relative absolute error                 65.664  %
Root relative squared error             84.4513 %
```

```
Total Number of Instances               26

=== Detailed Accuracy By Class ===

TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
0,913    0,333    0,955      0,913    0,933      0,513    0,841     0,974     Si
0,667    0,087    0,500      0,667    0,571      0,513    0,841     0,738     No
Weighted Avg.    0,885    0,305    0,902      0,885    0,892      0,513    0,841     0,947

=== Confusion Matrix ===

  a  b   <-- classified as
 21  2 |  a = Si
  1  2 |  b = No
```

The trained model and the cross-validation according to the Random Forest algorithm are shown in Table 3.

Table 3. Random Forest Algorithm Output

```
=== Run information ===

Scheme:       weka.classifiers.trees.RandomForest -P 100 -I 100 -num-slots 1 -K 0 -M 1.0
-V 0.001 -S 1
Relation:     Encuesta Valoración Master en Asesoramiento y Planificación Financiera (MAPF)
(respuestas) - Respuestas de formulario 1
Instances:    26
Attributes:   27
Test mode:    10-fold cross-validation

=== Classifier model (full training set) ===

RandomForest

Bagging with 100 iterations and base learner

weka.classifiers.trees.RandomTree -K 0 -M 1.0 -V 0.001 -S 1 -do-not-check-capabilities

Time taken to build model: 0.03 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances          23               88.4615 %
Incorrectly Classified Instances         3               11.5385 %
Kappa statistic                          0
Mean absolute error                      0.1626
Root mean squared error                  0.2897
Relative absolute error                 70.0927 %
Root relative squared error             87.8306 %
Total Number of Instances               26

=== Detailed Accuracy By Class ===

TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
1,000    1,000    0,885      1,000    0,939      ?        0,870     0,983     Si
0,000    0,000    ?          0,000    ?          ?        0,870     0,569     No
Weighted Avg.    0,885    0,885    ?          0,885    ?          ?        0,870     0,935

