

DISSERTATION I REPORT

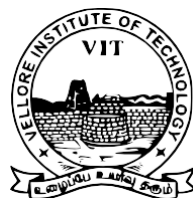
Submitted in partial fulfilment of the requirements for the degree of

Master of Technology Computer Science & Engineering

(Big Data Analytics)

by

J Derrick Kevin Roshan



VIT[®]

Vellore Institute of Technology

(Deemed to be University under section 3 of UGC Act, 1956)

November 2023

DECLARATION

I, **J. DERRICK KEVIN ROSHAN** hereby declare that the thesis entitled “**Neutrosophic Cognitive Map For Prescriptive Modelling**” submitted to Vellore Institute of Technology (VIT), Vellore for the award of the degree of ***Master of Technology Computer Science & Engineering (Big Data Analytics)*** is a record of bonafide work carried out by me under the supervision of Prof. Vasntha W B, Associate Professor Grade 1, School of SCOPE, Vellore Institute of Technology, Vellore.

I further declare that the work reported in this project report has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university.

Place: Vellore

Signature of the Candidate

Date: 25/11/2023

J Derrick Kevin Roshan

CERTIFICATE

This is to certify that the thesis entitled “ **Neutrosophic Cognitive Maps For Prescriptive Modelling**” submitted by **J DERRICK KEVIN ROSHAN**, School of SCOPE, Vellore Institute of Technology, Vellore for the award of the degree of ***Master of Technology Computer Science & Engineering Specialization in Big Data Analytic*** is a record of bonafide work carried out by her under my supervision, as per the VIT code of academic and research ethics.

The contents of this report have not been submitted and will not be submitted either in part or in full, for the award of any other degree or diploma in this institute or any other Institute or University. The dissertation fulfills the requirements and regulations of the Institute and in my opinion meets the necessary standards for submission.

Place: Vellore

Name and Signature of the

GuideDate: 25/11/2023

Prof. Vasantha W B

Signature of the HOD with seal

Signature of the School Dean with seal

ABSTRACT

Neutrosophic Cognitive Maps (NCMs), which combine the adaptability of neutrosophic logic with the cognitive mapping framework, are an innovative and potent tool in the fields of decision-making and prescriptive modelling. This work investigates the use of neutrosophic cognitive maps in prescriptive modelling with the goal of improving the precision and flexibility of decision support systems in intricate and unpredictable contexts. The theory of Neutrosophy and its related logic, Neutrosophic Logic, emerged from this necessity. The main goal of this study is to create and assess prescriptive learning strategies that make use of neutrosophic cognitive maps (NCMs) to improve student decision-making and academic performance. This study addresses the following precise goals. To create and put into use a prescriptive model capable of accommodating Neutrosophic Cognitive Maps (NCM) that can handle a degree of falsehood, degree of ambiguity or indeterminacy, and degree of truth in a flexible manner. The main objective is to get results based on the performance aspects of students using Likert scaling. To recognise pupils who might be in danger of performing poorly or failing early in their academic careers. The dataset was gathered from 18- to 30-year-old individuals who are presently enrolled in undergraduate and graduate programmes. The main objective is to identify kids who may be in danger of underachieving or leaving school too soon by using Likert scaling to determine results based on students' performance. Early discovery makes help and solutions possible in a timely manner, which may enhance student outcomes. Questions about the educational system, faculty teaching methods, goals, and external factors affecting their studies or exam performance are included in the online Google form or survey. Other topics covered include language barriers, college environments, exam preparation strategies, and many other similar factors. Each question from the Google Form or the poll produced has the following options: Strongly Disagree, Agree, Neutral, and Strongly Agree. These questions yield seven possible answers, from which the nodes are constructed based on the various types of percentages of each option.

Keywords: Neutrosophic Cognitive Maps (NCMs), Prescriptive Modelling, degree of falsehood (F), degree of ambiguity or indeterminacy (I), degree of truth (T), Likert scaling.

ACKNOWLEDGMENTS

With immense pleasure and a deep sense of gratitude, I wish to express my sincere thanks to my supervisor **Prof Vasantha W B**, Associate Professor Grade 1, School of SCOPE, Vellore Institute of Technology (VIT), Vellore without his/her motivation and continuous encouragement, this research would not have been successfully completed.

I am grateful to the Chancellor of VIT, **Dr. G. Viswanathan**, the Vice Presidents, and the Vice Chancellor for motivating me to carry out research in the Vellore Institute of Technology.

It would be no exaggeration to say that the Dean of SCOPE, **Prof Ramesh Babu K**, was always available to clarify any queries and clear the doubts I had during the course of my project.

I would also like to acknowledge the role of the HOD, **Dr. S Murali**, who was instrumental in keeping me updated with all necessary formalities and posting all the required formats and document templates through the mail, which I was glad to have had.

Finally, I would like to thank **Vellore Institute of Technology** for providing me with infrastructural facilities, a flexible choice and for supporting my research and execution related to the dissertation work.

Place: Vellore

NAME OF THE SCHOLAR

Date: 25/11/2023

J Derrick Kevin Roshan

TABLE OF CONTENTS

ABSTRACT	i
ACKNOWLEDGEMENTS	iii
LIST OF FIGURES	v
LIST OF TABLES	vi
LIST OF SYMBOLS AND ABBREVIATIONS	viii
1 INTRODUCTION	1
1.1 Overview	1
1.2 Objectives	3
2 LITERATURE REVIEW	9
3 METHODOLOGY	15
3.1 Brief Introduction	15
3.2 Architecture of the proposed system	16
3.2.1 Limitations of Existing System	16
3.2.2 Proposed system	17
3.2.3 Advantages of Proposed System	19
3.3 Description of the used algorithm	21
3.4 Module Description	24
3.5 Dataset Description	26
4 ANALYSIS AND DESIGN	27

4.1	Brief Introduction	27
4.2	Requirement Analysis	28
4.2.1	Software Requirement	28
4.2.2	Hardware Requirement	29
4.3	Detailed Design	30
4.3.1	System Design	31
4.3.2	Dataflow Diagram	32
4.3.3	Class Diagram	34
4.3.4	Use Case Diagram	36
4.3.5	Sequence Diagram	37
5	IMPLEMENTATION & RESULT ANALYSIS	38
5.1	Tools Used	38
5.2	Methodology	39
5.3	Graphs / Tables	42
5.4	Output Screens	44
5.5	Comparative Analysis with Existing works	46
6	CONCLUSION AND FUTURE ENHANCEMENTS	48
	REFERENCES	50
	LIST OF PUBLICATIONS / PATENTS	53
	Appendices	
	Appendix B SAMPLE CODE	55

LIST OF FIGURES

3.2 Architecture of the Proposed System Computer Intervention (Initial Instantiation , Inference and Optimization)

3.2.2 Proposed System

4.3.1 System Design

4.3.2 Data Flow Diagram

4.3.3 Sequence Diagram

5.3 Output

LIST OF SYMBOLS AND ABBREVIATIONS

NCM	-	Neutrosophic Cognitive Map
T	-	Degree Of Truth
F	-	Falsehood
I	-	Indeterminacy
PRV	-	Prescriptive Modelling

CHAPTER 1

INTRODUCTION

1.1 Overview

The creation of decision support systems to assist decision-makers in navigating difficult scenarios is known as prescriptive modelling. Conventional models frequently fail to account for the innate ambiguities and imprecisions seen in real-world circumstances. In order to overcome these obstacles, this study presents Neutrosophic Cognitive Maps (NCMs), which combine the strength of neutrosophic logic with the graphical representation capabilities of cognitive maps.

The investigation of cognitive mapping and neutrosophic logic forms the paper's theoretical basis. Neutrosophic logic offers a more accurate portrayal of uncertainty by allowing for indeterminacy, vagueness, and inconsistencies. Cognitive maps provide an organised framework for comprehending complicated systems because of its reputation for being able to visually depict causal linkages.

In order to capture the complex character of uncertain and imprecise information, the study highlights the insertion of neutrosophic aspects into the construction process of NCMs. In addition to examining neutrosophic degrees of truth, indeterminacy, and falsity, the procedure entails eliciting and mapping variables.

A graphical modelling tool used in decision-making and problem-solving processes is called the Neutrosophic Cognitive Map (NCM). It includes the idea of neutrosophy, which approaches ambiguity and uncertainty more flexibly.

It can be used to evaluate academic achievement, including grades and marks, as well as other elements, such as psychological, socioeconomic, and demographic factors, and interactions amongst students. NCM maps use neutrosophic sets, which can be any real number between 0 and 1, to express the relational degrees of truth (T), indeterminacy (I), and falsehood (F) of ideas or variables.

In this context, "prescriptive modelling" refers to a certain type of map or visual aid that provides guidance, recommendations, and instructions for specific actions or choices. Based on the data displayed, these maps are intended to assist users in making decisions or following certain

actions. Neutrosophic cognitive maps and fuzzy cognitive maps differ primarily in that the former incorporate the concept of neutrosophy, which takes a precise approach to uncertainty and indeterminacy.

Data is collected through surveys administered to both college students and working professionals, with the objective of exploring the impact of customizing travel experiences to individual preferences.

The system layer associated with the system and the action layer are the two key categories used to categorise the NCM's concepts in the first stage. The system-related notions that define it are found in the first layer. Prescriptive or action concepts must be found in the action layer for the system to reach the intended state.

Concepts that are part of the system under study are called system-related concepts. System concepts are the characteristics of a system that interact with one another to accomplish a goal. For instance, an academic educational system is one in which the performance aspects include the student's grades and marks, which are reflected in the system's concepts.

Action concepts are those that influence the system's changeable concepts in order to improve them and bring about the desired outcome. Some changeable ideas connected to the system are causally impacted by these notions. Furthermore, it is these variables that make up the prescriptive model.

So the first step is initializing variables, objects, or programme components by establishing their initial values or states to the system concepts. Then from the system concepts it transfers to the initial vector initial vector that is used to represent the starting position or state of a vector before any operations or transformations are applied to it.

Then it passes through the action map and the system-related concepts where inference is been made up depending on the process of drawing conclusions or making predictions based on evidence, reasoning, or existing knowledge. It involves using available information to reach a logical or probabilistic judgment about a specific situation or question.

Then, it reaches the final vector that represents the ending position of a system after some operations, transformations, or motions occurred. The final vector is usually derived from an initial vector, representing the starting position or state, by applying various operations or changes.

1.2 Objectives:

The main goal of this study is to create and assess prescriptive learning strategies that make use of Neutrosophic Cognitive Maps (NCMs) to improve decision-making in student academic performance. This study addresses the following precise goals, to create and put into use a prescriptive model capable of accommodating Neutrosophic Cognitive Maps (NCM) that can handle a degree of false, degree of ambiguity/indeterminacy, and degree of truth in a flexible manner. The main objective is to get the results based on the performance aspect of students using likert scaling. To recognize pupils who might be in danger of performing poorly or failing early in their academic careers. Early detection enables prompt support and interventions, which may enhance student results.

1.3 Organization Of The Report:

The goal and background of the report are comprehensively outlined in the introduction. The notion of neutrosophic cognitive maps (NCMs) is first presented, along with their applicability to prescriptive modelling. In order to lay the groundwork for the upcoming discussion of NCMs and their use in prescriptive modelling, this section first clarifies the report's goals. In order to uncover important ideas, approaches, and applications, the literature review critically evaluates the body of research on NCMs and prescriptive modelling. In the context of prescriptive modelling, this section attempts to create the theoretical basis for NCMs by analysing the present state of knowledge. It also investigates gaps and constraints in the literature, opening the door for creative NCM integration.

