Potential AI-based Use of Fuzzy Cognitive Mapping in Postgraduate Supervision in Higher Education

Vincent R. Nyirenda¹ [iD]

Charles B. Chisanga² [iD]

AFFILIATIONS

¹&²School of Natural Resources, The Copperbelt University, Kitwe, Zambia.

CORRESPONDENCE

Email: vincent.nyirenda@cbu.ac.zm

Abstract: Supervision in higher education is a complex and evolving process that necessitates adaptive, evidence-based decision-making to effectively guide postgraduate students. Conventional supervisory models often encounter difficulties in addressing uncertainties and the non-linear dynamics inherent in academic mentorship. This chapter examines the AI-based application of Fuzzy Cognitive Mapping (FCM) as an innovative framework to enhance supervisory practices by integrating expert insights, student progress data, and institutional guidelines within a structured yet flexible system. Employing a mental model approach, the study utilises fuzzy logic principles to simulate supervisory scenarios and assess causal relationships among critical factors, such as student motivation, research complexity, institutional support, and mentor–mentee engagement. The FCM-based framework enables supervisors to visualise interdependencies between variables, predict outcomes, and dynamically adjust mentoring strategies. Mixed methods, combining quantitative and qualitative data, are employed. Findings indicate that FCM enhances supervisory efficiency by promoting proactive interventions, improving communication, and supporting continuous monitoring of mentor–mentee relationships. Furthermore, the model advances a data-driven and transparent approach to supervision, minimising subjectivity while preserving contextual flexibility. By operationalising cognitive and computational intelligence, this chapter illustrates how FCM can bridge gaps between qualitative judgement and quantitative assessment in higher education supervision. The study contributes to emerging scholarship on artificial intelligence applications in academic contexts, underscoring the potential of cognitive modelling in improving student outcomes. It concludes by emphasising the necessity of empirical validation and the integration of adaptive mental models into institutional supervisory frameworks to strengthen postgraduate research management and mentoring effectiveness.

Keywords: Artificial intelligence, cognitive mapping, decision-making, higher education, mental models, mentor-mentee relationship.

1. Introduction

Postgraduate supervision within higher education is a multi-faceted and dynamic process that requires adaptive decision-making to enhance students' academic experiences, particularly through the utilisation of Artificial Intelligence (AI)-powered tools (Thong et al., 2025). These AI tools are continuously evolving (Michel-Villarreal et al., 2023). AI applications present both opportunities and challenges, particularly concerning graduate research, which must be operationalised through comprehensive training, collaboration, and the establishment of AI policies (Rajab et al., 2025). Furthermore, AI's transformative potential renders it suitable for

impactful research evaluations (Arsalan et al., 2025), particularly when utilising predictive models (Hoyos et al., 2023), and serves as an essential resource for monitoring student progress (Zhu & Zhang, 2023). The application of AI in student instruction and assessment demonstrates promising contributions to higher education (Hooda et al., 2022; Liang et al., 2025).

Conventional supervisory models typically operate within rigid frameworks that fail to account for the uncertainties and non-linear nature of academic mentorship in higher education, which are often exacerbated by time constraints (Impola, 2023). Additionally, as higher education diversifies, the changing needs of students, the complexities of research problems, and the evolving institutional academic policies necessitate more flexible and data-driven supervisory approaches. One such promising methodology for achieving this adaptability is Fuzzy Cognitive Mapping (FCM)—a computational technique for modelling, analysing, predicting, and decision-making concerning complex systems through co-production and visualisation (Bakhtavar et al., 2021; Barbrook-Johnson & Penn, 2022). FCMs have been developed to incorporate significant advancements in artificial intelligence, such as machine learning and deep learning, particularly in addressing uncertainty-linked decision-making (Apostolopoulos & Groumpos, 2023). FCMs serve as decision-making support tools through semi-quantitative modelling of complex systems (Barbrook-Johnson & Penn, 2022; Mehryar & Surminski, 2022; Borrero-Domínguez & Escobar-Rodríguez, 2023), informed by collective intelligence (Gray et al., 2020). FCMs have been applied across various domains, including risk analysis (e.g., Bakhtavar et al., 2021), infrastructure construction (e.g., Chen et al., 2024), academic research (e.g., Borrero-Domínguez & Escobar-Rodríguez, 2023), participatory research and decision-making (Sarmiento et al., 2024), nursing research (Andersson & Silver, 2019), and medical sciences (e.g., Apostolopoulos et al., 2024).

