Using Fuzzy Cognitive Maps and Chatbots to Evaluate Student Satisfaction in a University: A Comparison between Strong and Weak AI

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Abstract—**The project aims to create a Fuzzy Cognitive Map (FCM) to assess student satisfaction at the Federal Technological University of Paraná, Campus Cornélio Procópio (UTFPR-CP), Brazil. By integrating intelligent techniques, the FCM allows for inference through the causal relationships between variables like teacher training, facilities, housing, and cleanliness. Online surveys were used to quantify these influences and provide an institutional improvement tool. A comparison was made with a Microsoft AI chatbot, which produced similar results, although GPT-4.0 offers more nuanced, human-like understanding and reasoning capabilities. After validating the results, this work ends with a conclusion and addresses future scientific investigations.**

Keywords- Fuzzy Cognitive Maps, Quantitative Analysis, Chatbots, Operational Research.

I. INTRODUCTION

The text discusses various studies related to education and Fuzzy Cognitive Maps (FCMs). One study at Istanbul Technical University used FCMs to model critical success factors in control engineering, incorporating concepts like student and teacher profiles to assess program success. Another work applied Fuzzy Logic to identify trends in engineering education, focusing on achieving a "Global Dimension" for professional evaluation [9] [23].

One study explored student satisfaction and critical factors for improvement within universities [12]. At the same time, another used the Fuzzy Analytical Hierarchy Process (FAHP) to assess education quality at Nanyang Institute of Technology through four dimensions: government, university, society, and student. The FAHP framework guided quality evaluations by breaking these categories into sub-areas such as funding, curriculum, and student achievements [11][19].

Further research in Central New York examined K-12 school districts' transparency in communicating educational technology information, concluding that reporting needed to be more consistent with best practices in the literature [3]. Knowledge management approaches were also explored to enhance data understanding through cognitive processes like description and interpretation, using formal grammar for linguistic data description [2].

One study mapped educational contributions to human capital in China through Fuzzy Neural Networks (FNN), estimating contributions from various educational levels across different regions. This research emphasized the link between education and technological development [13].

Recent advancements in Artificial Intelligence (AI), such as ChatGPT 4, frequently regarded as a strong AI due to its substantial progress toward Artificial General Intelligence (AGI), more details in the circumscribed section), present new opportunities for educational analysis. Compared to FCMs and Fuzzy Logic-based systems, ChatGPT 4 demonstrates superior capabilities in nuanced comprehension, reasoning, and large-scale data processing, improving identifying patterns, critical success factors, and satisfaction metrics within complex educational systems.

Lastly, sustainability and innovation in Chinese universities were examined, and strategies for integrating sustainability into education were proposed through targeted faculty training, curriculum reform, and practical learning platforms.

The rest of the paper is structured as follows. In Section II, we present the background of fuzzy cognitive maps. Section III presents the development and outcomes of the proposed FCM-based tool. Section IV presents the results and discussions. We conclude in Section V.

II. FUZZY COGNITIVE MAPS: BACKGROUND

Since the pioneering work of Kosko [16], which extended Axelrod's cognitive maps [8] to include Fuzzy Logic, various applications of FCMs have been reported in the literature across different fields of knowledge. Of note are applications in artificial life [14][15], social systems [19], decision-making in the medical field [7], and the works of process control [22], which apply evolutions of FCM in autonomous mobile swarm robotics [4].

The work in [17] focuses on Supply Chain Quality Management (SCQM) modeling, a key research area in both academic and practical contexts. This paper introduces a Multi-Layer Fuzzy Cognitive Map (ML-FCM) model to enhance SCQM by structuring concepts into multi-layered Fuzzy Cognitive Maps (FCMs). Applied to a three-echelon supply chain in the personal care products sector, the model's construction and effectiveness were evaluated using density and strength metrics. The inference process results confirmed the initial concept selection in each FCM and quantified the impact of each echelon on SCQM performance. Key decision-making variables identified for SCQM improvement included total profit, quality costs, supplier rejections and returns, productivity, and customer rejections and returns.

In [24], a formal adaptation of the original FCM is presented. This new tool is designated as Timed Automata Fuzzy Cognitive Maps (TAFCM), among others. It is observed that these works also present semantic variations of the original proposal, adapting the FCM structure according to the problem being addressed.

