UNIVERSITY OF KWAZULU-NATAL

SCHOOL OF MATHEMATICS, STATISTICS & COMPUTER SCIENCE

Application of ELECTRE Algorithms in Ontology Selection

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Abstract

The field of artificial intelligence (AI) is expanding at a rapid pace. Ontology and the field of ontological engineering is an invaluable component of AI, as it provides AI the ability to capture and express complex knowledge and data in a form that encourages computation, inference, reasoning, and dissemination. Accordingly, the research and applications of ontology is becoming increasingly widespread in recent years. However, due to the complexity involved with ontological engineering, it is encouraged that users reuse existing ontologies as opposed to creating ontologies *de novo*. This in itself has a huge disadvantage as the task of selecting appropriate ontologies for reuse is complex as engineers and users may find it difficult to analyse and comprehend ontologies. It is therefore crucial that techniques and methods be developed in order to reduce the complexity of ontology selection for reuse.

Essentially, ontology selection is a Multi-Criteria Decision-Making (MCDM) problem, as there are multiple ontologies to choose from whilst considering multiple criteria. However, there has been little usage of MCDM methods in solving the problem of selecting ontologies for reuse. Therefore, in order to tackle this problem, this study looks to a prominent branch of MCDM, known as the ELimination Et. Choix Traduisant la RÉalite (ELECTRE). ELECTRE is a family of decision-making algorithms that model and provide decision support for complex decisions comprising many alternatives with many characteristics or attributes. The ELECTRE algorithms are extremely powerful and they have been applied successfully in a myriad of domains, however, they have only been studied to a minimal degree with regards to ontology ranking and selection. In this study the ELECTRE algorithms were applied to aid in the selection of ontologies for reuse, particularly, three applications of ELECTRE were studied.

The first application focused on ranking ontologies according to their complexity metrics. The ELECTRE I, II, III, and IV models were applied to rank a dataset of 200 ontologies from the BioPortal Repository, with 13 complexity metrics used as attributes. Secondly, the ELECTRE Tri model was applied to classify the 200 ontologies into three classes according to their complexity metrics. A preference-disaggregation approach was taken, and a genetic algorithm was designed to infer the thresholds and parameters for the ELECTRE Tri model. In the third application a novel ELECTRE model was developed, named ZPLTS-ELECTRE II, where the concept of Z-Probabilistic Linguistic Term Set (ZPLTS) was combined with the traditional ELECTRE II algorithm. The ZPLTS-ELECTRE II model enables multiple decision-makers to evaluate ontologies (group decision-making), as well as the ability to use natural language to provide their evaluations. The model was applied to rank 9 ontologies according to five complexity metrics and five qualitative usability metrics. The results of all three applications were analysed, compared, and contrasted, in order to understand the applicability and effectiveness of the ELECTRE algorithms for the task of selecting ontologies for reuse. These results constitute interesting perspectives and insights for the selection and reuse of ontologies.

Preface

The research contained in this dissertation was completed by Ameeth Sooklall under the supervision of Dr Jean Vincent Fonou-Dombeu, based in the School of Mathematics, Statistics & Computer Science, within the College of Agriculture, Engineering & Science. The study was performed at the University of KwaZulu-Natal, Pietermaritzburg Campus, between the months of January and November of the year 2022.

The contents of this study are original and have not been submitted in any form to another university or tertiary institution. The results reported are due to investigations by the candidate, and where use has been made of the work of others, it is duly acknowledged in the text.

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Declaration - Supervisor

As the candidates supervisor, I agree to the submission of this dissertation.

Dr Jean Vincent Fonou-Dombeu

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Declaration 1 - Plagiarism

I, Ameeth SOOKLALL, declare that

1. The research reported in this thesis, except where otherwise indicated, is my original research.
2. This thesis has not been submitted for any degree or examination at any other university.
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Declaration 2 - Publications

The research study has led to the following publications, the details of which are presented as follows.

1. A. Sooklall and J. V. Fonou-Dombeu, "**A Multi-Criteria Decision-Making Approach to Ontology Ranking with ELECTRE II and IV**," *International Conference on Artificial Intelligence, Big Data, Computing and Data Communication Systems (icABCD)*, Durban, South Africa, August 4-5, 2022. https://doi.org/10.1109/icABCD54961.2022.9856133

2. A. Sooklall and J. V. Fonou-Dombeu, "**Application of Genetic Algorithm for Complexity Metrics-Based Classification of Ontologies with ELECTRE Tri**," *Pan-African Artificial Intelligence and Smart Systems Conference (PAN-AFRICAN AIS 2022)*, Dakar, Senegal, November 2-4, 2022. (Accepted)

3. A. Sooklall and J. V. Fonou-Dombeu, "**Comparative Ranking of Ontologies with ELECTRE Family of Multi-Criteria Decision-Making Algorithms**," *The 24th International Conference on Information Integration and Web Intelligence (iiWAS2022)*, Bari, Italy, November 28-30, 2022. (Accepted)

4. A. Sooklall and J. V. Fonou-Dombeu, "**An Enhanced ELECTRE II Method for Multi-Attribute Ontology Ranking with Z-Numbers and Probabilistic Linguistic Term Set**," *Future Internet*, 2022, 14(10), pp. 271-307. https://doi.org/10.3390/fi14100271

Signed:

"Imagination is everything. It is the preview of life's coming attractions."

Albert Einstein

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I am grateful to my supervisor, Dr Jean Vincent Fonou-Dombeu, for his patience, guidance, encouragement, and most importantly, his invaluable knowledge.

I am especially grateful to my parents for their unwavering support, encouragement, tolerance, and guidance throughout my journey thus far, and to come.

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List of Abbreviations

AB	**A**verage **B**readth
AD	**A**verage **D**epth
ADO	**A**lzheimer's **D**isease **O**ntology
AI	**A**rtificial **I**ntelligence
ANP	**A**verage **N**umber of **P**aths
AP	**A**verage **P**opulation
AR	**A**ttribute **R**ichness
ARC	**A**bsolute **R**oot **C**ardinality
ALC	**A**bsolute **L**eaf **C**ardinality
BCGO	**B**reast **C**ancer **G**rading **O**ntology
CLO	**C**ell **L**ine **O**ntology
CMPO	**C**ellular **M**icroscopy **P**henotype **O**ntology
COGAT	**Cog**nitive **At**las Ontology
COGPO	**Cog**nitive **P**aradigm **O**ntology
CoP	**C**larity **of** **P**urpose
COPD	**C**hronic **O**bstruction **P**ulmonary **D**isease
CR	**C**lass **R**ichness
CRITIC	**Cr**iteria **I**mportance **T**hrough **I**ntercriteria **C**orrelation
DoCA	**D**escription **o**f **C**oncepts using **A**ttributes
DoCRNL	**D**escription **o**f **C**oncepts and **R**elations in **N**atural **L**anguage
EHR	**E**lectronic **H**ealth **R**ecord
ER	**E**quivalence **R**atio
ELECTRE	**El**imination **e**t **C**hoix **T**raduisant la **Re**alité
EPISEM	**Epi**lepsy **Sem**iology Ontology
HFLTS	**H**esitant **F**uzzy **L**inguistic **T**erm **S**et
IR	**I**nheritance **R**ichness
ISO	**I**nternational **O**rganization for **S**tandardization
LTS	**L**inguistic **T**erm **S**et
MADM	**M**ulti-**A**ttribute **D**ecision-**M**aking
MB	**M**aximal **B**readth
MCDM	**M**ulti-**C**riteria **D**ecision-**M**aking
MD	**M**aximal **D**epth
MF	**M**ental **F**unctioning Ontology
MHC	**M**ajor **H**istocompatibility **C**omplex
ML	**M**achine **L**earning
NCCN	**N**ational **C**omprehensive **C**ancer **N**etwork

NIFCELL	**N**euroscience **I**nformation **F**ramework **Cell** Ontology
OAE	**O**ntology of **A**dverse **E**vents
OBI	**O**ntology for **B**iomedical **I**nvestigations
OCMR	**O**ntology of **C**hinese **M**edicine for **R**heumatism
OCVDAE	**O**ntology of **C**ardio**v**ascular **D**rug **A**dverse **E**vents
OHMI	**O**ntology of **H**ost-**M**icrobe **I**nteractions
OHPI	**O**ntology of **H**ost-**P**athogen **I**nteractions
OMP	**O**ntology of **M**icrobial **P**henotypes
ONL-MSA	**O**nto**N**euro**L**og-**M**ental **S**tate **A**ssessment Ontology
OSM	**O**ntologia de **S**aúde **M**ental
PAV	**P**rovenance, **A**uthoring and **V**ersioning
PCO	**P**opulation and **C**ommunity **O**ntology
PDO	**P**arkinson's **D**isease **O**ntology
PLTS	**P**robabilistic **L**inguistic **T**erm **S**et
PTS	**P**athway **T**erminology **S**ystem
QoSD	**Q**uality **o**f **S**ubclass **Definition**
RR	**R**elationship **R**ichness
UoC	**U**nderstandability **o**f **C**onceptualization
UML	**U**nified **M**odelling **L**anguage
VO	**V**accine **O**ntology
ZPLTS-ELECTRE II	**Z**-**P**robabilistic **L**inguistic **T**erm **S**et-**ELECTRE II**

Chapter 1

Introduction and Background

1.1 Introduction

In this chapter the background and motivation for the research is presented, followed by a definition of the problem that this dissertation aims to solve. Thereafter, the aims and objectives of the research are enumerated, along with the research methodology. The chapter is then concluded by providing a succinct outline of the dissertation, together with the major contributions of this work.

1.2 Background and Motivation

An ontology, defined as an explicit specification of a shared conceptualization [1], is one of the core components facilitating knowledge representation and reasoning in artificial intelligence (AI). Ontologies describe different domains of discourse, and they play an integral role in expressing complex knowledge in a form that enables reasoning, dissemination, and computation. It is one of the prominent solutions to managing and advancing knowledge and information overload.

However, the excellence of ontology is not without its issues and challenges. Ontologies are extremely complex structures, which make them highly arduous to architect and develop. A wide range of expertise is required for the research and development of an ontology. Accordingly, this process can be very time consuming and costly. Whilst some projects may require a new ontology to be developed *de novo*, for most projects there is already a massive number of ontologies available to choose from. It is therefore more efficient to reuse [2] an existing ontology, possibly with some modifications, as opposed to developing new ontologies. However, users are often unable to comprehend and analyze existing ontologies. It is therefore evident that there is an urgent need for the development of techniques and methods for selecting and evaluating ontologies in order for their reuse. This is however, not at all an easy task. There are so many different perspectives and approaches one could consider when selecting an ontology, and therefore a one-size-fits-all approach cannot be taken.

While there have been attempts to solve the problem of selecting pertinent ontologies for reuse [3–7], these generally comprised of users expressing their requirements in search terms or other forms, and the similarity between the users requirements and the ontologies are determined – assigning the most similar ontologies to higher ranks, and the dissimilar ontologies to lower ranks. This has been effective to an extent, however there is also a need to evaluate and rank ontologies according to their characteristics. To this extent, there has been a small amount of research regarding ranking of ontologies in terms of their quality and attributes.

To evaluate the quality of ontologies researchers have developed different approaches. One effective approach is through the use of complexity metrics [8]. The complexity metrics allow a user to gain insights as to the design and complexity of ontologies. While there has been a vast amount of research related to ontology ranking [3–7], there has been only limited works regarding the ranking of ontologies based on their complexity metrics. This is concerning as it is crucial that techniques be developed that enable thorough evaluation of ontologies from multi-dimensional perspectives.

Another important perspective to consider when selecting ontologies for reuse is the extent to which the ontologies meet and satisfy the requirements of the users. In this regards, researchers have developed usability metrics to evaluate ontologies [9, 10]. There does, however, exist a gap between the characteristics of ontologies and their usability. In essence, an ontology may have well-performing characteristics and features, but it may align poorly with the requirements of a user. On the other hand, an ontology may have weak features, but may align very strongly with the requirements of the user. Therefore, to evaluate ontologies for reuse it is vital that both perspectives be considered.

Essentially, ontology ranking is a Multi-Criteria Decision-Making (MCDM) problem, as there are multiple ontologies to choose from whilst considering multiple criteria. Concernedly, there has been extremely little research that has applied decision-making techniques to enhance ontology ranking and selection. The field of MCDM is a mature and well-studied one, and it has proven successful in a variety of domains. Arguably one of the most widely used MCDM methods in research is the ELECTRE method [11]. ELECTRE has been developed over five decades ago, yet it continues to be applied in cutting-edge research and developments today [11]. The original ELECTRE method was developed as a tool for selecting a subset of non-dominated alternatives from a set of alternatives, named as ELECTRE I [12]. In subsequent years, researchers have enhanced ELECTRE I, leading to the development of the ELECTRE II [13], III [14], IV [15], and Tri [16] versions. Unfortunately, till date there exists an extremely small amount of research where ELECTRE was applied to the field of ontology engineering.

1.3 Problem Statement

The field of artificial intelligence is expanding at a rapid pace [17]. Knowledge representation plays a vital role in enabling and enhancing AI. A key technology for knowledge representation is ontology and ontological engineering. Currently, there exists a myriad of ontologies available online [18, 19] that users and engineers can reuse, but the process of selecting the applicable and pertinent ontologies can be problematic, and therefore ontology selection for reuse remains a challenging task in ontology engineering. Essentially, ontology selection is a Multi-Criteria Decision-Making (MCDM) problem, as there are multiple ontologies to choose from whilst considering multiple criteria. Despite this, very few studies have applied MCDM methods for the task of ontology selection [20–23]. This study explores the applicability of a prominent branch of MCDM, the ELECTRE family [24], for the task of selecting appropriate ontologies for reuse.

1.4 Research Aims and Objectives

The aim of this study seeks to apply the ELECTRE family of Multi-Criteria Decision-Making algorithms to address the issue of ontology selection for reuse. This is achieved through the following objectives:

- To investigate existing ELECTRE algorithms.
- To investigate existing studies that have implemented ELECTRE algorithms to rank ontologies to aid their selection.
- To gather the complexity metrics of existing ontologies.
- To implement and compare the performances of existing ELECTRE algorithms in ontology selection.
- To experiment the use of ELECTRE in the task of ontology classification.
- To investigate the use of both quantitative and qualitative metrics in ontology ranking and selection.

1.5 Research Methodology

The data was obtained by performing a comprehensive literature search and review on the pertinent topics. An emphasis was placed on obtaining data and studies from credible sources, including journal articles, conference proceedings, and books. The data comprising 200 biomedical ontologies was downloaded from the BioPortal ontology repository [18]. Thereafter, the 13 complexity metrics were calculated for each ontology using the online platform called OntoMetrics [25]. The full dataset can be found in Appendices A and B.

The experiments for all 3 applications were implemented using the Java[1] programming language with the IntelliJ[2] integrated development environment. The implementation of all methods and algorithms were performed using an object-oriented programming[3] approach with the use of classes and objects. The class diagrams and process flow diagrams for the software implementation of the algorithms are presented in Chapter 4.1.

The results of the first application, that is, ranking of the ontologies with ELECTRE, were analyzed and the top and bottom 15 ontologies ranked by each method were explored. The results were thereafter compared with the use of statistical rank correlation techniques, namely, the Spearman's Rho correlation coefficient [26], the Weighted Spearman's Rho coefficient [27], the Top-Down correlation [28], and the WS coefficient [29].

[1]https://www.java.com/en/
[2]https://www.jetbrains.com/idea/
[3]https://en.wikipedia.org/wiki/Object-oriented_programming

The results of the second application, that is, the classification of the ontologies using ELECTRE Tri, were analyzed and compared to the ranking results obtained from the first application. The classification results were also compared with the complexity metrics of the ontologies.

The third and final application saw the development of the novel ZPLTS-ELECTRE II model. In order to evaluate the model, it was applied to rank a dataset of mental-health ontologies. The results were then analyzed and compared with the results of the traditional ELECTRE II [13] and the PLTS ELECTRE II [30] methods. Furthermore, the ZPLTS-ELECTRE II method was compared with other fuzzy ELECTRE II enhancements, and with other MCDM methods that have been applied for ontology ranking.

1.6 Outline of Dissertation

The dissertation is organized as follows:

- Chapter 2 - Literature Review. This chapter provides an in-depth overview of the existing literature and research works pertaining to the study. An emphasis is placed on ontology and the ontology reuse problem, as well as multi-criteria decision-making with ELECTRE.
- Chapter 3 - Methods and Materials. This chapter provides a thorough presentation of the models and methods used in the study, along with their preliminaries. This chapter also presents the materials used in the three main experiments proposed and implemented in this research.
- Chapter 4 - Software Architecture and Design. The design and architecture of the software that was developed to implement the ELECTRE algorithms in this study are presented in this chapter.
- Chapter 5 - Experimental Results and Discussion. This chapter provides a presentation of the results obtained from the experiments performed, along with a comparative analysis and discussion.
- Chapter 6 - Conclusion and Future Work. Finally, the dissertation is concluded in this chapter and some future directions of research are provided.

1.7 Contributions of Dissertation

This dissertation made the following contributions to knowledge:

- The ELECTRE algorithms were applied to rank ontologies according to their complexity characteristics. For the first time, to the best of our knowledge, a dataset as large as the one used in this study (200 ontologies) was tested for ontology ranking. This study also provides a comparison between the different ELECTRE methods on the same task. The results achieved were presented and published at *The 2022 International Conference on Artificial Intelligence, Big Data, Computing and Data Communication Systems (icABCD2022)* in Durban, as well as at *The 24th International Conference on Information Integration and Web Intelligence (iiWAS2022)* in Italy, to be published in the Lecture Notes in Computer Science (LNCS) Springer Series.

- The ELECTRE Tri model was combined with a genetic algorithm to infer a set of thresholds from a set of assignment examples, which was then used to classify the dataset of ontologies into classes according to their complexity levels. The results obtained were submitted and accepted at the *Pan-African Artificial Intelligence and Smart Systems Conference (PAN-AFRICAN AIS 2022)* in Senegal, to be published in the Lecture Notes of the Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering (LNICST) Springer Series.

- A novel ELECTRE model, named ZPLTS-ELECTRE II, was proposed. The new model combines the ELECTRE II model with the concept of Z-Probabilistic Linguistic Term Sets. The model was applied to rank a set of 9 ontologies according to 5 complexity metrics, as well as 5 qualitative usability metrics. This model allows for ontology selection under a group decision-making environment, with the use of both numerical and linguistic attributes. The proposed ZPLTS-ELECTRE II model and its application to ontology selection was published in the *Future Internet* journal.

1.8 Conclusion

In this chapter a contextual background and motivation was presented for the research, followed by the definition of the research problem to be solved. This was then followed by an enumeration of the research aims and objectives, the research methodology that was applied, an outline of the dissertation, and the major contributions of the research. The next chapter presents the literature review and related works regarding ontology and the ELECTRE algorithms.

Chapter 2

Literature Review

2.1 Introduction

This chapter presents a comprehensive review of the concepts of *ontology*, *ontology evaluation*, and *ontology selection*. The chapter also presents a brief conceptualization of the *ELECTRE family* along with its main branches, its uses and applications, and its current trends. The aim of the chapter is to highlight the research gaps and fundamental issues in the research and developments pertaining to ontology selection for reuse.

2.2 Ontology

2.2.1 What is an Ontology?

The concept of *ontology* was first developed in the field of philosophy and metaphysics, where it is defined as the "science of being" [1]. Philosophers sought to capture and describe existence and the nature of being with the use of *ontology*. It is only in recent years that the philosophical concept of *ontology* is being used in the fields of computer science, information science, and knowledge engineering. From this perspective, *ontology* has been given many definitions. One of the most widely used definition was assigned by Gruber [1] in 1993 where he defined an *ontology* as an explicit specification of a shared conceptualization, defined as a representation of knowledge of a specific domain and consists of vocabulary representing the domain in the form of classes or concepts, properties and relationships existing between them. Another widely used definition was given by Staab and Studer in 2003 [31], where an ontology is defined as a formal logic-based description of a vocabulary that allows one to conceptualize a domain of discourse. Essentially, an ontology aims to capture and express the understanding of a group or community of people with the use of a shared and accepted vocabulary. This vocabulary is expressed in the form of concepts and relationships amongst the concepts, and it is generally expressed in a formal language in order to enable machine readability and reasoning, and facilitating interoperability.

An example of an ontology is provided in Fig. 2.1. The ontology expresses knowledge of a person and a vehicle, along with the relationship between the two. It can be seen that Person and Vehicle are classes, and Vehicle has two subclasses, namely Car and Motorbike. This implies that a Car is a Vehicle, and a Motorbike is a Vehicle. The dotted arrows depict properties of a class. A Person is the owner of a Vehicle, denoted by *ownerOf* relation, and a Vehicle has an owner who is a Person, denoted by *hasOwner* relation. It can also be observed that a Person has a property called name, which represents the name of the Person, e.g., John, Mary, etc. A Car has a property called carBrand, which represents the brand of the car, e.g., Toyota, Ferrari, etc. A Motorbike has a property called motorbikeBrand, representing the brand of the Motorbike, e.g., Suzuki, Harley Davidson, etc. All of the properties in this ontology are of the data-type string. This ontology captures the concepts of Person and Vehicle, along with their properties, and the relationships between the concepts.