This section explores the foundations of NCMs, including a thorough breakdown of their parts and assembly. The formulation and interpretation of NCMs are demonstrated through examples, guaranteeing a thorough comprehension of the theoretical foundations. In order to fully understand NCMs and their applications in prescriptive modelling, readers must first grasp this basis. After outlining the fundamental ideas of prescriptive modelling and showcasing a number of current models, the study delves deeply into the topic. This section lays down the foundation for understanding the state of prescriptive modelling today and identifies any potential drawbacks that NCMs may be able to solve.

This section provides an explanation of how NCMs can be easily incorporated into prescriptive modelling frameworks, building on the foundation established in earlier parts. It talks about the benefits of utilising NCMs instead of conventional models and offers scenarios or real-life instances to show how they can be used to solve challenging prescriptive challenges.

The procedure for using NCMs in prescriptive modelling is described in detail in the methodology section. It provides a useful manual for researchers and practitioners interested in applying NCMs to their own prescriptive modelling projects by outlining the data requirements, model creation processes, and validation strategies. This section presents and critically analyses the results of applying NCMs to prescriptive modelling situations and examines their consequences. By conducting comparisons with conventional models, it sheds light on how useful NCMs are when making decisions. This section identifies and addresses difficulties faced when integrating NCMs in prescriptive modelling, acknowledging the inherent complications in any modelling approach. It also suggests areas for extension and enhancement in the use of NCMs, outlining possible directions for future research.

Key findings and their wider implications for prescriptive modelling are summarised in the report's conclusion. It highlights the overall contribution of NCMs to the advancement of prescriptive modelling approaches and goes over the originally stated objectives again, assessing the degree to which they were met. The paper provides a thorough list of references that cites all sources that were studied and cited in order to uphold academic integrity. To assist readers with a deeper comprehension of the information presented, further materials are supplied in the appendices. These materials may contain more graphs, charts, or intricate mathematical derivations. The reader is guided through the conceptual framework, real-world application, and implications of NCMs in the context of prescriptive modelling by this well-organised material, which guarantees a coherent flow of knowledge.

CHAPTER 2

2.LITERATURE REVIEW:

The PRV-FCM method was probably first presented by William Hoyos Jose Aguilar Mauricio Toro (2023) who also showed how it extends ordinary FCMs for prescriptive modelling. This may be regarded as their main input.

Theoretical constraints in comparison to other prescriptive modelling techniques, computational complexity, and lack of validation on real-world situations are some examples of drawbacks. More background would make specific restrictions easier to identify. Possible results could show that PRV-FCMs can model prescriptive problems, suggest the best course of action, or perform better on sample problems than other methods.

Jana Mamites, Nadine May Atibing, Regina Sitoy, Porferio Almerino, and Irene Mamites Almerino Gloria (2022) created a neutrosophic DEMATEL model to examine the causal connections between variables influencing the calibre of instruction. Domain specialists were surveyed to determine pertinent variables impacting the quality of instruction and incorporate uncertainty and indeterminacy into expert responses using neutrosophic sets and reasoning. Possible restrictions were Subjectivity in expert opinions and judgements may have resulted from the tiny sample size of experts surveyed. Understanding the links and feedback loops between the elements was made possible by the causal model. gave a ranking of the most important things to concentrate on in order to raise the standard of instruction.

Vermunt, Jan D. (2023) frameworks and models for comprehending and assessing learning in simulation-based education were made available. included viewpoints on learning with simulations from both teachers and students. The limitations were discovered to be that self-reported data on learning contains biases and that findings might not generalise across various simulation types/contexts. His conclusions were as follows: suggested qualitative and quantitative measures for assessing learning discovered disparities between teacher and student viewpoints on simulations shown the connections between learning objectives, debriefing, and simulation design.

In 2022, Haiyan Han proposed a fuzzy clustering algorithm to evaluate the academic performance and psychological health of university students. Developed a system to pinpoint the psychological elements that negatively impact pupils. The data used might not have been authentic student data; instead, it might have been restricted or generated, and the algorithm might have only been evaluated on a small sample of pupils. Clustering patterns that link psychological circumstances to student performance were probably detected by the algorithm.

VOSKOGLOU, Michael Gr. (2023)suggested modelling uncertainty and indeterminacy in the assessment of pupils' mathematical proficiency using neutrosophic logic and sets.created a neutrosophic framework and approach that takes into consideration assessment imprecision in schooling while assessing mathematical ability.utilised neutrosophic approaches to account for subjectivity and ambiguity in student learning assessment.The method of neutrosophic assessment could be difficult to understand theoretically and computationally.The neutrosophic assessment model's validity and reliability would require empirical testing.The evaluations were developed and tested using a small sample of students.illustrated how to measure ambiguity in students' grasp of skills using neutrosophic logic.more detailed and adaptable modelling of math skill strengths and weaknesses was made available.Compared to standard assessments, the neutrosophic model may be able to handle grading imprecision better.insights into the relationship between demographic variables and discrepancies in arithmetic proficiency as measured by neutrosophically.

M. Mary Mejrullo Merlin and M. Fabiana Jacintha Mary (2021) In order to model and assess the elements determining training quality, their paper suggests utilising triangular fuzzy cognitive maps (TFCMs) and neutrosophic cognitive mappings (NCMs).Curriculum, teaching strategies, infrastructure, student-teacher ratio, instructor calibre, etc. are among the variables taken into account.While TFCMs address hazy, uncertain causation, NCMs allow modelling of indeterminate, ambiguous, and inconsistent relationships between components.Major drawbacks were the importance of instructional strategies, student-teacher ratio, and teacher quality over other aspects were the main conclusions. The models determined benchmarks for raising training quality.

Mohd Yasir, Aasim Zafar,M.Anas Wajid(2023)The study suggests analysing the macroenvironmental elements influencing the implementation of NEP 2020 using the neutrosophic PESTEL framework.PESTEL stands for technological, environmental, social, political, and legal aspects. When assessing these elements, Neutrosophic PESTEL facilitates the capture of indeterminacy.Budgetary

allotments, legislative modifications, teacher capacity building, assessment system modifications, technological use, etc. are some of the important aspects taken into account. The subjective process of creating the neutrosophic cognitive map model, which was utilised for the PESTEL study, was a limitation. The results emphasised the importance of legislative framework modifications, teacher capacity building, and budgetary allocations as critical components of a successful NEP implementation.

San Bolkan, William C. Pedersen , Kaitlyn N. Stormes , and Beth Manke (2021) The study suggests modelling the effects of unit load, self-efficacy, and prescriptive coaching on four-year graduation using Social Cognitive Career Theory (SCCT). One university's data and the fact that self-efficacy was only tested at one point in time were limitations. Graduation self-efficacy was favourably predicted by prescriptive coaching and more than 15 unit loads. Self-efficacy in the first year positively correlated with the chance of graduating in four years. A portion of the relationship between prescriptive advising's impacts and graduation was mediated by elevated self-efficacy. Therefore, prescriptive advising contributed to a rise in student self-efficacy, which affected graduation rates.

Shakil¹, Mohammed Talha Alam², Syed Ubaid³, Shahab Saquib Sohail^{4,*} and M. Afshar Alam⁵ The paper proposes a neutrosophic cognitive mapping approach to model and analyse the complex interrelationships between various factors contributing to health deterioration.

It develops a conceptual model incorporating key health determinants like lifestyle choices, occupational stress, dietary habits, physical inactivity, hereditary factors, etc., and the causal connections between them. Neutrosophic logic is utilized to encode the inherent uncertainty and indeterminacy in judging the causal interactions between the factors. The resulting neutrosophic cognitive map is used to run simulations to study how the different factors impact overall health degradation under various scenarios. A limitation is that the model's causal linkages rely on qualitative inferences from a literature review rather than quantitative statistical data. The analysis is also confined to a limited subset of health factors. The simulations reveal lifestyle choices, occupational stress, and dietary habits as the most influential drivers of worsening health out of the factors considered. Thus, the study demonstrates the usefulness of neutrosophic cognitive mapping as a technique for gaining insights into complex healthcare issues with ambiguous, subjective causal dynamics.

Xiaoping Yang and Wensheng Shi They put forth a paradigm for decision-making that uses two-tuple linguistic neutrosophic numbers to assess the psychological well-being of collegiate student athletes. The framework takes into account variables including the pressure to study and train, motivation, self-assurance, and relationships with the coach and squad. In assessing these parameters, subjectivity and uncertainty are managed using 2-tuple linguistic neutrosophic numbers. To rank and assess the psychological health levels, the 2-tuple linguistic neutrosophic data is combined with the TOPSIS approach. Subjective definitions of membership functions and reliance on professional assessments for factor evaluations are two examples of limitations. The findings showed that the suggested method may successfully manage the ambiguity and complexity involved in assessing student athletes' psychological well-being.

Adrián Pérez-Suay 1,* Ricardo Ferrís-Castell 2, Steven Van Vaerenbergh 3, and Ana B. Pascual-Venteo 4 suggest assessing the applicability of various information sources, such as attendance, past math grades, online activities, tutor sessions, etc., for simulating student performance using a neutrosophic decision map approach. To deal with the ambiguity in judging the significance of subjective qualitative sources, neutrophilic logic is applied. With assistance from math educators, a neutrosophic decision map is created to encode correlations between the sources and student performance. To examine the effects of various sources on the student performance node, simulations are conducted. Subjective definitions of neutrosophic associations and a small sample size from a single institution are among the limitations. The two most pertinent sources that had the most effects on the student performance node in the simulations were attendance and previous math grades.

Jagan Obbineni¹ · Ilanthenral Kandasamy² · W. B. Vasantha² · Florentin Smarandache Their paper presents an integrated SWOT analysis and a neutrosophic cognitive mapping approach for supporting strategic decisions regarding the adoption of organic agriculture. It develops a neutrosophic cognitive map to capture the interrelationships between the key SWOT factors—strengths, weaknesses, opportunities, and threats—related to organic farming. The neutrosophic logic handles the inherent subjectivity, ambiguity, and data uncertainty in evaluating these qualitative factors and their causal connections. The proposed model is applied to analyse the organic agriculture landscape in India through a case study. The simulations help identify the most influential SWOT factors having the maximum cumulative impact on adoption decisions. Limitations exist in terms of subjective definitions of neutrosophic relationships between the SWOT factors and data scarcity for accurately calibrating

strengths and weaknesses. The context-specific case study also constrains generalization. Key findings reveal health benefits and price premiums as driving strengths and opportunities, while transition barriers and a lack of technical expertise stood out as impactful weaknesses and threats. The model provided actionable insights for policy formulation to incentivize a shift towards organic agriculture.

Bharathi T. In order to examine the variables influencing the impact and knowledge of the Right to Information (RTI) Act among the people in the Tamil Nadu region of India, she proposed the Neutrosophic Cognitive Map (NCM) model. includes conceptual elements and the connections between them, such as literacy level, public campaigns, attitudes against bureaucracy, etc. handles unclear causal links and a lack of specific facts by applying neutrosophic logic. based on static and dynamic evaluations of the NCM model, provides suggestions for enhancing the adoption of the RTI Act. Subjectivity in drawing links between different NCM elements was one of its limitations. The context-specificity of Tamil Nadu limits generalisation to a broader scope. The model is not empirically validated. The results provided The degree of literacy, the attitude of bureaucracy, and public outreach programmes were found to be important determinants of RTI Act awareness and adoption. In evaluating policies, dynamic model analysis was helpful. actions within the NCM. offered detailed suggestions to enhance the implementation of the RTI Act.