III. Development and Outcomes of the Proposed FCM-Based Tool

Fuzzy Cognitive Maps (FCMs) can be considered a mathematical model of a person or group's "belief structure", allowing the inference or prediction of the consequences this organization of ideas causes in the represented universe. This mathematical model was adapted to include uncertainties through Fuzzy Logic by [14], creating Fuzzy Cognitive Maps. Like the original Cognitive Maps, FCMs are directional graphs (digraphs) where numerical values are variables or Fuzzy sets. The "nodes" of these graphs are linguistic concepts, represented by Fuzzy sets, and each "node" is connected to others through links. Each of these links is associated with a numerical weight, which represents a Fuzzy variable related to the level of causality between the concepts.

$$A_i = \int \left(\sum_{\substack{j=1 \\ j \neq i}}^{n} (A_j x W_{ji}) \right) \quad (1)$$

$$F(x) = \frac{1}{1 + e^{-\lambda x}} \quad (2)$$

To address the problem and obtain quantitative results utilizing expert knowledge, a Fuzzy Cognitive Map (FCM) was developed to assess student satisfaction at the Cornélio Procópio campus of the Federal University of Technology - Paraná. Pursuing continuous quality improvement necessitates using both qualitative and quantitative evaluation tools, with Fuzzy Cognitive Maps representing a suitable approach to this challenge [23].

Fuzzy Cognitive Maps, whether Fuzzy or classical, serve as a modeling tool to represent experts' collective or individual knowledge. It is achieved by assigning values to specific concepts and weights to their causal relationships. The explicit knowledge within these maps is conveyed through the values attached to the concepts and their relationships, while implicit knowledge is embedded in the overall structure of the map. One of the primary difficulties in constructing conceptual maps is converting knowledge into accurate models of human behavior. This challenge is particularly evident in defining the semantics of the concepts and the precise nature of their interrelationships [20]. Beyond this, careful data acquisition is essential to ensure that raw data is transformed into consistent and meaningful information for the cognitive map.

In general, FCMs integrate aspects of Artificial Neural Networks [5], Fuzzy Logic [6], and Semantic Networks [20], as well as other intelligent computational techniques. Conceptually, an FCM can be understood as a methodology for modeling complex decision-making systems based on causal knowledge derived from the combination of Fuzzy Logic and Artificial Neural Networks [14]. Each concept within an FCM represents a distinct entity, state, variable, or characteristic of the modeled system. This framework provides a structured way to describe and predict the behavior of complex, often poorly understood, systems [21].

A classic example of a Fuzzy Cognitive Map (FCM) is represented by a graph structure with classical weights, as described in [4]. In some cases, however, FCMs may not achieve stability, leading to oscillatory or even chaotic behavior [22]. For systems that behave predictably, it is typically observed that after a finite number of iterations, the values of the concepts converge to either a fixed equilibrium point or a limit cycle (this work). This stabilization process can be seen in the evolution of the FCM depicted in Figure 2, where, after approximately four iterations, the values of the modeled concepts reach a steady state.

In the specific case of control, such as valve actuation used in the work of Mendonça and collaborators [22], the technique of cognitive maps is widely used for structuring complex problems through iterations, as shown in equation (2), until they typically stabilize at a fixed point or a limit cycle [4].

TABLE I. FCM CONCEPTS

C1: Student Satisfaction Level
C2: Professor’s Performance
C3: Pedagogic Structure – i.e. Library
C4: Habitation
C5: University Restaurant Quality
C6: Cleaning - Accessibility
C7: Entertainment and Sports Activities
C8: Access to the internship

The concepts listed in Table I represent all the variables determining student satisfaction. It is noted that in this study, parking and municipal transportation for faculty/students (with distinct parking facilities) are also considered.

