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Article

Applying neural networks in student satisfaction analysis: Implications for university management

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Abstract: This study analyzes student satisfaction at a university using a structured survey and advanced artificial intelligence techniques, specifically neural networks. The main objective is to identify the key factors in students' perception of educational quality. The methodology involved a survey with 38 items on a Likert scale of 1 to 7, applied to a diverse sample of undergraduate, postgraduate, and exchange students during the years 2022 and 2023. The final sample consisted of 9623 valid records. Artificial intelligence techniques were employed to analyze the data, with neural networks trained under the supervised learning paradigm to predict levels of student satisfaction. The results show a high correlation between satisfaction with the cashier service and overall student satisfaction, highlighting the importance of administrative services. Additionally, a close relationship was identified between the institutional mission and the educational process, suggesting that a clear and accessible mission improves student perception. The effectiveness of neural networks was demonstrated, achieving high precision and sensitivity in their predictions. In conclusion, this study provides valuable insights into the factors influencing student satisfaction and demonstrates the potential of artificial intelligence techniques to improve educational management. The findings offer a solid foundation for future research and practical improvements in higher education.

Keywords: student satisfaction; artificial intelligence; neural networks; educational management; educational quality

1. Introduction

This research examines the application of neural networks, a subset of artificial intelligence (AI), to analyze student satisfaction surveys, offering valuable insights for optimizing educational management. Neural networks, specialized algorithms for detecting complex data patterns, are particularly effective in studies that involve multiple variables and dimensions, such as those assessing student satisfaction across services, academic quality, and alignment with institutional goals (LeCun et al., 2015; Rumelhart et al., 1986). These networks facilitate both the analysis of past data and the prediction of future satisfaction levels, establishing a strong foundation for strategic decision-making. Employing a supervised learning approach, the neural network model processes large datasets, adapting its parameters to represent student perceptions accurately. This enables institutions to pinpoint priority areas for improvement (Goodfellow et al., 2016; Mitchell, 1997).

Using AI to analyze satisfaction surveys equips university management with a robust tool for customizing services and enhancing responsiveness to student needs. Neural networks' predictive capabilities strengthen the implementation of data-driven management adjustments, directly supporting student retention and fostering loyalty to the institution. Higher education has recently experienced transformative shifts, driven by innovations such as AI and blended learning. These advancements enable institutions to adapt teaching methods to offer more personalized, accessible learning experiences, thus enhancing student satisfaction and performance (Noroozi et al., 2024). García-Peñalvo (2023) found generative AI models, including ChatGPT, effective for providing instant feedback and customizing content according to each student's progress, fostering an inclusive and personalized educational experience. While these technologies can enhance academic assessment and support educators, they also highlight the importance of ethical oversight to address potential biases and privacy issues (González-Calatayud et al., 2021; Farrokhnia et al., 2023). This integration of AI into higher education marks a shift toward flexible, collaborative, and ethically responsible pedagogical practices, redefining education in today's rapidly evolving digital landscape (Jones and Wynn, 2023).

Since its origins in the late 19th century, management has been understood as a dynamic process encompassing the planning, organization, direction, and control of organizational activities. This approach has endured through decades, underscoring the value of efficient resource allocation to achieve defined objectives (Stoner et al., 1996). In educational contexts—especially within higher education—this concept has expanded to include the management of physical and financial resources, academic governance, and the pursuit of educational quality.

In higher education, strategic planning involves setting well-defined goals and developing both reactive and proactive strategies to navigate current educational and societal challenges. The organizational structure within institutions supports these strategies through a hierarchical framework that enables the efficient allocation of academic and administrative resources, fostering a collaborative and productive educational environment (Evans and Lindsay, 2008).

Effective management within universities and educational centers encompasses administrative leadership, academic guidance, and the cultivation of an environment that promotes innovation and continuous learning. Equally essential is the role of control, ensuring that the institution remains aligned with its academic mission and adapts to the evolving needs of its student community and the broader socioeconomic landscape.

In today's globalized and competitive environment, higher education institutions face the challenge of imparting knowledge while fostering critical skills to prepare students as capable, global citizens. This has rendered quality management integral, assuring that the education and services provided meet or exceed the expectations of students and all stakeholders involved (UNESCO, 2005).

Academic and support services are pivotal in supporting student success and reinforcing the value of educational programs. Student support services emphasize the quality and modernization of offerings, while academic areas focus on curriculum innovation and the adoption of best practices in pedagogy. Collaboration across these areas is essential to deliver a comprehensive educational experience that addresses academic needs, labor market requirements, and societal expectations (Suleman, 2017).

Looking to the future, institutions must continue evolving to meet the demands of an increasingly dynamic global landscape. Higher education must anticipate changes in educational and employment trends and adapt strategies that effectively prepare future generations. This evolution calls for maintaining rigorous academic and administrative standards, fostering a culture of innovation and social responsibility, and equipping students to contribute positively to society.

Thus, effective administration in higher education transcends traditional management principles, requiring an in-depth understanding of contemporary educational and societal needs. By integrating quality management with innovative pedagogy and a commitment to excellence, institutions ensure sustainable success. Quality education management demands comprehensive strategies to uphold educational standards and meet student satisfaction, where the planning, organization, and oversight of academic and administrative activities are central to fulfilling institutional objectives.

Educational quality is defined by an institution's capacity to deliver an education that aligns with the expectations of students and stakeholders. As noted by UNESCO, quality in higher education encompasses academic excellence, relevance, and the suitability of academic programs to the labor market and societal needs (UNESCO, 2005).

Research underscores the importance of factors such as administrative service quality and institutional mission in influencing student satisfaction. Specifically, the perceived quality of administrative services, including cashiering and other student support services, significantly impacts overall satisfaction. Furthermore, a well-defined and accessible institutional mission enhances students' perceptions of educational quality (Cheng and Tam, 1997; Kotler and Fox, 1995).