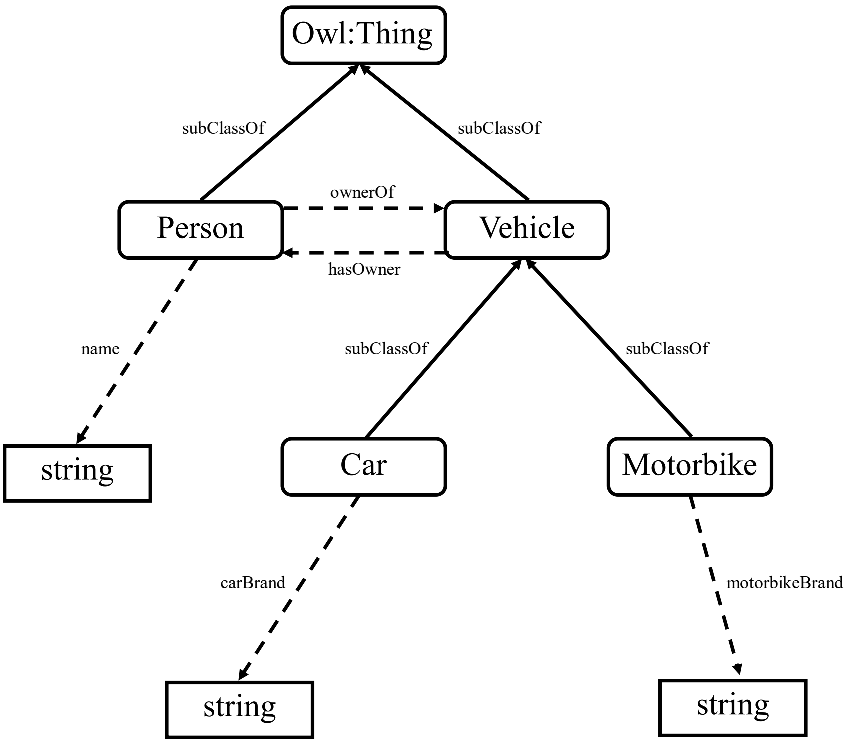


FIGURE 2.1: An example of a simple ontology

The ontology in Fig. 2.1 contains only five classes, but real-world ontologies are often much more complex. Accordingly, there are a number of languages that were developed to create ontologies [32]. Some of these include Resource Description Framework[1] (RDF), Resource Description Framework Schema[2] (RDFS), and Web Ontology Language[3] (OWL). The OWL is the most advanced amongst these languages, therefore, the ontologies used in this study were represented in OWL language.

2.2.2 Benefits of Ontologies

Ontologies are proving to be beneficial in a range of areas, including the semantic web, AI, and big data. The semantic web is essentially an enhanced version of the internet where machines are able to do more than just contain and transfer data, but are also able to understand

[1]https://www.w3.org/RDF/
[2]https://www.w3.org/wiki/RDFS
[3]https://www.w3.org/OWL/

and comprehend the data - allowing for reasoning and inference [33]. Ontologies play a major role in the semantic web as they are the main method eliciting data integration, sharing, and discovery [33]. As the semantic web expands, there is a strong requirement of containing and expressing vast amounts of knowledge and data, and as a consequence, more and more ontologies are being developed to express various domains of knowledge. In terms of AI, ontologies play multiple roles. One essential role is that ontologies allow engineers to express knowledge for systems and technologies, such as robots and machines, to function and perform their duties. Ontologies also provide a rich structure for containing and exploiting myriads of data, as is greatly required in this age of big data. According to Gruninger and Lee [34], the benefits of ontologies can be differentiated into three classes. The first class is *Communication*, the second class is *Computational inference*, and the third class is *Reuse and organization of knowledge*. These three classes are expanded on as follows.

1. Communication
   - Ontologies enable interoperability between humans and computers at the data and processing level.
   - The meaning of different concepts are uniquely identified in a particular subject domain.
   - The usage of formal semantics eliminate undesired interpretations and facilitate an efficient transfer of knowledge.
2. Computational inference
   - Ontologies enable computational inference which enhances aspects pertaining to browsing and retrieval due to the automatic derivation of implicit facts.
   - The ontology is able to provide a structure to model knowledge independently of the underlying system and infrastructure.
   - Errors in the modelling of knowledge, as well as logical errors are able to be easily identified within ontologies.
3. Reuse and organization of knowledge
   - Ontologies provide the ability to structure and organize knowledge in reusable artifacts.
   - Ontologies are able to develop systematic and widely accepted domain descriptions.
   - The ability of ontologies to be extended enable their reusability, which then eliminates the need of new developments, saving time and resources.
   - The ability of ontologies to be extended has the implication of the overall quality of the ontologies to improve over time.

2.2.3 Applications of Ontologies

Ontologies are being applied in a wide range of domains, such as finance [35–37], agriculture [19, 38, 39], e-government [40–42], education [43–45], and information technology [46–48].

However, one of the greatest advantages of ontology is its implications to the medical domain. The need for accurate and timely medical knowledge and expertise is of massive importance – it is essentially a matter of life and death. Unfortunately, it is very difficult to acquire medical knowledge, or rather accurate medical knowledge. This is addressed with the usage of ontology and ontological engineering. The BioPortal Ontology Repository [18] is one such example of an invaluable ocean of medical knowledge. The BioPortal is one of many ontology repositories stimulating the applications and integration of ontology with other AI technologies – like machine learning, data mining, computer vision, and robotics. Some of the studies that have made use of the BioPortal Repository are as follows. In 2011, Visser et al. [49] developed the BioAssay Ontology[4] to describe High-throughput Screening (HTS) as an approach to organize, standardize and access HTS data. A study by Robinson et al. [50] developed the Human Phenotype Ontology[5] in order to represent individual phenotypic anomalies. The ontology comprises over 8000 terms and has the aim of enhancing computational analysis for phenotypic data, providing insight into the thousands of hereditary diseases in human beings. In order to model the major novel coronavirus (SARS-CoV-2) entities, the COVID-19[6] Ontology was developed [51]. The ontology expresses the roles of cellular and molecular entities in virus-host interactions, along with a range of medical and epidemiological concepts pertaining to COVID-19. The Cognitive Paradigm Ontology[7] [52] was developed to describe the experimental conditions within experiments related to cognition and behavior, particularly within humans. The aim of the ontology is to define the conditions of experiments in a standardized format. A study by Malhotra et al. [53] developed the Alzheimer's Disease Ontology[8] as a disease-specific ontology with a focus on representing knowledge regarding the Alzheimer's disease, enabling knowledge exchange and inference for the complex but common Alzheimer's disease. Despite the aforementioned studies, there are many more applications in the medical field, such as those related to cardiovascular diseases [54–56], cancer [57–59], neurology [60–62], nutrition [63–65], and pharmaceutical drugs [66–68]. In fact, the BioPortal ontology repository is witnessing a tremendous growth in recent years. In March 2008 the repository contained 72 ontologies, with 300 000 classes in total [69]. In the next year that number almost doubled to 134 ontologies, with 680 000 classes [69]. The year 2011 saw the repository grow to 260 ontologies with 4.8 million classes [70]. Today, the BioPortal ontology repository has grown to host over 1000 ontologies, containing almost 15 million classes, 36 000 properties, and almost 80 million mappings [18].

2.2.4 A Downside of Ontologies

Despite the excellence of ontologies, there exists some pressing issues that need to be solved. This research aims to tackle one such issue. Ontologies are inherently complex structures and accordingly a range of experts and specialists are required in order to design and develop ontologies. These include logicians, developers, knowledge engineers, information scientists and

[4]https://bioportal.bioontology.org/ontologies/BAO
[5]https://hpo.jax.org/app/
[6]https://bioportal.bioontology.org/ontologies/COVID-19
[7]http://www.cogpo.org/index.html
[8]https://bioportal.bioontology.org/ontologies/ADO

technologists, as well as subject matter experts. For this reason, it is often encouraged that existing ontologies be reused, possibly with some modification, as opposed to developing ontologies *de novo*. This is a good strategy to enable a wider range of people to utilize ontologies, but this leads to another problem. That is, due to the increasing number of existing ontologies available online, it is becoming more and more difficult to analyze and select the appropriate ontologies for reuse. The process of analyzing and comprehending an ontology's structural and knowledge components can be complex and time-consuming. Therefore, the process of evaluating and selecting appropriate ontologies for (re)use is an extremely complex problem.

2.3 ELECTRE

2.3.1 Overview of the ELECTRE Family

The ELECTRE methods are an excellent tool for modelling real-world decision-making problems. They provide support for making complex decisions where there exists a range of alternative options to choose from, whilst simultaneously considering a range of characteristics and features for each option. Fig. 2.2 depicts the typical structure of the ELECTRE methods. If a decision-maker is required to make a decision from m alternatives or options, and each of the options have n criteria or characteristics, then the m alternatives or options are evaluated according to each of the n criteria.

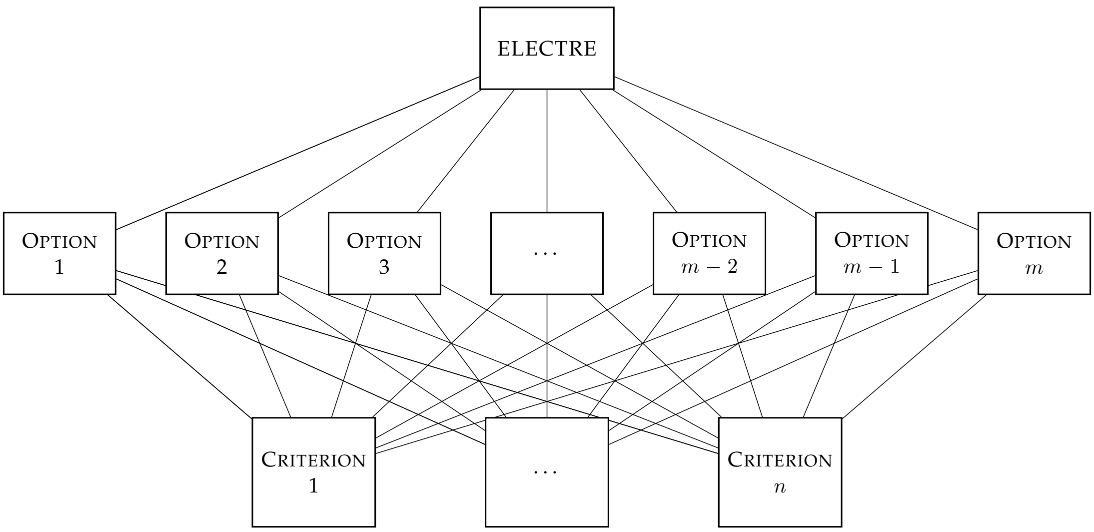


FIGURE 2.2: The structure of the ELECTRE methods

The original version of ELECTRE, named ELECTRE I, was developed in 1968 by French mathematician, Bernard Roy [12], who developed the method as part of the workings of a real-world problem for the European company SEMA. ELECTRE I was developed as a selection tool, where a subset of non-dominated options were identified from a set of alternatives, according to the concepts of concordance and discordance. In 1971 the ELECTRE II method was developed by Roy and Bertier [13], which had similar concepts to its predecessor but was intended to solve the ranking problem. ELECTRE II made use of 5 thresholds, as opposed to the

2 thresholds used by ELECTRE I. Both ELECTRE I and II made use of true criteria, but in 1978 the ELECTRE III method was developed by Roy [14] which made use of pseudo-criteria. This method was also developed for ranking problems and required decision-makers to set indifference, preference, and veto thresholds. Four years later, Roy and Hugonnard [15] developed the ELECTRE IV model for ranking problems, which was also based on pseudo-criteria and made use of the same thresholds as its predecessor, ELECTRE III. However, ELECTRE IV was the first and only method in the ELECTRE family that did not make use of criteria importance weightings. The ELECTRE Tri method is the first sorting method in the ELECTRE family developed by Yu [16] in 1992. This method also made use of the thresholds that ELECTRE III and IV used but requires the decision-maker to define classes *a priori* along with the boundaries of those classes. A succinct timeline is presented in Fig. 2.3 depicting the main developments of the ELECTRE family.

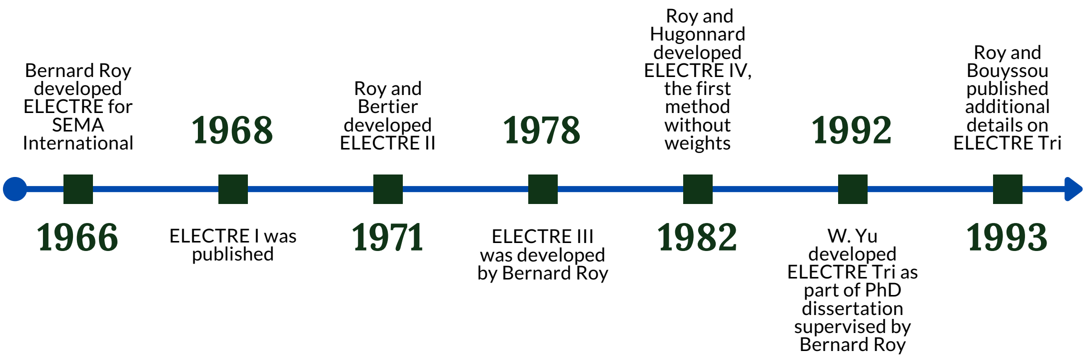


FIGURE 2.3: Timeline of the developments in the ELECTRE family

ELECTRE has been applied to a myriad of fields and applications, including Finance and Investment [71–73], Engineering [74–76], Energy and Resources [77–80], Human Resources and Management [81–83], Construction and the Built Environment [84–86], Information Technology and Software [87–89], and Agriculture and Farming [90–92]. The survey paper by Govindan et al. [11] can be consulted with for more studies pertaining to the applications of ELECTRE. Surprisingly, despite the wide usage of the ELECTRE algorithms in various fields, there is very little work done with ELECTRE in the field of ontology and ontological engineering [21, 23].

2.3.2 State-of-the-Art of ELECTRE

In recent years, researchers have developed various enhancements of the ELECTRE family in order to expand its capabilities given the task of modelling decision problems. One major area of research is the integration of the concept of *fuzzy set theory* with the ELECTRE algorithms. This enables the ELECTRE models to deal with uncertain and imprecise data, thereby providing a solution to the problem of obtaining accurate information from decision-makers.

The fuzzy set allows for an object to belong to a set with a membership value and a non-membership value. The concept of fuzzy sets was combined with ELECTRE II in [93] to deal with uncertain data. Variations of the fuzzy set were also combined with the ELECTRE method, such as the triangular fuzzy set and ELECTRE I [94]. However, due to hesitation by a decision-maker, the concept of intuitionistic fuzzy sets was proposed in [95] whereby a criterion can be evaluated with a membership value, a non-membership value, and a hesitance value. Many ELECTRE variants were developed using this concept, such as [96, 97]. As the development of novel concepts in the field of fuzzy mathematics and fuzzy set theory emerged, researchers in the field of ELECTRE followed suit by enhancing the ELECTRE methods to perform with the new concepts. These include the Bipolar Fuzzy ELECTRE II [98], the Hesitant Fuzzy ELECTRE II [99], the Single-valued Neutrosophic ELECTRE II [100], the Pythagorean ELECTRE I [101], among others. One issue that the aforementioned studies have is that they deal with numerical values, but in many decision-making problems it is more appropriate for decision-makers to express their views using natural language.

In the year 1975, Zadeh [102] proposed the concept of linguistic variables, allowing decision-makers to express their opinions in a more natural manner. Since decision-makers are often hesitant when providing their evaluations, the hesitant fuzzy linguistic term set (HFLTS) was proposed by Rodriguez et al. [103] in 2012. This allowed decision-makers to provide more than one linguistic term for each evaluation. The concept of HFLTS was applied to ELECTRE in 2018 by Liao et al. [104]. However, the main disadvantage of HFLTS is that it assigns an equal importance weighting to all linguistic terms, which is often not desired in real-world decision-making scenarios. To overcome this, Pang et al. [105] developed the concept of probabilistic linguistic term set (PLTS) whereby a decision-maker is able to specify different probability values for each of their selected linguistic terms. In 2018, Pan et al. [106] developed the PL-ELECTRE II model to solve the problem of evaluating therapeutic scheduling for patients suffering from brain-metastasized non-small cell lung cancer. In another study by Shen et al. [107], the authors developed the PLTS-ELECTRE II model for solving a venture capital evaluation problem. The PLTS-ELECTRE II was able to model both quantitative criteria and qualitative linguistic criteria.

Even though the PLTS has been fairly successful in modelling real-world decision problems, they suffer from one weakness. Oftentimes, different decision-makers provide their evaluations for a decision-problem from different perspectives. They have different skill-sets and experiences. The PLTS does not factor this and therefore the PLTS was combined with the concept of Z-Numbers by Chai et al. [108] in 2021, leading to the Z-Probabilistic Linguistic Term Set (ZPLTS). The concept of Z-Numbers has been around since 2011, when it was proposed by Zadeh [109] as a way of assigning a credibility value to an evaluation value. ZPLTS combines the PLTS with Z-Numbers in order to allow a decision-maker to express their evaluation along with a credibility, both in the form of linguistic values with associated probabilities. The ZPLTS enables for richer modelling and decision-making capabilities for real-world decision problems. However, to the best of our knowledge, despite its capabilities the ZPLTS has not been integrated with the ELECTRE methods as it is done in this study.

2.4 Related Work

2.4.1 Ontology Evaluation

The concept of evaluating ontologies refers to the technical judgement of the content of an ontology, with regards to a frame of reference [110]. In order to adopt and improve ontologies, it is crucial that effective methods of comprehending and evaluating them be developed. Accordingly, with the absence of ontology evaluation methods it would be extremely difficult to select ontologies for reuse, and most ontology projects would end up unsuccessful. Pak and Zhou [110] differentiated the concept of ontology evaluation into two categories depending on the approach they take to elicit the evaluation. The first category is *quality-attributes based approaches* and the second category is *task-oriented approaches*.

The quality-attributes based approach performs evaluation according to some pre-defined quality criteria. These criteria are generally in the form of metrics that measure some aspects or characteristics of an ontology. There are a range of metrics that have been proposed by different authors. One of the first attempts to formalize the concept of ontological analysis was in [111], where the authors took a philosophical approach to evaluate the taxonomical structures of ontologies. The study proposed four core ontological notions, that is, rigidity, unity, identity, and dependence, in order to identify semantic and formal inconsistencies in ontologies. Yao et al. [112] derived some metrics based on mathematical concepts for evaluating ontologies. Most of the proposed metrics were cohesion metrics, the three main ones being the number of root classes, average depth of inheritance, and tree of leaf nodes. In [8], the authors proposed metrics for evaluating ontologies based on their graph representations, such as absolute depth, average depth, absolute breadth, absolute leaf cardinality, cycle ratio, and axiom/class ratio.

The task-oriented approach considers the practical use of ontologies in applications, with an emphasis on the user types, usefulness, use cases, and usability. This type of evaluation perspective can be more beneficial to practical applications than the quality-attribute based approaches. One prominent study was performed by Lozano-Tello and Gomez-Perez [10], where the authors proposed the OntoMetric model that allows users to evaluate the suitability of ontologies in light of the requirements of their projects. The study made use of 160 characteristics to compare ontologies, which yielded a score that was used to rank the ontologies. However, the system had the drawback of being time-consuming to perform such a large number of evaluations, and it also has the potential to be extremely bias depending on the decision-maker [9]. To overcome this issue, Ma et al. [9] proposed an Ontology Usability Scale. The authors extracted 10 items from the 160 characteristics in [10] that were related to the usability of ontologies, which they then used to form the Ontology Usability Scale. The scale allows a user to provide their evaluation for the 10 items in light of each ontology, with the use of a Likert scale. In this study, the aim is to provide a solution to the problem of ontology selection with the use of the ELECTRE models, from the perspectives of both the quality-attributes based approach and the task-oriented approach, and essentially developing a model to combine the two perspectives.

2.4.2 Ontology Ranking

The concept of ranking ontologies refers to their evaluation and ordering from best to worst according to some predefined metrics or perspectives. Ranking a set of ontologies generally results in a ranking list of ontologies in order of best to worst, or a hierarchical ordering of the ontologies from best to worst. Ranking of ontologies has been quite an active research topic in recent years [3–7, 113]. In [6], the authors developed the system known as AKTiveRank which uses the search terms of users' as input, and then processes this input in a knowledge engine to output a score. This score is then used to rank ontologies. A range of metrics were employed including the Centrality and the Class Match Measures. This research gave rise to some significant questions which required the subject to be investigated further. For this reason, the authors did a subsequent study [7] where they modified the AKTiveRank system to rank ontologies based on some structural metrics such as the Betweenness, Density and Semantic Similarity Measures. In the same manner as the initial version, an AKTiveRank score is given to each ontology which determines its ranking results.