Figure 1 represents a Fuzzy Cognitive Map (FCM), a directed graph where nodes (concepts) are connected by weighted edges, symbolizing the influence between concepts. In this FCM: Nodes (C1 to C8) represent different concepts or variables within the modeled system. For instance, C1 is a central concept connected to several other nodes like C2, C3, C6, and C8, suggesting it plays a significant role in the system's dynamics. Edges between the nodes indicate causal relationships between the concepts. The weights on these edges (represented by numbers along the connecting lines) denote the degree and type of influence: Positive weights (e.g., 0.80, 0.85) indicate a positive influence of one concept on another. Negative weights (e.g., -0.40, -0.20) suggest a negative influence, where an increase in one concept decreases the other. Directional arrows show the flow of influence from one concept to another. For example, C1 influences C3 with a weight of 0.80, and C2 influences C1 with a weight of 0.46, among others. The color-coded connections likely indicate different types or strengths of relationships between concepts, further detailing the complexity of the system being modeled. Overall, this FCM graph visually represents how each concept is interrelated, with specific concepts like C1 and C2 appearing to hold more central roles based on their numerous connections.

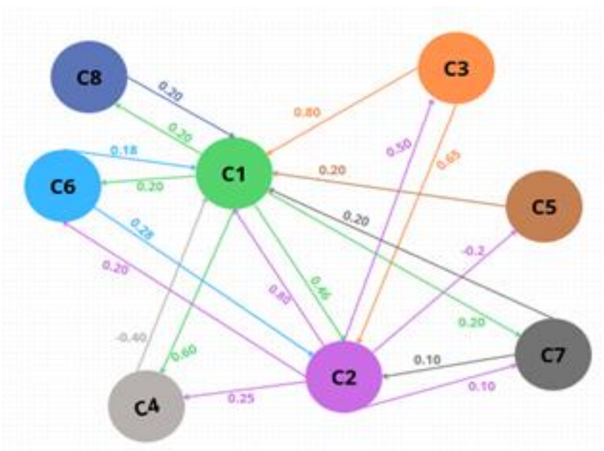

Figure 1. Student Satisfaction Level FCM.

VI. RESULTS AND DISCUSSIONS (FCM, ChatGPT)

A. *Fuzzy Cogntive Maps*

After modelling the concepts and causal relationships, particularly the numerical values assigned by the students, the model is calculated using Equations 2 and 3. This process allows the system to evolve toward the final values representing the study's objective: a quantitative evaluation of the central theme [10].

Initially, the concept values are set to zero. As shown in Figure 2, the evolution of each modelled concept is represented on a scale from zero to 10, with particular emphasis on the central concept—student satisfaction at UTFPR-CP. The FCM demonstrated stable behaviour, reaching a near-equilibrium point with only minor variations around the result, see Figure 2.

However, specific critical issues emerged during the research and model construction, such as the parking conditions near the university. This challenge is linked to the institution's rapid growth over the past decade and should be addressed by the university administration and government authorities to ensure future improvements [1].

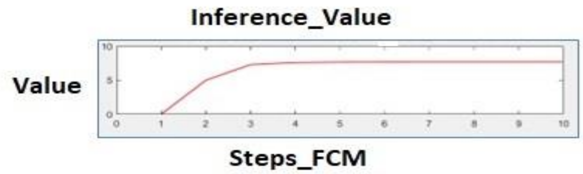

Figure 2. Student Satisfaction Level FCM.

Figure 2 presents the evolution of the Inference Value over successive FCM Steps in a Fuzzy Cognitive Map (FCM) model. The horizontal axis represents the number of Steps FCM taken, while the vertical axis indicates the corresponding Value of the inference at each step.

Key observations from the figure include:

a) Initial Growth: At the beginning (Steps 0 to 2), the inference value shows a steep increase, indicating that the system is rapidly adjusting as it begins to process the interactions between the concepts modeled in the FCM.

b) Stabilization: After Step 3, the inference value begins to plateau, suggesting that the model is approaching equilibrium. The value stabilizes around 0.8, indicating that the FCM has reached a steady state or a limit cycle where further iterations result in minimal to no significant changes in the concept values.

c) Minor Variations: The slight upward adjustment after Step 2 suggests minor refinements in the FCM behavior, but overall, the system stabilizes quickly. This stable convergence implies that the FCM is well-behaved, with the concepts interacting in a way that leads to consistent and predictable outcomes after a few iterations [20]. The final inference value provides a quantitative representation of the central theme being evaluated, likely reflecting a key metric like student satisfaction, as discussed in the context of the study