Over the past decade, higher education has transformed significantly, spurred by the rise of emerging technologies, particularly artificial intelligence (AI) and blended learning models. These advancements have enabled institutions to adopt more personalized and adaptive approaches, better aligning with the evolving needs of students and enhancing the overall learning experience. Banihashem et al. (2023) describe blended learning as an optimal post-pandemic educational format, blending online and face-to-face instruction to create a flexible environment that mitigates structural limitations while promoting social interaction among students and instructors. This model has been shown to increase student satisfaction and boost academic performance by accommodating diverse learning styles (Banihashem et al., 2023).

AI has similarly reshaped higher education by enabling large-scale data analysis and personalized content delivery. Alammary et al. (2014) explain that AI allows educators to implement systems that adapt educational content according to students' performance and needs. This customization not only facilitates students' self-paced progress but also provides educators with valuable insights into learning patterns and areas requiring support. Research by van der Spoel et al. (2020) underscores that the successful adoption of technology in education is bolstered by an AI infrastructure that simplifies the implementation of digital tools, such as automated feedback and personalized assignments.

Blended learning further addresses the growing demand for flexibility in higher education, allowing students to alternate between online and in-person learning across varied settings and times. Sharma and Shree (2023) argue that blended learning improves academic performance and engagement by offering multiple interaction formats. Supporting this, Tahir et al. (2022) highlight that blended environments facilitate the practical application of knowledge, enhancing both retention and real-world applicability.

Beyond improving the student experience, these technological advancements offer critical tools for managing and planning instruction. Abdel-Rahim (2021) shows that satisfaction with digital tools has a direct impact on teachers' perceived effectiveness in blended learning environments. In studies on digital tool efficacy within higher education, both students and instructors expressed appreciation for the flexibility and accessibility that blended learning offers, thus enhancing the overall educational experience (Abdel-Rahim, 2021)

The integration of artificial intelligence (AI) techniques, particularly neural networks, has profoundly transformed educational management by enabling the analysis of vast data volumes and uncovering complex patterns critical for strategic decision-making (Mitchell, 1997). Neural networks are especially proficient at predicting student satisfaction levels, offering educational institutions a robust tool for enhancing management practices through predictive analytics (Rumelhart et al., 1986).

The integration of artificial intelligence (AI) into higher education is swiftly reshaping teaching and learning, facilitating personalized educational approaches and enhancing academic efficiency. Noroozi et al. (2024) note that generative AI, including platforms like ChatGPT, can customize educational content to individual student needs and has been effectively deployed to provide tailored feedback across diverse academic disciplines. Such technologies allow educators to design flexible and interactive learning environments that bolster student engagement and improve academic outcomes (Noroozi et al., 2024).

AI also facilitates collaborative and computational learning activities that promote critical thinking and problem-solving skills for both students and instructors. García-Peñalvo (2023) explains that generative AI models can adapt course materials to students' progress and modify content difficulty based on individual performance, making learning more accessible and personalized across a diverse student body.

Furthermore, AI has demonstrated its effectiveness in academic assessment, with tools like ChatGPT providing automated feedback on assignments and evaluations, which supports objectivity and efficiency in grading processes (González-Calatayud et al., 2021). However, while automation enhances efficiency, human oversight remains crucial to mitigate potential risks concerning accuracy and ethics in automated assessments (Farrokhnia et al., 2023). This evidence suggests that AI can effectively complement, rather than replace, human judgment in education, working alongside instructor guidance.

Despite its numerous benefits, the ethical and privacy considerations of AI integration require careful attention. Issues such as bias in AI-generated content and the privacy of student data underscore the importance of implementing robust ethical frameworks and security protocols. Transparent AI practices and comprehensive training for educators are vital for ensuring responsible and ethical adoption within educational environments (Jones and Wynn, 2023).

2. Materials and methods

The current study aims to assess the satisfaction of university students through a structured survey. The survey, composed of 38 items on a Likert scale from 1 to 7, was applied to a diverse sample that included undergraduate, graduate, and exchange students between the years 2022 and 2023. The Likert scale is a common tool in educational research to measure attitudes or perceptions, where 1 indicates the lowest satisfaction, and 7 indicates the highest (Boone and Boone, 2016).

The initial database contained 10,051 observations corresponding to individual answers. After a data-cleaning process that excluded incomplete records, the sample was reduced to 9623 valid records, ensuring a reliable representation of student perceptions (Osborne, 2010).

Data collection was conducted in two consecutive phases during the specified years. Each participant was assured anonymity, and informed consent was obtained before answering the survey, following ethical guidelines for human research. Data preparation included cleaning and preprocessing, removing duplicates, correcting errors, and managing missing values. This stage ensured data quality before statistical analysis (Tabachnick and Fidell, 2013).

Afterward, the independent variables were normalized to fit the neural network model. Average satisfaction scores were evaluated for each evaluative dimension, adjusting the data to ensure that certain variables did not dominate the model (Goodfellow et al., 2016).

Artificial intelligence techniques, specifically neural networks, were applied to analyze the data. Neural networks allow for handling large volumes of data and learning complex patterns, which is fundamental in studies involving multiple variables and dimensions of analysis (LeCun et al., 2015).

The model was trained under the supervised learning paradigm, aiming to predict student satisfaction levels based on survey responses. Model performance was evaluated using standard cross-validation techniques, thus ensuring the generalizability of the results (James et al., 2013).

The effectiveness of the model was measured using standard metrics such as precision, accuracy, and sensitivity, which allow for the correct classification of satisfaction levels (Fawcett, 2006).

In summary, the main characteristics of the participants are presented in **Table 1**.

Table 1. Participant characteristics.

Variable	**Category**	***N***	**%**
Study Level	Undergraduate	6872	71.4
	Graduate	2148	22.3
	International Exchange	603	6.3
Faculty	Social Sciences	3142	32.6
	Engineering and Technology	2941	30.6
	Health Sciences	1854	19.3
	Arts and Humanities	1686	17.5

Table 1. (*Continued*).