In another study by Yu et al. [113], the authors devised an approach known as ARRO to rank ontologies. ARRO shares a substantial amount of design with AKTiveRank [7] in that it also performs the ranking based on the relevance of the ontologies to the user's search queries. It makes use of features such as the hierarchy structure to rank the ontologies.

Alipanah et al. [3] performed a study to rank ontologies in which they outlined an algorithm that uses an information theory measurement, Entropy Based Distribution (EBD), as a distance measure to identify similarity between ontology pairs. They used naïve and bisecting k-medoid clustering algorithms along with these similarity pairs to rank the ontologies. The authors also proposed the use of heuristics and pruning methods for future ranking studies.

A study by Butt et al. [4] developed a framework, namely, DWRank, that performs the ranking of ontologies based on relationships and the retrieval of the top-k concepts. This comprises two phases, an online evaluation and query phase, and an offline phase for learning. DWRank uses concepts of authority and centrality to determine the weights of ontologies.

Subhashini and Akilandeswari [5] proposed a ranking algorithm named Onto-DSB that is based on the internal structure of the ontology and its link to the semantic web. It uses Betweenness, Depthness, and Semantic Informative measures. It was tested on an ontology set from Swoogle [114] and the results outperformed the Swoogle and AKTiveRank techniques. The above studies focus on ranking ontologies but do not employ decision-making techniques.

In recent years, several MCDM methods were applied in ontology ranking. A study by Fonou-Dombeu and Viriri [20] proposed a framework named as C-Rank that ranked ontologies using the Weighted Linear Combination Ranking Technique (WLCRT) according to their complexity metrics. Another study in [22] applied three MCDM techniques to rank 70 ontologies according to their complexity metrics. The three methods were the Weighted Sum Model (WSM), the Weighted Product Model (WPM), and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS).

2.4.3 Classification of Ontologies

Although there have been numerous studies pertaining to ontology ranking, there have been very few studies pertaining to the classification of ontologies. In fact, a number of studies have addressed the "classification of ontology" or "ontology classification" [115–118], to mean different things. For authors [116, 117], ontology classification is the measurement of the consistency and satisfiability of ontology with reasoner systems. In molecular biology [115], ontology classification related to the classification of proteins. Classification of ontology pertained to the manual grouping of ontologies related to the software engineering domain, into various categories based on criteria such as the scope of application, information content and the corresponding software engineering phase [118]. In this study, the classification of ontologies is also treated as the task of grouping ontologies that display the same characteristics or properties into various categories to aid their selection for reuse. To this extent only a small number of studies have addressed the issue of classification of ontologies. In one such study, the authors applied the k-means clustering method to partition ontologies into clusters [119], and in another study, authors applied the k-nearest neighbors machine learning model to classify ontologies [120] based on their degree of complexity. These are the only studies, to the best of our knowledge, that have addressed the classification of ontologies - both of which applied machine learning techniques, and no MCDM methodologies were used.

2.4.4 ELECTRE and Ontology

Despite the flexibility and modelling capabilities of ELECTRE, together with the variety of studies in various domains that have applied ELECTRE, there is only very limited work focusing on applying the ELECTRE methods in ontological engineering and ontology selection. One study was performed by Fonou-Dombeu in 2019 [21] where the ELECTRE I model was applied to rank a dataset of ontologies. The dataset comprised 70 ontologies with 8 complexity metrics used as attributes. Another study to apply ELECTRE in the task of ontology ranking was performed by Esposito et al. [23] where a dataset of 12 ontologies were ranked using a set of criteria adapted from the AKTiveRank [7] study. Both studies suffer from a significant weakness pertaining to the size of their datasets. Real-world ontology repositories contain a much larger number of ontologies than 12 and 70, and furthermore search engines, recommendation systems, and decision support systems may need to rank hundreds of ontologies. Furthermore, the study in [23] ranked ontologies according to their similarities with users search terms, which is essentially taking the same approach as the traditional ontology ranking studies discussed in Section 2.4.2. There is also, to the best of our knowledge, no studies that have applied ELECTRE modelling for ontology selection using natural language linguistic terms, nor any study that have applied ELECTRE or other MCDM models for group ontology selection. There is a significant gap in the literature regarding the ELECTRE methods applicability to the ranking of large real-world datasets of ontologies.

2.5 Conclusion

In this chapter, a comprehensive overview of ontology and the ontology selection problem was presented. The ELECTRE methods were also discussed along with their history and their current trends. Thereafter, the existing work pertaining to ontology selection was explored, with an emphasis on the applications of ELECTRE to ontology selection. In Chapter 3, the methods and materials that were employed to perform this study are presented and explained.

Chapter 3

Materials and Methods

3.1 Introduction

In this chapter three applications of ELECTRE for ontology selection are presented, along with the necessary preliminaries and materials. The first application performs ranking of ontologies based on 13 complexity metrics. The second application performs the classification of ontologies based on 13 complexity metrics. The third and final application proposes a novel ELECTRE algorithm that enables group ontology ranking with linguistic terms. The algorithm is then applied to rank ontologies based on 5 complexity metrics and 5 usability metrics.

3.2 Ranking Ontologies with ELECTRE

The first application proposes the use of the ELECTRE methods for ranking ontologies. The ELECTRE I, II, III, and IV algorithms are applied and the attributes used are 13 complexity metrics. The criteria importance weights are determined with the use of the CRITIC weighting method. The methods and preliminaries are elaborated on as follows.

3.2.1 ELECTRE Algorithms

The main ELECTRE variants for ranking are the ELECTRE I, ELECTRE II, ELECTRE III, and ELECTRE IV. These are modeled as follows.

3.2.1.1 ELECTRE I

The ELECTRE I [12] method determines the concordance and discordance values between all alternative pairs. In order for an alternative to outrank another alternative, its concordance must be at least equal to the concordance threshold, and its discordance value must be at most equal to the discordance threshold. The original ELECTRE I method was developed as a selection tool for selecting a subset of non-dominated solutions from a set of alternatives. In this study, the ELECTRE I method performs ranking by calculating the net ranking scores for each alternative. The ELECTRE I algorithm is modeled as follows.

Criteria Importance Weights

A set of criteria importance weights must be specified by the decision-maker, representing the importance of each criterion. The j^{th} criterion of n criteria has an associated weight, ω_j, where

$0 < \omega_j \leq 1$, and $\sum_{j=1}^{n} \omega_j = 1$.

Concordance Relations

The first step in ELECTRE I is to determine the concordance values between all alternative pairs. This is shown in Eq. (3.1), where $C(x, y)$ is the concordance relationship between alternative x and y. The concordance value lies in the range $[0, 1]$ and measures the extent to which the statement 'x is at least as good as y' is true.

$$C(x, y) = \frac{\sum_{\forall j: g_j(x) \geq g_j(y)} \omega_j}{\sum_{j=1}^{n} \omega_j} \tag{3.1}$$

Discordance Relations

The discordance values are then calculated by using Eq. (3.2). $D(x, y)$ represents the discordance relation between alternatives x and y. The discordance value lies in the range $[0, 1]$ and measures the extent to which the statement 'x is outranked by y' is true.

$$D(x, y) = \begin{cases} 0, & \text{if } g_j(x) \geq g_j(y), \forall j \\ \frac{\max\limits_{j}\{g_j(y) - g_j(x)\}}{\max\limits_{x,y,j}\{g_j(y) - g_j(x)\}}, & \text{otherwise} \end{cases} \tag{3.2}$$

Concordance and Discordance Thresholds

The concordance threshold, $\bar{c}$, and the discordance threshold, $\bar{d}$, are calculated by applying Eqs. (3.3) and (3.4).

$$\bar{c} = \frac{\sum_{x=1}^{m} \sum_{y=1}^{m} C(x, y)}{n(n-1)} \tag{3.3}$$

$$\bar{d} = \frac{\sum_{x=1}^{m} \sum_{y=1}^{m} D(x, y)}{n(n-1)} \tag{3.4}$$

Dominance Matrix

A binary dominance matrix, $\mathcal{S} = [s_{x,y}]_{m \times m}$, is developed where each element, $s_{x,y}$, expresses whether alternative x outranks alternative y. To determine whether an alternative x outranks an alternative y, the concordance value between x and y, that is, $C(x, y)$, must be at least as large as the concordance threshold $\bar{c}$, and the discordance between x and y, $D(x, y)$, must not exceed the discordance threshold $\bar{d}$. The $\mathcal{S}$ matrix is shown in Eq. (3.5).

$$\mathcal{S} = [s_{x,y}]_{m \times m} = \begin{bmatrix} s_{1,1} & s_{1,2} & \cdots & s_{1,m} \\ \vdots & \vdots & \ddots & \vdots \\ s_{m,1} & s_{m,2} & \cdots & s_{m,m} \end{bmatrix} \tag{3.5}$$

where $s_{x,y} \in \{0, 1\}$ and is determined by Eq. (3.6).

$$s_{x,y} = \begin{cases} 1, \text{ if } C(x,y) \geq \bar{c} \text{ and } D(x,y) \leq \bar{d} \\ 0, \text{ otherwise} \end{cases} \tag{3.6}$$

Exploit Dominance Matrix

In order to exploit the dominance matrix and rank the alternatives, a score is assigned to each alternative. This score is formulated as the difference between the number of alternatives that the particular alternative outranks, and the number of alternatives that outrank the particular alternative, as in Eq. (3.7).

$$\delta(x) = \sum_{y=1}^{m} s_{x,y} - \sum_{y=1}^{m} s_{y,x} \tag{3.7}$$

All alternatives are assigned a score, where the alternative with the highest score is the best alternative, and the alternative with the lowest score is the worst alternative.

3.2.1.2 ELECTRE II

The ELECTRE II [13] method is similar to ELECTRE I [12] but introduces the concepts of strong and weak outranking graphs. After constructing the graphs, they are exploited with the application of a forward and reverse ranking procedure, yielding two sets of rankings. Finally, the two rankings are intersected to form a final ranking of all alternatives from best to worst. The ELECTRE II algorithm is modeled as follows.

Weights and Thresholds

The ELECTRE II model requires a set of criteria importance weights to be specified. The importance weighting for the j^{th} criterion is expressed by ω_j, where $\sum_{j=1}^{n} \omega_j = 1$. The model also requires five thresholds, three of which are concordance thresholds (c^-, c^0, c^+), and two are discordance thresholds (d_1, d_2). The thresholds must be defined such that $0.5 \leq c^- \leq c^0 \leq c^+ \leq 1$ and $0 \leq d_2 \leq d_1 \leq 1$.

Concordance Relations

The concordance value between alternatives x and y represents the weights of all criteria where alternative x is at least as good as y. This value expresses the degree to which the criteria agree with the statement that alternative x is at least as good as y. The global concordance value, $C(x, y)$ is determined by applying Eq. (3.8).

$$C(x,y) = \frac{\sum_{\forall j: g_j(x) \geq g_j(y)} \omega_j}{\sum_{j=1}^{n} \omega_j} \tag{3.8}$$

Strong and Weak Outranking Relations

The ELECTRE II method has two outranking relations, a strong outranking relation, S^F, and a weak outranking relation, S^f. The strong outranking relation firmly asserts that alternative x outranks alternative y, whereas the weak outranking relation has a weaker assertion that alternative x outranks alternative y. The S^F and S^f relations are defined in Eq. (3.9) and (3.10).

$$\mathrm{S}^F \Leftrightarrow \begin{cases} C(x,y) \geq c^+,\ g_j(y) - g_j(x) \leq d_1, \forall j \\ \text{or} \\ C(x,y) \geq c^0,\ g_j(y) - g_j(x) \leq d_2, \forall j \end{cases} \tag{3.9}$$

$$\mathrm{S}^f \Leftrightarrow \begin{cases} C(x,y) \geq c^-, \\ g_j(y) - g_j(x) \leq d_1, \forall j \end{cases} \tag{3.10}$$

Exploitation of Outranking Relations

In order to exploit the outranking relations, first the strong and weak outranking graphs are constructed, where each alternative is represented as a node, and an outranking relation is represented as a directed edge. Three pre-orders, V_1, V_2, and $\bar{V}$, are constructed. V_1 is determined by an iterative process whereby there are l iterations, starting from $l = 0$. At each iteration some alternatives from the strong outranking relation are ranked and removed from the strong outranking graph, the remaining unranked items are denoted by Y_l. The set A_l denotes the best alternatives in the l^{th} iteration, receiving the rank of $l + 1$. The set D denotes those alternatives within Y_l that are not outranked by any other alternatives in a strong relation. All alternatives in set D that have a weak outranking relationship with each other form the set U, and the set B denotes those alternatives in U that are not weakly outranked by another alternative from the set U. For each iteration, l, an alternative or a set of alternatives are ranked by combining sets D, U, and B, as in Eq. (3.11), where A_l is the set of alternatives given the $(l + 1)^{th}$ rank during the l^{th} iteration.

$$A_l = (D - U) \cap B \tag{3.11}$$

The ranked alternatives are removed from the strong outranking graph, as in Eq. (3.12), and the procedure terminates when the set Y_{l+1} is empty, that is, all alternatives are assigned a rank.

$$Y_{l+1} = Y_l - A_l \tag{3.12}$$

In order to obtain the second pre-order, V_2, the direction of the strong and weak outranking graphs is reversed and the same procedure that was used to obtain V_1 is applied. The ranks assigned are modified using Eq. (3.13), where $r_2(a)$ represents the rank given to an alternative in V_2, $r'_2(a)_{\text{max}}$ represents the number of ranks, and $r'_2(a)$ represents the rank given to the alternative by V_1.

$$r_2(a) = 1 + r'_2(a)_{\text{max}} - r'_2(a) \tag{3.13}$$

After obtaining V_1 and V_2, a final ranking, $\bar{V}$, is determined as the median ranking for each alternative, as in Eq. (3.14).

$$\bar{V} = \frac{V_1 + V_2}{2} \tag{3.14}$$

3.2.1.3 ELECTRE III

The ELECTRE III method was developed by Roy [14] and it introduces preference, indifference, and veto thresholds. The method is also based on concordance and discordance like ELECTRE I and II, but it introduces a distillation procedure for exploiting the credibility values. ELECTRE III is modeled as follows.

Weights and Thresholds
The ELECTRE III method [14] requires the decision-maker to define a set of criteria importance weights, where the weight of the j^{th} criterion is given by ω_j, and $\sum_{j=1}^{n} \omega_j = 1$. Three thresholds are also required, the indifference threshold q_j, the preference threshold p_j, and the veto threshold v_j. The thresholds are constrained such that $v_j \geq p_j \geq q_j$.

Concordance Relations
The concordance index for all alternative pairs is calculated by Eq. (3.15), where $c_j(x, y)$ represents the concordance between alternatives x and y regarding the j^{th} criterion. $C(x, y)$ represents the weighted sum of all $c_j(x, y)$ for all n criteria. Eq. (3.16) represents $c_j(x, y)$.

$$C(x, y) = \frac{\sum_{j=1}^{n} \omega_j c_j(x, y)}{\sum_{j=1}^{n} \omega_j} \tag{3.15}$$

$$c_j(x, y) = \begin{cases} 1, \text{ if } g_j(x) + q_j(g_j(x)) \geq g_j(y) \\ 0, \text{ if } g_j(x) + p_j(g_j(x)) < g_j(y) \\ \frac{g_j(x) - g_j(y) + p_j(g_j(x))}{p_j(g_j(x)) - q_j(g_j(x))}, \text{ otherwise} \end{cases} \tag{3.16}$$

Discordance Relations
The discordance relation between alternative x and y at criterion j is given by Eq. (3.17).

$$D_j(x, y) = \begin{cases} 1, \text{ if } g_j(y) \leq g_j(x) + p_j(g_j(x)) \\ 0, \text{ if } g_j(y) > g_j(x) + v_j(g_j(x)) \\ \frac{g_j(x) - (g_j(y) - p_j(g_j(x)))}{v_j(g_j(x)) - p_j(g_j(x))}, \text{ otherwise} \end{cases} \tag{3.17}$$

Credibility Index

After the concordance and discordance indices are determined, the credibility between all alternative pairs, $S(x,y)$, is determined by applying Eq. (3.18), where $\mathcal{J}(x,y)$ represents the criteria for which $D_j(x,y) > C(x,y)$. The degree of credibility is the index of concordance if there exists no criterion that is discordant when comparing an alternative pair, otherwise the degree of credibility is decreased proportionally to the discordances within the alternative pair.

$$S(x,y) = \begin{cases} C(x,y), \text{ if } D_j(x,y) \leq C(x,y), \forall j \\ C(x,y) \prod_{j \in \mathcal{J}(x,y)} \frac{1-D_j(x,y)}{1-C(x,y)}, \text{ if } D_j(x,y) > C(x,y) \end{cases} \tag{3.18}$$

Descending and Ascending Distillation

In order to obtain a final ranking, a distillation procedure is applied resulting in two pre-orders, a descending pre-order Z_1 and an ascending pre-order Z_2 [14, 24]. The first phase of the distillation process requires the qualification score for each alternative to be calculated. This is done as follows. λ_{max} is determined as the maximum credibility value, as in Eq. (3.19), and a cut-off level, λ, is defined as in Eq. (3.20). $s(\lambda)$ is a discrimination threshold given by Eq. (3.21), where α and β are parameters defined by the decision-maker.

$$\lambda_{\text{max}} = \max_{x,y}\{S(x,y)\} \tag{3.19}$$

$$\lambda = \max_{S(x,y) < \lambda_{\text{max}} - s(\lambda_{\text{max}})} \{S(x,y)\} \tag{3.20}$$

$$s(\lambda) = \alpha\lambda + \beta \tag{3.21}$$

The outranking relation between alternatives x and y at a cut-off level λ, denoted as $xS^{\lambda}y$, is given by Eq. (3.22). $xS^{\lambda}y$ means that alternative x outranks alternative y at the cut-off level λ.

$$xS^{\lambda}y \Leftrightarrow \begin{cases} S(x,y) > \lambda, \\ S(x,y) - S(y,x) > s(S(x,y)) \end{cases} \tag{3.22}$$

Based on the relation defined in Eq. (3.22), the strength, $p_D^{\lambda}(x)$, and the weakness, $f_D^{\lambda}(x)$, of alternative x at the λ cut-off level can be defined using Eqs. (3.23) and (3.24), where D is a subset of all alternatives, A, containing those alternatives that are not yet ranked.

$$p_D^{\lambda}(x) = \left|\{xS_{\lambda}^{D}y \mid y \in D\}\right| \tag{3.23}$$

$$f_D^{\lambda}(x) = \left|\{yS_{\lambda}^{D}x \mid y \in D\}\right| \tag{3.24}$$

After the strength and weakness of alternative x are determined, their difference, denoted $q_D^\lambda(x)$, is regarded as the qualification of x, as in Eq. (3.25).

$$q_D^\lambda(x) = p_D^\lambda(x) - f_D^\lambda(x) \tag{3.25}$$

For the cut-off level λ, a corresponding subset of alternatives, C_i, from D, is obtained by applying Eq. (3.26). The alternatives in C_i are those having the highest qualification score.

$$C_i = \left\{ \max_{x \in D} q_D^\lambda(x) \right\} \tag{3.26}$$

If C_i contains many alternatives, then the process is repeated only for those options within C_i. This continues until there remains only 1 alternative in C_i or all alternatives in C_i are indistinguishable. After a set C_i has been formed, the next iteration proceeds generating a new λ cut-off level and new qualification scores, to obtain a set, $C_{(i+1)}$, of alternatives. Those alternatives that are contained in C_i are removed from the set D when determining the set $C_{(i+1)}$. The process continues until all alternatives have been ranked.

The ascending distillation follows the same process with the set C_i determined as the alternatives with the minimum qualification scores within the set D, as shown in Eq. (3.27).

$$C_i = \left\{ \min_{x \in D} q_D^\lambda(x) \right\} \tag{3.27}$$

After obtaining Z_1 and Z_2, a final ranking is obtained by combining the pre-orders to obtain their average, as in the ELECTRE II method, that is, $\bar{Z} = \frac{Z_1 + Z_2}{2}$.

3.2.1.4 ELECTRE IV

The ELECTRE IV method was developed by Roy [15] and is built similarly to the ELECTRE III method. However, ELECTRE IV is the only method in the ELECTRE family that does not make use of criteria importance weights. The exploitation procedure for ELECTRE IV follows the same distillation concepts as that of ELECTRE III. ELECTRE IV is modeled as follows.