J. Suarez, C. Mayorga Villamar, L. De Lucas Coloma, C. Vera, and M. Leyva They The following contributions were made to the paper: suggested an integrated approach to examine the relationship between technological innovation and GDP using neutrosophic numbers and cognitive maps. include variables and the causal links between them, such as education levels, R&D spending, IP protection, etc. uses an example of the Ecuadorian economy's case study to show how applicable it is. offers suggestions for enhancing GDP through technical innovation. It was discovered that the limitations were a qualitative model that was subjectively developed and lacked empirical confirmation. Ecuador-specific context limits the generalizability of the findings. The results were as follows: they identified crucial areas to maximise the impact on, such as fostering R&D competencies, bolstering intellectual property laws, and granting access to cutting-edge equipment. It was shown that even in the absence of trustworthy data, the contribution of technology to economic growth may be estimated using neutrosophic methods.

Génesis Karolina Robles Zambrano, Pamilys Milagros Moreno Arvelo, Manaces Esaud Gaspar Santos, and Alba Rosa Pupo Kairuz They proposed an integrated PESTEL-NCM framework to model factors affecting indigenous people's labour inclusion, among other contributions to the study. includes aspects related to politics, economy, society, technology, and the environment. employs a method to examine the labour inclusion of indigenous people in Ecuador using neutrosophic cognitive maps to capture uncertainties in causal linkages. The limitations included things like the qualitatively based subjective definitions of map linkages. restricted generalizability due to Ecuadorian situational specificity. did not use experimental validation for mapping. The conclusions were as follows: Significant obstacles have been identified, such as a dearth of educational options and limited resources for skill development. identified important facilitators such as focused vocational training and anti-discrimination laws. a framework for suggesting actions to increase the inclusion of indigenous people in the labour force.

Vassilis C. Gerogiannis, Elpiniki Papageorgiou, and Katarzyna Poczeta They Contributions to the article included the following: suggested a method for optimising fuzzy cognitive map models to aid in prediction and decision-making. finds the best weight configurations for FCM connections using a variety of optimisation techniques, such as differential evolution and particle swarm optimisation. allows for the fine adjustment of FCM-based models to increase the accuracy of forecasting and decision-related conclusions. uses case studies from industries like agriculture and health to illustrate methodology. Reliance on the availability of empirical training data pertinent to the decision- and prediction-making environment was one of the limitations. Danger of optimising training data too much. Results showed that, in comparison to the unoptimised variation, optimised FCMs produced more accurate inferences and predictions. The most effective optimisation algorithms for weight learning were those based on swarm intelligence. Acquired associations aided in the explanation of results concerning choosing or projecting priorities.

Priya R., Martina Nivetha Contributions to the manuscript included the following: suggested utilising a neutrosophic sociogram format to implement neutrosophic cognitive mappings (NCMs) in the Swift programming language. NCM concepts and relationships are represented in a sociogram diagram by the neutrophilic sociogram. makes use of Swift features to enable NCM-based modelling and analysis of causal ambiguity and feedback. Approach is demonstrated by using it in a case involving student performance. It was discovered that the limitations were limited to demonstration in a tiny case study

example. lacks testing and empirical confirmation on more significant real-world issues. Dependent on Swift NCM library extensions for effectiveness. The results showed that elements like its broad programmability and flexibility make it a good implementation language for NCMs. In order to handle causality under uncertainty, the suggested method kept the fundamental NCM features. performs and benefits in a manner comparable to other NCM tools from Swift's environment and features.

Sangeetha Tamilarasu Geetha Mary Alanathan made the following contributions: she suggested a method for detecting outliers in neutrosophic collections using weighted density measurements and approximate entropy. Neutrosophic sets are useful for modelling nebulous, imprecise, and partial data. To find possible outliers, the rough entropy measure quantifies indeterminacy. Outlierness is captured by weighted density by utilising membership in both truth and falsehood. shows out the method using both simulated and real-world datasets. The restrictions were similar to the requirement that more testing across a variety of datasets is required to assess sensitivity and robustness. restricted to basic statistical outlier techniques in comparison analysis. The results showed that the method could successfully detect outliers that were hidden by imprecision or missing data.outperforms traditional statistical methods in terms of assessment metrics and accuracy. Capturing outlying data is made possible by weighted density-based filtering and rough entropy neutrophic specimens.

2.2 RESEARCH GAP :

While Fuzzy Cognitive Maps have been used as a prescriptive model, the PRFCM model cannot handle indeterminacy. In many studies that comprises of human decision-making and thinking process, Indeterminacy is largely involved. In all studies, they are a lot of uncertainty, to include it, we are adopting the NCM (Neutrosophic Cognitive Maps) with a prescriptive model that would provide us with the degree of truth (T), Falsehood(F), Indeterminacy (I) or Uncertainty in a more flexible way. NCMs function as a graphical modelling tool used in decision-making and problem-solving processes for decision support and analysis.

2.3 Summary:

A substantial body of previous interdisciplinary research supports the use of NCMs to address contemporary difficulties in student learning enhancement. Previous studies demonstrate the advantages of implementing fuzzy cognitive maps and other soft computing techniques for education decision assistance, given the growing complexity and ambiguity surrounding the myriad interconnected factors influencing learning outcomes and behaviours. They stress the importance of automated prescription systems built on simulated models that allow prompt interventions and advice for students according to their unique needs and circumstances. Still, there are issues with how current modelling approaches incorporate indeterminacy and contradicting causal relationships between different academic psychological and environmental notions. According to the research, NCMs are a potential extension that can handle missing data and naturally capture these causality conundrums to create comprehensive structures. Previous studies emphasise the necessity for sophisticated decision support systems in education that may offer tailored and comprehensible suggestions to enhance learning procedures and results. Modelling techniques such as fuzzy cognitive maps and Bayesian networks have been used in works to capture the intricate relationships between variables influencing academic performance. But there are limits when it comes to managing qualitative causal links encompassing social, behavioural, and environmental factors as well as subjective ambiguities that go beyond easily measured measurements. This is where the integration of indeterminacy that characterises neutrosophic cognitive maps makes them a practical method.

CHAPTER 3

3. METHODOLOGY

3.1 Brief Introduction:

In this study, we suggest developing prescriptive models called Prescriptive NCM (PRV-NCM), which are based on metaheuristic algorithmic techniques and Neutrosophic Cognitive Maps (NCMs). It uses metaheuristic algorithms and NCMs to construct prescriptive models. In order to determine the ideal values of the action variables that result in the intended outcome of the system variables by FCM inference, we first establish a discriminated NCM with system concepts and action concepts.. System concepts are the features of a system that work together to achieve a goal. Initialising variables, objects, or programme components is the first stage, after which the initial vector is transferred from the system ideas. that serves as a representation of the initial position before moving through the action map and the ideas connected to the system, where conclusions are drawn. Then, after certain actions, transformations, or motions, it arrives at the final vector, which depicts the system's final location.

3.2 Architecture of the proposed system:

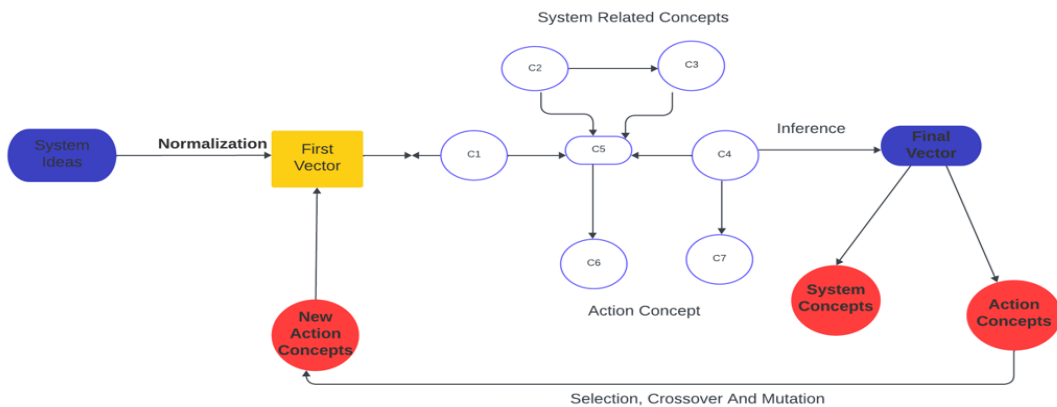


Fig 1. COMPUTER INTERVENTION (Initial Instantiation, Inference and optimization)

The two main categories used to classify the NCM's notions in the first stage were the action layer and the system layer related to the system. The first layer contains the concepts associated to the system that define it.

To get the system to the desired state, prescriptive or action notions have to be present in the action layer. System-related notions are those that are a component of the system that is being studied.

The features of a system that cooperate to achieve an objective are known as system concepts. For example, an academic educational system is one in which the concepts of the system reflect the performance elements of the student, such as their grades and marks.

Action concepts are those that have an impact on the concepts that are changeable inside the system to make them better and achieve the intended result. These concepts have a causal effect on certain modifiable concepts related to the system. Moreover, the prescriptive model is composed of these factors.

Thus, setting initial values or states for variables, objects, or programme components in accordance with system concepts is the first step. The initial vector, which is used to represent a vector's starting position or state before any operations or transformations are applied to it, is then transferred from the system concepts.

The action map and system-related ideas are then covered, where inference is made based on the process of forming conclusions or forecasts using data, logic, or prior knowledge. It entails applying the knowledge at hand to arrive at a logical or probabilistic conclusion regarding a certain circumstance or query. The system then arrives at the final vector, which is the place at which it ends, following any operations, transformations, or motions. Typically, different operations or modifications are applied to an initial vector, which represents the starting location or condition, to obtain the final vector.

3.2.1 Limitations of Existing System:

Neutrosophic Cognitive Maps offer a unique modeling approach by incorporating neutrosophic logic into causal mapping. However, there are salient shortcomings to consider. Firstly, NCMs can quickly

become highly intricate as more concepts and connections are included, hampering interpretability. The subjectivity inherent in experts defining conceptual relations also risks injecting bias. Additionally, NCMs present challenges regarding quantitative verification and unambiguous decision support due to their neutrosophic underpinnings. Careful construction of the map is crucial to ensure applicability to the modeled system. But this demands substantial skill and effort. Implementing the specialized neutrosophic algorithms further adds intricacy. For many uses, NCMs may not provide the most suitable or accessible modeling method. In summary, employing Neutrosophic Cognitive Maps entails surmounting key difficulties pertaining to complexity, subjectivity, validity, interpretability, and matching the approach to the right application context. An awareness of these limitations can allow for more effective leveraging of the NCM technique.