Variable	Category	*N*	%
Gender	Male	4568	47.5
	Female	5055	52.5
Age	18–24 years	5872	61.0
	25–30 years	2484	25.8
	Over 30 years	1267	13.2

2.1. Statistical methodology

In this study, a feedforward neural network was employed to predict student satisfaction levels, trained using a supervised learning approach. The network architecture was optimized to ensure both accuracy and generalizability. The neural network consists of three layers: an input layer, two hidden layers, and an output layer. The input layer includes 38 nodes corresponding to the survey variables, while the hidden layers each have [number of neurons] neurons. This number was determined through a cross-validation process to balance accuracy and computational complexity (Goodfellow et al., 2016).

Each hidden layer uses a Rectified Linear Unit (ReLU) activation function due to its effectiveness in deep network convergence (Nair and Hinton, 2010). The initial learning rate was set to 0.001, allowing gradual model adaptation during training and preventing overfitting. This value was tuned using the Adam optimization algorithm, which adapts learning rates for each parameter automatically (Kingma and Ba, 2015).

To ensure reproducibility, all experiments were conducted under the same conditions, utilizing a fixed seed for random weight initialization. These parameters were chosen based on the literature on neural network models for perception surveys and have demonstrated robust performance in classification scenarios with multiple dimensions (Rumelhart et al., 1986).

AI and, in particular, neural networks have undergone several phases of development since their initial conception by Warren McCullough and Walter Pitts in 1944. These systems have evolved significantly, especially with the increase in the processing power of graphics chips, enabling a resurgence of the technique since the 1980s.

Machine learning in AI is based on improving task performance through experience. This is mainly categorized into:

- Supervised learning: the model learns from a labeled dataset to predict outcomes.
- Unsupervised learning: the model discovers patterns without predefined labels.
- Reinforced learning: an agent learns to make decisions based on maximizing a cumulative reward.

2.2. Artificial neural networks (ANNs)

ANNs are fundamental to machine learning and consist of nodes or neurons organized in layers that process input data and produce outputs. **Figure 1** illustrates a basic neural network where data moves in one direction from input to output, showing how data is processed through the network.

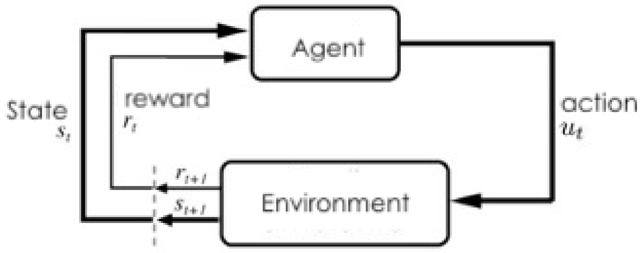

Figure 1. Basic neutral network.

Figure 2 shows the basic structure of a neural network, including input, hidden, and output layers. It highlights how each neuron receives and processes external stimuli, which is central to information processing.

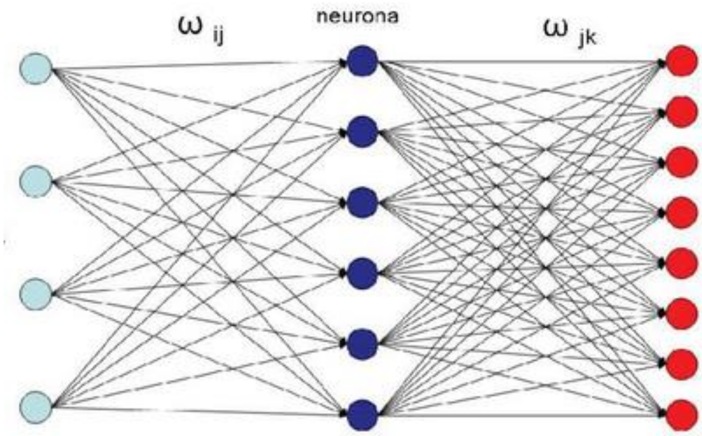

Figure 2. Basic structure of a neural network.

Transfer functions can be linear or nonlinear and are essential for determining the output of a neuron based on the input received. **Figures 3** and **4** show transfer functions and how the output of a neuron is calculated based on them, with examples of tight-limit and log-sigmoid transfer functions.

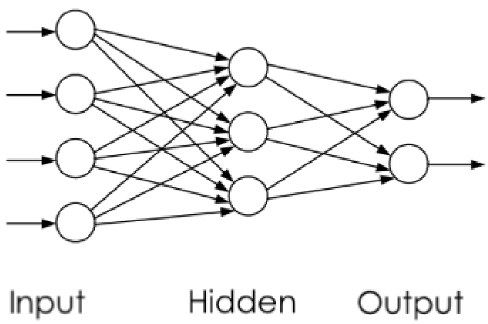

Figure 3. Structure of the transfer functions.

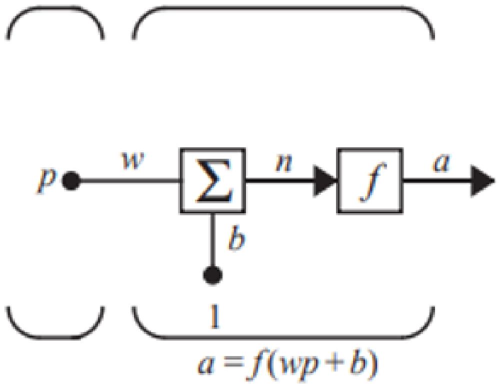

Figure 4. Structure of the transfer functions.

The evaluation of ANN models is performed using metrics, including precision, accuracy, and sensitivity, which are crucial to determining the network's effectiveness on specific tasks. **Figures 5** and **6** show multi-layered neural network architectures and how these complex structures process information from input to output.