=== Confusion Matrix ===

  a  b   <-- classified as
 23  0 |  a = Si
  3  0 |  b = No
```

We observe that the accuracy achieved in the retrospective validation of the model is as follows:
- J48: 84.6%
- Bayes: 88.4%
- Random Forest: 88.4%

Furthermore, we note in the "Detailed Accuracy by Class" statistics that all values approximate 1, indicating high precision and reliability in the trained models. It is noteworthy that when using a target variable with heterogeneous values, where the majority of observations are "yes" and only three observations are "no," a model that always predicts "yes" would have a very high accuracy rate. This is evident with the Random Forest algorithm, but not with decision trees (J48) and Bayesian networks, demonstrating that the predictors are sensitive to "no" responses and dissatisfaction with the master's program. Therefore, since the accuracy in all cases is above 50%, the null hypothesis H0 of this study is validated.

DISCUSSION

This study investigates the use of artificial intelligence (AI) models to predict student recommendations for a university master's program. The research collected data through surveys from 26 participants and employed various AI algorithms, including J48 decision trees, Bayesian networks, and Random Forest, to analyze the dataset. The study aims to validate the hypothesis that AI models can accurately forecast student recommendations for the master's program.

The findings of this study suggest that utilizing artificial intelligence (AI) models to predict student recommendations for a university master's program can yield promising results. The high accuracy rates achieved by algorithms such as J48, Bayes, and Random Forest demonstrate the efficacy of AI in discerning patterns and making predictions based on diverse datasets. However, the models exhibit sensitivity to student dissatisfaction, displaying variations in predictive capability depending on the algorithm utilized. Despite fluctuating model accuracies, the findings generally support the hypothesis that AI can forecast master's program recommendations.

The study underscores the importance of addressing student concerns and enhancing program satisfaction. Limitations include the modest sample size, potential respondent bias, and the retrospective nature of the validation process. The primary limitation is the relatively small number of received surveys, totaling only 26 observations. Secondly, among the 26 respondents, only 3 did not recommend the master's program. While indicative of the program's quality, this statistically skews the supervised machine learning model's target variable. Therefore, increasing the number of observations and diversifying the dataset will instill greater confidence in the conclusions drawn from this study. Additionally, the survey data may be subject to respondent bias, as individuals who have strong opinions, either positive or negative, may be more inclined to participate. This could influence the accuracy of the predictive models. Moreover, while AI algorithms demonstrate high accuracy rates, they may not capture the nuanced factors contributing to student satisfaction. Qualitative methods such as interviews or focus groups could provide deeper insights into student experiences and perceptions. Furthermore, the study's reliance on retrospective validation may not fully capture real-time fluctuations in student sentiments and preferences.

This investigation contributes to understanding the efficacy of AI in predicting student recommendations for master's programs. It highlights the potential of AI models to inform program enhancements and optimize student experiences, while also emphasizing the need for robust research methodologies and considerations of student satisfaction factors. While AI demonstrates promise in predicting student recommendations, further research with larger, more diverse samples and complementary qualitative methods is warranted. Furthermore, the ability of AI models to accurately predict student recommendations highlights their potential utility in optimizing educational experiences and identifying areas for improvement within master's programs.

Thus, the study highlights several future research directions aimed at enhancing the understanding of student satisfaction in master's programs and improving prediction accuracy.

Increasing the sample size and diversity of master's students surveyed will provide a more comprehensive and representative view of student satisfaction. This expansion can capture a broader range of perspectives and experiences, leading to more robust conclusions regarding program satisfaction.

Exploring and integrating other pertinent variables beyond those considered in the current study, such as the social environment, quality of administrative support, and external events' impact, will offer a more nuanced understanding of the factors influencing student satisfaction. Incorporating these variables into future analyses can enrich predictive models and inform targeted interventions to enhance student experiences. Moreover, examining how student satisfaction (Olmedo-Cifuentes & Martínez-León, 2022; Gómez López, et al., 2022) evolves over time is crucial for understanding the dynamic nature of student experiences in master's programs. Long-term follow-up studies with students and graduates can provide insights into the trajectory of satisfaction levels and identify critical periods where interventions may be needed to address potential concerns or enhance program satisfaction.

Conducting comparative analyses across different master's programs allows for the identification of factors contributing to varying levels of student satisfaction. By examining differences in educational approaches, curriculum structures, and program delivery methods, researchers can uncover best practices and areas for improvement to optimize student satisfaction across programs.

The AI model for assessing student predictions may need adjustments based on the legitimacy of the master's program. Factors such as reputation, perceived quality, and program accreditation may necessitate fine-tuning the model to accurately reflect student recommendations (Barba Rey, et al., 2023; Miotto et al., 2023). Exploring alternative machine learning algorithms or AI techniques can enhance prediction accuracy and deepen the understanding of student satisfaction patterns. By diversifying the analytical approaches used, researchers can identify the most effective models for predicting student recommendations and tailor interventions to address specific areas of concern identified through predictive analyses.

Social media has the potential to exert a significant influence on students' perceptions and recommendations regarding master's programs, potentially impacting the predictions of AI models trained using such data. Understanding the intricacies of social media influence (Vila-Boix, et al. 2023) is critical for the development of precise and dependable AI models aimed at predicting student recommendations within the realm of master's programs.

Gender may indeed exert an influence on the predictions made by the artificial intelligence (AI) model regarding master's program recommendations from students. Students of different genders may hold distinct perceptions and preferences regarding various aspects of the master's program (Díez-Martín, et al. 2023; Gordo-Molina & Diez-Martin, 2021). Thus, gender may emerge as a pertinent factor impacting the predictions of the AI model regarding master's program recommendations by students. Understanding the ways in which these gender disparities affect student responses and the accuracy of the AI model is imperative for devising effective strategies for enhancing and customizing master's programs.

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CRediT AUTHOR STATEMENT

All authors have contributed equally to all parts of the work.