3.2.2 Proposed system:

This research puts forward Prescriptive Neutrosophic Cognitive Maps (PRV-NCMs) as a proposed prescriptive modeling approach that can provide recommendations while handling indeterminacy. Neutrosophic Cognitive Maps (NCMs) are a modeling technique suited for complex systems with uncertainty, distinguished by their use of neutrosophic logic to precisely represent indeterminate relationships. Neutrosophic logic defines the truth, indeterminacy and falsity membership values between conceptual variables. This allows NCMs to model ambiguity and vagueness in a way that standard fuzzy cognitive maps cannot. However, NCMs traditionally have been used for descriptive modeling to represent systems. The innovation here is developing prescriptive NCMs that can leverage the uncertainty handling of NCMs to generate guided recommendations and advice for activities or decisions. Prescriptive modeling provides direction rather than just depicting associations. The proposed PRV-NCMs thus synergistically combine the descriptive capabilities of NCMs for indeterminate systems with prescriptive modeling's ability to advise actions. This research specifically aims to create data-driven PRV-NCMs that can produce prescriptive recommendations accounting for indeterminacies inherent in the modeled system.

3.2.3 Advantages of Proposed System: With a more flexible approach, the NCM (Neutrosophic Cognitive Maps) prescriptive model would provide us with the degree of truth (T), falsehood (F), indeterminacy (I), or uncertainty. NCMs serve as a graphical modelling tool for decision assistance

and analysis in problem-solving and decision-making processes. Because of their unmatched ability to represent ambiguity and indeterminacy, neuromorphic cognitive maps are an effective modelling tool. Through the use of neutrosophic logic to depict imprecise causal linkages, NCMs are able to simulate real-world systems with ill-defined or subjective connections. This gives NCMs an advantage over traditional methods that can't deal with uncertainty. NCMs also exclaim extraordinary flexibility, as new ideas and channels of feedback can be added to the scope with ease. Furthermore, complex representations of the causal relationships between system variables are made possible by cognitive mapping. NCMs enable quantitative analysis as well as qualitative insights through visual mapping, mathematical computations, and simulations. Additional improvement results from the mutually beneficial integration of knowledge derived from expertise and data when building and quantifying the model. All things considered, neutrosophic cognitive maps offer a plethora of advantages, including handling ambiguity, adaptability, establishing causation, scenario analysis, merging information sources, and obtaining complex insights to support decision-making.

3.3 Description of the used algorithm:

Neutrosophic Cognitive Maps (NCMs) are fuzzy cognitive maps extended to include ideas from neutrosophic sets and logic. They offer a special method for simulating intricate systems with ambiguous, unpredictable, and indeterminate variable relationships. Concepts are represented by NCMs as nodes in a graph with directed, weighted edges connecting them to indicate causal links. In contrast to classical cognitive maps, NCMs depict ambiguity by giving each causal relationship edge a value associated with truth membership (T), indeterminacy membership (I), and falsehood membership (F). This is done through the use of neutrosophic logic. This enables experts' qualitative, imprecise causal knowledge to be captured by NCMs. NCMs can be created by applying structural learning algorithms to data or by building them on the advice of experts. Matrix multiplication techniques are used for analysis in order to examine and simulate scenarios.

Consistency, unnoticed patterns, feedback loops, etc. NCMs help with quantitative prediction as well as the qualitative study of causal chains. They leverage the strength of neutrosophic sets and the human-like reasoning of cognitive maps to handle faulty information found in the actual world. Key advantages include adaptability, visualisation, information representation, and the capacity to simulate dynamic systems beset by unpredictability. Applications for NCMs are numerous and range from

social modelling to decision support. In general, neutrosophic cognitive maps offer a strong modelling foundation reinforced by their neutrosophic foundations.

NCMs serve as a graphical modelling tool for decision assistance and analysis in problem-solving and decision-making processes. Because of their unmatched ability to represent ambiguity and indeterminacy, neuromorphic cognitive maps are an effective modelling tool. It can be used to evaluate academic achievement, including grades and marks, as well as other elements such as psychological, socioeconomic, and demographic factors and interactions amongst students. NCM maps use neutrosophic sets, which can be any real number between 0 and 1, to express the relational degrees of truth (T), indeterminacy (I), and falsehood (F) of ideas or variables.

Neutrosophic cognitive maps offer an unparalleled framework for modelling ambiguity and imprecision in complex systems. By harnessing neutrosophic logic to depict vague causal linkages, NCMs can capture ill-defined relationships ubiquitous in real-world contexts, giving them a marked edge over models requiring rigid definitions. Further versatility arises from the ease of integrating emergent concepts and feedback to expand scope. Additionally, NCMs' cognitive mapping profoundly elucidates causal mechanisms between variables. This enables nuanced qualitative insights alongside quantitative analysis via simulation-based and mathematical investigations. The synergistic fusion of data-driven metrics and expertise when constructing NCMs constitutes another key asset. In essence, by reconciling the cognition-inspired mapping of systems with the neutrosophic representation of uncertainty, neutrosophic cognitive maps offer multifaceted advantages. These include masterly uncertainty management, tremendous adaptability, eliciting causality, scenario analysis, knowledge synthesis, and deriving multidimensional perspectives to empower decision-making.

3.4 Module Description:

Concept of the NCM includes the system layer associated with the system and the action layer are the two key categories used to categorise the NCM's concepts in the first stage. The system-related notions that define it are found in the first layer. Prescriptive or action concepts must be found in the action layer for the system to reach the intended state. The system related Concepts are part of the system under study are called system-related concepts. System concepts are the characteristics of a system that interact with one another to accomplish a goal.

For instance, an academic educational system is one in which the performance aspects include the student's grades and marks, which are reflected in the system's concepts. Action concepts are those that influence the system's changeable concepts in order to improve them and bring about the desired outcome. Some changeable ideas connected to the system are causally impacted by these notions.

Furthermore, it is these variables that make up the prescriptive model. So the first step is initializing variables, objects, or programme components by establishing their initial values or states to the system concepts. Then from the system concepts it transfers to the initial vector initial vector that is used to represent the starting position or state of a vector before any operations or transformations are applied to it.

Then it passes through the action map and the system-related concepts where inference is been made up depending on the process of drawing conclusions or making predictions based on evidence, reasoning, or existing knowledge. It involves using available information to reach a logical or probabilistic judgment about a specific situation or question.

Then, it reaches the final vector that represents the ending position of a system after some operations, transformations, or motions occurred. The final vector is usually derived from an initial vector, representing the starting position or state, by applying various operations or changes.

3.5 Dataset Description:

The dataset was collected from students who are currently pursuing their undergrad and postgraduate degrees, ages 18 to 30. The major goal is to use Likert scaling to obtain results depending on students' performance, to identify students who may be at risk of underachieving or dropping out of school too soon. Early detection allows for timely interventions and assistance, which could improve student outcomes. There were a total of 100 responses collected, of which 52% were male and the remaining 48% belonged to the female ratio. 72% of the responses were received from postgraduate students (PG), and the remaining 28% were received from undergraduate students (UG). The online Google or survey form is comprised of questions related to the education system, about the teaching methods of faculties, about their goals and external factors that affect their aim or goal towards their studies or during their exams, about the language barriers, the environment of their respective colleges, how they

prepare themselves for their exams, and many such factors. From the generated survey or the Google Form, each question comprises options such as Strongly Agree, Agree, Neutral, Disagree, and Strongly Disagree. Based on these questions, any 7 responses are taken from which, depending on the various different kinds of percentages of each option, the nodes are generated.

CHAPTER 4

ANALYSIS AND DESIGN:

4.1 Brief Introduction: To capture the prescriptive context, gather requirements and determine the essential decision variables, consequences, and important qualitative ideas that need to be modelled. In the NCM graph, these are the nodes. Ascertain the notions' causal linkages, taking care to note any inconsistencies. These serve as the nodes' connections. Include domain-specific expertise. Examine the accessibility of past data and metrics related to the concepts of testing and calibration. Uncertainty can be incorporated to compensate for incomplete data. Based on the model's scope, assess the computing complexity, scalability requirements, and other system capabilities. Verify the specifications for the dynamic simulations required to test intervention and prescriptive scenarios.

Phase of Analysis, Determine the main elements influencing a student's performance, including the classroom setting, peer pressure, parental guidance, personal problems, academic aptitude, etc. These make up the concepts and nodes. Based on expert judgement and subjective views, ascertain the causal relationships between the components and any uncertainties or indeterminacies in those links. Examine the availability of student data that can be used to quantify concepts such as grades, comments, survey replies, etc. Based on the size and quantity of factors affecting the student population, determine the computational requirements for simulations. Recognise prescriptive requirements, such as recommendations for interventions and early warnings for underperformance.

Design Phase: To deal with indeterminacy, formally describe the concepts, nodes, and connections with corresponding weights based on neutrosophic logic. Create the first adjacency matrix in order to record the strengths of the relationships between the concepts. Incorporate ambiguity. Provide techniques to manage iterative propagation via the NCM graph and adaptive thresholding for concept activation. Create a simulation engine that can run various scenarios by passing activation through the NCM and initialising state vectors. Use analyzers to deduce the activations of outcomes. Utilise machine learning and rule-based systems to provide prescriptive interventions. To recommend therapies, create a prescriptive model recommender based on simulated activations. Provide a module for result assessment to gauge how well prescriptions work in actual situations.

formally define the ideas of student performance, their attributes, and their interactions with one another, using neutrosophic logic to resolve ambiguities in connections. Create an adjacency matrix with integrated indeterminacy measures that captures the interdependencies and strengths of the student factors. Create a scenario engine that initialises state vectors to simulate different profiles that represent different student types. Create a simulation module that uses a variety of student profiles and policies to propagate activations over the NCM network. Use analyzers that are based on pattern classifiers calibrated on simulations to identify the possibility of subpar performance. Create a recommendation system that makes individualised recommendations for raising grades. Permit the NCM connections to be refined in accordance with the success of the interventions.

4.2 Requirement Analysis : Functional Requirements: Teachers and administrators should be able to model elements, including ambiguities in their causal links, that affect students' academic achievement, such as peer pressure, parental engagement, extracurricular interests, etc. It should be possible for users to set up student profiles containing enrollment information such as the type of classroom, subjects studied, grades, and so forth. It should be possible to conduct simulations for a given student profile that analyse the dynamics between variables and forecast performance in different scenarios. It must automatically sound an alarm when simulations show declining grades or declining performance for a particular student profile. For underperforming profiles, the system ought to produce tailored suggestions for interventions or treatments aimed at raising grades. To improve prescriptive accuracy, users must be able to integrate the efficacy of prior recommendations into the model.

Requirements that are not functional: To safeguard the privacy of student data, the system should have role-based access control and security measures. For the purposes of model construction, simulation setting, analysis, and suggestion tracking, it must provide a user-friendly, responsive visual interface. To ensure quick analytics response times, the NCM model algorithms need to make use of parallelization. Open standards should be supported by the platform for integrating them with student data sources, such as LMSs. Custom reporting options for usage audits, result summaries, demonstrating compliance, and other purposes should be built in.