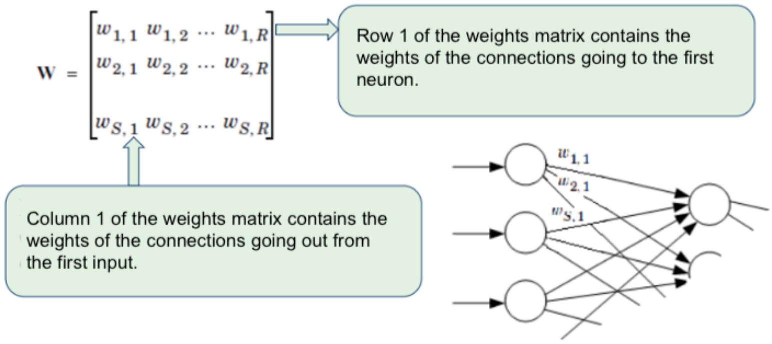

Figure 5. Multi-layered neural network architecture.

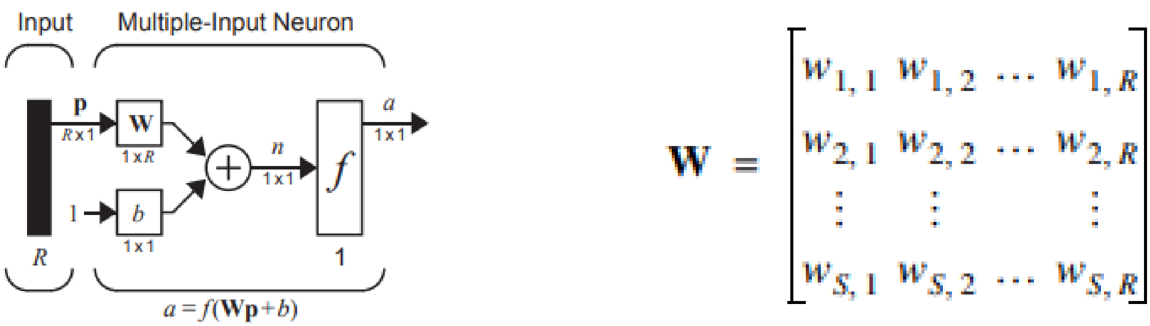

Figure 6. Multi-layered neural network architecture.

DFNs (Deep Feedforward Network) (**Figures 6** and **7**) are a type of deep network characterized by their direct feedforward structure, allowing layer-by-layer processing without cycles.

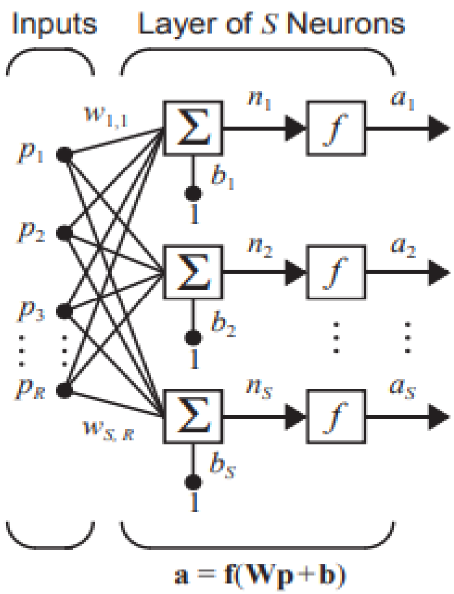

Figure 7. Architecture of a Deep Feedforward Network.

Finally, **Figure 8** describes the architecture of a DFN. It highlights how information flows from input to output through multiple hidden layers, allowing the network to learn the complex characteristics of the data.

The neural network model describing the investigative process can be represented as shown in the **Figure 9**.

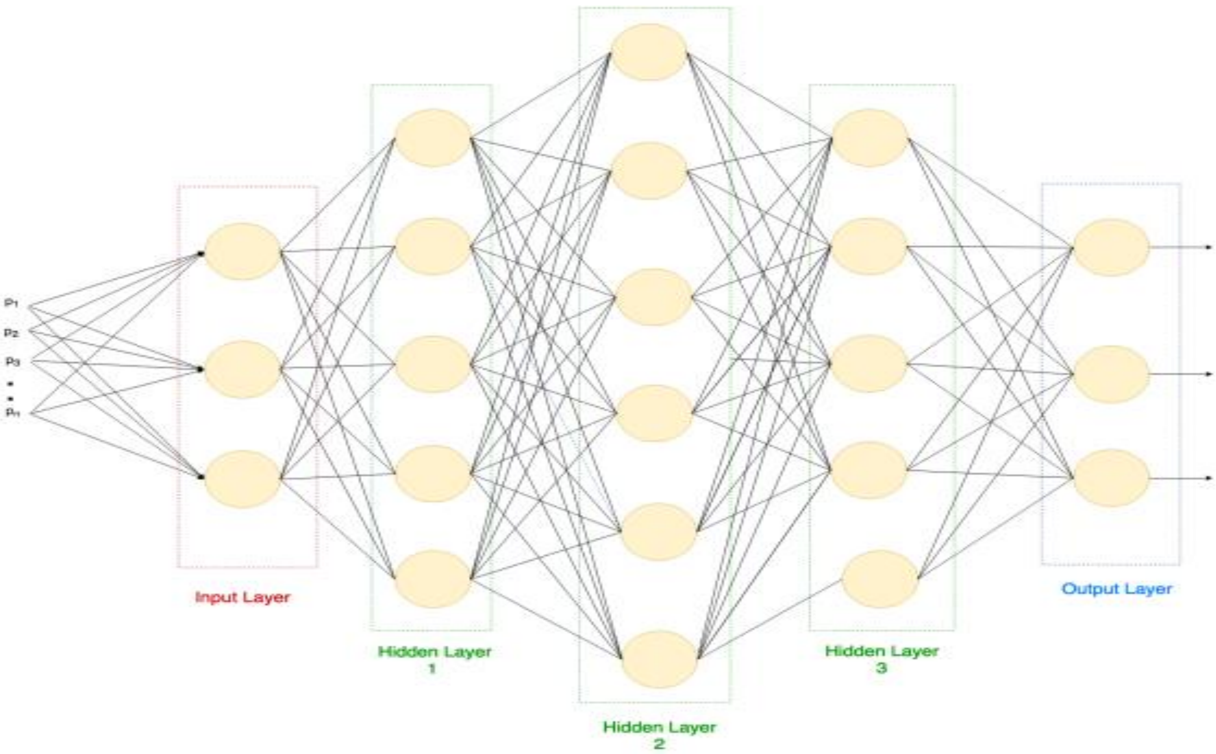

Figure 8. Heatmap of correlations between survey items: Represents the correlations among survey questions, helping to visualize the relationships across different satisfaction dimensions.