Thresholds

The ELECTRE IV method requires the decision-maker to define a set of three thresholds, the indifference threshold q_j, the preference threshold p_j, and the veto threshold v_j. The thresholds are constrained such that $v_j \geq p_j \geq q_j$.

Pairwise Comparative Relationships

All alternative pairs are compared and are categorized into four relationships, that is, m_p, m_q, m_i, and m_o. When comparing alternative x with y, the comparative relations can be determined by Eqs. (3.28) to (3.31).

$$m_p(x,y) = \begin{cases} 1, \text{ if } g_j(y) - g_j(x) > p_j, \forall j \\ 0, \text{ otherwise} \end{cases} \tag{3.28}$$

$$m_q(x,y) = \begin{cases} 1, \text{ if } g_j(y) - g_j(x) > q_j \text{ and } g_j(y) - g_j(x) \leq p_j, \forall j \\ 0, \text{ otherwise} \end{cases} \tag{3.29}$$

$$m_i(x,y) = \begin{cases} 1, \text{ if } g_j(y) - g_j(x) \geq -q_j \text{ and } g_j(y) - g_j(x) \leq q_j \text{ and } g_j(y) - g_j(x) > 0, \forall j \\ 0, \text{ otherwise} \end{cases} \tag{3.30}$$

$$m_o(x,y) = \begin{cases} 1, \text{ if } g_j(y) - g_j(x) = 0, \forall j \\ 0, \text{ otherwise} \end{cases} \tag{3.31}$$

where $n = m_p(x,y) + m_p(y,x) + m_q(x,y) + m_q(y,x) + m_i(x,y) + m_i(y,x) + m_o$, and n is the number of criteria.

Outranking Relations

According to the parameters in Eqs. (3.28) to (3.31), five outranking relations can be developed. These are Quasi-Dominance S_q, Canonical Dominance S_c, Pseudo-Dominance S_p, Sub-Dominance S_s, and Veto Dominance S_v. These relations are defined in Eqs. (3.32) to (3.36).

$$x\mathrm{S}_q y \Leftrightarrow \Big\{ m_p(x,y) + m_q(x,y) = 0, \text{ and } m_i(x,y) < m_i(y,x) + m_q(y,x) + m_p(y,x) \tag{3.32}$$

$$x\mathrm{S}_c y \Leftrightarrow \begin{cases} m_p(x,y) = 0 \text{ and } m_q(x,y) \leq m_q(y,x), \text{ and} \\ m_q(x,y) + m_i(x,y) \leq m_i(y,x) + m_q(y,x) + m_p(y,x) \end{cases} \tag{3.33}$$

$$x\mathrm{S}_p y \Leftrightarrow \Big\{ m_p(x,y) = 0 \text{ and } m_q(x,y) < m_q(y,x) + m_p(y,x) \tag{3.34}$$

$$x\mathrm{S}_s y \Leftrightarrow \Big\{ m_p(x,y) = 0 \tag{3.35}$$

$$x\mathrm{S}_v y \Leftrightarrow \begin{cases} m_p(x,y) = 0, \text{ or} \\ m_p(x,y) = 1 \text{ and } m_p(y,x) \geq \frac{m}{2} \text{ and } g_j(y) - g_j(x) \geq -v_j \end{cases} \tag{3.36}$$

Credibility Degree

After determining the outranking relations, the degree of credibility, $S(x,y)$, is determined. Eqs. (3.37) to (3.41) show the formulation of the credibility degree.

$$xS_q y \Leftrightarrow S(x,y) = 1 \tag{3.37}$$

$$xS_c y \Leftrightarrow S(x,y) = 0.8 \tag{3.38}$$

$$xS_p y \Leftrightarrow S(x,y) = 0.6 \tag{3.39}$$

$$xS_s y \Leftrightarrow S(x,y) = 0.4 \tag{3.40}$$

$$xS_v y \Leftrightarrow S(x,y) = 0.2 \tag{3.41}$$

Descending and Ascending Distillation

In order to exploit the credibility degrees of the alternative pairs, ELECTRE IV applies the same descending and ascending distillation procedures as ELECTRE III in Eqs. (3.19) to (3.27), with only one difference, that is, ELECTRE IV makes use of a constant discrimination threshold $s(\lambda)$. The discrimination threshold for ELECTRE III varies according to the α, β, and λ parameters, as in Eq. (3.21), but the discrimination threshold for ELECTRE IV is set as a constant value by the decision-maker.

After applying the distillation processes as in Eqs. (3.19) to (3.27), the obtained rankings, Z_1 and Z_2, are combined to form the final ranking. This is done, as with ELECTRE III, by taking the median rank $\bar{Z}$, where $\bar{Z} = \frac{Z_1+Z_2}{2}$.

3.2.2 The CRITIC Weighting Method

In order to assign a criteria importance weight to each criterion, the Criteria Importance Through Inter-criteria Correlation (CRITIC) method was applied. The CRITIC method was developed by Diakoulaki et al. in 1995 [121] and provides an unbiased approach to determine criteria weighting by quantifying the intrinsic information of the criteria. The method is defined as follows [121].

Let A be a set of M alternatives with N evaluation criteria. A general multicriteria decision problem can be expressed as $\max_{a \in A}\{f_1(a), f_2(a), \ldots, f_N(a)\}$, where $f_j(a)$ represents the performance for the j^{th} criterion at alternative a, and a is an alternative within the set of all alternatives, A. The first step of the CRITIC method is to normalize the decision matrix by applying the concept of ideal point, as in Eq. (3.42), where x_{aj} represents the normalized performance value of criterion j of alternative a. This value signifies the closeness of the performance to f_j^*, the best performing value for criterion j, and the farness from f_{j*}, the worst performing value for the criterion j.

$$x_{aj} = \frac{f_j(a) - f_{j*}}{f_j^* - f_{j*}} \tag{3.42}$$

The next step involves isolating each criterion j to create a vector for the performance of the j^{th} criterion at all M alternatives. This is expressed as $x_j = x_j(1), x_j(2), \dots, x_j(M)$. The standard deviation for each criterion j is then determined using Eq. (3.43), where σ_j represents the standard deviation for the j^{th} criterion, and $\bar{x_j}$ represents the mean of the x_j vector.

$$\sigma_j = \sqrt{\frac{\sum_{a=1}^{M}(x_{aj} - \bar{x_j})^2}{M}} \tag{3.43}$$

Thereafter, a $N \times N$ matrix is determined with each value, r_{jk}, representing the linear correlation between the j^{th} and k^{th} criteria. This is shown in Eq. (3.44).

$$r_{jk} = \frac{\sum_{a=1}^{M}(x_{aj} - \bar{x_j})(x_{ak} - \bar{x_k})}{\sqrt{\sum_{a=1}^{M}(x_{aj} - \bar{x_j})^2 \sum_{a=1}^{M}(x_{ak} - \bar{x_k})^2}} \tag{3.44}$$

The next step is to quantify the amount of information emitted by criterion j, denoted as C_j, which is calculated by Eq. (3.45). A high C_j value implies that the j^{th} criterion has a large amount of information transmitted, which in-turn signifies that the criterion should have a high importance.

$$C_j = \sigma_j \cdot \sum_{k=1}^{M}(1 - r_{jk}) \tag{3.45}$$

The final weights are determined by normalizing the C_j values calculated in Eq. (3.45) by applying Eq. (3.46).

$$\omega_j = \frac{C_j}{\sum_{j=1}^{N}(C_j)} \tag{3.46}$$

3.2.3 Dataset

The dataset used in this study was obtained from the BioPortal ontology repository [18] and comprises 200 ontologies of the biomedical domain. These ontologies model knowledge pertaining to various biomedical aspects such as:

- Mental health, neuroscience, and psychology
- Human and animal anatomy

- Healthcare drug treatments and their affects
- Molecular biology, protein and cellular compositions
- Diseases, infections, and illnesses
- Nutrition and food

The full dataset of the 200 ontologies can be found in Appendix B. Each of these ontologies had 13 of their complexity metrics calculated in order to evaluate their characteristics. These metrics are explored in the next section.

3.2.4 Complexity Metrics

In order to evaluate the ontologies, four quality dimensions were considered. These dimensions are *accuracy*, *understandability*, *cohesion*, and *conciseness*. To express these four dimensions, 13 complexity metrics that measure the design complexity of ontologies were utilized. These complexity metrics are:

1. Attribute Richness (AR)
2. Inheritance Richness (IR)
3. Relationship Richness (RR)
4. Equivalence Ratio (ER)
5. Average Depth (AD)
6. Maximal Depth (MD)
7. Average Breadth (AB)
8. Maximal Breadth (MB)
9. Average Number of Paths (ANP)
10. Absolute Leaf Cardinality (ALC)
11. Absolute Root Cardinality (ARC)
12. Average Population (AP)
13. Class Richness (CR)

The *accuracy* dimension expresses to what extent an ontology is representative of a real world domain. The metrics that measure this quality dimension are ANP, AD, AB, MD, MB, ER, RR, AR, and IR. *Understandability* is an indicator of the comprehensiveness of the ontology's constituents such as the concepts and relations. The ALC metric can be used to measure this dimension. The *Cohesion* quality dimension measures how related the constituents of the ontology are, and can be quantified with the ALC and ARC metrics. The *Conciseness* quality dimension measures how useful the knowledge in the ontology is to the domain it represents. The CR and AP metrics are indicators of this quality dimension. The 13 complexity metrics used as attributes are modeled as follows.

3.2.4.1 Attribute Richness

The Attribute Richness, also referred to as slots, represents both the amount of information regarding instances, and design quality of the ontology. An ontology with a high Attribute Richness has a higher number of attributes per class than one with a lower Attribute Richness. Accordingly, an ontology that has a high value for this metric generally contains more knowledge than an ontology with a lower value. Attribute Richness, AR, is calculated using Eq. (3.47).

$$AR = \frac{|att|}{|C|} \tag{3.47}$$

where the total number of attributes within all classes are denoted by att. The att value is divided by C, the total number of classes, to obtain the AR value [122].

3.2.4.2 Inheritance Richness

The Inheritance Richness [122] metric expresses the distribution of the information within the various levels of the inheritance tree in an ontology. This enables one to get a sense of the manner in which knowledge is grouped and categorized. The Inheritance Richness value represents the average number of subclasses per class within an ontology. An ontology with a low Inheritance Richness value would comprise a very detailed type of knowledge, whereas an ontology with a high Inheritance Richness would represent a broader span of a more general type of knowledge. The metric is calculated by Eq. (3.48).

$$IR_S = \frac{\sum_{C_i \in C} |H^C(C_1, C_i)|}{|C|} \tag{3.48}$$

where IR_S represents the Inheritance Richness value, C_1 represents the subclasses and C_i represents the the i^{th} class in the ontology. $|H^C(C_1, C_i)|$ represents the number of subclasses C_1 for the i^{th} class C_i.

3.2.4.3 Relationship Richness

The Relationship Richness expresses the ratio of the connections that are rich relationships compared to all possible connections in the ontology. It represents the relation diversity as well as the placements of the relations. An ontology having a Relationship Richness value close to zero would comprise mainly class-subclass relationships, and accordingly, an ontology having a Relationship Richness value close to one would mainly comprise relationships other than class-subclass relations [122]. The metric is calculated by Eq. (3.49).

$$RR = \frac{|P|}{|SC| + |P|} \tag{3.49}$$

where RR represents the Relationship Richness, P represents the number of relationships, and SC represents the number of subclasses.

3.2.4.4 Equivalence Ratio

The Equivalence Ratio metric expresses the relationship between the number of similar classes and the total number of classes within an ontology [123]. The metric is calculated by Eq. (3.50), where ER represents the Equivalence Ratio, $SameAsClasses$ represent those classes which are similar, and C represents the total number of classes in the ontology.

$$ER = \frac{|SameAsClasses|}{|C|} \tag{3.50}$$

3.2.4.5 Average Depth

Depth is a graph property of an ontology relating to the number of paths within the graph, considering is-a arcs only. The Average Depth metric, abbreviated to AD, is determined by dividing the sum of the cardinalities of every path within a graph by the cardinality of the set of all paths in that graph [8]. AD is an indicator of the degree to which an ontology has a vertical modelling of its hierarchy [124]. The metric is calculated by Eq. (3.51). The m value represents the AD value, N is the cardinality of the paths j, P represents the set of paths within the graph g, and n represents the cardinality of P.

$$m = \frac{1}{n_{P \subseteq g}} \sum_{P}^{j} N_{j \in P} \tag{3.51}$$

3.2.4.6 Maximal Depth

The Maximal Depth value is a representation of the longest depth of inheritance of the concepts within an ontology, where the depth of a concept is determined as the longest path from that concept to the inheritance hierarchy's root concept [125]. Essentially, the Maximal Depth of a graph represents the height of that graph [124]. The metric is calculated by Eq. (3.52).

$$m = N_{j \in P}, \forall i \exists j (N_{j \in P} \geq N_{i \in P}) \tag{3.52}$$

where m represents the Maximal Depth value, N represents the cardinality of a path, P represents the set of all paths within the graph g, i and j represent any paths within P.

3.2.4.7 Average Breadth

The Average Breadth metric, abbreviated to AB, expresses the average cardinality value of a generation in a graph. It is calculated by dividing the sum of the cardinalities of all generations by the number of generations in the graph [8]. The metric is an indicator of the degree to which the ontology has a horizontal modelling of its hierarchy [124]. AB is calculated by Eq. (3.53), where m represents the AB value, N represents the cardinality of a generation, j represents a particular generation, $n_{L\subseteq g}$ represent the cardinality of L, and L represents the set of all generations within a digraph g.

$$m = \frac{1}{n_{L\subseteq g}} \sum_{L}^{j} N_{j\in L} \tag{3.53}$$

3.2.4.8 Maximal Breadth

The Breadth describes the cardinality of the generations within a graph, considering is-a arcs [8]. The Maximal Breadth is a generation from the set of all generations in the graph that has the largest cardinality [8]. The Maximal Breadth metric is calculated by Eq. (3.54), where m represents the value for the Maximal Breadth metric, N represents the cardinality of a generation, $N_{j\in L}$ and $N_{i\in L}$ represent the cardinalities of generations j and i, respectively, and L represents the set of generations that is within a graph g.

$$m = N_{j\in L}, \forall i \exists j (N_{j\in L} \geq N_{i\in L}) \tag{3.54}$$

3.2.4.9 Average Number of Paths

The Average Number of Paths, abbreviated ANP, expresses the relationship between a concept and the root concept within the taxonomy hierarchy of the ontology. An ontology that has a high ANP value contains a large number of taxonomy/inheritance relationships, along with a large number of interconnections between the classes within the ontology. If the ANP value is 1 then it signifies the inheritance hierarchy of the ontology is a tree [125]. The ANP is calculated by Eq. (3.55).

$$m = \frac{\sum_{i=1}^{n} p_i}{|C|} \tag{3.55}$$

where, m is the ANP value, p_i is the number of paths for a given concept, and $|C|$ is the total number of concepts.

3.2.4.10 Absolute Leaf Cardinality

The Absolute Leaf Cardinality metric, abbreviated to ALC, is a measure of the fan-outness of a graph. It expresses the dispersion aspects of graph nodes, considering is-a arcs. Absolute Leaf Cardinality is an indicator of the number of leaf nodes within a graph [8, 25]. The metric is calculated by Eq. (3.56), where m represents the ALC metric, n represents the cardinality of the set LEA, and LEA is a subset of the directed graph g.

$$m = n_{LEA\subseteq g} \tag{3.56}$$

3.2.4.11 Absolute Root Cardinality

The Absolute Root Cardinality metric, abbreviated to ARC, expresses the number of root nodes in a graph [25, 124]. The metric is calculated by Eq. (3.57), where m represents the ARC metric, n represents the cardinality of the set ROO, and ROO is a subset of the directed graph g.

$$m = n_{ROO \subseteq g} \tag{3.57}$$

3.2.4.12 Average Population

The Average Population expresses the relationship between the number of classes and the number of instances within an ontology, or sometimes referred to as the average distribution of instances among all classes in an ontology. It is determined, as in Eq. (3.58), by dividing the number of instances, $|I|$, by the number of classes, $|C|$, within the ontology. The Average Population is a real number that expresses the extent to which the data extraction process was successful in populating the knowledgebase. If the Average Population value is low then it implies that the instances in the knowledgebase that were extracted are insufficient to express all the knowledge within the schema [122].

$$AP = \frac{|I|}{|C|} \tag{3.58}$$

3.2.4.13 Class Richness

The Class Richness metric expresses the distribution of instances across classes in an ontology. It is calculated by dividing the number of classes used in the ontology, $|C^{'}|$, by the total number of classes in the ontology schema, $|C|$, as in Eq. (3.59). The metric is expressive of how rich in classes an ontology is by comparing the number of classes that have instances to the total number of classes within the ontology. A low Class Richness value implies that the knowledgebase does not have sufficient data to illuminate all the knowledge in the schema. Accordingly, a high Class Richness value implies that the data within the knowledgebase is expressive of most of the knowledge contained in the schema [122].

$$CR = \frac{|C'|}{|C|} \tag{3.59}$$

3.2.5 Proposed Model

The first application of ELECTRE in this study comprises three phases. The first phase is the data collection phase, where the ontologies are collected and their complexity metrics are calculated using the OntoMetrics platform. The importance weights for each criterion is also calculated using the CRITIC method. These form the decision matrix. The application then proceeds to the second phase, where the ranking takes place. The ELECTRE I, II, III, and IV models are applied to the decision matrix, yielding a ranking of the 200 ontologies. Finally, the rankings are compared in the analysis phase. The four rankings are compared with each other, and the top and bottom ontologies are analysed. The statistical rank correlation between the four rankings is also calculated and analysed. The diagram in Fig. 3.1 shows the process of the first application of ELECTRE for ranking ontologies.

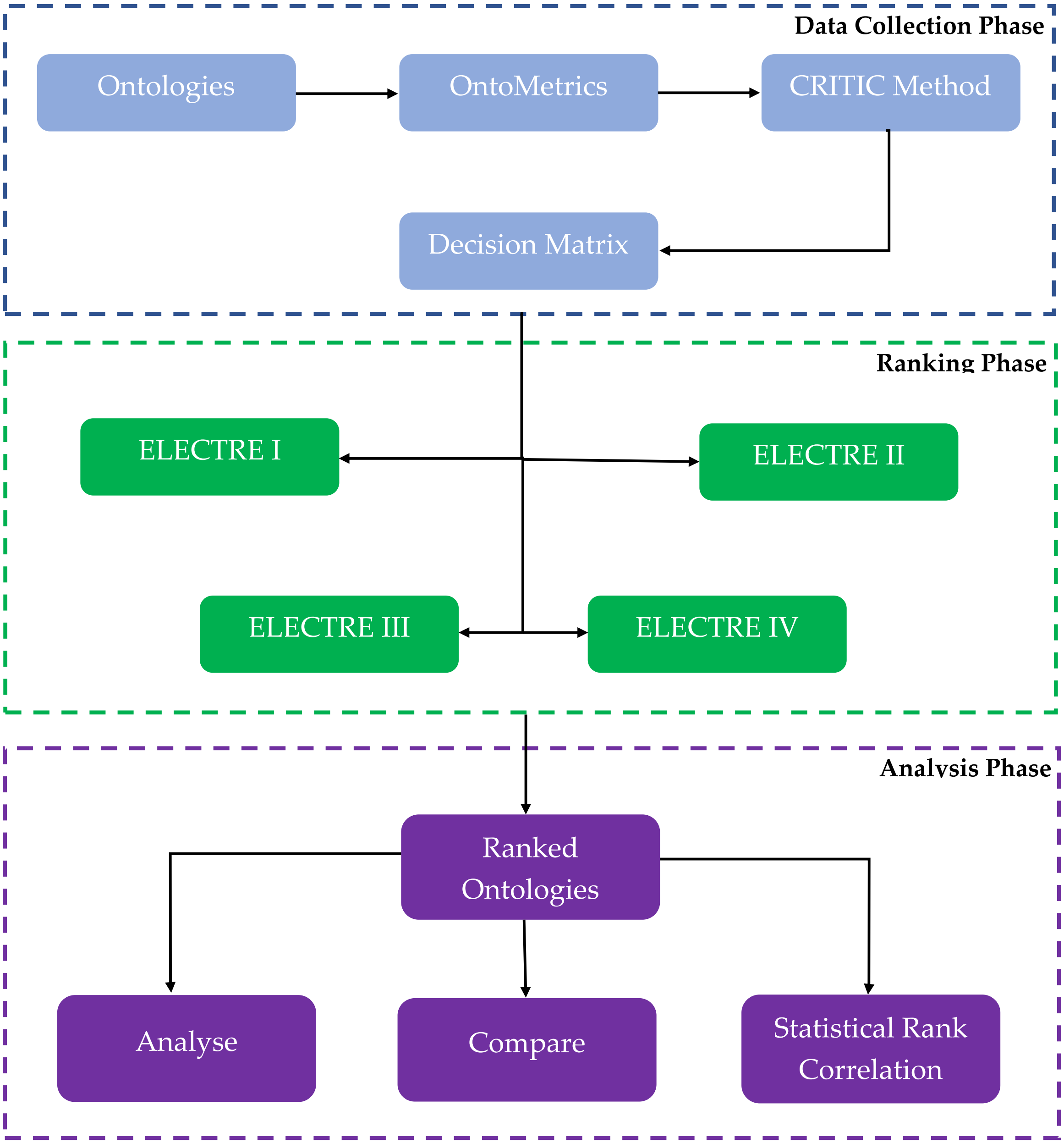


FIGURE 3.1: Model for applying ELECTRE algorithms for ontology ranking

3.2.6 Techniques of Statistical Rank Correlation

In order to understand the relationship between different rankings, statistical measures were applied to measure their correlation. In this study four methods were applied to measure the correlation between the rankings obtained by the different ELECTRE algorithms, that is, the Spearman's Rho Correlation, the Weighted Spearman's Rho Correlation, the Top-Down Correlation, and the WS Coefficient. These techniques are elaborated on as follows.