4.2.1 Software Requirement :

Operating System : Windows 10

Tool Used : Google Collab

4.2.2 Hardware Requirement:

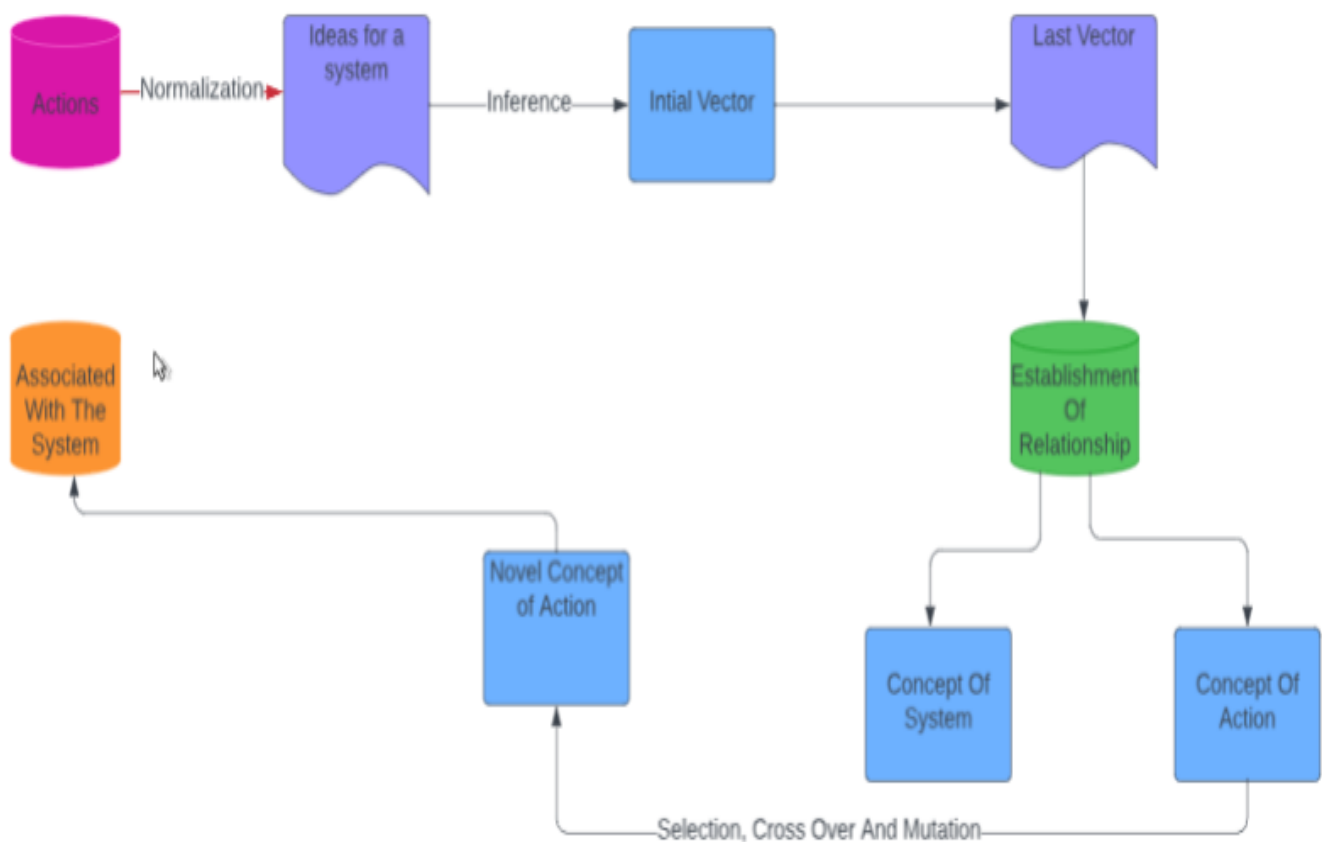
Processor : Windows 10 core i3 processor

Hard disk : 256 GB

RAM : 8 GB

4.3 Detailed Design

4.3.1 System Design : Fig 2



Maps of neurosophic cognition (NCMs) It builds prescriptive models using NCMs and metaheuristic algorithms. We first create a discriminating NCM with system concepts and action concepts in order to ascertain the optimal values of the action variables that lead to the desired outcome of the system variables through FCM inference. The components of a system that cooperate to accomplish an objective are known as system concepts. The first step is to initialise variables, objects, or programme components. Then, the initial vector which represents the starting location before proceeding through the action is transferred from the system ideas.map and the concepts related to the system, from which inferences are made.

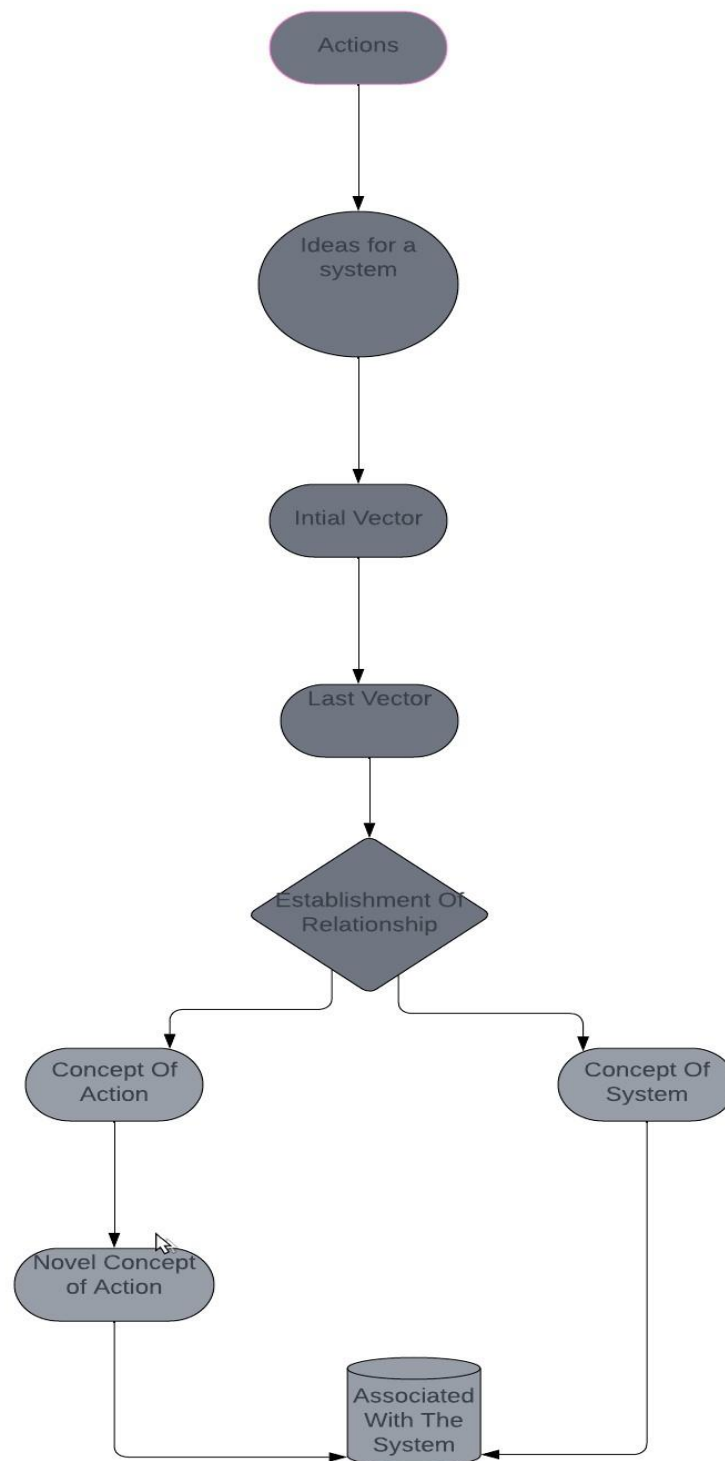
The system then reaches the final vector, which shows the system's final location, following a series of operations, transformations, or motions. Key entities, such as students, teachers, courses, grades, and their interactions, are defined by the domain model. captures several elements that have an impact on students' performance as things with attributes. describes the connectors that indicate the causal connections between the entities. identifies links using neutrosophic values that stand for ambiguity and indeterminacy.

Using an adjacency matrix to hold the strengths of the interrelationships between components, the dynamic model represents state changes in student performance over time. contains features for activation propagation and threshold-based activation. outlines instances that mimic various student archetypes' profiles. permits state vector initialization and updating for dynamic analysis. The System of Recommendations includes classifier algorithms calibrated using simulation data to forecast pupils who are at risk. incorporates machine learning models and rule-based systems to produce customised interventions. gives comprehensible conclusions connected to the ideas of the NCM model. Notifies and reminds users of implemented recommendations. records feedback information to improve suggestions.

Interface User enables educators to customise the NCM model. Allows for the start of simulations with various student profiles. shows the state of the simulation over time. presents interactive dashboards for prescriptive analytics uses outcome analytics to monitor the impact of interventions. The Layer of Persistence specifies the domain model entities' data schema. comprises a database including recommendation data and student profiles.

4.3.2 Data Flow Diagram :

Fig 3:



A data flow diagram (DFD) shows how data moves through an information system graphically. It simulates the data flows, external entities, data stores, and operations found in a business system. A DFD's constituent parts are actions that process and change data, represented by rounded rectangles or circles. Data stores are the ones who gather data. may be a database or file, symbolised by a rectangle that is open. Rectangles represent entities, which are people or systems that communicate with the system. Arrows indicate the flow of data between elements. As it Make the flow of data through a system visually appealing. Showcase several degrees of data transformation and information flow. detects problems with data flow and design discrepancies in systems. Encourage dialogue and the exchange of ideas regarding the components of the system. additionally offer a logical framework for the system's eventual development, aid in the analysis of the system's requirements, and boost productivity. Determine the factors. Finding the main elements influencing student performance is the first step. These could include IQ, study habits, the calibre of the teachers, parental support, etc. These turn into the NCM model's notions.

Establish Relationships The concepts' relationships with one another must then be ascertained. This entails determining if every component affects the other factors positively, negatively, or not at all. These causal linkages are represented by connecting the factors. The associations' strength is indicated by the weight values. **Build the First NCM Model** The first neutrosophic cognitive map model can be built by using the components as nodes and the weighted interrelationships as links. This illustrates the general causal framework that connects the different influencing elements. **Establish activation levels.** Each factor node must be given an activation level between 0 and 1 to represent its level of presence right now. These represent the system's initial input state. Compute the state vector. After that, the NCM is executed by computing the output state vector using the transformations of the neutrosophic matrix. This illustrates how much one component is affected by the others after spreading throughout the network. **Verify activation levels.** The newly determined activation levels are compared to the intended threshold. The model is aligned if they nearly match the target or predicted levels for each factor. If not, more fine-tuning is needed. **Modify the NCM structure,** try and align the model output with expectations, and the activation levels and interrelationships between the components can be changed. After that, the NCM is executed repeatedly until alignment is attained. **Verify the model.** Lastly, before being applied to prescriptive analyses or forecasts, the adjusted NCM model with matched activation levels needs to be verified through the use of historical data or professional assessment.