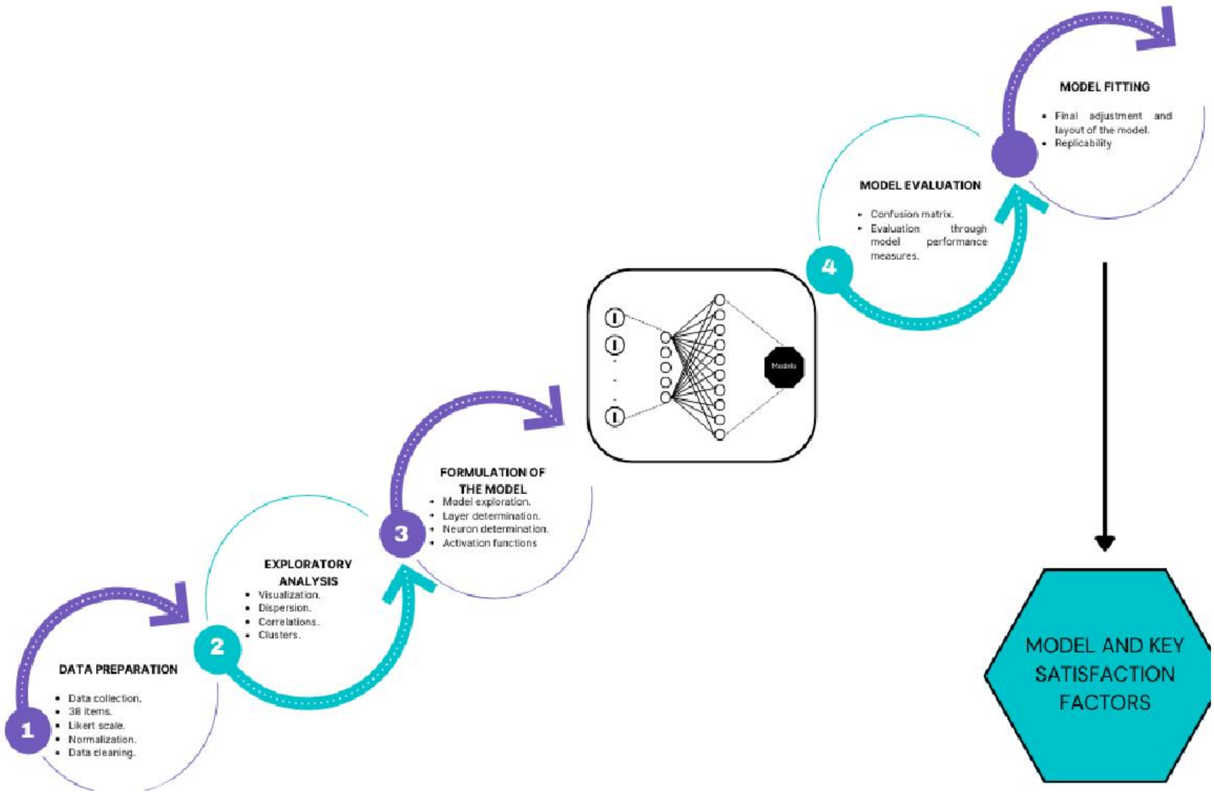

Figure 9. The neural network model.

3. Results and discussion

The methodology used to analyze student satisfaction within the university yielded significant insights into the factors that influence student satisfaction, loyalty, and renewal. The visualizations displayed in the following figures show the most significant interactions and patterns in the data.

Figure 8 is a heat map that displays the correlations between all the survey questions, using a range of colors to indicate the strength of the correlation. Question 38 stands out for its high correlation with all other questions and reflects a significant influence of satisfaction with the cashier service on the overall perception of university services. This result suggests that the efficiency and quality of this specific service may be determining factors in overall student satisfaction. In addition, the Figure highlights the questions related to prestige and loyalty (questions 3 to 7). It shows how these aspects are closely linked and can influence each other, reinforcing the importance of reputation and loyalty in the student experience.

Figures 10 and **11** present a cluster analysis that groups the survey questions into clusters according to their response patterns. This analysis reveals that specific dimensions, such as Mission and Accessibility, along with Formative Process, are clustered together, indicating that students see a direct connection between the university's accessibility and mission and how these aspects are implemented in their education. This result is particularly valuable for the university administration, as it highlights areas that are critical to student satisfaction and, therefore, those where improvements could significantly impact the overall perception of the institution.