The application of computational intelligence, particularly Fuzzy Cognitive Maps (FCMs), in postgraduate supervision within higher education offers a systematic approach to model mentor-mentee relationships, anticipate challenges, identify critical success pathways, and provide timely interventions. This methodology incorporates various components, including expert and collective knowledge, student progress data, and institutional policies or guidelines, to facilitate structured and dynamic real-time decision-making within transformative postgraduate supervision in higher education (Nagaraj et al., 2023). FCMs can also be utilised in conjunction with other methodologies, such as Techniques for Order Preference by Similarity to Ideal Solution (TOPSIS) and Strengths, Weaknesses, Opportunities, and Threats (SWOT) analysis (Baykasoğlu & İlker Gölcük, 2015). Furthermore, FCMs function as a hybrid artificial intelligence tool, integrating expert knowledge, causal reasoning, and fuzzy logic to model complex, dynamic systems while ensuring interpretability and transparency (Apostolopoulos & Groumpos, 2023; Orang et al., 2023). Recent studies illustrate that the integration of FCMs with machine learning, optimisation algorithms, or data-driven techniques enhances predictive

accuracy and scenario simulation, thereby providing robust decision support in environmental and socio-ecological contexts (Duhayyim et al., 2023; Shrivastava & Shukla, 2025).

Contemporary research concerning academic mentorship emphasises the significance of mentor-mentee engagement, student motivation, and institutional support in influencing student mental health and learning outcomes (Rasul et al., 2024). However, conventional models present challenges for students, as these frameworks lack a structured mechanism to visualise the complex, dynamic, and interdependent relationships among these components. The utilisation of FCMs in postgraduate supervision enables a proactive approach to co-assess and respond to evolving student needs. This inclusive process is likely to enhance mentorship effectiveness and student performance, thereby supporting the programmatic Theory of Change (ToC) (Reinholz & Andrews, 2020). The ToC posits that the supervision process, accompanied by a series of activities, should culminate in predefined student success goals, such as positive changes in students' learning, mental health, critical thinking, and research skills.

This chapter aims to contribute to postgraduate supervision in higher education through the use of AI-based FCMs. By co-producing an FCM-based framework, this chapter demonstrates beneficial causal relationships and provides supervisors with predictive tools to effectively guide their decision-making processes. It considers multiple situations in postgraduate supervision but does not, by any means, claim comprehensiveness for all the possible and existing situations in higher education. Therefore, the chapter provides illustrations as examples only. Individual supervisors and students need to co-examine their own supervision situations and co-produce the models in various scenarios, together with possible beneficial interventions.

1.1 Statement of the problem

Postgraduate supervision is a highly dynamic process that requires a nuanced approach to mentorship. It supports the United Nations' Sustainable Development Goals (SDGs), particularly SDG 4 (Quality Education). Conventional supervision methods often struggle to manage the uncertainties and risks associated with student motivation, research complexity, and institutional support, resulting in inefficiencies and dissatisfaction among students and funders (Deeley et al., 2019; Skinner et al., 2022). In current research on postgraduate supervision, there is an emphasis on the importance of mentor-mentee engagement; however, limited efforts have been made to operationalise these interactions within a structured and predictive framework (Gamage et al., 2021; Goh & Richardson, 2024). Consequently, the inadequate or lack of use of adaptable decision-support tools hampers the supervision process in addressing diverse student needs and academic expectations.

Furthermore, FCMs provide an additional approach to conventional supervision models to tackle these challenges by integrating various components influencing postgraduate supervision into computational models. By incorporating expert-driven weights and fuzzy logic principles (e.g., the use of IF-THEN rules and integrating categorical variables such as low, medium, and

high, using a degree of truth that lies between 0 and 1), FCMs enable the simulation of multiple supervisory scenarios, offering supervisors a proactive mechanism to enhance mentorship effectiveness. Therefore, this chapter aims to illustrate the applicability of FCMs in postgraduate supervision, demonstrating their potential to improve decision-making, engagement strategies, and overall student success at the higher education level.