B. *ChatBot 4.0*

In 2022, OpenAI introduced a new model of ChatGPT, an NLP system capable of maintaining contextual natural conversations. Since its release, ChatGPT has spurred extensive research into its societal impacts, particularly in education. This article investigates ChatGPT's influence on university education by analyzing over 50 essay papers across various topics, focusing on its use in exams, programming tasks, and term papers. The study assessed misuse levels, including copying ChatGPT's outputs, and examined the effect on student performance, especially given the occasional inaccuracies in its responses. While concerns about academic dishonesty are highlighted, the article also emphasizes the tool's potential benefits, such as aiding learning and improving assignment comprehension. The findings suggest that ChatGPT can assist in generating coherent, informative work but stress the need for new assessment formats that emphasize critical thinking and creativity, areas where AI cannot fully substitute human effort [26].

In short, GPT-4 is a "weak AI" specialized in specific tasks, such as language processing, and it does not possess consciousness, proper understanding, or the ability for independent thought. While it is impressive in language tasks and has shown significant advancements in interaction and content generation, it operates based on patterns and statistics from the texts on which it was trained. It does not have a fundamental understanding of the world or itself.

The GPT-4 version, like other similar AIs, is still not considered a "strong AI" (or AGI - Artificial General Intelligence) [25]. The concept of "strong AI" refers to an artificial intelligence capable of performing any cognitive task a human could, including deep understanding, reasoning, creative adaptation to new problems, and autonomy.

The current version represents a significant advance in artificial intelligence and is closer to the so-called "Strong AI" or Artificial General Intelligence (AGI) than previous versions.

For now, "strong AI" remains within research and theory, and it is uncertain when (or if) this technology will be developed

Question: What is the level of satisfaction of a student with generally good and high-level professors, good university infrastructure in the laboratories, and most students being able to walk to the university? The university and the city offer a reasonable level of entertainment, but the university town is small and there are difficulties in securing internships

The level of satisfaction of a student in such a scenario can be influenced by several factors. Let us break down the specifics to get a clearer picture:

a) Professors and Academics:

High-Level Professors: Generally, students appreciate knowledgeable and experienced professors, which can lead to high satisfaction in terms of the quality of education and academic guidance

Academic Reputation: Good professors can enhance the university's reputation, positively impacting student satisfaction.

b) University Infrastructure:

Good Laboratories: High-quality laboratory facilities are crucial for hands-on learning and research, especially in science and engineering disciplines. This likely increases student satisfaction

Overall Infrastructure: Good infrastructure beyond labs, such as libraries, study spaces, and classrooms, also contributes to a positive learning environment.

c) Proximity to University:

Walking Distance: Most students being able to walk to the university is highly convenient and can significantly improve satisfaction due to the ease of access and saving on transportation costs**.**

d) Social and Entertainment Aspects:

Reasonable Entertainment Options: While a reasonable level of entertainment is available, the small size of the town might limit diverse social activities, which could slightly lower satisfaction for students seeking more vibrant social lives.

University Town Size: A smaller town might offer a close-knit community feeling, which some students prefer, while others might find it lacking in variety and excitement.

e) Internship Opportunities:

Difficulty Securing Internships**:** Challenges in finding internships can be a significant drawback, as internships are essential for gaining practical experience, networking, and improving employability. This factor might lower overall satisfaction

Overall, the student satisfaction level in this scenario would likely be high in terms of academic and infrastructure aspects but might be tempered by the limited entertainment options and difficulties in securing internships. Here's a summarized view:

f) Positive Factors: Highly qualified professors

- Good university infrastructure, particularly well-equipped laboratories

- Proximity to the university for the majority of students
- A reasonable level of entertainment and activities

Negative Factors:

- The university is located in a small town with limited entertainment options
- Difficulties in securing internships, which underscores their importance in the overall student experience

Different weights were assigned to each aspect based on their perceived significance to quantify the impact of these factors. The proposed weighting scheme is as follows:

High-Level Professors: 20%
Good University Infrastructure (Laboratories): 20%
Good University Infrastructure (Overall): 15%
Proximity to University: 15%
Social and Entertainment Aspects (Entertainment): 10%
Social and Entertainment Aspects (Town Size): 10%
Internship Opportunities: 10%