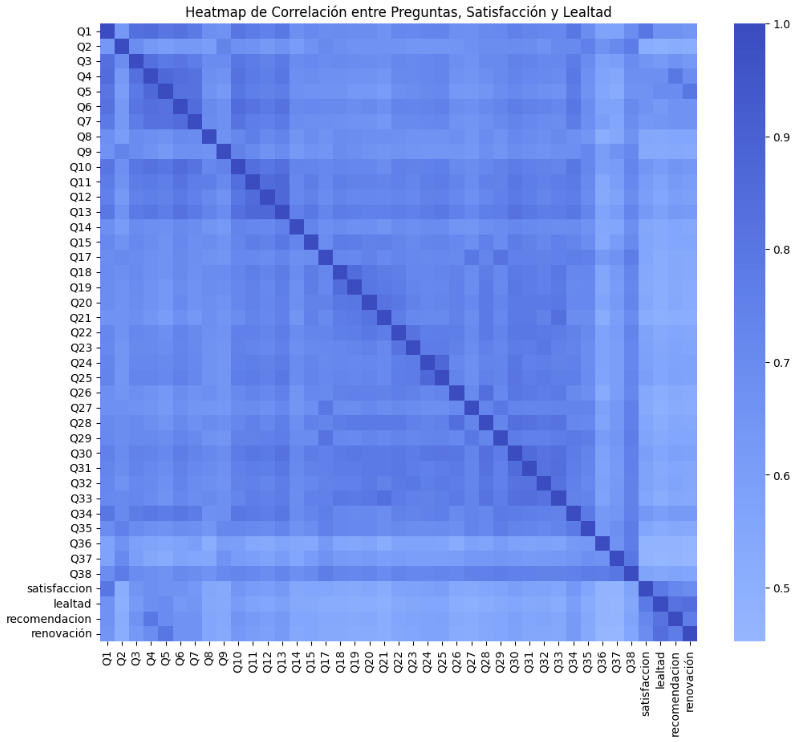

Figure 10. Cluster analysis of student satisfaction dimensions: Cluster analysis, grouping survey questions based on similar response patterns, allowing identification of factor groups related to satisfaction.

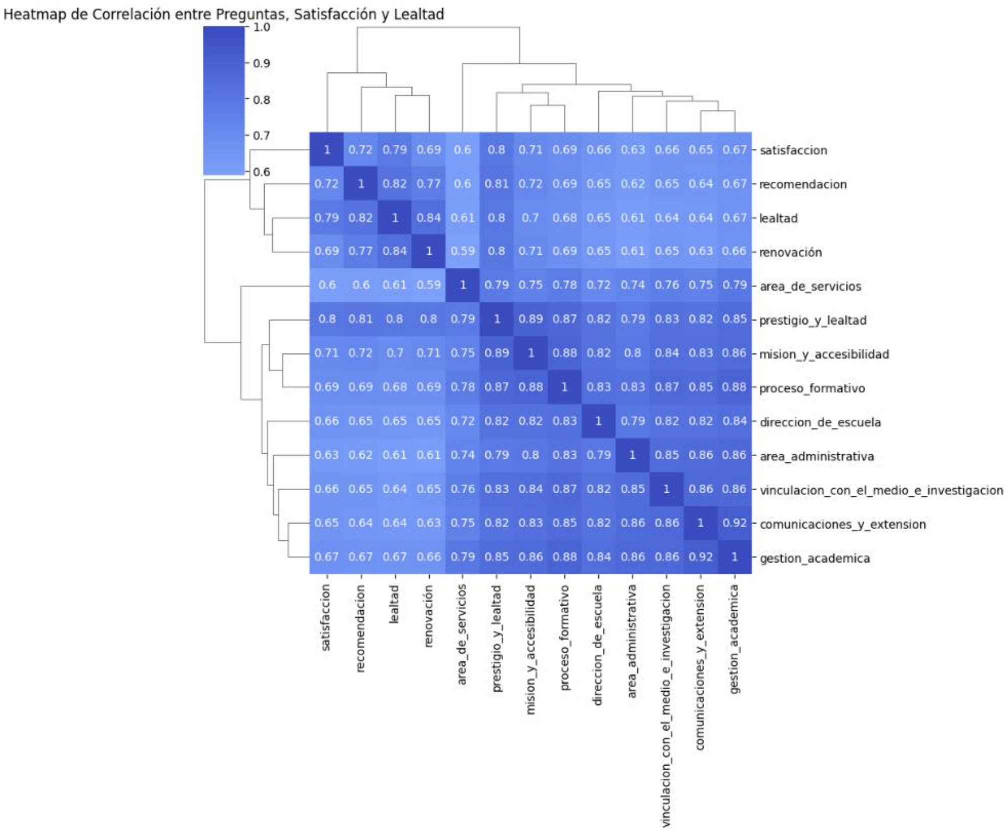

Figure 11. Grouping of mission and accessibility factors in perceived educational Quality: Institutional mission and accessibility factors, and how they are grouped in students' perception of educational quality.

Figure 12 shows the learning curve of the neural network model. It points out the exponential decrease in prediction errors as the model is trained with more data. This decline indicates an effective optimization of the model parameters, including neuron weights and biases, which improves the model's ability to generalize and predict student satisfaction accurately. The visualization verifies that the model is not overfitting or underfitting, ensuring that the predictions will be reliable and applicable in real-world scenarios.

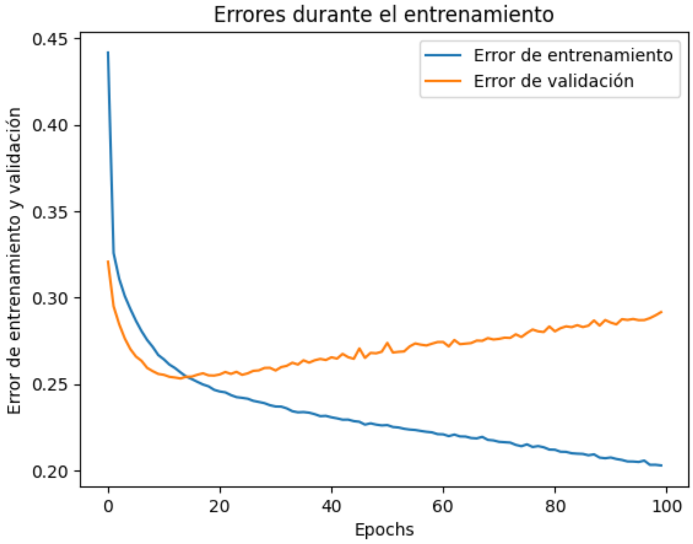

Figure 12. Learning curve of the neural network model in satisfaction prediction: Learning curve of the neural network model, showing how accuracy improves with training.