1.2 Research question

In this chapter, the following research question is explored to demonstrate the potential use of FCMs in postgraduate supervision in higher education: *How can AI-reinforced FCMs be used to model key variables that shape effective mentor–mentee relationships and supervisory decision-making in postgraduate education?*

2. Materials and Methods

As this chapter generically explores the potential use of FCMs in postgraduate supervision within higher education, the data collection is not linked to any specific institution. Instead, it broadly draws on the expert knowledge of authors to provide a discursive framework for supervisors (mentors) and students (mentees). Furthermore, it is envisaged that users will be inspired to co-develop their own relevant mental models, co-evaluate them, and further refine their applicability in different scenarios while conducting their postgraduate supervision.

The data used in this chapter was collated from multiple sources, including online supervision protocols (e.g., https://www.timeshighereducation.com) and long-term interactions with staff and students at The Copperbelt University over a decade, since 2014, during the authors' course of duty. This period (2014-2025) coincided with the AI boom in several sectors, including higher education (Pisica et al., 2023; Mah & Groß, 2024; An et al., 2025). The data collected from these sources included the identification of key components, the direction of effects between components (whether positive or negative), the magnitude of the effects between components, and participants' perspectives regarding postgraduate supervision. The variables used in the study were generated and consolidated with the help of a generative AI model, GPT-4o, in October 2024. Following the compilation of the variables, expert knowledge was sought from 27 participants (15 academic staff and 12 graduate students) whose opinions aligned with those of the extant variables. In the next step, involving data collection in November 2024, 36 participants (16 academic staff and 20 graduate students from different disciplines) were randomly selected and asked to independently establish relationships between the variables and weight them against a 5-point Likert scale, represented by 1-very weak, 2-somewhat weak, 3-neutral, 4-somewhat strong, and 5-very strong relationship.

The study was ethically overseen by The Copperbelt University, in accordance with the 2024 Helsinki declaration on human participants in research. Mixed methods, combining quantitative and qualitative data, were employed as a case study at The Copperbelt University. Only academics with experience supervising graduate students and students in their final research year

participated in the exercise. The average weight of the magnitude of each relationship between components or elements was then integrated into the FCM.

2.1 Model elicitation

The shared perceptions of the participating individuals formed the key areas of agreement within the shared mental models. Differences in the data were not assessed, as they are beyond the scope of this chapter. Intentionally, no questionnaires or guides were employed, as it was intended to build a framework that would be illustrative only. The key elements or components for model development were identified from the sources until the saturation point, where components became repetitive. A 1-5 Likert scale was used to assign weights by gauging participants' collective assertions and providing the magnitude. Clear directional dimensions (negative or positive), annotated as – or +, respectively, between pairs of elements in relationships, were also provided by the participants. The ratings were transformed into a -1 to +1 number scale to meet the model's requirements.

2.2 Data analysis

The data were analysed using Mental Modeller (https://www.mentalmodeler.com/) – an open FCM software for shared mental models that includes scenario analysis. Mental Modeller has four key features: components with relationships that include magnitudes and dimensions; adjacency matrices; model validation; and scenario analysis. The scenario analysis helps to highlight anticipated system performance when dealing with different parameterised settings. Model validation encompasses the network's structural properties (indegrees, outdegrees, and centrality), where indegree reflects the number of incoming connections, outdegree represents outgoing connections, and centrality indicates the importance of a component within the system.

Corrective measures in supervision performance are implemented based on decision-making informed by the preferred scenarios, which are determined through mentor-mentee engagement. As system influencers, the drivers identified in the validation interface, when increased or decreased, lead to predictable scenario outcomes in the supervision processes. Receivers, however, tend to be influenced or impacted by other elements, while ordinaries are regular, unspecialised elements that create domino effects within the system. Manipulating these types of elements will help to comprehend the potential outcomes of interventions in real time. The number of scenarios that can be created is as many as desired in a particular setting, and some examples will be provided. By refining alterations in system elements through stakeholders' in-depth consultations, scenario analysis can yield comparably higher value outcomes (Goswami et al., 2021).