The final assessment is calculated using Equation 3, which integrates the weighted values of each factor into the overall evaluation:

$$\text{Overall} = 1.8 + 1.8 + 1.2 + 1.2 + 0.6 + 0.5 + 0.4 = 7.5 \qquad (3)$$

This score provides a comprehensive view of student satisfaction, considering both academic and social factors

g) Interpretation:

An overall satisfaction score of 7.5 out of 10 suggests that students are generally satisfied with their experience at the university. While academic and infrastructural aspects are highly appreciated, the limited entertainment options and challenges in securing internships reduce overall satisfaction.

A similar question applied to the accessible version of ChatGPT 3.5 (free version); the answer was close to 7.4 but with fewer details. That said, the answer from the free version was not included, and its result was to help validate the correlation between FCM and ChatGPT.

IV. CONCLUSION AND FUTURE WORK

The study concluded that student satisfaction at UTFPR-CP reached an overall score of 7.5/10, reflecting strong satisfaction with faculty quality and general infrastructure, while identifying areas for improvement in laboratory and library facilities. Despite recent course expansions and ongoing infrastructure upgrades, gaps remain in resources. The use of Fuzzy Cognitive Maps (FCM) successfully quantified qualitative data, and results were further validated by ChatGPT 3.5 and 4.0, both yielding consistent outcomes. Given the alignment between FCM and AI-based tools, the study is recommended as a continuous assessment tool for guiding university improvements.

Future work should increase sample size, incorporate diverse metrics, and employ longitudinal studies for tracking satisfaction trends, while qualitative methods could provide deeper insights into student experiences.

ACKNOWLEDGMENT

The authors would like to thank the Federal University of Technology – CP/PR for the financial support provided for this research.

REFERENCES

[1] Y. Gao, J. Yang, and F. Liu, "The Research on the Comprehensive Assessment of Higher Engineering Education Based on Fuzzy Comprehensive Evaluation Method," in *Future Information Technology and Management Engineering, 2009. FITME '09. Second International Conference on*, pp. 124-127, 13-14 Dec. 2009.

[2] L. Ogiela and M. R. Ogiela, "Knowledge Management Approaches for Data Understanding," in *2016 International Conference on Intelligent Networking and Collaborative Systems (INCoS)*, Ostrava, Czech Republic, 2016, pp. 270-273.

[3] J. MacLeod and H. H. Yang, "Life-Cycle Efficacy for Educational Technology: Best-Practices for Leading Schools," in *2016 International Conference on Educational Innovation through Technology (EITT)*, Tainan, Taiwan, pp. 139-142, 2016.

[4] M. Mendonça, H. S. Kondo, L. Botoni de Souza, R. H. C. Palácios, and J. Paulo Lima Silva de Almeida, "Semi-Unknown Environments Exploration Inspired by Swarm Robotics using Fuzzy Cognitive Maps," in *2019 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, New Orleans, LA, USA, pp. 1-8, 2019.

[5] S. Haykin, *Neural Networks and Learning Machines*, 3rd ed. Upper Saddle River, NJ: Pearson Education, 2009.

[6] W. Pedrycz and F. Gomide, An Introduction to Fuzzy Sets: Analysis and Design, MIT Press, 1998.

[7] G. A. Krimpas, N. A. Krimpas, and P. P. Groumpos, "An Overview of Making Decisions on Medical Problems Using Fuzzy Cognitive Maps," in *2023 14th International Conference on Information, Intelligence, Systems & Applications (IISA)*, Volos, Greece, pp. 1-6, 2023.

[8] R. Axelrod, Structure of Decision: The Cognitive Maps of Political Elites. Princeton, NJ: Princeton Univ. Press, 1976.

[9] L. A. Franco and G. Montibeller, "Facilitated modeling in operational research," *European Journal of Operational Research*, vol. 205, no. 3, pp. 489-500, 2010.

[10] E. Yesil, C. Ozturk, M. F. Dodurka, and A. Sahin, "Control engineering education critical success factors modeling via Fuzzy Cognitive Maps," in *Information Technology Based Higher Education and Training (ITHET), 2013 International Conference on*, pp. 1-8, 10-12 Oct. 2013.