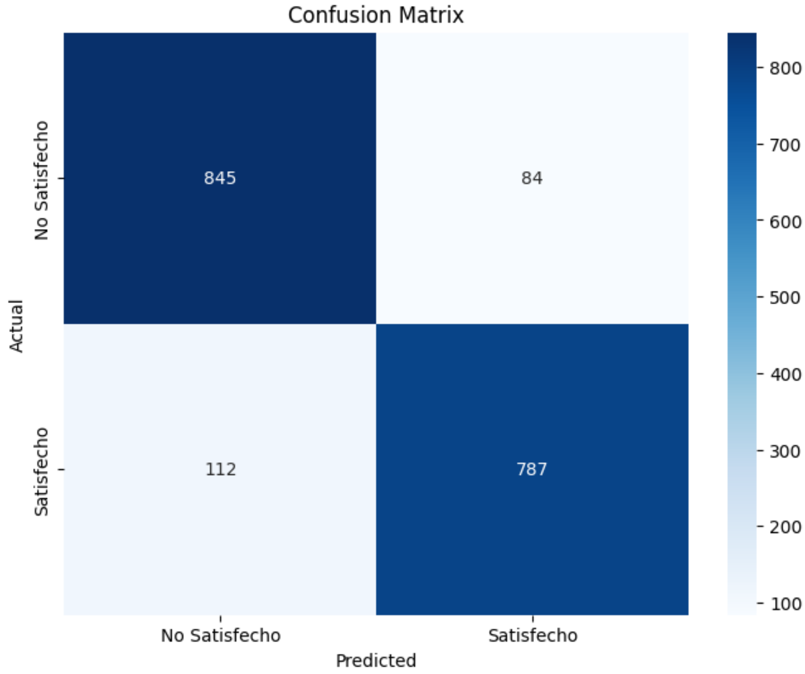

Figure 13. Confusion matrix and model evaluation metrics: Confusion matrix along with metrics such as accuracy and sensitivity, providing a detailed view of model performance in terms of correct and incorrect classifications.

Figure 13 illustrates the confusion matrix and model evaluation metrics, providing a detailed view of the performance of the model in terms of precision, accuracy, and sensitivity. The confusion matrix, which compares model predictions to actual values, reveals that the model has high accuracy (90%) and sensitivity (88%). These metrics indicate that the model effectively identifies satisfied and dissatisfied students. Furthermore, they provide robust confirmation that the model is a reliable and accurate tool for university administration, i.e., it could be used to make informed decisions on improving student services and satisfaction.

The results show the correlation between different dimensions of the survey and satisfaction, emphasizing specific areas where the institution can intervene to improve the educational experience and consequently increase loyalty and enrollment renewal rates. These findings provide a strong basis for strategic decision-making aimed at improving educational quality and student satisfaction.

4. Discussion

The results of this study offer a robust foundation for understanding key factors influencing student satisfaction in higher education. Building upon these insights, it is essential to explore the broader implications and challenges associated with implementing AI-driven management strategies in educational institutions. By integrating neural networks into student satisfaction analysis, this research not only highlights significant determinants, such as administrative service quality and mission alignment, but also underscores the transformative potential of AI in strategic decision-making. However, the deployment of such technologies entails several critical considerations, ranging from practical implementation and ethical data management to potential advancements in model application and implications for policy-making.

Practical Implementation: Implementing neural networks in educational management presents substantial challenges, not only from a technological standpoint but also due to organizational dynamics. Integrating AI tools into decision-making processes may face resistance within institutional culture, as it involves changes to established practices and potentially requires additional training for administrative and academic staff (Evans and Lindsay, 2008). Although these adjustments may initially be challenging, they can significantly enhance operational efficiency and student satisfaction by enabling more accurate and timely responses to student needs, as evidenced by the impact of cashier service satisfaction highlighted in this study.

Ethics and Privacy in AI Usage: The integration of AI to analyze student satisfaction surveys raises ethical considerations, especially regarding student privacy and the responsible handling of personal data. Literature suggests that while AI systems can improve personalization in education, transparency and control over data usage are essential to address ethical concerns (González-Calatayud et al., 2021). For educational institutions, this implies establishing clear protocols and communicating how data will be protected and utilized, fostering a trustworthy environment (Farrokhnia et al., 2023).

Comparison with Other Analytical Methods: Neural networks provide significant advantages over conventional statistical methods due to their capacity to identify complex patterns in large datasets (Goodfellow et al., 2016). Unlike traditional methods, which often require strict assumptions about data distribution, neural networks can adapt to diverse data structures, allowing for more accurate classification and prediction of student satisfaction (Rumelhart et al., 1986). This demonstrates the added value of neural networks in applying advanced techniques to the analysis of educational quality.

Model Evolution: In future implementations, the AI model could be expanded to incorporate additional variables that impact student satisfaction, such as emotional and socioeconomic factors. According to the literature, enriching the model by increasing the diversity of variables could lead to a deeper, multidimensional understanding of the student experience (Mitchell, 1997). This approach would provide a comprehensive view of the factors contributing to student well-being and performance beyond traditional variables.

Implications for Educational Policy: The findings of this study are also relevant to educational policy, particularly in directing institutional resources towards services that influence satisfaction, such as administrative services and institutional mission alignment. Research by Cheng and Tam (1997) highlights that a clear alignment between institutional mission and student needs can enhance perceptions of educational quality, a consideration that should inform policy development to ensure high-quality, accessible education (Unesco, 2005).

The current study has analyzed student satisfaction at the university through a mixed quantitative approach combining structured surveys and advanced artificial intelligence techniques. The implemented methodology, including neural networks for predictive analysis, has allowed us to obtain a detailed view of the factors influencing student perception and satisfaction.

One of the most significant findings is the high correlation between satisfaction with the cashiering service and overall satisfaction with university services. The result confirms previous studies that stress the importance of administrative services in the general perception of educational quality (Cheng and Tam, 1997). Therefore, this result would indicate that improving administrative services could positively impact student satisfaction.