2.3 The scope

The illustrations of FCM presented in this chapter are based on online resources, expert knowledge, and stakeholder engagement spanning over a decade. They adopt broad-brush

approaches in identifying components or elements for illustrative purposes only. The FCM connects to an array of focus, inter alia: (i) student progress monitoring through real-time tracking from multiple perspectives, such as the levels of acquisition of research skills; (ii) adaptive decision-making support for personalised student supervision; (iii) prediction of student outcomes regarding potential delays, drop-out risks, and success probabilities; (iv) improving supervisor-student communication by reducing misunderstandings and enhancing research collaboration; (v) optimising resource allocation, such as mentorship time and research funding; and (vi) identifying and addressing stress- and wellbeing-related effects through appropriate social, emotional, and psychological remedial mechanisms.

3. Results

3.1 Model validation

There are specific measures to note. In the exemplar shown in Figure 1, there were 23 components (elements), 27 connections, a density of 0.053, 1.173 connections per component, 12 driver components, 5 receiver components, 6 ordinary components, and a complexity score of 0.41. These various model measures may differ depending on the co-created situation relevant to postgraduate supervision.
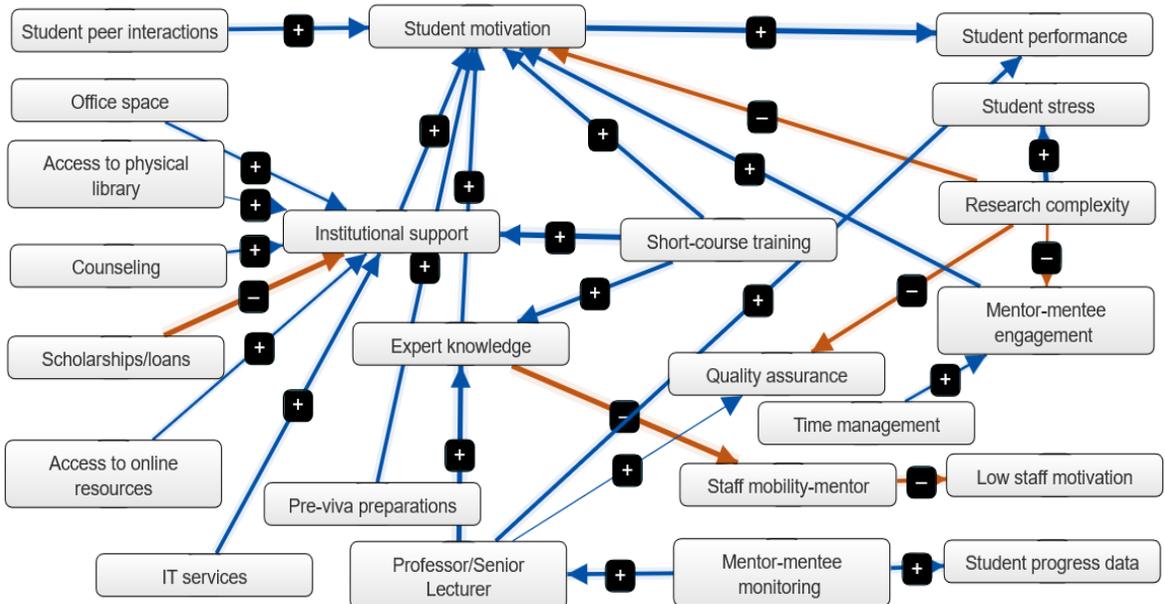

Figure 1: *Illustration of AI-retrieved components and their FCM-generated relationships*

3.2 Component performance

Table 1 reflects the features presented in the model (Figure 1) and provides specific measures of the network. In this network, the software indicates that student motivation has the highest sum of indegree.