[11] Y. Hezhan, "Application of Fuzzy Analytical Hierarchy Process in innovation education quality evaluation of higher education institution," in *Information Management, Innovation Management and Industrial Engineering (ICIII), 2012 International Conference on*, vol. 1, pp. 438-441, Oct. 20-21, 2012.

[12] S. Yu and K. Zhu, "Fuzzy Neural Network Applications on Estimating the Contribution of Different Education Levels on Human Capital of China," in *Service Systems and Service Management, 2007 International Conference on*, pp. 1-4, June 9-11, 2007.

[13] P. Xiang, "Research on the Emotion Recognition Based on the Fuzzy Neural Network in the Intelligence Education System," in *Digital Manufacturing and Automation (ICDMA), 2011 Second International Conference on*, pp. 1030-1033, Aug. 5-7, 2011.

[14] J. A. Dickerson and B. Kosko, "Virtual worlds as Fuzzy cognitive maps," *Presence*, vol. 3, no. 2, pp. 173-189, 1994.

[15] J. A. Dickerson and B. Kosko, "Virtual worlds as Fuzzy dynamical systems," in *Technology for Multimedia*, B. Sheu, Ed. New York: IEEE Press, 1996.

[16] B. Kosko, "Fuzzy cognitive maps," *International Journal of Man-Machine Studies*, vol. 24, no. 1, pp. 65-75, 1986.

[17] J. Cogollo and A. Correa, "Modeling Supply Chain Quality Management using Multi-Layer Fuzzy Cognitive Maps," in *2019 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, New Orleans, LA, USA, pp. 1-6, 2019.

[18] J. MacLeod and H. H. Yang, "Life-Cycle Efficacy for Educational Technology: Best-Practices for Leading Schools," in *2016 International Conference on Educational Innovation through Technology (EITT)*, Tainan, Taiwan, pp. 139-142, 2016.

[19] C. Neocleous, M. Papaioannou, and C. Schizas, "Important issues to be considered in developing fuzzy cognitive maps," in *2011 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE 2011)*, Taipei, Taiwan, 2011, pp. 662-665.

[20] E. Papageorgiou, "Learning Algorithms for Fuzzy Cognitive Maps," *IEEE Transactions on Systems and Cybernetics, Part C: Applications and Reviews*, vol. 42, pp. 150-163, 2012.

[21] E. Papageorgiou, C. Stylios, and P. Groumpos, "Novel for supporting medical decision making of different data types based on Fuzzy Cognitive Map Framework," in *Proceedings of the 29th Annual International Conference of the IEEE EMBS*, Lyon, France, pp. 23-26, Aug. 2007.

[22] M. Mendonça, B. Angélico, L. V. R. Arruda, and F. Neves, "A dynamic fuzzy cognitive map applied to chemical process supervision," *Engineering Applications of Artificial Intelligence*, vol. 26, pp. 1199-1210, 2013.

[23] L. B. de Souza, R. V. P. D. Barros, P. P. Soares, J. G. Ferreira, and M. Mendonça, "Fuzzy Cognitive Maps and Weighted Classic Fuzzy Applied on Student Satisfaction Level," in *ICAS 2017*, pp. 60, 2017.

[24] G. Acampora and V. Loia, "On the Temporal Granularity in Fuzzy Cognitive Maps," *IEEE Transactions on Fuzzy Systems*, vol. 19, no. 6, 2011.

[25] A. F. Mohammad, B. Clark, R. Agarwal, and S. Summers, "LLM/GPT Generative AI and Artificial General Intelligence (AGI): The Next Frontier," in *2023 Congress in Computer Science, Computer Engineering, & Applied Computing (CSCE)*, Las Vegas, NV, USA, 2023, pp. 413-417.

[26] A. F. Mohammad, B. Clark, R. Agarwal, and S. Summers, "LLM/GPT Generative AI and Artificial General Intelligence (AGI): The Next Frontier," 2023 Congress in Computer Science, Computer Engineering & Applied Computing (CSCE), Las Vegas, NV, USA, 2023, pp. 413-417.