3.2.6.1 Spearman's Rho Correlation Coefficient

The Spearman's Rho [26] measure was developed as a special case of the Pearson coefficient. It is one of the most widely used techniques for quantifying relationships between ranks. In essence, the Spearman's Rho value determines the degree to which a monotonic relationship exists between two variables, that is, monotonic increasing or monotonic decreasing. The value is calculated by applying Eq. (3.60), where r_s represents the Spearman's Rho coefficient, n represents the number of ranks, and d_i represents the difference between the ranks given to the i^{th} element by the first and second ranker. The Spearman's Rho coefficient treats the disagreements of ranks given by different rankers with the same importance regardless of the location of the disagreement. This means that whether a disagreement occurs towards the top or the bottom, it will have the same effect on the correlation score.

$$r_s = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \tag{3.60}$$

3.2.6.2 Weighted Spearman's Rho Correlation Coefficient

The Weighted Spearman's Rho measure was developed by Costa and Soares [27] as an enhancement to the Spearman's Rho coefficient (Eq. (3.60)). This technique, unlike the Spearman's Rho, does not treat all rank positions the same. Disagreements that occur at the top of the ranks are given higher importance than those occurring at the bottom of the ranks. This is done by weighting the distance between two ranks as a linear function of the ranks. The Weighted Spearman's Rho value is calculated using Eq. (3.61), where R_{x_i} represents the rank given to the i^{th} element by R_x, R_{y_i} represents the rank given to the i^{th} element by R_y, and n represents the number of ranks.

$$r_w = 1 - \frac{\sum_{i=1}^{n}(R_{x_i} - R_{y_i})^2((n - R_{x_i} + 1) + (n - R_{y_i} + 1))}{n^4 + n^3 - n^2 - n} \tag{3.61}$$

3.2.6.3 Top-Down Correlation

The Top-Down Correlation measure was developed by Iman and Conover [28] as a concordance measure with higher sensitivity to agreement at the top of the rankings, and a lower sensitivity to agreement at the bottom of the rankings. This method has been around since 1987 and is one of the first attempts to measure correlation between rankings with an emphasis on the top agreements. Top-Down Correlation is based on Savage Scores, and is calculated in Eq. (3.62), where S_{Q_i} represents the Savage Score for the i^{th} rank given by Q, S_{R_i} represents the Savage Score for the i^{th} rank given by R, and n represents the number of ranks. The Savage Score S_i is given in Eq. (3.63).

$$r_T = \frac{\sum_{i=1}^{n} S_{R_i} S_{Q_i} - n}{n - S_1} \tag{3.62}$$

$$S_i = \sum_{j=1}^{n} \frac{1}{j} \tag{3.63}$$

3.2.6.4 WS Coefficient

Sałabun and Urbaniak [29] developed a method to measure the similarity between rankings obtained using MCDM methods. The WS coefficient was proposed as a weighted similarity measure, giving more importance to upper ranks, and less importance to lower ranks. This means that a rank disagreement occurring at the top of the rankings will be more significant than a rank disagreement occurring at the bottom of the rankings. The coefficient is calculated using Eq. (3.64), where *WS* is the value of the similarity between rankings R_x and R_y, N represents the length of the rankings, R_{x_i} represents the ranking given by R_x for the i^{th} element, and R_{y_i} represents the ranking given by R_y for the i^{th} element.

$$WS = 1 - \sum_{i=1}^{n} \left(2^{-R_{xi}} \cdot \frac{|R_{x_i} - R_{y_i}|}{\max\{|1 - R_{x_i}|, |N - R_{y_i}|\}} \right) \tag{3.64}$$

3.3 Classifying Ontologies with ELECTRE Tri

The second application of ELECTRE in this study focused on classifying ontologies into classes according to their complexity metrics. The ELECTRE Tri model was used as a classifier and three classes were defined. In order to define the thresholds a preference disaggregation approach was taken, wherein a genetic algorithm was designed and applied to infer a set of appropriate thresholds from a set of assignment examples. The application is discussed as follows.

3.3.1 ELECTRE Tri

The ELECTRE Tri [16] method was developed as a resolution to the classification problem. The method assigns alternatives to predefined categories. The decision-maker is required to define a set of boundaries or profiles that express the limits of the different categories.

Classes and Limiting Profiles

The decision-maker must specify a set of $p+1$ classes, $C_1, C_2, \ldots, C_p, C_{p+1}$. Each class is bounded by lower and upper profiles, b_i, such that the upper profile for the category C_p is b_p, and the lower profile for the category $C_{(p+1)}$ is also b_p. For $p+1$ categories, p boundaries must be defined. The boundaries must be defined such that the i^{th} boundary is not greater than the $i+1^{th}$ boundary, that is, $g_j(b_i) \leq g_j(b_{(i+1)})$. The definition of the classes and boundaries are shown in Fig. 3.2, where C_1 to C_{p+1} represent the $p+1$ classes to be defined, the horizontal lines g_1 to g_n represent the n criteria, and the blue lines b_1 to b_p represent the boundaries for each class. The space within two boundaries form a class.

Weights and Thresholds

A set of n weights is required to be specified, where the weight of the j^{th} criterion is represented by ω_j. The decision-maker is also required to define three thresholds, the indifference threshold q_j, the preference threshold p_j, and the veto threshold v_j, where $v_j \geq p_j \geq q_j$.

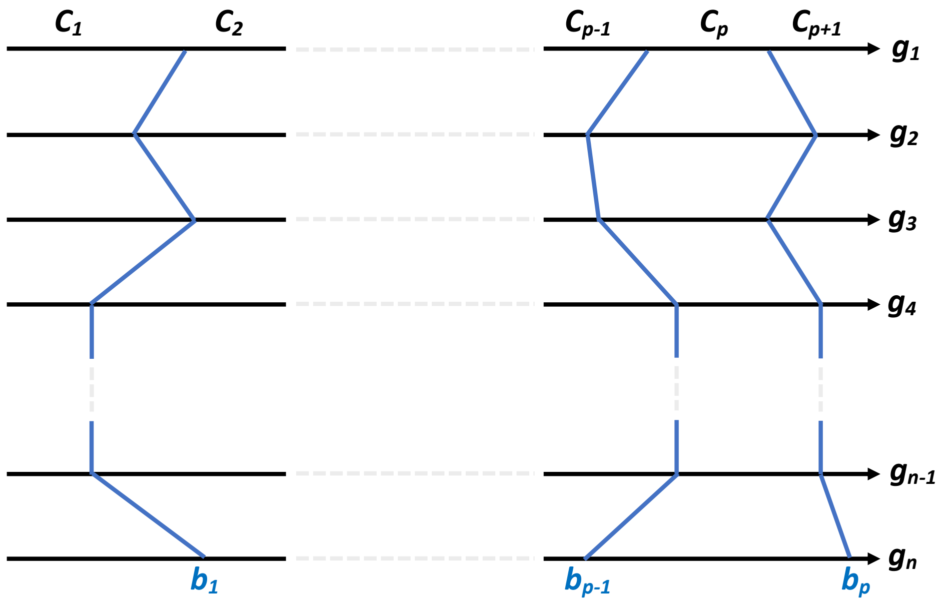


FIGURE 3.2: Definition of classes with their boundaries

Concordance Relations

The concordance values for comparing alternatives x_i with boundaries b_h are calculated as $c(x_i, b_h)$ in Eq. (3.65), where $c_j(x_i, b_h)$ is given by Eq. (3.66) and ω_j represents the weight for the j^{th} criterion.

$$\mathrm{c}(x_i, b_h) = \frac{\sum_{j=1}^{n} \omega_j \mathrm{c}_j(x_i, b_h)}{\sum_{j=1}^{n} \omega_j} \tag{3.65}$$

$$c_j(x_i, b_h) = \begin{cases} 0, & \text{if } g_j(b_h) - g_j(x_i) \geq p_j \\ 1, & \text{if } g_j(b_h) - g_j(x_i) < q_j \\ \frac{p_j + g_j(x_i) - g_j(b_h)}{p_j - q_j}, & \text{if } q_j \leq g_j(b_h) - g_j(x_i) < p_j \end{cases} \tag{3.66}$$

The concordance values for comparing boundaries b_h with alternatives x_i are calculated as $c(b_h, x_i)$ in Eq. (3.67), where $c_j(b_h, x_i)$ is given by Eq. (3.68).

$$\mathrm{c}(b_h, x_i) = \frac{\sum_{j=1}^{n} \omega_j \mathrm{c}_j(b_h, x_i)}{\sum_{j=1}^{n} \omega_j} \tag{3.67}$$

$$c_j(b_h, x_i) = \begin{cases} 0, & \text{if } g_j(x_i) - g_j(b_h) \geq p_j \\ 1, & \text{if } g_j(x_i) - g_j(b_h) < q_j \\ \frac{p_j + g_j(b_h) - g_j(x_i)}{p_j - q_j}, & \text{if } q_j \leq g_j(x_i) - g_j(b_h) < p_j \end{cases} \tag{3.68}$$

Discordance Relations

Thereafter the discordance values for comparing alternative x_i with boundary b_h, and the discordance values for comparing boundaries b_h with alternatives x_i are calculated using Eqs. (3.69) and (3.70), respectively.

$$d_j(x_i, b_h) = \begin{cases} 0, & \text{if } g_j(b_h) - g_j(x_i) < p_j \\ 1, & \text{if } g_j(b_h) - g_j(x_i) \geq v_j \\ \frac{-p_j - g_j(x_i) + g_j(b_h)}{v_j - p_j}, & \text{if } p_j \leq g_j(b_h) - g_j(x_i) < v_j \end{cases} \tag{3.69}$$

$$d_j(b_h, x_i) = \begin{cases} 0, & \text{if } g_j(x_i) - g_j(b_h) < p_j \\ 1, & \text{if } g_j(x_i) - g_j(b_h) \geq v_j \\ \frac{-p_j - g_j(b_h) + g_j(x_i)}{v_j - p_j}, & \text{if } p_j \leq g_j(x_i) - g_j(b_h) < v_j \end{cases} \tag{3.70}$$

Credibility Index

After determining the concordance and discordance values, the credibility index is determined. This represents the degree of credibility for asserting that alternative x_i outranks boundaries b_h. The credibility index between alternatives x_i and boundary b_h, denoted as $\sigma(x_i, b_h)$, is calculated by Eq. (3.71), where $\mathcal{J} = \{j \mid d_j(x_i, b_h) > C(x_i, b_h), j = 1, 2, \ldots, n\}$, which is the set of criteria whose discordance values exceed their concordance values. The credibility index between boundaries b_h and alternatives x_i, denoted as $\sigma(b_h, x_i)$, is calculated by Eq. (3.72). This allows the credibility to be lowered in accordance with the discordance values.

$$\sigma(x_i, b_h) = c(x_i, b_h) \prod_{j \in \mathcal{J}} \frac{1 - d_j(x_i, b_h)}{1 - c(x_i, b_h)} \tag{3.71}$$

$$\sigma(b_h, x_i) = c(b_h, x_i) \prod_{j \in \mathcal{J}} \frac{1 - d_j(b_h, x_i)}{1 - c(b_h, x_i)} \tag{3.72}$$

Exploitation of Credibility Index

The credibility index is then exploited by defining a cut-off threshold, λ, that lies between 0.5 and 1, that is, $\lambda \in [0.5, 1]$. The credibility index $\sigma(x_i, b_h)$ and $\sigma(b_h, x_i)$ must be compared with λ to determine the relations between alternatives and boundaries. The indifference relation, $x_i \mathrm{I} b_h$, is shown in Eq. (3.73). In this case $x_i \mathrm{S} b_h$ and $b_h \mathrm{S} x_i$ are both true, which means that x_i is indifferent to b_h, where $x_i \mathrm{S} b_h$ signifies that x_i outranks b_h.

$$\sigma(x_i, b_h) \geq \lambda \text{ and } \sigma(b_h, x_i) \geq \lambda \Rightarrow x_i \mathrm{I} b_h \tag{3.73}$$

The preference relation, $x_i \mathrm{S} b_h$, is shown in Eq. (3.74). In this case $x_i \mathrm{S} b_h$ is true and $b_h \mathrm{S} x_i$ is false, which means that x_i is preferred to b_h.

$$\sigma(x_i, b_h) \geq \lambda \text{ and } \sigma(b_h, x_i) < \lambda \Rightarrow x_i \mathrm{S} b_h \tag{3.74}$$

The preference relation, $b_h\mathrm{S}x_i$, is shown in Eq. (3.75). In this case $x_i\mathrm{S}b_h$ is false and $b_h\mathrm{S}x_i$ is true, which means that b_h is preferred to x_i.

$$\sigma(x_i, b_h) < \lambda \text{ and } \sigma(b_h, x_i) \geq \lambda \Rightarrow b_h \mathrm{S} x_i \tag{3.75}$$

The incomparability relation, $x_i\mathrm{R}b_h$, is shown in Eq. (3.76). In this case $x_i\mathrm{S}b_h$ is false and $b_h\mathrm{S}x_i$ is false, which means that x_i is incomparable to b_h.

$$\sigma(x_i, b_h) < \lambda \text{ and } \sigma(b_h, x_i) < \lambda \Rightarrow b_h \mathrm{R} x_i \tag{3.76}$$

Assignment of Alternatives

Lastly, the alternatives are assigned to categories. There are two procedures that can be applied here. The pessimistic procedure assigns alternatives in the direction of best to worst, whilst the optimistic procedure assigns alternatives in the direction of worst to best. The pessimistic procedure begins by comparing alternative x to boundary b_h, where $h = p, p-1, \ldots, 1$ with $p+1$ classes. The first profile b_h for which $x\mathrm{S}b_h$ will be the category that alternative x is assigned to, that is, $x \to C_{h+1}$. The optimistic procedure begins by comparing alternative x to boundary b_h, where $h = 1, 2, \ldots, p-1, p$, with $p+1$ defined classes. The first profile b_h where $b_h > x$, is used to assign the alternative, that is, $x \to C_h$.

3.3.2 Preference Disaggregation

The ELECTRE Tri method requires many thresholds and parameters to be specified, such as the limiting profiles, the preference thresholds, the indifference thresholds, the veto thresholds, the criteria weights, and the cut-off level. There are two manners in which these preferences may be defined, that is, *directly* or *indirectly*. The direct method requires the decision-maker to specify their preferences and parameters to build the ELECTRE Tri model. However, in some decision-making problems it may be very difficult to specify these parameters, or in some cases the nature of the problem may not allow a decision-maker to specify the parameters. To overcome this issue, indirect preference disaggregation methods were proposed [126] to infer preferences given a set of assignment examples. The idea is that a decision-maker may find it easier to assign a subset of alternatives to classes, as opposed to specifying direct preferences and thresholds to build a classifier model. These assignments could also come from decisions made in past scenarios.

The diagram in Fig. 3.3 depicts the flow of a preference disaggregation problem. Essentially, the concept of preference disaggregation works by the decision-maker assigning a subset A^*

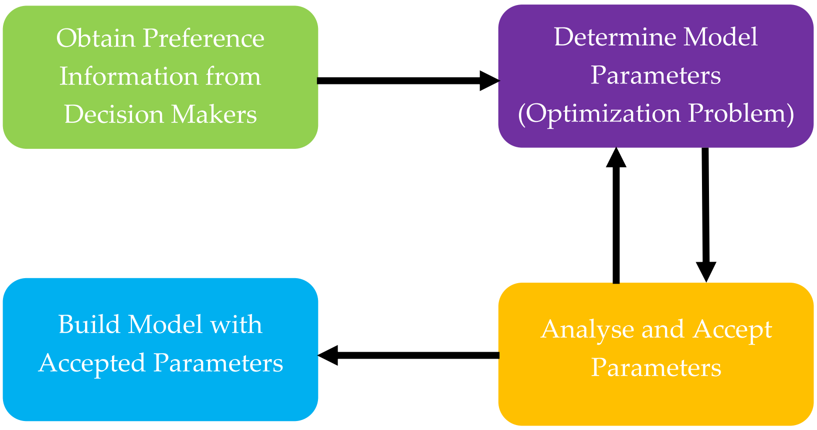


FIGURE 3.3: Flowchart depicting the general preference disaggregation process

from the set of all alternatives A, that is, $A^* \subset A$, to categories. Using some form of optimization, a set of preference thresholds are inferred. These thresholds are evaluated according to the accuracy of which the model they represent is able to assign the alternatives in A^* to the categories originally chosen by the decision-maker. When a set of appropriate parameters are realised then a model is built using those parameters. Traditionally, authors have modeled the preference disaggregation problem using mathematical programming optimization techniques. One of the earlier studies was performed by Mousseau and Slowinski [127], where they developed a model for inferring the parameters based on the assignment examples provided by decision-makers. The authors proposed an interactive approach based on a non-linear optimization problem. A further study by Mousseau et al. [128] focused on applying a linear optimization program for determining the weights only, with the class boundaries and thresholds being pre-defined already. Researchers have also attempted to convert the problem into a linear programming model by attempting to infer only some thresholds [128–130]. However, the complexity associated with developing and solving these mathematical programs are generally high, especially for non-linear models as needed for the preference disaggregation with ELECTRE Tri. To overcome this challenge, authors have proposed the use of metaheuristic techniques as an alternative to mathematical optimization.

One of the first studies to take a metaheuristic approach for ELECTRE Tri preference disaggregation was by Doumpous et al. [131], where the differential evolution algorithm was applied to infer a set of thresholds for building an ELECTRE Tri model. The model was then successfully applied on an artificially generated dataset and a real-world banking dataset. In 2019 Fernandez et al. [132] applied the genetic algorithm to infer a set of parameters for ELECTRE Tri. The authors inferred the veto thresholds, cutting level, class boundaries, and criteria importance weights. Another study by Barros et al. in 2021 [133] developed a model for inferring ELECTRE Tri parameters using the genetic algorithm. The study proposed the use of K-means++ clustering to produce assignment examples as opposed to a decision-maker providing the assignment examples. Evidently, there has been much interest in learning ELECTRE Tri models with the use of metaheuristic techniques. The genetic algorithm has also had great success in previous applications for preference disaggregation [131–133]. Accordingly, this study applies the genetic algorithm in order to infer a set of appropriate thresholds for building an ELECTRE Tri model, thereby reducing the complexity associated with building a model for the classification of ontologies. The genetic algorithm is explained further in the next section.

3.3.3 The Genetic Algorithm

The genetic algorithm is a metaheuristic optimization algorithm inspired by the process of evolution [134]. It is a search algorithm that is designed according to the concepts of natural selection and genetics. The idea is that in each population only the fittest survive and move on to the next generations, hence with time the quality of solutions become stronger.

The genetic algorithm [134] begins by defining a candidate solution to an optimization problem in the form of a chromosome. A population of chromosomes is then created, randomly or implicitly. The population is then exploited using some operations such as *selection*, *crossover*, and *mutation* to form a new population - keeping only the strongest performing candidate solutions. In order to evaluate each candidate solution a fitness function must also be defined. The process continues in an iterative manner, developing new populations, until either a specified level of performance is met from a candidate solution, or the maximum number of populations were generated. The flowchart in Fig. 3.4 illustrates the process of a genetic algorithm.