Table 1: *Adjacency matrix for indegrees, outdegrees, and centrality of individual components.*

Components	Indegree	Outdegree	Centrality	Type
Student motivation	5.18	0.88	6.06	Ordinary
Institutional support	3.75	0.68	4.43	Ordinary
Expert knowledge	1.71	1.67	3.38	Ordinary
Research complexity	0	2.61	2.61	Driver
Short-course training	0	2.43	2.43	Driver
Professors or senior lecturers	0.53	1.74	2.27	Ordinary
Student performance	1.62	0	1.62	Receiver
Staff mobility-mentor	0.84	0.6	1.44	Ordinary
Mentor-mentee engagement	0.65	0.66	1.31	Ordinary
Mentor-mentee monitoring	0	1.23	1.23	Driver
Student stress	1.00	0	1.00	Receiver
Scholarship or loans	0	0.99	0.99	Driver
Pre-viva preparations	0	0.81	0.81	Driver
Student peer interactions	0	0.80	0.80	Driver
Quality assurance	0.80	0	0.80	Receiver
Student progress data	0.70	0	0.70	Receiver
IT services	0	0.65	0.65	Driver
Low staff motivation	0.60	0	0.60	Receiver
Access to online resources	0	0.47	0.47	Driver
Time management	0	0.44	0.44	Driver
Counselling	0	0.37	0.37	Driver
Office space	0	0.22	0.22	Driver
Access to physical library	0	0.13	0.13	Driver

Outdegree and centrality values serve as a mediating component. Other important mediating components include the availability of institutional support, expert knowledge, and supervisors (professors or senior lecturers). The key drivers of postgraduate supervision, however, are research complexity, short-course training, mentor-mentee monitoring, the availability of scholarships or education loans, pre-viva preparations, and student peer interactions. The potential outcomes (receivers) encompass student performance, levels of student stress (mental health), quality assurance, and student progress data. Together, all these elements function to support the levels of postgraduate supervision.

3.3 Scenario development

For illustration purposes, a 5-component scenario is implemented in Mental Modeller to develop a model with the outcomes shown in Figure 2. The five components used in the model include student motivation, research complexity, mentor-mentee engagement, availability of student scholarships or education loans, and professors or senior lecturers. Consequently, the model suggests that postgraduate supervision is likely to improve through student performance, expert knowledge, institutional support and quality assurance, and reduced student stress (mental health), by increasing student motivation, mentor-mentee engagement, availability of student scholarships or education loans, and professors or senior lecturers, while decreasing research complexity.
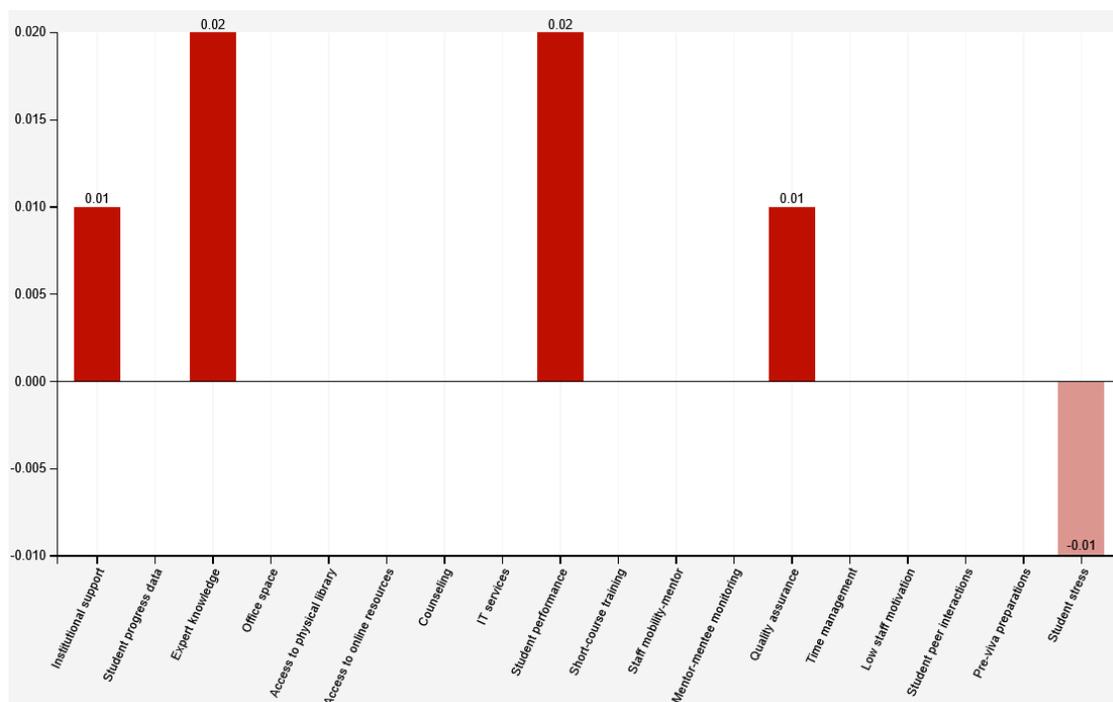
Figure 2: *An example of parameterising*