In addition, through the cluster analysis, it has been identified that the mission and accessibility of the university and the educational process are closely related to student perception. This indicates that students value an education that is accessible and aligned with the institutional mission, which reinforces the need for universities to focus not only on academic quality but also on ensuring that their values and objectives are clear and accessible to all students (Kotler and Fox, 1995).

The neural network method constituted a significant tool for predicting student satisfaction, achieving high accuracy and sensitivity in its predictions. This validates the effectiveness of artificial intelligence techniques in the educational field, which provides valuable insights for strategic decision-making in university management (Rumelhart et al., 1986).

However, a limitation of the data is the work with self-reported surveys, which may introduce biases. Although data cleaning and validation measures were implemented, there is always a risk of undetected errors emerging (Osborne, 2010). Future research could benefit from integrating other qualitative data collection methods, such as in-depth interviews or focus groups, to gain a deeper understanding of student satisfaction.

This study reinforces the importance of administrative services and the clarity of institutional mission in student satisfaction. Furthermore, it demonstrates the value of neural networks as an analytical tool in higher education.

The findings of this study are based on self-reported data from participants, collected through student satisfaction surveys. The literature suggests that while such data is useful for capturing perceptions, it does not always reflect students' actual learning or behavior. Noroozi et al. (2024) indicate that a significant discrepancy often exists between perceived learning and actual performance, particularly in online feedback contexts, where students may overestimate their competencies (Caspi and Blau, 2008). Barzilai and Blau (2014) found that perceived learning is subject to cognitive and socio-emotional biases, which can distort students' assessments of their progress. This discrepancy implies that, although self-reported data is valuable for understanding the learning experience, it should be interpreted with caution. Future studies should consider complementing these measures with objective assessments to provide a more balanced view (Porat et al., 2018).

While the use of self-reported survey data provides valuable insights into student satisfaction, this approach inherently presents certain biases that may impact the study's findings. Notably, response bias—a tendency for participants to respond in a manner they perceive as favorable or socially acceptable—can skew results, potentially overstating satisfaction levels (Tourangeau and Yan, 2007). Additionally, sample diversity limitations may affect the generalizability of the findings; studies indicate that diverse demographic factors, such as cultural background and academic discipline, influence satisfaction responses (Umbach and Porter, 2002). Future research could address these biases by incorporating mixed-methods approaches, such as complementing surveys with in-depth interviews or focus groups, to capture a more comprehensive and objective understanding of student perceptions (Podsakoff et al., 2003). This multi-faceted approach would mitigate response bias and allow for a deeper analysis of factors influencing student satisfaction across diverse contexts.

5. Conclusion

The study has focused on analyzing student satisfaction at the university, using a combination of structured surveys and advanced artificial intelligence techniques, specifically neural networks. The results obtained provide a comprehensive view of the determining factors in students' perceptions of educational quality and offer a basis for improving university management.

Regarding the importance of administrative services, the study has shown the correlation between satisfaction with the cashier's office service and overall student satisfaction. This result indicates that administrative services are important in evaluating educational quality.

In addition, the relationship between institutional mission and satisfaction emphasizes the importance of an education aligned with institutional values and goals. Therefore, a clear and accessible mission can improve student perception and satisfaction.

Regarding the methodology used, neural networks were found to be effective in predicting student satisfaction, achieving high accuracy and sensitivity. This technological advance provides a powerful tool for analysis and strategic decision-making in university management.

One limitation of our study was the use of self-reported survey data, which may introduce biases in the results. Thus, future research could benefit from methods such as interviews and focus groups to gain a more complete understanding of the study phenomenon. Moreover, future research may explore other factors that influence student satisfaction.

This study provides significant results on the factors influencing student satisfaction. It also shows the potential of artificial intelligence techniques in improving educational management, contributing to the quality and sustainability of higher education.

This study presents significant theoretical and practical contributions to the field of educational management through the application of neural networks for analyzing student satisfaction. Theoretically, our findings advance the understanding of artificial intelligence applications within higher education, offering a novel methodological perspective for perception studies. Unlike traditional statistical methods, neural networks manage complex, multivariate data more effectively, demonstrating their potential to uncover nuanced insights that might otherwise remain undetected. This theoretical contribution establishes neural networks as a viable, robust tool in educational research, setting a foundation for more advanced analyses in the future.

Practically, our results have immediate applications for university administration. By identifying specific services, such as administrative support, as strong influencers of overall satisfaction, this model equips institutions with actionable insights to enhance student experiences. Improved satisfaction in critical areas not only impacts student retention but also fosters loyalty, making these findings valuable for universities striving to adapt to evolving student needs. The implications for administrative decisions are clear: data-driven management strategies can target areas for improvement with precision, ultimately supporting institutional goals of student-centered service quality.

Additionally, this study offers insights with broader policy implications. Institutions can leverage these results to inform resource allocation and quality assurance strategies, potentially influencing educational policies at an institutional or even national level. This alignment of administrative services with perceived quality reaffirms the strategic role of student satisfaction metrics in educational policy, highlighting their value in shaping responsive, high-quality education systems.

While this study provides a solid foundation for understanding student satisfaction through self-reported data, future research could benefit from incorporating qualitative approaches, such as in-depth interviews or focus groups. These qualitative methods would capture nuances and individual perspectives that structured surveys might overlook, offering a more holistic and detailed understanding of the student experience. This mixed-methods approach would enrich the analysis and could reveal additional factors influencing satisfaction, enabling institutions to more accurately tailor their strategies to student needs.

Finally, we recommend that future research build upon this foundation by incorporating additional variables, such as emotional well-being and social integration, to further enrich the understanding of student satisfaction. Expanding this approach across various educational contexts could also validate the model's applicability and generalizability, establishing a comprehensive framework for satisfaction analysis in diverse institutional settings. These recommendations position our study as a stepping stone for subsequent research, aiming to deepen the impact of artificial intelligence in the educational field.

This section is not mandatory but can be added to the manuscript if the discussion is unusually long or complex.

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