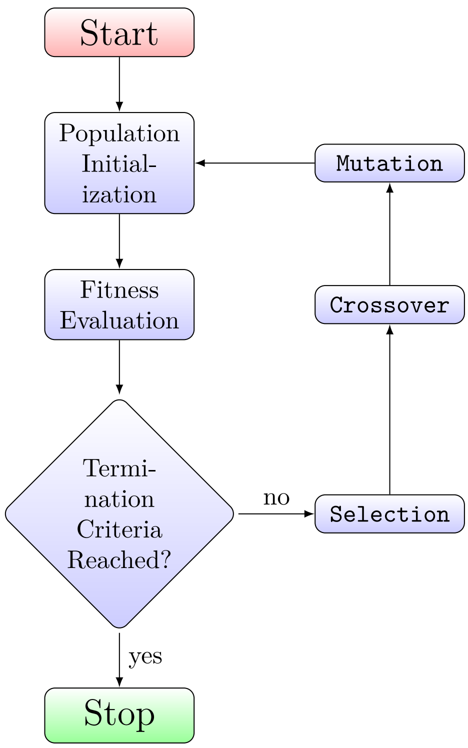


FIGURE 3.4: Flowchart of the genetic algorithm

3.3.4 Proposed Model

The Genetic Algorithm is used to search for a set of parameters that can build an ELECTRE Tri model to accurately satisfy the alternative assignments. In order to infer a set of thresholds, a set of assignments are required. A denotes the set of all ontologies and A^* represents the set of assignments, $A^* \subset A$. An ELECTRE Tri model requires many parameters and thresholds, as listed below.

1. Limiting Profiles b_h
2. Preference Thresholds p_j
3. Indifference Thresholds q_j
4. Veto Thresholds v_j
5. Criteria Importance Weights ω_j
6. Cut-off Level λ

Accordingly, it may be difficult for decision-makers to specify all the required thresholds. Therefore, in this application, the limiting profiles and the criteria importance weights are specified directly, and the remaining parameters are inferred through the Genetic Algorithm. Since there are m ontologies, n criteria, and t classes, then $(1 + 3n)$ thresholds have to be inferred, specifically, n veto thresholds v_j, n preference thresholds p_j, n indifference thresholds q_j, and 1 cut-off level λ.
The algorithm expresses a candidate solution in the form of a chromosome, with each component of the chromosome referred to as a gene. The chromosome for this application is shown in Fig. 3.5. The first n genes of the chromosome represent the veto thresholds v_1 to v_n, the second n genes represent the preference thresholds p_1 to p_n, the third set of n genes represent the indifference thresholds q_1 to q_n, and the last gene represents the cut-off level λ. Accordingly, each chromosome representing a candidate solution has $(1 + 3n)$ individual genes. The values that the cut-off level gene can take are constrained such that $0.5 \leq \lambda \leq 1$, and the other genes are constrained such that $q_j \leq p_j \leq v_j, \forall j \in n$.

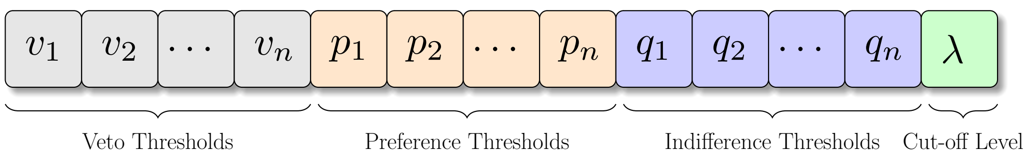


FIGURE 3.5: Chromosome representing a solution for the Genetic Algorithm

In order to evaluate the fitness of each candidate solution, a fitness function is defined as in Eq. (3.77). The fitness score for a chromosome X, represented as $\mathcal{F}(X)$ is calculated as the number of assignment examples in A^* that are correctly classified from the ELECTRE Tri model built with the parameters X, denoted as $\mathcal{C}(X, A^*)$, divided by the total number of assignment examples A^*.

$$\mathcal{F}(X) = \frac{\mathcal{C}(X, A^*)}{|A^*|} \tag{3.77}$$

An important part of the Genetic Algorithms design is the manner in which it creates new candidate solutions. There are three main aspects to control this, namely, selection, crossover, and mutation. The selection aspect determines how chromosomes are chosen to be used as parent solutions, that is, to create new solutions from. The tournament selection process is used in this application, with a tournament size of 2. Tournament selection essentially treats the selection process as a tournament, where the challengers are randomly chosen chromosomes. The number of challengers that are chosen are known as the tournament size, and are set by the user, in this case it is 2. Two chromosomes are chosen randomly and the chromosome with the highest fitness score beats its opponent chromosome. The winning chromosomes are combined in order to form new candidate solution chromosomes.

The process of combining two chromosomes to create a new candidate solution chromosome involves a crossover technique and a mutation technique. The crossover technique used in this application is the Arithmetic Crossover. The idea is that the genes from either parent chromosome is combined using an arithmetic operation to produce the new gene, which is done for all genes to produce a new chromosome. This study creates a new gene by determining the arithmetic mean of the two parent genes.

The mutation aspect creates a change in the chromosome randomly in order to enhance its exploration process. The cut-off level λ gene was selected to be mutated in this application, with a mutation rate of 0.04. This means that each chromosome has a 4% chance of having its gene mutated. The range that the mutation can take is a random value between 0.5 and 1.

Finally, to ensure that the well-performing candidate solutions are not lost during each new population, a process of elitism is applied. This keeps a number of the best performing solutions, called elites, from the previous generation. The number of elites to be kept were set to 4. The model of the proposed application is shown in Fig 3.6

3.3.5 Dataset

The dataset used in this application is the same as the one used in the previous application, that is, 200 biomedical ontologies obtained from the BioPortal ontology repository [18]. The metrics used in this application are also the same as those used in the previous application, that is, 13 complexity metrics. These metrics are:

1. Attribute Richness (AR)
2. Inheritance Richness (IR)
3. Relationship Richness (RR)

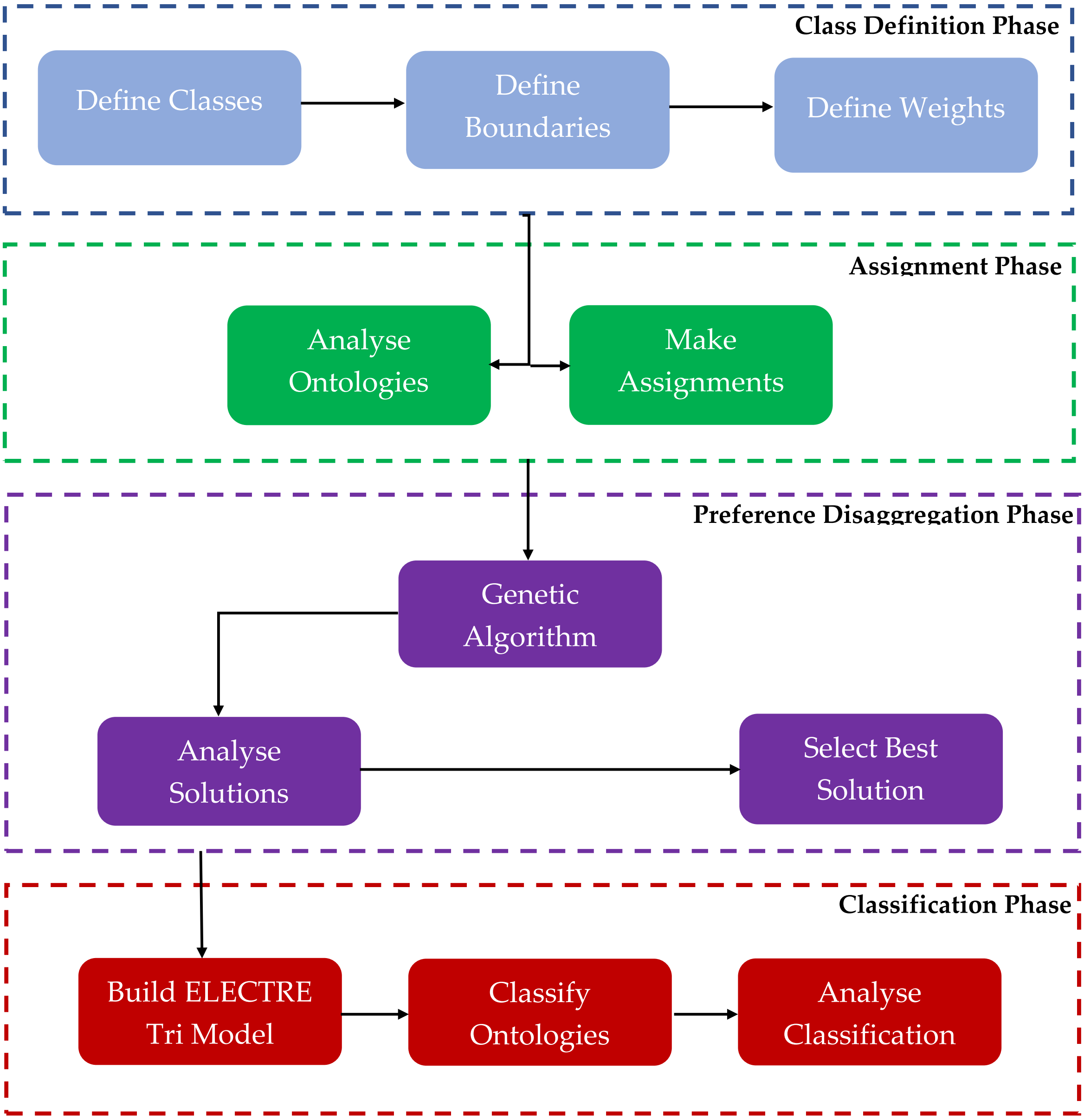


FIGURE 3.6: Model for applying ELECTRE Tri and the Genetic Algorithm for classification of ontologies

4. Equivalence Ratio (ER)
5. Average Depth (AD)
6. Maximal Depth (MD)
7. Average Breadth (AB)
8. Maximal Breadth (MB)
9. Average Number of Paths (ANP)
10. Absolute Leaf Cardinality (ALC)
11. Absolute Root Cardinality (ARC)

12. Average Population (AP)

13. Class Richness (CR)

A comprehensive explanation of the metrics is presented in Section 3.2.4. The 13 metrics are expressive of 4 dimensions of ontology evaluation, namely, *accuracy*, *understandability*, *cohesion*, and *conciseness*. These dimensions are further explained in Section 3.2.4. The full dataset is presented in Appendices A and B.

3.4 A Novel ZPLTS-ELECTRE II Algorithm for Ranking Ontologies

The previous two applications involved ranking and classification of ontologies according to their complexity metrics. In real-world scenarios, when a group of stakeholders require an ontology for reuse they would need to evaluate and select an appropriate ontology from a choice of many ontologies. They may make use of complexity metrics to evaluate the ontologies, but an emphasis will also be placed on how well each ontology aligns with their needs and requirements. Therefore, there is a need for techniques that enable stakeholders to evaluate ontologies from not only a complexity perspective, but also from a usability perspective. The third application of ELECTRE in this study involves the development of a novel ELECTRE method, named ZPLTS-ELECTRE II. The traditional ELECTRE II method is combined with the concept of Z-Probabilistic Linguistic Term Set in order to overcome the following challenges:

1. Whilst there are some studies that have applied Multi-Criteria Decision-Making (MCDM) techniques for the tasks of ontology selection and ranking [20–23, 39, 40], none of them have made use of fuzzy concepts to enhance the modelling and selection process. This is, to the best of our knowledge, the first application to take a fuzzy MCDM approach to ranking ontologies for selection and reuse.

2. There are very few studies that combine both the complexity metrics and the qualitative usability metrics for ranking ontologies. This application provides a framework for combining complexity metrics with usability metrics and may even be extended to combine other metrics to rank ontologies for selection and reuse.

3. Current methods for modelling usability attributes of ontologies do not factor in the varying levels of credibility associated with different users and stakeholders. To overcome this problem, this application makes use of the Z-Probabilistic Linguistic Term Set (ZPLTS) which enables the evaluator to express their credibility levels.

4. The process of evaluating and selecting ontologies for reuse in real-world scenarios would require a group of stakeholders to provide their evaluation according to some requirements, as opposed to only a single person as seen in theoretical studies. However, there is very little work that effectively enables a succinct modelling of an ontology selection problem within a group environment. This application enables a group of stakeholders to perform the evaluation and ranking of ontologies.

The newly developed method is modelled below and its applicability is ascertained by ranking a set of nine mental-health ontologies from the BioPortal Repository. A mixture of complexity metrics and usability metrics are used, specifically, five complexity metrics and five usability metrics are employed. The usability metrics are adapted from the Ontology Usability Scale [9].

3.4.1 Ontology Usability Scale

The Ontology Usability Scale (OUS) was proposed by Ma et al. [9] in 2018 as a model for ontology engineers to evaluate ontologies in terms of their usability. The authors extracted the metrics from the OntoMetric study [10] and reduced the 160 characteristics to 10 aspects. The framework for evaluating ontologies is modelled as a 10-item Likert scale, which a user may complete in order to evaluate a given ontology. The original OUS is given in Table 3.1.

TABLE 3.1: Ontology Usability Scale

Number	Statement	1	2	3	4	5
1	I think the documentation provides sufficient examples for me to make sure how to use the ontology.					
2	The purpose of the ontology is clear.					
3	I found the concepts and relations in this ontology properly described in natural language.					
4	I think the relations in this ontology relate appropriate concepts.					
5	I am confident I understand the conceptualization of the ontology.					
6	I would imagine that most domain experts would understand this ontology very quickly.					
7	I think the attributes in this ontology describe the concepts well.					
8	I found the subclasses in this ontology are properly defined.					
9	I found the formal specification of concepts and relations in this ontology coincides with the descriptions in natural language.					
10	I do not need the support of a person experienced with this ontology to be able to use it.					

Each statement in the OUS has a scale of 1 to 5 to allow the user to express their evaluation. The scale represents the level of agreement that the user feels towards each statement in light of the ontology being evaluated, with the levels being “strongly disagree”, “disagree”, “neutral”, “agree”, and “strongly agree”, from 1 to 5 respectively. In order to evaluate and rank the ontologies, each ontology is assigned a score. The score, denoted as s_t, is calculated by the summation of the individual scores for each of the 10 statements, $s_1, s_2, \ldots, s_{10}$, as shown in Eq. (3.78). The ontologies having higher scores are associated with better usability than those with lower scores. Based on the scores the ontologies can be ranked from best to worst.

$$s_t = \sum_{i=1}^{10} s_i \tag{3.78}$$

The different statements forming the OUS pertain to different aspects of ontology evaluation. The statements 4, 7, 8, and 9 are related to the syntax of the ontology and pertain to the ontology's content structure. The statements 2, 3, and 5 are related to the semantics and documentation of the ontology. The statements 1, 6, and 10 deal with the pragmatics of the ontology, that is, the first-hand experience necessity for comprehending the ontology.

3.4.2 A Downside of Ontology Ranking with ELECTRE

The first application proposed applies the ELECTRE ranking models (I, II, III, and IV) to rank the dataset of 200 ontologies according to their 13 complexity metrics. It is definitely useful to evaluate ontologies according to their quality and complexity, however, it is equally useful to evaluate ontologies according to their usability. Even though MCDM provides excellent modelling capability for ontology selection, the traditional ELECTRE methods only allow for numerical criteria. Whilst it is possible to evaluate the usability aspects of ontologies using numerical criteria, it is much more natural for decision-makers to use linguistic natural language terms. Current ELECTRE methods do not allow for the use of natural language terms, therefore this study considers the concept of Z-Probabilistic Linguistic Term Sets.

3.4.3 The Concept of Z-Probabilistic Linguistic Term Set

In recent years there has been a trend in combining the ELECTRE methods with concepts based upon fuzzy set theory in order to expand their capabilities and performance. In this study, the Z-Probabilistic Linguistic Term Set (ZPLTS) is combined with ELECTRE II to enhance the modelling capabilities of the traditional ELECTRE II. The concepts and preliminaries of Linguistic Term Sets (LTS), Probabilistic Linguistic Term Set (PLTS), Z-Numbers, and Z-Probabilistic Linguistic Term Sets (ZPLTS) are introduced in this section, together with the model of the novel ELECTRE II method.

3.4.3.1 Linguistic Term Set and Hesitant Fuzzy Linguistic Term Set

During the decision making process it is often difficult for decision-makers to express their opinions using numerical values. Therefore the concept of Linguistic Term Set (LTS) [102] was proposed to provide decision-makers the opportunity to better express themselves. An LTS is a set of linguistic terms that a decision-maker may pick from to evaluate a particular criterion. An LTS, S, can be defined in Eq. (3.79), where each element of the set S represents a linguistic term, and ς and $-\varsigma$ are the upper and lower bounds of the set, respectively. The midterm is symbolic of indifference and the other linguistic terms are placed symmetrically centered around the midterm.

$$S = \{S_t \mid t = -\varsigma, \ldots, -1, 0, 1, \ldots, \varsigma\} \tag{3.79}$$

An example of an LTS used when evaluating the quality of different motor vehicles is the set $S = \{s_{-2} = \text{'very bad'}, s_{-1} = \text{'bad'}, s_0 = \text{'normal'}, s_1 = \text{'good'}, s_2 = \text{'very good'}\}$, where there are 5 linguistic terms in S, $\varsigma = 2$, and $-\varsigma = -2$. A decision-maker may select a linguistic term from S when expressing their opinion for some criteria. They may select s_{-1} for the first car and s_2 for the second car, meaning that the quality of the first car is *bad*, and the quality of the second car is *very good*.

One issue that arises with the LTS is that a decision-maker may feel hesitant to provide their opinion for a criterion. Given the choice to select only one term from an LTS, a decision-maker may feel unsure which one to pick, or they may want to pick more than one term. To overcome this issue, the Hesitant Fuzzy Linguistic Term Set (HFLTS) [103] was proposed, whereby a decision-maker is able to select more than one linguistic value from an LTS. If S is an LTS, then rather than only selecting a single term, an HFLTS may comprise multiple terms, allowing the decision-maker more flexibility in their expressions.

As an example, consider the LTS $S = \{s_{-2} = \text{very low}, s_{-1} = \text{low}, s_0 = \text{medium}, s_1 = \text{high}, s_2 = \text{very high}\}$. A decision-maker may select an HFLTS as the set $\{s_1, s_2\}$, which signifies high and very high. Another HFLTS signifying 'at least medium' is the set $\{s_0, s_1, s_2\}$, which is a subset of linguistic terms from S comprising 'medium', 'high', and 'very high'.

3.4.3.2 Probabilistic Linguistic Term Set

One problem that arises with HFLTSs is that it assumes that all linguistic values that are chosen are given equal probability. This is not always the case as sometimes a decision-maker may wish to assign varying probability distributions across the different terms in an HFLTS. To accomplish this the concept of Probabilistic Linguistic Term Set (PLTS) [105] was proposed. A PLTS allows a decision-maker to select multiple terms from an LTS, along with the ability to assign probability values to each term selected. A PLTS, $L(p)$, can be defined in Eq. (3.80), with L^m being a linguistic term, p^m is its associated probability, and the number of linguistic terms in $L(p)$ is denoted by $\#L(p)$.

$$L(p) = \{L^m(p^m) \mid L^m \in S, p^m \leq 0, m = 1, 2, \ldots, \#L(p), \sum_{m=1}^{\#L(p)} p^m \leq 1\} \tag{3.80}$$

Consider the task of evaluating the size of a house, given an LTS $S = \{s_{-1} = \text{small}, s_0 = \text{medium}, s_1 = \text{large}\}$. A decision-maker may want to express their opinion that the house is between small and medium, specifically with 60% certainty it is small and 40% certainty it is medium. An HFLTS would be insufficient to express this opinion, and hence a PLTS is better suited. A PLTS would be formed as $L(p) = \{s_{-1}(0.6), s_0(0.4)\}$. Accordingly, PLTSs have more modelling capabilities than the HFLTSs.

3.4.3.3 Z-Number

In real-world decision-making environments, different decision-makers and stakeholders are often involved in the decision-making process. Accordingly, there are different levels of credibility associated with the different decision-makers, as each decision-maker has a unique perspective. To encompass the varying credibility levels associated with different decision-makers, the concept of Z-Numbers was proposed by Zadeh [109]. A Z-Number is defined as a tuple $Z = (A, B)$, with the A value being the description or restriction value, and the B value representing the credibility of that A value. For example, a Z-Number to express the opinion that a stock has a quality level of 0.7, and the evaluator is 50% certain, would be $Z = (0.7, 0.5)$. A Z-Number enhances the process of selecting linguistic terms by adding a credibility variable, allowing different decision-makers to not only evaluate a criterion, but also to specify their credibility levels.