Figure 2 is an example of parameterising (increasing or reducing) values of particular components to obtain the desired results in scenario planning. In this case, student motivation, mentor-mentee engagement, scholarships or loans, and the availability of professors or senior lecturers are increased, while research complexity is reduced based on the principle of parsimony.

4. Discussion

In our model illustrations, student motivation is the most influential mediating component in postgraduate supervision. This outcome is consistent with past research, emphasising its role in academic persistence and research productivity among postgraduate students (Litalien & Guay, 2015; Shen & Jiang, 2021; Khosa et al., 2023). In addition, the model identifies other key mediators, such as institutional support, expert knowledge, and supervisor involvement, reinforcing previous studies that underscore these components as essential to effective supervision, particularly when addressing uncertainties in supervision processes (Albertyn & Bennett, 2020). Notably, the study delineates critical drivers of postgraduate supervision, including research complexity, short-course training, mentor-mentee monitoring, availability of scholarships or education loans, pre-viva preparations, and student peer interactions. These drivers align with the literature advocating for structured coaching or training programmes and financial support, which are vital for the well-being and resilience of postgraduate students, thus enhancing research outcomes (Casey et al., 2022).

The application of AI-based FCMs using Mental Modeler offers an approach to understanding postgraduate supervision dynamics amid the uncertainties faced by students in their studies. The five-component scenario—comprising student motivation, research complexity, mentor-mentee engagement, scholarships or education loans, and supervisory expertise—yields outcomes that corroborate various aspects of supervisory practice (Taylor & Kiley, 2024). The exploration of these aspects should be conducted inductively and comprehensively, especially with the use of AI, and personalised for individual students throughout the study period. Furthermore, our illustrative model suggests that reducing research complexity positively impacts supervision quality, complementing studies that advocate for structured, well-scaffolded research processes to mitigate cognitive overload (Kiley, 2015; Auhl & Bain, 2023). FCM can be applied to define challenges and articulate solutions in postgraduate supervision (Andersson & Silver, 2019). It can also assist in formalising stakeholder knowledge, supporting learning in supervision, and promoting remedial actions.

FCMs facilitate a nuanced representation of interdependencies among key components or elements for supervisory decision-making. The ability to visualise causal relationships, with a sense of direction and weighted magnitude of effects, provides supervisors with a data-driven basis for real-time interventions. This supports computational pedagogical modelling for improved supervisory quality (Yao & Lin, 2023; Bond et al., 2024). Furthermore, scenario analysis in Mental Modeler for FCMs helps predict supervisory outcomes, particularly those fostering supervisory effectiveness through more targeted dialogue and decision-making. This approach permits supervisors to tailor mentorship programmes and allocate resources effectively. This aligns with recent advancements advocating for AI and machine learning in academic decision-making within higher education (Hu et al., 2024; Kalnina et al., 2024). Andersson and Silver (2019) elaborated that FCMs can be used to formalise steps that connect and evaluate students' progress in research and studies in achieving their learning objectives.

However, despite their merits, the application of FCMs in postgraduate supervision may present certain challenges, namely: (i) the complexity of capturing qualitative supervisory interactions in a computational model remains a limitation; (ii) although the average outcomes from FCMs are reliable (Aminpour et al., 2021), there is a reliance on accurate expert-driven weight assignments for model calibration; and (iii) additionally, the dynamism of supervision and variations in supervisory styles across disciplines and cultural contexts may limit the generalisability of FCM-based frameworks (Sarmiento et al., 2024). These constraints highlight the need for individualised applications and further refinement and empirical validation of FCM applications in postgraduate supervision.