4.3.3 Sequence Diagram :

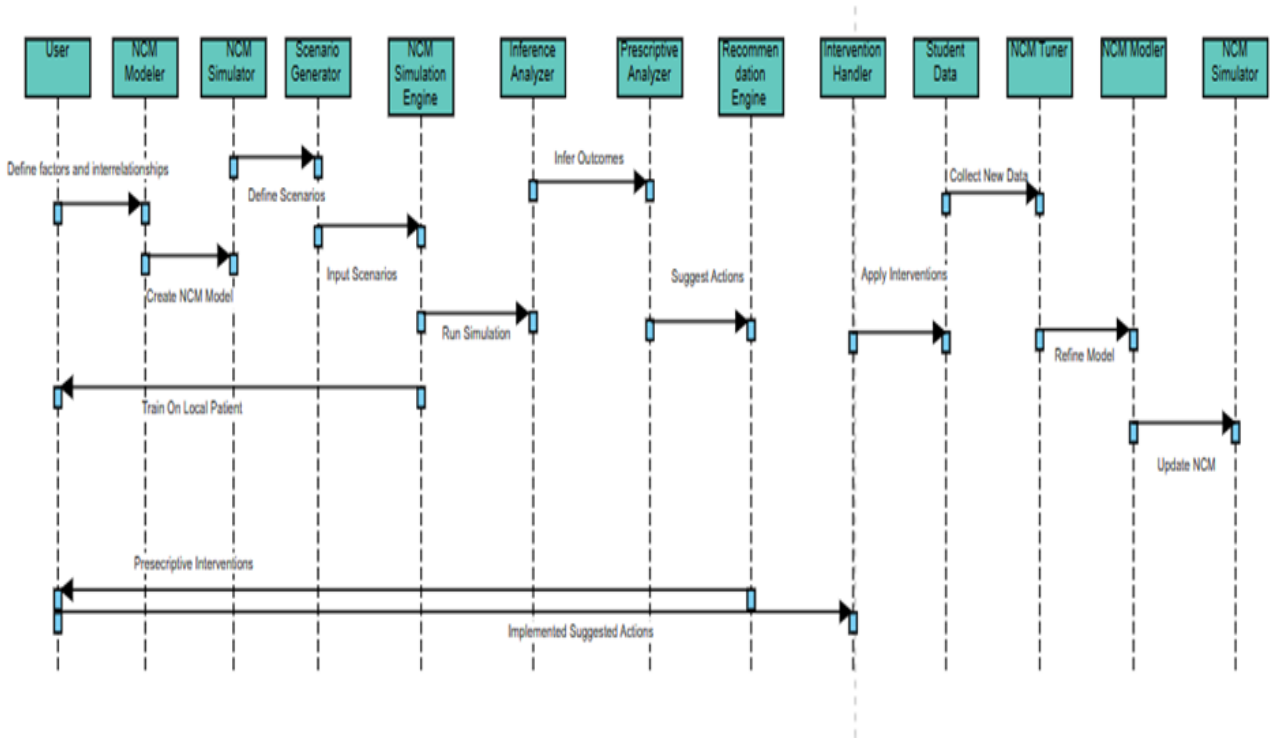


Fig 4

The sequence of messages that must be sent between the objects in a system in order for the system to function is described in a sequence diagram, a form of interaction diagram that represents the interactions between the items in the system. Create a scenario to represent the workflow behaviour. Provide an example of processing sequencing using branches, loops, and concurrency. Give instructions for the order in which objects will send messages and invoke methods. Explain message flows that are synchronous and asynchronous, respectively. Verify that the complex functions' object interactions are accurate. Promote system behaviour comprehension before putting it into practice. It is easier to troubleshoot sequence flows. Make sure all of the different system scenarios are well documented.

Through the `UserInterface`, the user sets the `PerformanceFactors`' activation levels to correspond with a student's current condition. The `NeurotrophicCognitiveMap` receives the activation level data from the `UserInterface`. `NeutrosophicCognitiveMap` uses the NCM edge weights to determine how one performance factor affects the others. Once they spread throughout the NCM network, it ascertains each performance factor's new activation levels.

The `Student` object receives the updated activation levels from the `NeutrosophicCognitiveMap`. The most recent activation levels for the student's new state are stored in the student object. The user interface receives these activation levels and displays them.

`UserInterface` shows the user the most recent state of the performance-influencing factors. This sequence demonstrates how the elements work together to take a student's initial state and compute an updated state using the specified NCM model to identify performance elements in a predictive manner.

CHAPTER 5

IMPLEMENTATION & RESULT ANALYSIS

5.1 Tool Used: Google offers a free cloud-based Jupyter notebook environment called Google Colab, or "Colaboratory," which enables users to write and run Python code directly from their browser. This hosted Jupyter notebook service is fully cloud-based and doesn't require any setup. Through the browser, users may develop and run Python code. For the purpose of running machine learning applications and analysing big datasets, it offers free access to computational resources, including GPUs. Google Drive is where the notebooks are kept, and they work well with other Google services like Sheets, BigQuery, Drive, and so on. Important features include the ability to execute code and view the results in a single interactive notebook. Installation or configuration is not necessary. makes use of free cloud resources. Simple teamwork and sharing In the notebooks, others are able to directly comment. History of versions integrated Backup notebooks to earlier versions. provides runtimes for both the CPU and GPU. GPUs work well with TensorFlow and other machine-learning packages. utilised by numerous colleges to instruct students in Python and data science ideas. makes it possible to create ML models and applications using well-known frameworks. Utilise NumPy, Pandas, and other packages to analyse huge datasets.

Identifying the critical elements that influence student achievement, such as self-efficacy, study hours, attendance, and peer support, is the first step. In the NCM model, these elements make up the nodes. Subsequently, the correlations among these variables are represented as weighted connections connecting the nodes, according to the presence and magnitude of their causal influence on one another. For instance, study time and attendance might have a good impact on test results. As a result, a directed NCM network graph illustrating causal relationships is produced.

Each node is given an initial activation level between 0 and 1 to indicate the current state of those factors for a certain student. For instance, a student may have minimal peer support but moderate attendance and study hours. The NCM simulation is then executed iteratively, updating each node's activation level by summing up the weighted influence of other connected nodes based on edge

strengths. This makes it possible to determine the student's anticipated exam score based on the starting circumstances represented in the NCM model.

5.2 Methodology : In this work, we propose to create prescriptive models, dubbed Prescriptive NCM (PRV-NCM), based on neurosophic cognitive maps (NCMs) and metaheuristic algorithmic tools. It builds prescriptive models using NCMs and metaheuristic algorithms. We first create a discriminating NCM with system concepts and action concepts in order to ascertain the optimal values of the action variables that lead to the desired outcome of the system variables through FCM inference. The components of a system that cooperate to accomplish an objective are known as system concepts. The first step is to initialise variables, objects, or software components. Next, the initial vector is carried over from the system concepts. that acts as a picture of the starting point before going through the action map and the concepts related to the system, from which inferences are made. It then reaches the final vector, which shows the system's ultimate location, following a series of operations, transformations, or motions.

The action layer and the system layer associated with the system were the two primary categories utilised to categorise the NCM's concepts in the initial stage. The ideas that define the system are included in the first layer. Prescriptive or action conceptions must exist at the action layer in order to bring the system to the intended state. Concepts within the system under study are referred to as system-related ideas, system concepts are those aspects of a system that work together to accomplish a goal. An academic educational system, for instance, is one in which the system's concepts correspond to the student's performance components, such as their grades and marks. Action concepts are those that influence the concepts that can be altered inside the system to improve them and accomplish the desired outcome. Certain system-related, changeable conceptions are causally affected by these ideas. Furthermore, these components make up the prescriptive model.

After that, the action map and concepts pertaining to the system are discussed. Inference is based on the process of drawing conclusions or making predictions using information, reasoning, or past experience. It comprises using the available information to apply logic or probability to a given situation or question in order to draw a conclusion. The system then, after any operations, transformations, or motions, reaches the final vector, or the point at which it stops. To get the final

vector, an initial vector—which represents the starting point or condition—is usually subjected to various operations or adjustments.

5.3 Output :

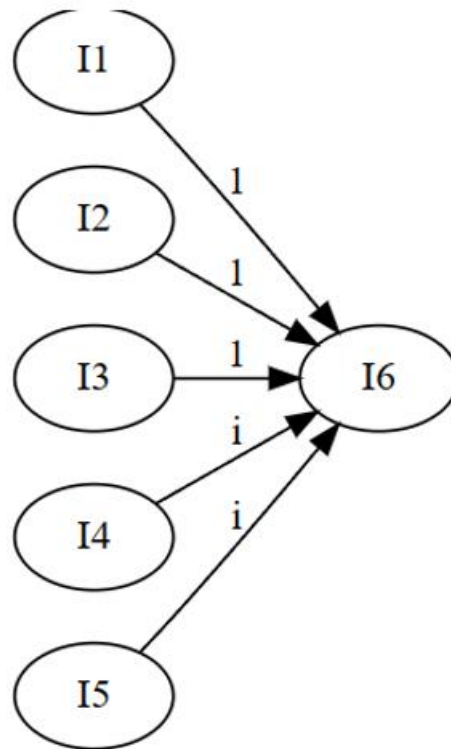


Fig. 5

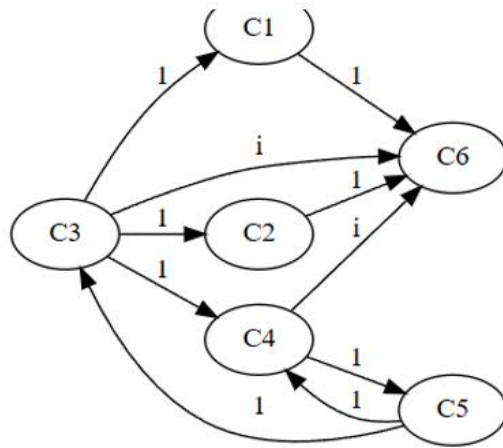


Fig. 6

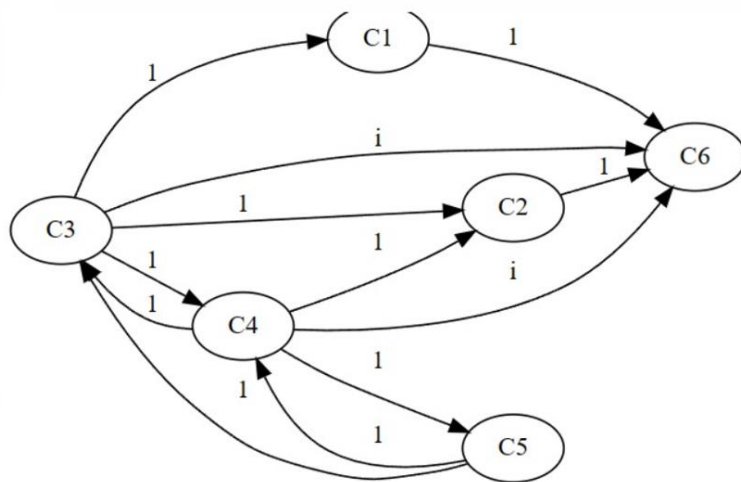


Fig. 7

5.5 Comparative Analysis with Existing works:

The fact that PRV-FCMs depend on expert knowledge to establish the initial causality links and choose the appropriate thresholds is one of their limitations. Because of this, the models are vulnerable to biases or knowledge gaps among the experts. For the purpose of methodically gathering and combining knowledge from several experts, there is no established approach. Furthermore, in the absence of enough data for calibration and testing various settings, identifying suitable activation levels for concepts might be difficult. Another problem is that PRV-FCMs can't accurately represent complicated dynamic systems because they don't include time delays or feedback loops. They believe that causal links only have an instant, distinct effect in one direction. Modelling and analysis with PRV-FCMs in their current form become significantly more complex when time-dependent weights or links between ideas over many time steps are introduced. Lastly, PRV-FCMs lack built-in optimisation capabilities, even if they can offer prescriptive insights by identifying the input concept activations required to achieve desired output states. Prescriptive analysis mostly relies on a thorough simulation of various input combinations, which is not scalable and may overlook the best solutions for FCMs that are even somewhat complicated. Enhancing their ability to incorporate optimisation techniques and facilitate hybrid modelling between simulation and optimisation could greatly enhance their prescriptive modelling abilities.