3.4.3.4 Z-Probabilistic Linguistic Term Set

The concept of PLTS is very powerful but one downside is that it ignores different credibility's of decision-makers. This can lead to inaccurate results in the decision-making process. To overcome this, the concepts of Z-Numbers and PLTSs were combined to create the Z-Probabilistic Linguistic Term Set (ZPLTS) [108]. A ZPLTS can be defined in Eq. (3.81), where $\hat{Z}^{\#}$ is a ZPLTS, $\hat{Z}$ is a Z-Probabilistic Linguistic Value (ZPLV), and X is a non-empty set.

$$\hat{Z}^{\#} = \{\langle x, \hat{Z}\rangle \mid x \in X\} \tag{3.81}$$

A ZPLV is essentially a tuple of two PLTSs, or formally it can be defined using Eq. (3.82).

$$\hat{Z} = (\hat{A}, \hat{B}) = (L_{\hat{A}}(p), L_{\hat{B}}(p)) \tag{3.82}$$

where $L_A(p)$ and $L_B(p)$ are 2 PLTSs, and S and S' are LTSs, with
$L_{\hat{A}}(p) = \{L^m_{\hat{A}}(p^m_{\hat{A}}) \mid L^m_{\hat{A}} \in S, p^m_{\hat{A}} \leq 0, m = 1, 2, \ldots, \#L_{\hat{A}}(p_{\hat{A}}), \sum_{m=1}^{\#L_{\hat{A}}(p_{\hat{A}})} p^m_{\hat{A}} \leq 1\}$,
$L_{\hat{B}}(p) = \{L^n_{\hat{B}}(p^n_{\hat{B}}) \mid L^n_{\hat{B}} \in S', p^n_{\hat{B}} \leq 0, n = 1, 2, \ldots, \#L_{\hat{B}}(p_{\hat{B}}), \sum_{n=1}^{\#L_{\hat{B}}(p_{\hat{B}})} p^n_{\hat{B}} \leq 1\}$, and
$S = \{-\varsigma, \ldots, -1, 0, 1, \ldots, \varsigma\}$ and $S' = \{-\zeta, \ldots, -1, 0, 1, \ldots, \zeta\}$.

As an example, consider 2 LTSs, $S = \{s_{-1} = \text{'bad'}, s_0 = \text{'average'}, s_1 = \text{'good'}\}$, and $S' = \{s'_{-1} = \text{'not confident'}, s'_0 = \text{'confident'}, s'_1 = \text{'very confident'}\}$. When evaluating the performance of a student in a class, a ZPLV to express the evaluation that the students performance is *average*, with the evaluator being *very confident*, is represented as (s_0, s'_1). Another ZPLV to express a students performance being *bad*, with the evaluator being *very confident*, is given by (s_{-1}, s'_1). The 2 ZPLVs can be combined to form a ZPLTS, $(\{s_{-1}(0.5), s_0(0.5)\}, \{s'_1(1)\})$.

In this study the concept of ZPLTS is combined with ELECTRE II to create a novel algorithm, the ZPLTS-ELECTRE II. The authors in [108] proposed a technique for normalizing ZPLTSs, as well as some methods for comparing ZPLTSs, specifically the concepts of score, deviation degree, and distance. These concepts are elaborated on as follows.

Normalization of ZPLVs

In order to normalize a ZPLV, both the value and the credibility set, that is, $L_{\hat{A}}(p)$ and $L_{\hat{B}}(p)$, must be normalized. A ZPLV is normalized in 2 stages. Firstly, the probability distribution of the linguistic terms are normalized, and thereafter the number of linguistic terms are normalized. The first stage is required whenever the sums of the probabilities are less than 1, then the probabilities must be normalized to equate to 1. If $\hat{Z}$ is a ZPLV with $\hat{Z} = (L_{\hat{A}}(p), L_{\hat{B}}(p))$, $\sum_{m=1}^{\#L_{\hat{A}}(p_{\hat{A}})} p_{\hat{A}}^m \leq 1$ and $\sum_{n=1}^{\#L_{\hat{B}}(p_{\hat{B}})} p_{\hat{B}}^n \leq 1$, then the associated ZPLV after normalizing the probability distributions can be defined in Eq. (3.83).

$$\hat{Z} = (\dot{L}_{\hat{A}}(p), \dot{L}_{\hat{B}}(p)) = (\{L_{\hat{A}}^m(\dot{p}_{\hat{A}}^m)\}, \{L_{\hat{B}}^n(\dot{p}_{\hat{B}}^n)\}) \tag{3.83}$$

where $\dot{p}_{\hat{A}}^m = \frac{p_{\hat{A}}^m}{\sum_{m=1}^{\#L_{\hat{A}}(p_{\hat{A}})} p_{\hat{A}}^m}$, $\dot{p}_{\hat{B}}^n = \frac{p_{\hat{B}}^n}{\sum_{n=1}^{\#L_{\hat{B}}(p_{\hat{B}})} p_{\hat{B}}^n}$, $m = 1, 2, \ldots, \#L_{\hat{A}}(p_{\hat{A}})$ and $n = 1, 2, \ldots, \#L_{\hat{B}}(p_{\hat{B}})$.

After the first normalization stage, that is, normalizing the probabilities to equate to 1, the second stage is to normalize the number of linguistic terms. This is required in order to calculate the distance between two ZPLVs. If $\hat{Z}_1$ and $\hat{Z}_2$ are ZPLVs with $\hat{Z}_1 = (L_{\hat{A}1}(p), L_{\hat{B}1}(p))$ and $\hat{Z}_2 = (L_{\hat{A}2}(p), L_{\hat{B}2}(p))$. The number of linguistic terms in a PLTS is given by $\#L(p)$. In the case that $\#L_{\hat{A}1}(p_{\hat{A}1}) > \#L_{\hat{A}2}(p_{\hat{A}2})$ then the number of terms need to be normalized as follows:

1. $L_{\hat{A}2}$ is increased by adding ϕ terms to $L_{\hat{A}2}$, where $\phi = \#L_{\hat{A}1}(p_{\hat{A}1}) - \#L_{\hat{A}2}(p_{\hat{A}2})$. The ϕ linguistic terms to be added may be any linguistic terms in $L_{\hat{A}2}(p)$.

2. The probabilities of the ϕ linguistic terms that were added must be set to 0.

3. The processes in 1. and 2. also applies when $\#L_{\hat{B}1}(p_{\hat{B}1}) > \#L_{\hat{B}2}(p_{\hat{B}2})$.

Consider an example of normalizing 2 ZPLVs, with $\hat{Z}_1$ and $\hat{Z}_2$ being ZPLVs, where
$\hat{Z}_1 = (\{s_0(0.2), s_1(0.8)\}, \{s'_1(0.4), s'_2(0.2), s'_3(0.2)\})$ and
$\hat{Z}_2 = (\{s_{-2}(0.2), s_{-1}(0.4), s_0(0.2)\}, \{s'_{-2}(0.2), s'_0(0.2), s'_2(0.4)\})$. In order to normalize the ZPLVs, firstly all probabilities must add up to 1. This results in
$\hat{Z}_1 = (\{s_0(0.2), s_1(0.8)\}, \{s'_1(0.5), s'_2(0.25), s'_3(0.25)\})$ and
$\hat{Z}_2 = (\{s_{-2}(0.25), s_{-1}(0.5), s_0(0.25)\}, \{s'_{-2}(0.25), s'_0(0.25), s'_2(0.5)\})$. The next step is to ensure that the cardinalities of the evaluation and credibility values for each ZPLV are equal, resulting in
$\hat{Z}_1 = (\{s_0(0.2), s_1(0.8), s_1(0)\}, \{s'_1(0.4), s'_2(0.2), s'_3(0.2)\})$ and
$\hat{Z}_2 = (\{s_{-2}(0.2), s_{-1}(0.4), s_0(0.2)\}, \{s'_{-2}(0.2), s'_0(0.2), s'_2(0.4)\})$.

Score of ZPLVs

In order to make use of ZPLVs they need to be comparable with each other. Chai et al. [108] proposed the score method to compare two ZPLVs. Larger scores correlate with larger ZPLVs, allowing for their comparison. Let $\hat{Z} = (\hat{A}, \hat{B}) = (L_{\hat{A}}(p), L_{\hat{B}}(p))$, where $(L_{\hat{A}}(p), L_{\hat{B}}(p))$ is

$(\{L^m_{\hat{A}}(p^m_{\hat{A}}) \mid m = 1, 2, \ldots, \#L_{\hat{A}}(p_{\hat{A}})\}, \{L^n_{\hat{B}}(p^n_{\hat{B}}) \mid n = 1, 2, \ldots, \#L_{\hat{B}}(p_{\hat{B}})\})$. The subscripts of $L^m_{\hat{A}}$ and $L^n_{\hat{B}}$ are denoted as $v^m_{\hat{A}}$ and $v^n_{\hat{B}}$, respectively. The score of $\hat{Z}$ is defined in Eq. (3.84).

$$S(\hat{Z}) = (\bar{\alpha} + \varsigma)(\bar{\alpha}' + \zeta) \tag{3.84}$$

where $\bar{\alpha} = \frac{\sum_{m=1}^{\#L_{\hat{A}}(p_{\hat{A}})} v^m p^m_{\hat{A}}}{\sum_{m=1}^{\#L_{\hat{A}}(p_{\hat{A}})} p^m_{\hat{A}}}$ and $\bar{\alpha}' = \frac{\sum_{n=1}^{\#L_{\hat{B}}(p_{\hat{B}})} v^n p^n_{\hat{B}}}{\sum_{n=1}^{\#L_{\hat{B}}(p_{\hat{B}})} p^n_{\hat{B}}}$.

Deviation Degree of ZPLVs

Sometimes two ZPLVs may have the same score, despite the ZPLVs being unequal. For this reason, Chai et al. [108] proposed the concept of deviation degree of ZPLVs. Let $\hat{Z} = (\hat{A}, \hat{B}) = (L_{\hat{A}}(p), L_{\hat{B}}(p))$, where $(L_{\hat{A}}(p), L_{\hat{B}}(p))$ is $(\{L^m_{\hat{A}}(p^m_{\hat{A}}) \mid m = 1, 2, \ldots, \#L_{\hat{A}}(p_{\hat{A}})\}, \{L^n_{\hat{B}}(p^n_{\hat{B}}) \mid n = 1, 2, \ldots, \#L_{\hat{B}}(p_{\hat{B}})\})$. The subscripts of $L^m_{\hat{A}}$ and $L^n_{\hat{B}}$ are denoted as $v^m_{\hat{A}}$ and $v^n_{\hat{B}}$, respectively. The deviation degree of $\hat{Z}$ is defined in Eq. (3.85).

$$D(\hat{Z}) = \sqrt{\frac{\sum_{m=1}^{\#L_{\hat{A}}(p_{\hat{A}})} \sum_{n=1}^{\#L_{\hat{B}}(p_{\hat{B}})} ((p^m_{\hat{A}} v^m_{\hat{A}} + \varsigma)(p^n_{\hat{B}} v^n_{\hat{B}} + \zeta) - (\bar{\alpha} + \varsigma)(\bar{\alpha}' + \zeta))^2}{\#L_{\hat{A}}(p_{\hat{A}}) \#L_{\hat{B}}(p_{\hat{B}})}} \tag{3.85}$$

Comparison of ZPLVs

After determining the score and deviation degree of ZPLVs, they can be compared as follows. Let $\hat{Z}_1$ and $\hat{Z}_2$ be two ZPLVs. The comparison between $\hat{Z}_1$ and $\hat{Z}_2$ is defined as:

1. If $S(\hat{Z}_1) > S(\hat{Z}_2)$ then $\hat{Z}_1 > \hat{Z}_2$.
2. If $S(\hat{Z}_1) < S(\hat{Z}_2)$ then $\hat{Z}_1 < \hat{Z}_2$
3. If $S(\hat{Z}_1) = S(\hat{Z}_2)$ then the deviation degree is required to compare $\hat{Z}_1$ and $\hat{Z}_2$ as follows:
   (a) If $D(\hat{Z}_1) > D(\hat{Z}_2)$ then $\hat{Z}_1 < \hat{Z}_2$.
   (b) If $D(\hat{Z}_1) < D(\hat{Z}_2)$ then $\hat{Z}_1 > \hat{Z}_2$.
   (c) If $D(\hat{Z}_1) = D(\hat{Z}_2)$ then $\hat{Z}_1 \approx \hat{Z}_2$.
   (d) If $L_{\hat{A}1}(p) = L_{\hat{A}2}(p)$ and $L_{\hat{B}1}(p) = L_{\hat{B}2}(p)$ then $\hat{Z}_1 = \hat{Z}_2$.

As an example, let $\hat{Z}_1$ and $\hat{Z}_2$ be two ZPLVs, with $\hat{Z}_1 = \{\{s_0(0.2), s_1(0.8)\}, \{s'_1(0.55), s'_2(0.45)\}\}$ and $\hat{Z}_2 = \{\{s_{-1}(0.75), s_0(0.25)\}, \{s'_1(0.1), s'_2(0.9)\}\}$. There are 2 terms is $L_{\hat{A}1}(p_{\hat{A}1})$, 2 terms in $L_{\hat{B}1}(p_{\hat{B}1})$, 2 terms in $L_{\hat{A}2}(p_{\hat{A}2})$, and 2 terms in $L_{\hat{B}2}(p_{\hat{B}2})$. The ς and ζ values are both 3. The scores of $\hat{Z}_1$ and $\hat{Z}_2$, denoted as $S(\hat{Z}_1)$ and $S(\hat{Z}_2)$, are calculated as follows.

$S(\hat{Z}_1) = (\bar{\alpha} + 3)(\bar{\alpha}' + 3)$, and $\bar{\alpha} = \frac{0 \times 0.2 + 1 \times 0.8}{0.2 + 0.8} = 0.8$, and $\bar{\alpha}' = \frac{1 \times 0.55 + 2 \times 0.45}{0.55 + 0.45} = 1.45$

$\therefore S(\hat{Z}_1) = (0.8+3)(1.45+3) = 16.91$

Similarly, the score of $\hat{Z}_2$ can be calculated as follows.

$S(\hat{Z}_2) = (\bar{\alpha}+3)(\bar{\alpha}'+3)$, and $\bar{\alpha} = \frac{-1\times0.75+0\times0.25}{0.75+0.25} = -0.75$, and $\bar{\alpha}' = \frac{1\times0.1+2\times0.9}{0.1+0.9} = 1.9$

$\therefore S(\hat{Z}_2) = (-0.75+3)(1.9+3) = 11.025$

$\because S(\hat{Z}_1) > S(\hat{Z}_2) \Rightarrow \hat{Z}_1 > \hat{Z}_2$.

In the above example, the scores were not equal and therefore the deviation degree was not required to compare the 2 ZPLVs. However, consider the following example where the ZPLV scores are equal. Let $\hat{Z}_1$ and $\hat{Z}_2$ be two ZPLVs, with $\hat{Z}_1 = \{\{s_0(0.8), s_1(0.2)\}, \{s'_0(0.3), s'_1(0.7)\}\}$ and $\hat{Z}_2 = \{\{s_0(0.9), s_2(0.1)\}, \{s'_0(0.65), s'_2(0.35)\}\}$. There are 2 terms is $L_{\hat{A}1}(p_{\hat{A}1})$, 2 terms in $L_{\hat{B}1}(p_{\hat{B}1})$, 2 terms in $L_{\hat{A}2}(p_{\hat{A}2})$, and 2 terms in $L_{\hat{B}2}(p_{\hat{B}2})$. The ς and ζ values are both 3. The scores of $\hat{Z}_1$ and $\hat{Z}_2$, denoted as $S(\hat{Z}_1)$ and $S(\hat{Z}_2)$, are calculated as follows.

$$S(\hat{Z}_1) = (0.2+3)(0.7+3) = 11.84, \text{ and } S(\hat{Z}_2) = (0.2+3)(0.7+3) = 11.84.$$

Since $S(\hat{Z}_1) = S(\hat{Z}_2)$, the deviation degrees of $\hat{Z}_1$ and $\hat{Z}_2$ are required to be calculated in order to compare the ZPLVs further. This is done as follows.

$$D(\hat{Z}_1) = \sqrt{\frac{(3\times3-11.84)^2+(3\times3.7-11.84)^2+(3.2\times3-11.84)^2+(3.2\times3.7-11.84)^2}{2\times2}} \approx 1.85$$

Similarly, the deviation degree for $\hat{Z}_2$ can be calculated as follows.

$$D(\hat{Z}_2) = \sqrt{\frac{(3\times3-11.84)^2+(3\times3.7-11.84)^2+(3.2\times3-11.84)^2+(3.2\times3.7-11.84)^2}{2\times2}} \approx 1.85$$

Since $S(\hat{Z}_1) = S(\hat{Z}_2)$ and $D(\hat{Z}_1) = D(\hat{Z}_2)$, it implies that $\hat{Z}_1 \approx \hat{Z}_2$.

Distance Between ZPLVs

To calculate the distance between two ZPLVs, the authors in [108] proposed a Euclidean-based distance measure. Let $\hat{Z}_1$ and $\hat{Z}_2$ be two ZPLVs defined as $\hat{Z}_1 = (\hat{A}_1, \hat{B}_1) = (L_{\hat{A}_1}(p), L_{\hat{B}1}(p))$, where $(\{L^m_{\hat{A}1}(p^m_{\hat{A}1}) \mid m = 1, 2, \ldots, \#L_{\hat{A}1}(p_{\hat{A}1})\}, \{L^n_{\hat{B}1}(p^n_{\hat{B}1}) \mid n = 1, 2, \ldots, \#L_{\hat{B}1}(p_{\hat{B}1})\})$, and $\hat{Z}_2 = (\hat{A}_2, \hat{B}_2) = (L_{\hat{A}_2}(p), L_{\hat{B}_2}(p))$, where $(\{L^h_{\hat{A}2}(p^h_{\hat{A}2}) \mid h = 1, 2, \ldots, \#L_{\hat{A}2}(p_{\hat{A}2})\}, \{L^k_{\hat{B}2}(p^k_{\hat{B}2}) \mid k = 1, 2, \ldots, \#L_{\hat{B}2}(p_{\hat{B}2})\})$. If $\#L_{\hat{A}1}(p_{\hat{A}1}) = \#L_{\hat{A}2}(p_{\hat{A}2})$ and $\#L_{\hat{B}1}(p_{\hat{B}1}) = \#L_{\hat{B}2}(p_{\hat{B}2})$, then the distance between the two ZPLVs, $\hat{Z}_1$ and $\hat{Z}_2$, is defined in Eq. (3.86).

$$d(\hat{Z}_1, \hat{Z}_2) = \sqrt{\frac{\sum_{m=1}^{\#L_{\hat{A}1}(p_{\hat{A}1})} \sum_{n=1}^{\#L_{\hat{B}1}(p_{\hat{B}1})} ((p^m_{\hat{A}1} v^m_{\hat{A}1} + \varsigma)(p^n_{\hat{B}1} v^n_{\hat{B}1} + \zeta) - (p^m_{\hat{A}2} v^m_{\hat{A}2} + \varsigma)(p^n_{\hat{B}2} v^n_{\hat{B}2} + \zeta))^2}{\#L_{\hat{A}1}(p_{\hat{A}1}) \#L_{\hat{B}1}(p_{\hat{B}1})}} \tag{3.86}$$

As an example, let $\hat{Z}_1$ and $\hat{Z}_2$ be two ZPLVs, with $\hat{Z}_1 = \{\{s_0(0.2), s_1(0.8)\}, \{s'_1(0.55), s'_2(0.45)\}\}$ and $\hat{Z}_2 = \{\{s_{-1}(0.75), s_0(0.25)\}, \{s'_1(0.1), s'_2(0.9)\}\}$. The distance between $\hat{Z}_1$ and $\hat{Z}_2$, denoted as $d(\hat{Z}_1, \hat{Z}_2)$, is calculated as follows. There are 2 terms is $L_{\hat{A}1}(p_{\hat{A}1})$, 2 terms in $L_{\hat{B}1}(p_{\hat{B}1})$, 2 terms in $L_{\hat{A}2}(p_{\hat{A}2})$, and 2 terms in $L_{\hat{B}2}(p_{\hat{B}2})$. The ς and ζ values are both 3.

$$d(\hat{Z}_1, \hat{Z}_2) = \sqrt{\frac{(3\times 3.55-2.25\times 3.1)^2+(3\times 3.9-2.25\times 4.8)^2+(3.8\times 3.55-3\times 3.1)^2+(3.8\times 3.9-3\times 4.8)^2}{2\times 2}}$$

$$d(\hat{Z}_1, \hat{Z}_2) \approx 2.83$$

3.4.4 A Novel ZPLTS-ELECTRE II Algorithm

The traditional ELECTRE II method is modified to perform under a ZPLTS environment. The new algorithm is designed to model both numerical and linguistic criteria, which will be beneficial to modelling ontology selection problems. The enhanced algorithm is modelled as follows.