Interestingly, this study diverges from some prior literature in its assertion that research complexity should be actively reduced to enhance supervision effectiveness, especially when students find it extremely challenging to handle. However, conventional perspectives postulate that exposure to complex research environments fosters intellectual resilience (Wisker &

Robinson, 2016). The discrepancy may stem from differing conceptualisations of research complexity—where structured complexity benefits students, while unstructured, excessive difficulty may hinder progress. Therefore, future studies could further delineate these distinctions, refining the role of research complexity in postgraduate supervision models.

5. Conclusions

This chapter elucidates that fuzzy cognitive maps (FCMs) serve as a potent instrument for revealing the fundamental dynamics that govern postgraduate supervision. The model identifies student motivation as the most significant mediating component, bolstered by institutional support, expert knowledge, and supervisory involvement. It additionally uncovers that research complexity, financial support, mentor-mentee monitoring, and training function as critical drivers that influence outcomes such as student performance, stress levels, quality assurance, and research progress. Moreover, the findings indicate that the quality of supervision can be enhanced by augmenting motivational and supervisory enablers, while concurrently managing excessive research complexity, thus emphasising a distinction between productive and obstructive forms of complexity.

The utilisation of FCMs via Mental Modeller exemplifies how AI-supported computational modelling can enhance traditional supervisory practices by visualising causal structures, quantifying influence pathways, and facilitating predictive scenario analysis. This analytical capability furnishes supervisors with a data-driven foundation for timely, targeted interventions and more personalised mentorship strategies. By formalising stakeholder knowledge and integrating AI-aligned decision-support tools, institutions can improve supervisory consistency, bolster student resilience, and strengthen overall research outcomes.

5.1 Social and practical implications

The findings of this study convey significant social implications by highlighting the central role of student motivation, institutional support, and manageable research complexity in fostering healthier and more equitable postgraduate research environments. By recognising how these factors influence student stress, performance, and persistence, higher education institutions can better design support systems that alleviate mental health burdens, promote inclusive academic participation, and enhance students' overall well-being. Enhancing motivational supports and reducing unnecessary research barriers can also contribute to improved retention and completion rates, thereby advancing broader societal goals related to human capital development and knowledge production.

Practically, the integration of FCMs and AI-enabled modelling provides supervisors and higher education institutions with a structured, evidence-based tool for improving decision-making in real time. The ability to visualise causal pathways and test supervisory scenarios enables more targeted mentorship, efficient allocation of resources, and earlier identification of students who

may be at risk of delayed progress or disengagement. This approach supports more transparent supervision practices, strengthens quality assurance processes, and offers a scalable method for training supervisors. Therefore, higher education institutions adopting FCMs can enhance supervisory effectiveness, streamline postgraduate management, and embed data-driven strategies into routine academic practice.

5.2 Recommendations

To enhance postgraduate supervision, several targeted recommendations emerge from this study. First, student motivation should be bolstered through structured support programmes and mentorship initiatives designed to sustain engagement throughout the research process. Research complexity should be simplified by providing clear guidelines, phased research targets, and well-scaffolded methodologies to minimise cognitive overload. Mentor-mentee engagement must be strengthened through regular feedback sessions and monitoring mechanisms that ensure close supervision and timely interventions. Institutions of higher education should also expand postgraduate support services to improve access to funding, training opportunities, and administrative assistance. Increasing financial aid, through scholarships, student loans, research grants, and stipends, remains critical for alleviating the financial pressures that often impede student progress.

Additionally, institutions of higher education should implement short-course training in research methodology and academic writing to equip students with essential competencies, while standardising pre-viva preparation programmes to ensure students are adequately prepared for thesis defence. The inductive adoption of AI-based supervision models, such as FCMs, as part of supervisory practice that embeds evidence-based, AI-informed decision-making in postgraduate research management, can further enhance personalised progress tracking and intervention strategies. Integrating scenario-based planning using tools such as Mental Modeller will help supervisors anticipate challenges and optimise supervision strategies. Developing adaptive, discipline-sensitive supervision frameworks is also essential to accommodate variations in research complexity and cultural contexts. Finally, continuous empirical validation is necessary to refine and strengthen FCM-based supervision models to ensure their long-term relevance and applicability across academic disciplines.

6. Declarations

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