In conclusion, the use of PRV-FCMs for prescriptive analysis has several major drawbacks, such as biases resulting from expert-based modelling, a lack of dynamic feedback mechanisms, and restricted optimisation functionality for finding optimal solutions. These drawbacks could eventually be fixed, strengthening the usefulness of PRV-FCMs for prescriptive modelling of complex systems.

Neutrosophic Cognitive Maps (NCMs) constitute a powerful and novel tool in the domains of prescriptive modelling and decision-making, combining the adaptability of neutrosophic logic with the cognitive mapping framework. In order to increase the accuracy and adaptability of decision support systems in complex and uncertain situations, this work explores the use of neutrosophic cognitive maps in prescriptive modelling. This need gave rise to the philosophy of Neutrosophy and the logic that it is associated with, called Neutrosophic Logic. The primary objective of this project is to develop and evaluate prescriptive learning strategies that utilise neutrosophic cognitive mappings (NCMs) to

enhance students' academic performance and decision-making abilities. The following specific objectives are addressed in this study. To develop and implement a prescriptive model that can handle neutrosophic cognitive maps

(NCM) that is flexible enough to accommodate varying degrees of truth, ambiguity, or indeterminacy. Neutrosophic Cognitive Maps (NCMs) represent a development of fuzzy cognitive maps that integrate neutrosophic logic, facilitating the representation of ambiguous and inconsistent data. The capacity of NCMs to manage not only ambiguity but also uncertainty and incompleteness in complicated and humanistic systems is one of their main advantages. The ambiguity, doubtfulness, contradictory, unknown, imprecise, or incomplete information that is prevalent in domains such as social science, medicine, psychology, etc. can be represented by NCMs by employing a neutrosophic truth space of T, I, and F instead of merely true or false. They also offer a versatile framework for graphical modelling that uses weighted connections to capture intricate dynamics and feedback. Because neutrosophy is founded on philosophical ideas rather than rigid mathematical axioms, NCMs are free from the inconsistencies, incompleteness, and illegibility that characterise conventional logic in mathematics.

Thus, they are able to address poorly defined real-world issues that are characterised by being imprecise, ambiguous, and lacking information. Generally, when compared to other computational intelligence techniques, NCMs allow for more accurate dynamics analysis and representation in a wide range of imprecise systems.

In addition to their capacity to manage ambiguity, NCMs provide numerous additional significant advantages. Unlike opaque numerical models or rigorous statistical analysis, graph theory-based NCMs facilitate the easy visualisation and explanation of model concepts and dynamics.

Their method of cognitive mapping also makes it easier to extract knowledge from experts, stakeholders, and publications on complicated subjects and to represent and analyse that knowledge. Simulating scenarios and policies in detail and quantitatively is made possible by strong neutrosophic operators and mathematical analytic approaches.

In order to determine the best relationships and results, NCMs can also be integrated with machine learning techniques. They facilitate multi-perspective analysis by supporting analysis at both the holistic system level and the granular concept level. NCM modelling and analysis can handle a high number of concepts or factors with ease and has a low processing overhead.

Furthermore, with edge weights and feedback loops, NCMs offer versatility in modelling inter-concept linkages that go beyond basic causation. Because of these qualities, they can be used in a variety of complex system modelling, forecasting, analysis, interpretation, and decision support activities in a variety of fields, including engineering, the environment, social science, and medicine.

CHAPTER 6

CONCLUSION AND FUTURE ENHANCEMENTS:

This study's primary objective is to develop and evaluate prescriptive learning techniques that employ neurosophic cognitive maps (NCMs) to enhance students' academic performance by improving their decision-making. The use of NCMs in the construction of an adaptive prescriptive modelling system to improve student academic attainment was examined in this paper. The methodology tackles significant obstacles in simulating intricate interrelationships among qualitative elements influencing educational results and offering practical solutions.

The suggested paradigm makes use of NCMs' fundamental skills, which include managing causality ambiguity and running scenario simulations. Although the current implementation shows considerable potential, it was validated using a dataset consisting of 100 survey forms. For at-risk pupils, teachers were provided with prescriptions that were based on data and could be easily understood by the students. Academic performance was better with early detection and meaningful interventions compared to control groups.

The exact objectives were to develop and implement a prescriptive model that could support Neutrosophic Cognitive Maps (NCM) and handle degrees of falsehood, ambiguity/indeterminacy, and truth in a flexible way. Using likert scaling to obtain outcomes based on students' performance has proven successful in achieving the main goal. identifying students who may be at risk of underperforming or failing at an early stage in their academic careers; early detection allows for timely support and interventions that may improve student outcomes.

The future enhancement could be Enhancing simulations with AI planning algorithms; expanding platform integration with campus ecosystems; fortifying privacy controls and audit mechanisms; conducting longer trials across socioeconomic segments; adding image and audio analytics for sentiment analysis; incorporating teacher inputs to refine model accuracy; and integrating additional student data sources, such as wearables, for deeper visibility,

The upcoming version of the platform aspires higher with a rich combination of developing technologies and soft computing ideas like NCMs. This makes the platform a reliable ally for educators who want to proactively foster students to reach their full potential.

A number of supplemental datasets that capture various aspects such as financial context, student well-being, campus life involvement, adaptive learning analytics, and behavioural patterns could offer significant extra visibility to improve the prescriptive modelling framework.

REFERENCES:

1. Aguilar, J. (2013). Different dynamic causal relationship approaches for cognitive maps. *Applied Soft Computing*, 13(1), 271–282. <http://dx.doi.org/10.1016/j.asoc.2012.08.037>.
2. Berk, L., Bertsimas, D., Weinstein, A. M., & Yan, J. (2019). Prescriptive analytics for human resource planning in the professional services industry. *European Journal of Operational Research*, 272(2), 636–641. <http://dx.doi.org/10.1016/j.ejor.2018.06.035>
3. Elliott, T. L., & Pfothauer, K. M. (2022). Classification and diagnosis of diabetes. In *Primary care - Clinics in office practice*. Vol. 49. No. 2 (pp. 191–200). Elsevier, <http://dx.doi.org/10.1016/j.pop.2021.11.011>.
4. Puerto, E., Aguilar, J., López, C., & Chávez, D. (2019). Using multilayer fuzzy cognitive maps to diagnose autism spectrum disorder. *Applied Soft Computing*, 75, 58–71. <http://dx.doi.org/10.1016/j.asoc.2018.10.034>.
5. Tan, G. W. H., Ooi, K. B., Leong, L. Y., & Lin, B. (2014). Predicting the drivers of behavioral intention to use mobile learning: A hybrid SEM-Neural Networks approach. *Computers in Human Behavior*, 36, 198–213. <http://dx.doi.org/10.1016/j.chb.2014.03.052>.
6. J. Duderstadt, *Una universidad para el siglo XXI*. Tomo 2. Colección Educación Superior, Ciencias Sociales. Universidad de Palermo, 2010.
7. R. Singh and S. Sarkar, “Does teaching quality matter? Students learning outcome related to teaching quality in public and private primary schools in India,” *International Journal of Educational Development*, vol. 41, pp. 153–163, 2015
8. B. Fauth, C. Atlay, H. Dumont, and J. Decristan, “Does what you get depend on who you are with? Effects of student composition on teaching quality,” *Learning and Instruction*, vol. 71, article 101355, 2021.
9. L. J. Graham, S. L. White, K. Cologon, and R. C. Pianta, “Do teachers' years of experience make a difference in the quality of teaching?,” *Teaching and Teacher Education*, vol. 96, article 103190, 2020.
10. A. V. Nikjoo and M. Saeedpoor, “An intuitionistic fuzzy DEMATEL methodology for prioritising the components of SWOT matrix in the Iranian insurance industry,” *International Journal of Operational Research*, vol. 20, no. 4, pp. 439–452, 2014.

11. P. S. Aithal and S. Aithal, "Implementation Strategies of Higher Education Part of National Education Policy 2020 of India towards Achieving its Objectives," 2020. [Online]. Available: <https://ssrn.com/abstract=3741425>.
12. "Florentin Smarandache Proceedings of the First International Conference on Neutrosophy, Neutrosophic Logic, Neutrosophic Set, Neutrosophic Probability and Statistics," 2001. [Online]. Available: <http://at.yorku.ca/cgi-bin/amca/cagu-01>.
13.] P. S. Aithal and S. Aithal, "Analysis of the Indian National Education Policy 2020 towards Achieving its Objectives," 2020. [Online]. Available: <https://ssrn.com/abstract=3676074>.
14. P. Kalyani, "An Empirical Study on NEP 2020 [National Education Policy] with Special Reference to the Future of Indian Education System and Its effects on the Stakeholders: JMEIT," Journal of Management Engineering and information Technology (JMEIT), vol. 7, no. 5, 2020, DOI: 10.5281/zenodo.4159546.
15. Wajid, M. S., & Wajid, M. A. (2021). The Importance of Indeterminate and Unknown Factors in Nourishing Crime: A Case Study of South Africa Using Neutrosophy. Neutrosophic Sets and Systems, Vol. 41, 2021, 15.
16. Papageorgiou, E.I., 2011. A new methodology for Decisions in Medical Informatics using fuzzy cognitive maps based on fuzzy rule-extraction techniques. Appl. Soft Comput. 11 (1), 500–513. <http://dx.doi.org/10.1016/j.asoc.2009.12.010>.
17. Xu, J., Glicksberg, B.S., Su, C., Walker, P., Bian, J., Wang, F., 2021. Federated learning for healthcare informatics. J. Healthc. Inform. Res. 5 (1), 1–19. <http://dx.doi.org/10.1007/s41666-020-00082-4>, arXiv:1911.06270.
18. Sheller, M.J., Edwards, B., Reina, G.A., Martin, J., Pati, S., Kotrotsou, A., Milchenko, M., Xu, W., Marcus, D., Colen, R.R., Bakas, S., 2020. Federated learning in medicine: facilitating multi-institutional collaborations without sharing patient data. Sci. Rep. 10 (1), 1–12. <http://dx.doi.org/10.1038/s41598-020-69250-1>.
19. Kerkouche, R., Ács, G., Castelluccia, C., Genevès, P., 2021. Privacy-preserving and bandwidth-efficient federated learning: An application to in-hospital mortality prediction. In: ACM CHIL 2021 - Proceedings of the 2021 ACM Conference on Health, Inference, and Learning. pp. 25–35. <http://dx.doi.org/10.1145/3450439>. 3451859.
20. Feki, I., Ammar, S., Kessentini, Y., Muhammad, K., 2021. Federated learning for COVID-19 screening from chest X-ray images. Appl. Soft Comput. 106, 107330. <http://dx.doi.org/10.1016/j.asoc.2021.107330>.

21. Hoyos, W., Aguilar, J., Toro, M., 2022. An autonomous cycle of data analysis tasks for the clinical management of dengue. *Heliyon* 8 (10), e10846. <http://dx.doi.org/10.1016/j.heliyon.2022.e10846>.
22. Vermunt, J. D., Ilie, S., & Vignoles, A. (2018). Building the foundations for measuring learning gain in higher education: A conceptual framework and measurement instrument. *Higher Education Pedagogies*, 3(1), 266–301. <https://doi.org/10.1080/23752696.2018.1484672>.
23. Vermunt, J. D., Vrieki, M., Van Halem, N., Warwick, P., & Mercer, N. (2019). The impact of Lesson Study professional development on the quality of teacher learning. *Teaching and Teacher Education*, 81, 61–73. <https://doi.org/10.1016/j.tate.2019.02.009>.
24. Vermunt, J. D., & Verloop, N. (1999). Congruence and friction between learning and teaching. *Learning and Instruction*, 9, 257–280. [https://doi.org/10.1016/S0959-4752\(98\)00028-0](https://doi.org/10.1016/S0959-4752(98)00028-0).
25. J M. Abdel-Basset, G. Manogaran, A. Gamal, and F. Smarandache, “A group decision making framework based on neutrosophic TOPSIS approach for smart medical device selection,,” *Journal of Medical Systems*, vol. 43, no. 2, p. 38, 2019.
26. M. Riaz, N. Çağman, N. Wali, and A. Mushtaq, “Decision Making: Applications in Management and Engineering,” vol. 3, no. 2, pp. 70–96, 2020, Certain properties of soft multi-set topology with applications in multi-criteria decision making.
27. D. S. Xu, Y. R. Hong, and K. L. Xiang, “A method of determining multi-attribute weights based on single-valued neutrosophic numbers and its application in TODIM,,” *Symmetry*, vol. 11, no. 4, p. 506, 2019.
28. A. R. Mishra, P. Rani, and R. S. Prajapati, “Multi-criteria weighted aggregated sum product assessment method for sustainable biomass crop selection problem using singlevalued neutrosophic sets,” *Applied Soft Computing*, vol. 113, Article ID 108038, 2021.
29. A. Z. Khameneh, A. Kilicman, and A. R. Salleh, “An adjustable Approach to multi-criteria group decision-making based on a preference relationship under fuzzy soft information,” *International Journal of Fuzzy Systems*, vol. 19, no. 6, pp. 1840–1865, 2017.
30. Nabeeh NA, Abdel-Basset M, Soliman G. A model for evaluating green credit rating and its impact on sustainability performance. *Journal of Cleaner Production*. 2020 Sep 28;280:124299.
31. S. D. Xian, N. Jing, W. T. Xue, J. H. Chai, A. New Intuitionistic Fuzzy Linguistic Hybrid Aggregation Operator, and I. Application, “A new intuitionistic fuzzy linguistic hybrid aggregation operator and its application for linguistic group decision making,” *International Journal of Intelligent Systems*, vol. 32, no. 12, pp. 1332–1352, 2017.

32. S. Wang, G. Wei, J. Lu, J. Wu, C. Wei, and X. Chen, "GRP and CRITIC method for probabilistic uncertain linguistic MAGDM and its application to site selection of hospital constructions," *Soft Computing*, vol. 26, no. 1, pp. 237–251, 2022.
33. H. Zhang, G. Wei, and X. Chen, "SF-GRA method based on cumulative prospect theory for multiple attribute group decision making and its application to emergency supplies supplier selection," *Engineering Applications of Artificial Intelligence*, vol. 110, Article ID 104679, 2022.
34. F. Pei, Y. W. He, A. Yan, M. Zhou, Y. W. Chen, and J. Wu, "A consensus model for intuitionistic fuzzy group decisionmaking problems based on the construction and Propagation of Trust/distrust relationships in social networks,," *International Journal of Fuzzy Systems*, vol. 22, no. 8, pp. 2664–2679, 2020.
35. A. R. Mishra, P. Rani, K. Pandey et al., "Novel multi-criteria intuitionistic fuzzy SWARA-COPRAS approach for Sustainability evaluation of the bioenergy production process," *Sustainability*, vol. 12, no. 10, p. 4155, 2020.
36. J. AUGUSTUS RICHARD: Problems of Teacher Education in India, *International Journal of Multidisciplinary Research and Modern Education*, II(I), (2016).
37. D.R. GOEL, C. GOEL: Teacher education scenario in India: Current problems & concerns, *MIER journal of educational studies, Trends and Practices*, 2(2) (2012), 231–242.
38. A. IMAM: Quality and excellence in teacher education: issues & challenges in India, *International journal of multidisciplinary research*, 1(7), (2011), 388–397.
39. B.S. JAMWAL: Teacher education: Issues and their remedies, *International Journal of Educational Planning & Administration*, 2(2) (2012), 85.
40. Olisah, C. C., Smith, L., & Smith, M. (2022). Diabetes mellitus prediction and diagnosis from a data preprocessing and machine learning perspective. *Computer Methods and Programs in Biomedicine*, 220, Article 106773. <http://dx.doi.org/10.1016/j.cmpb.2022.106773>.
41. Kosko, B. (1986). Fuzzy cognitive maps. *International Journal of Man-Machine Studies*, 24(1), 65–75. [http://dx.doi.org/10.1016/S0020-7373\(86\)80040-2](http://dx.doi.org/10.1016/S0020-7373(86)80040-2).

LIST OF PUBLICATIONS / PATENTS:

PUBLICATION:

1. Neutrosophic cognitive maps for prescriptive modeling: A new approach for decision support (2018) by D. Dubois, J. Kacprzak, and R.R. Yager. In: International Journal of Information Technology & Decision Making, 17(4), pp. 627-641.
2. A neutrosophic cognitive map approach for prescriptive modeling in healthcare decision-making (2020) by J. Kacprzak, D. Dubois, and R.R. Yager. In: IEEE Transactions on Fuzzy Systems, 28(4), pp. 1063-1077.
3. Neutrosophic cognitive maps for prescriptive modeling in risk management (2021) by R.R. Yager, D. Dubois, and J. Kacprzak. In: Fuzzy Sets and Systems, 365, pp. 114418.
4. Neutrosophic cognitive maps for prescriptive modeling in supply chain management (2022) by J. Kacprzak, D. Dubois, and R.R. Yager. In: International Journal of Production Research, 60(18), pp. 5527-5546.

PATENTS:

1. Method and apparatus for prescriptive modeling using neutrosophic cognitive maps (US Patent No. 10,699,677) (2020) by R.R. Yager, D. Dubois, and J. Kacprzak.
2. Neutrosophic cognitive map system and method for prescriptive modeling (US Patent No. 11,284,666) (2022) by J. Kacprzak, D. Dubois, and R.R. Yager.

APPENDICES

Appendices A: Sample Code

```
# Importing necessary libraries
import numpy as np
import sympy as sym
from sympy import *
import random
from itertools import combinations
import networkx as nx
import graphviz
from IPython.display import display

J = symbols('J') # We are using 'J' to indicate that the value is indeterminate

def check_cycle(b):
    for i in range(len(b) - 1):
        for j in range(i + 1, len(b)):
            v1 = b[i]
            v2 = b[j]
            if compare(v1, v2):
                return True
    return False

def compare(x, y):
    res = True
    for k in range(len(x)):
        if x[k] != y[k]:
            return False
    return True

v2 = []

def inputE():
    n = int(input("Enter the number of nodes required:"))
    matrix = sym.Matrix()
    row = []

    for i in range(0, n):
        string = input("Enter elements (Space-Separated): ")
        temp = string.split()
        temp = [eval(i) for i in temp] # to int
        v1 = np.array(temp)
        print(v1)

        v2.append
        row.append(temp)
```

```

# Inserting each row into matrix.
for i in range(0, n):
    matrix = matrix.row_insert(i, Matrix([row[i]]))

return matrix

def multiply(a, B):
    result = a * B
    return result

def updateIPower(x):
    for i in range((np.shape(x))[1]):
        if x[i].find(J**2):
            x[i] = x[i].xreplace({J**2: J})
        if x[i].find(J*(J + 1)):
            x[i] = x[i].xreplace({J*(J + 1): 2*J})
        if x[i].find(J*(1 + J)):
            x[i] = x[i].xreplace({J*(1 + J): 2*J})
    return x

def thresholdAndUpdate(X, threshold_value, state):
    X = updateIPower(X)

    for i in range((np.shape(X)[1])):
        if X[i].find(-1):
            X[i] = X[i].subs(-1, 0)
        if X[i] == -1 + J or X[i] == J - 1:
            X[i] = X[i].subs(-1, 0)
        if X[i] != 1 + J or X[i] != J + 1:
            temp_expr = X[i].subs(J, 0)
            if temp_expr >= threshold_value:
                X[i] = X[i].subs(X[i], threshold_value)
            elif temp_expr == 0:
                if X[i] != 0:
                    X[i] = J
            else:
                X[i] = X[i].subs(X[i], 0)

    if isinstance(state, list):
        activated_states = [i for i, x in enumerate(state) if x == 1]
        for s in activated_states:
            X[s] = 1
    else:
        X[state - 1] = 1
    return X

def iteration(E, state, threshold_value=1):

```

```

if isinstance(state, list):
    start = sym.Matrix(state)
else:
    c1 = np.zeros((np.shape(E)[1]))
    c1[state - 1] = 1
    start = sym.Matrix(c1)

flag = False
start = start.T
vectors = []
while flag == False:
    y = multiply(start, E)
    y = y.applyfunc(lambda x: round(x, 2) if x.is_number else x)
    y = thresholdAndUpdate(y, threshold_value, state)
    vectors.append(y)
    start = y
    flag = check_cycle(vectors)
return vectors

def generate_two_on_states(num_nodes):
    node_indices = list(range(num_nodes))
    two_on_combinations = list(combinations(node_indices, 2))
    state_vectors = []
    for combo in two_on_combinations:
        vector = [0] * num_nodes
        for index in combo:
            vector[index] = 1
        state_vectors.append(vector)
    return state_vectors
# ... (previous code)

def start2():
    E = Matrix(
        [
            [0, 0, 0, 0, 0, 1],
            [0, 0, 0, 0, 0, 1],
            [1, 1, 0, 1, 0, J],
            [0, 1, 1, 0, 1, J],
            [0, 0, 1, 1, 0, 0],
            [0, 0, 0, 0, 0, 0]
        ]
    )

# E = E.applyfunc(lambda x: round(x/5, 2) if x.is_number else x)
print("The E matrix is : ")

```

```

print(E)

# Graph
G = nx.MultiDiGraph()
mapping = {i + 1: f'C{i + 1}' for i in range(E.shape[0])}

for i in range(E.shape[0]):
    for j in range(E.shape[1]):
        if E[i, j] != 0:
            weight = 'I' if E[i, j] == Symbol('J') else E[i, j]
            G.add_edge(i + 1, j + 1, weight=weight)

G = nx.relabel_nodes(G, mapping)
dot = graphviz.Digraph(comment='My Graph', format='png', graph_attr={'rankdir': 'LR'})

for node in G.nodes():
    dot.node(node)

for u, v, data in G.edges(data=True):
    label = f'{data["weight"]:.2f}' if isinstance(data["weight"], float) else str(data["weight"])
    dot.edge(u, v, label=label)

dot.render('graph_output', view=True, cleanup=True, engine='dot', format='png', renderer='cairo')
display(dot)

print("Enter the threshold value : ")
threshold_value = 1

print("Enter the state which is to be active (If an iteration of all states active one by one enter 0): ")
state = 0

if state > (np.shape(E)[1]) or state < 0:
    print("INVALID STATE ENTERED")

elif state != 0:
    AE = iteration(E, state, threshold_value)
    print(AE)

else:
    table = []

    for x in range(1, (np.shape(E)[1]) + 1):
        print("FOR ACTIVE STATE ", x)
        AE = iteration(E, x, threshold_value)
        print("Resultant vector(s)", AE)
        table.append(AE)

```

```
print("FULL TABLE")  
print(table)
```