Quantitative Decision Matrix
The first step is to model the decision problem. A quantitative matrix, denoted as Λ, represents the performances of all m alternatives in light of only the t quantitative criteria. Λ is defined in Eq. (3.87). Each element of Λ, a_{ij}, represents the performance of the i^{th} alternative in light of the j^{th} criterion.

$$\Lambda = [a_{i,j}]_{m\times t} = \begin{bmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,t} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m,1} & a_{m,2} & \cdots & a_{m,t} \end{bmatrix} \tag{3.87}$$

Qualitative Decision Matrix
After modelling the quantitative data, the qualitative linguistic data from the decision-makers are to be modelled. If the number of decision-makers to give their opinions is denoted by r, then there will be r decision matrices. Each matrix is denoted by Γ^b, where $b = 1, 2, \ldots, r$. There are m alternatives that each decision-maker needs to evaluate, hence there are m rows in each matrix, and there are $(n-t)$ criteria that each decision-maker must judge for each alternative, which is why there are $(n-t)$ columns in each decision matrix. Γ^b is defined in Eq. (3.88). Each element $\hat{Z}_{ij}$ is a ZPLV that represents the linguistic evaluation for the i^{th} alternative regarding the j^{th} criterion, along with the linguistic term for the decision-makers credibility regarding that evaluation.

$$\Gamma^b = [\hat{Z}_{i,j}]^b_{m\times(n-t)} = \begin{bmatrix} \hat{Z}_{1,1} & \hat{Z}_{1,2} & \cdots & \hat{Z}_{1,n-t} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{Z}_{m,1} & \hat{Z}_{m,2} & \cdots & \hat{Z}_{m,n-t} \end{bmatrix} \tag{3.88}$$

Decision Matrix

The final decision matrix is then created by combining the quantitative and qualitative matrices. First, the Γ^b matrices are combined to form one matrix, Γ, by combining the probability values for like terms. Thereafter, the matrix is normalized in two stages, first, the probability distribution is normalized, and second, the number of linguistic variables is normalized. To normalize the probability distribution, whenever the sums of the probabilities are less than 1, the remaining probability value needs to be further allocated. That is, if $\hat{Z} = (L_{\hat{A}}(p), L_{\hat{B}}(p))$ is a ZPLV with $\sum_{m=1}^{\#L_{\hat{A}}(p_{\hat{A}})} p_{\hat{A}}^m < 1$ and $\sum_{n=1}^{\#L_{\hat{B}}(p_{\hat{B}})} p_{\hat{B}}^n < 1$, then the remaining probabilities must be allocated so that the probability sums are equal to 1. This is done by applying Eq. (3.83).

After normalizing the probability distributions, the next step is to normalize the number of linguistic variables by making the number of terms in $L_A(p)$ and $L_B(p)$ equal, that is, $\#L_A(p) = \#L_B(p)$.

After combining and normalizing the ZPLV decision matrices to form one matrix, Γ, the decision matrix E is built by concatenating Λ with Γ, as shown in Eq. (3.89).

$$E = [\Lambda\Gamma] = \begin{bmatrix} d_{1,1} & \cdots & d_{1,t} & \hat{Z}_{1,1} & \cdots & \hat{Z}_{1,n-1} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ d_{m,1} & \cdots & d_{m,t} & \hat{Z}_{m,1} & \cdots & \hat{Z}_{m,n-t} \end{bmatrix} \tag{3.89}$$

Weights and Thresholds

A set of weights, $\omega = \{\omega_1, \omega_2, \ldots, \omega_n\}$, must be defined, where the i^{th} element in ω represents the importance weight for the i^{th} criterion. Three concordance thresholds, α_1, α_2, and α_3, must be defined such that $0.5 \leq \alpha_1 \leq \alpha_2 \leq \alpha_3 \leq 1$. An upper and a lower discordance threshold must be defined for each criterion. β_j^- represents the lower discordance threshold, and β_j^+ represents the upper discordance threshold for criterion j, where $\beta_j^+ \geq \beta_j^- \geq 0$.

Comparative Sets

Three sets are determined in order to compare each alternative with every other alternative. $\mathcal{B}^-(x,y)$ represents those criteria for which alternative x performs worst than alternative y. $\mathcal{B}^0(x,y)$ represents those criteria for which alternative x performs equally well as alternative y. $\mathcal{B}^+(x,y)$ represents those criteria for which alternative x performs better than alternative y.

In the case of quantitative criteria, $\mathcal{B}^-(x,y)$ is defined in Eq. (3.90) with $1 \leq j \leq t$, and for ZPLV criteria in Eq. (3.91) where $t+1 \leq j \leq n$.

$$\mathcal{B}^-(x,y) = \{j \mid x_j < y_j\} \tag{3.90}$$

$$\mathcal{B}^-(x,y) = \{j \mid (S(\hat{Z}_{x,j}) < S(\hat{Z}_{y,j})) \text{ or } (S(\hat{Z}_{x,j}) = S(\hat{Z}_{y,j}) \text{ and } D(\hat{Z}_{x,j}) > D(\hat{Z}_{y,j})\} \tag{3.91}$$

In the case of quantitative criteria, $\mathcal{B}^0(x,y)$ is defined in Eq. (3.92) where $1 \leq j \leq t$, and for ZPLV criteria in Eq. (3.93) where $t+1 \leq j \leq n$.

$$\mathcal{B}^0(x,y) = \{j \mid x_j = y_j\} \tag{3.92}$$

$$\mathcal{B}^0(x,y) = \{j \mid S(\hat{Z}_{x,j}) = S(\hat{Z}_{y,j}) \text{ and } D(\hat{Z}_{x,j}) = D(\hat{Z}_{y,j}))\} \tag{3.93}$$

$\mathcal{B}^-(x,y)$ is defined in Eq. (3.94) in the case of quantitative criteria, where $1 \leq j \leq t$, and in Eq. (3.95) for ZPLV criteria with $t+1 \leq j \leq n$. $S(\hat{Z}_{i,j})$ represents the score given in Eq. (3.84) and $D(\hat{Z}_{i,j})$ represents the deviation degree given in Eq. (3.85).

$$\mathcal{B}^+(x,y) = \{j \mid x_j > y_j\} \tag{3.94}$$

$$\mathcal{B}^+(x,y) = \{j \mid (S(\hat{Z}_{x,j}) > S(\hat{Z}_{y,j})) \text{ or } (S(\hat{Z}_{x,j}) = S(\hat{Z}_{y,j}) \text{ and } D(\hat{Z}_{x,j}) < D(\hat{Z}_{y,j}))\} \tag{3.95}$$

Concordance Relations

The concordance values for every alternative, (x,y), can be determined by applying Eq. (3.96). This represents the weighting of criteria that concord with the statement that alternative x is at least as good as alternative y.

$$C(x,y) = \frac{\sum_{j\in\mathcal{B}^+(x,y)} \omega_j + \sum_{j\in\mathcal{B}^0(x,y)} \omega_j}{\sum_{j=1}^{n} \omega_j} \tag{3.96}$$

Discordance Relations

The discordance value measures how true the statement is that alternative x is outranked by alternative y. In order to determine the discordance values for each alternative pair, three discordance sets are formed. The high discordance set $\mathcal{Q}^+(x,y)$, the medium discordance set $\mathcal{Q}^0(x,y)$, and the low discordance set $\mathcal{Q}^-(x,y)$. The discordance sets are formulated as follows.

The high discordance set is formulated by applying Eq. (3.97) for quantitative criteria, where $j = 1, 2, \ldots, t$, and in the case of qualitative criteria Eq. (3.98) is applied, where $j = n-t+1, n-t+2, \ldots, n$.

$$\mathcal{Q}^+(x,y) = \{j \mid y_j - x_j \geq \beta_j^+\} \tag{3.97}$$

$$\mathcal{Q}^+(x,y) = \{j \mid d(x_j, y_j) \geq \beta_j^+, j \in \mathcal{B}^+(y,x)\} \tag{3.98}$$

The medium discordance set is formulated by applying Equation (3.99) for quantitative criteria, where $j = 1, 2, \ldots, t$, and in the case of qualitative criteria Eq. (3.100) is applied, where $j = n-t+1, n-t+2, \ldots, n$.

$$\mathcal{Q}^0(x,y) = \{j \mid \beta_j^- < y_j - x_j < \beta_j^+\} \tag{3.99}$$

$$\mathcal{Q}^0(x,y) = \{j \mid \beta_j^- < d(x_j, y_j) < \beta_j^+, j \in \mathcal{B}^+(y,x)\} \tag{3.100}$$

The low discordance set is formulated by applying Eq. (3.101) for quantitative criteria, where $j = 1, 2, \ldots, t$, and in the case of qualitative criteria Eq. (3.102) is applied when the discordance threshold is larger than 0 ($\beta^- > 0$), and when the discordance threshold is equal to 0 ($\beta^- = 0$) then Eq. (3.103) is applied, where $j = n - t + 1, n - t + 2, \ldots, n$.

$$\mathcal{Q}^-(x,y) = \{j \mid y_j - x_j \leq \beta_j^-\} \tag{3.101}$$

$$\mathcal{Q}^-(x,y) = \{j \mid (d(x_j, y_j) \leq \beta_j^-, j \in \mathcal{B}^+(y,x)) \text{ or } (j \in \mathcal{B}^+(x,y)) \text{ or } (j \in \mathcal{B}^0(x,y))\} \tag{3.102}$$

$$\mathcal{Q}^-(x,y) = \{j \mid (j \in \mathcal{B}^0(x,y)) \text{ or } (j \in \mathcal{B}^+(x,y))\} \tag{3.103}$$

Strong and Weak Outranking Graphs

Each alternative pair may have a strong outranking relation, xS^Fy, or a weak outranking relation, xS^fy. According to these relations, a strong outranking graph, and a weak outranking graph can be drawn. The conditions for the strong outranking relations are given in Eq. (3.104) and (3.105).

$$xS^Fy \Leftrightarrow \begin{cases} C(x,y) \geq \alpha_3 \\ j \in \mathcal{Q}^0(x,y) \text{ or } \mathcal{Q}^-(x,y), \forall j \\ \frac{\sum_{j \in \mathcal{B}^+(x,y)} \omega_j}{\sum_{j \in \mathcal{B}^-(x,y)} \omega_j} \geq 1 \end{cases} \tag{3.104}$$

or

$$xS^Fy \Leftrightarrow \begin{cases} C(x,y) \geq \alpha_2 \\ j \in \mathcal{Q}^-(x,y), \forall j \\ \frac{\sum_{j \in \mathcal{B}^+(x,y)} \omega_j}{\sum_{j \in \mathcal{B}^-(x,y)} \omega_j} \geq 1 \end{cases} \tag{3.105}$$

The conditions for the weak outranking relations are given in Equations (3.106) and (3.107).

$$xS^fy \Leftrightarrow \begin{cases} C(x,y) \geq \alpha_2 \\ j \in \mathcal{Q}^0(x,y), \forall j \\ \frac{\sum_{j \in \mathcal{B}^+(x,y)} \omega_j}{\sum_{j \in \mathcal{B}^-(x,y)} \omega_j} \geq 1 \end{cases} \tag{3.106}$$

or

$$xS^f y \Leftrightarrow \begin{cases} C(x,y) \geq \alpha_1 \\ j \in \mathcal{Q}^-(x,y), \forall j \\ \frac{\sum_{j \in \mathcal{B}^+(x,y)} \omega_j}{\sum_{j \in \mathcal{B}^-(x,y)} \omega_j} \geq 1 \end{cases} \tag{3.107}$$

Exploit Outranking Relations

To build the strong and weak outranking graphs, the following procedures are followed. Regarding the strong outranking graph, if alternative x strongly outranks alternative y then a directed arc is drawn from x to y. Similarly, if alternative x weakly outranks alternative y then a directed arc is drawn in the weak outranking graph. According to these two graphs, a ranking can be determined as follows.

The ranking proceeds in three stages, first the forward order is performed, then the backward order is performed, and finally the results of the two orders are combined to produce a final ranking. The forward order is performed as follows:

1. Let N_1^F denote the set of non-dominate alternatives in the strong outranking graph G_1^F. N_1^F comprises those alternatives that are not outranked by any other alternatives, that is, all alternatives that have no arcs going into them. The same is done for the weak outranking graph, G_1^f, with the set N_1^f.

2. The intersection of N_1^F and N_1^f, $N_1^f \cap N_1^f$, is determined to produce the set N_1. The alternatives in N_1 are those that are not outranked in both the strong and the weak outranking graphs. All those alternatives in N_1 are given the forward rank of 1, that is, $\psi_1(x) = 1$ for all alternatives in N_1.

3. The nodes of those alternatives contained in N_1 can now be removed from the strong and weak outranking graphs, along with their associated edges. After removing the nodes and edges, the resulting graphs are G_2^F and G_2^f.

4. The steps 1 to 3 are repeated until all alternatives have been ranked, with each iteration producing a new set of graphs G_v^F and G_v^f. Eventually all alternatives should be assigned a forward rank.

Thereafter, the reverse order is performed as follows:

1. All the arrows in the strong and weak outranking graphs, G_1^F and G_1^f, are reversed to form the mirror image graphs.

2. Each alternative is assigned a rank, $\psi_2(x)$, in the same way as done in the forward order from steps 1 to 3.

3. Due to the graph reversals, each rank is transformed by applying the Eq. (3.108).

$$\psi_3(x_i) = 1 + \max_{A_v \in A} \psi_2(A_v) - \psi_2(x_i) \tag{3.108}$$

The final ranking can be obtained by combining the forward and reverse order rankings. This is done by taking the mid-point of both rankings, as in Equation (3.109).

$$\bar{\psi}(x_i) = \frac{\psi_1(x_i) + \psi_3(x_i)}{2} \tag{3.109}$$

The steps and processes of the ZPLTS-ELECTRE II method presented above are summarized in Algorithm 1.

Algorithm 1 ZPLTS-ELECTRE II

1: Build quantitative matrix Λ comprising m alternatives with t quantitative criteria

2: Build ZPLTS decision matrices by obtaining evaluation from r decision-makers. Each decision-maker expresses their evaluation in a decision matrix Γ^b

3: Combine quantitative and linguistic decision matrices to form decision matrix E, with dimensions $m \times n$

4: Define set of criteria importance weights, ω_j, along with three concordance thresholds, α_1, α_2, and α_3, as well as two discordance thresholds, β_j^- and β_j^+, for the j criteria

5: Construct comparative sets, $\mathcal{B}^-(x,y)$, $\mathcal{B}^0(x,y)$, and $\mathcal{B}^+(x,y)$, representative of the criteria for which an alternative is beaten by another alternative, is equal to another alternative, and beats another alternative

6: Determine concordance relations for every alternative pair, $C(x,y)$, by applying Eq. (3.96)

7: Determine the high, medium, and low discordance sets for every alternative pair, $\mathcal{Q}^+(x,y)$, $\mathcal{Q}^0(x,y)$, and $\mathcal{Q}^-(x,y)$

8: Build strong and weak outranking graphs, xS^Fy and xS^fy

9: Assign a rank to each alternative using the forward and reverse order processes, $\psi_1(A_i)$ and $\psi_3(A_i)$, and thereafter combine the ranks

3.4.5 Application of ZPLTS-ELECTRE II Method in Ontology Ranking

In order to demonstrate the feasibility of the novel ZPLTS-ELECTRE II algorithm for ontology selection and ranking, it was applied to rank a set of 9 mental health ontologies. The design of the experiment used to apply the ZPLTS-ELECTRE II method is presented in Fig. 3.7. The design of the experiment involves the choice of the dataset, and the quantitative and qualitative attributes of the ontologies used as alternatives. The experiment is then carried out to apply the proposed ZPLTS-ELECTRE II method to rank the ontologies. Thereafter, to analyze the results the performance of the ZPLTS-ELECTRE II method is firstly compared against that of the traditional ELECTRE II and the PLTS ELECTRE II methods, on the same dataset; thereafter, the ZPLTS-ELECTRE II method is compared against previous studies that have used MCDM methods in ontology ranking as well as the existing fuzzy ELECTRE II methods implemented in related studies.

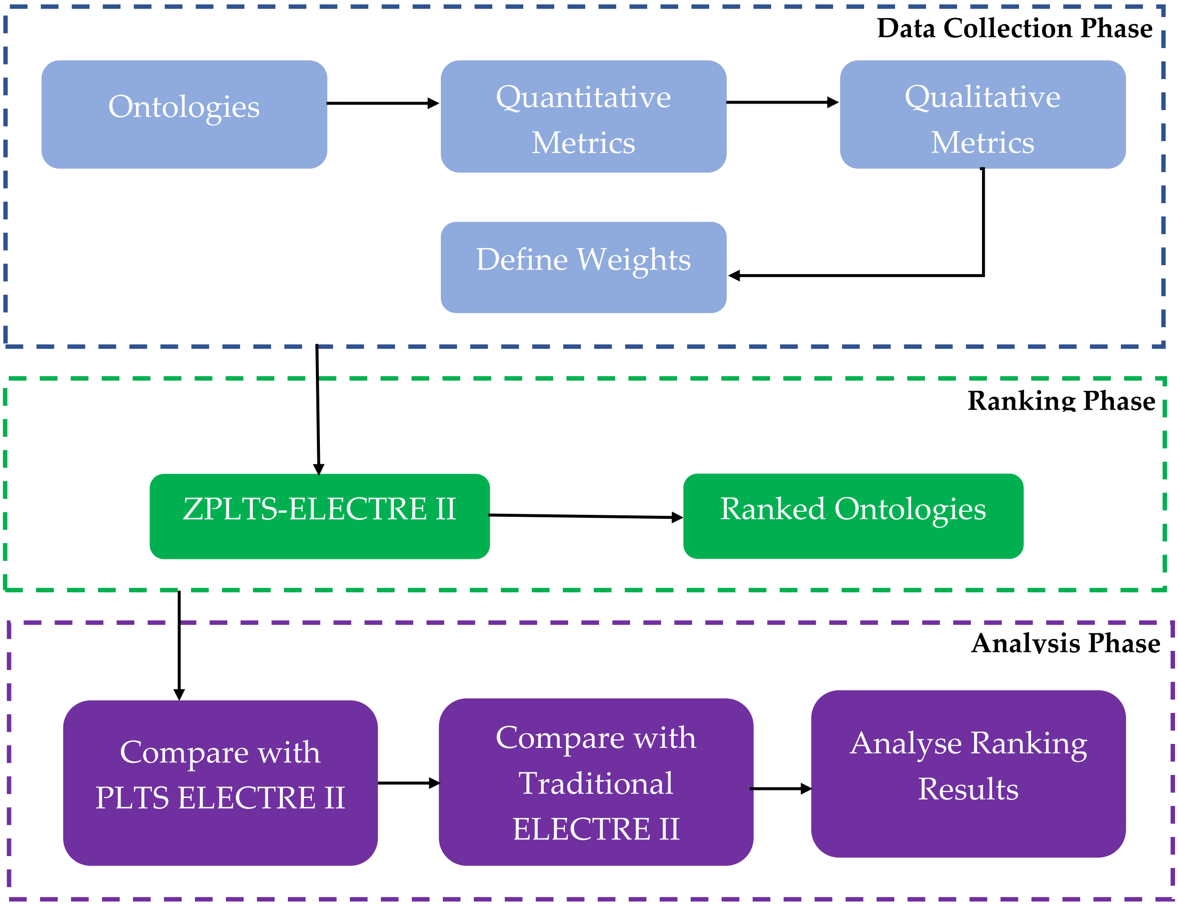


FIGURE 3.7: Model for applying ZPLTS-ELECTRE II for ontology ranking

The dataset used in this experiment comprises 9 mental health ontologies obtained from the BioPortal ontology repository [18]. In fact, the quality and state of mental well-being have seen a drastic decline in recent years [135, 136]. The World Health Organization (WHO) estimated that 6.6 billion people around the world suffered from at least one form of mental health disorder [137]. Therefore, the issue of mental health and well-being is a growing concern around the world. Moreover, the advent of COVID-19 has further worsened the matters [138]. It is clear that there is an urgent need to study and develop techniques for automated monitoring and management of the state of mental well-being throughout the world. Ontologies may also play a role in the development of technologies and systems to facilitate and provide support structures for mental health issues. For this reason, this study focused on the selection and ranking of real-world ontologies that model knowledge pertaining to mental wellness. The ontologies were obtained from the BioPortal Ontology Repository [18] and include:

1. The *Mental State Assessment Ontology (ONL-MSA)* - ONL-MSA is a module of the OntoNeuroLOG [139] ontology, which was developed in the NeuroLog [1] project for enhancing the field of neuroimaging. The ONL-MSA ontology models knowledge pertaining to

[1]http://neurolog.i3s.unice.fr/

the mental state assessments.

2. The *APA Neuro Cluster Ontology (APANEUROCLUSTER)* - it models the APA neuropsychology and neurology and includes the Assessment Diagnosis, Neurosciences, Neurological Disorders, and Neuroanatomy categories.

3. The *Ontologia de Saúde Mental (OSM)* - it is the Portuguese equivalent of Mental Health Ontology, it was developed to assist in managing the Psycho-Social Care Network in the Brazilian context, enabling the creation of intelligent computational tools and the development of mental health indicators.

4. The *Mental Functioning Ontology (MF)* - it is an ontology that represents aspects of mental functioning, such as cognition and intelligence.

5. The *Alzheimer's Disease Ontology (ADO)* - it represents knowledge regarding the Alzheimer's disease. The main categories of the ontology include Health, Human, Neurologic Disease, and Neurological Disorder.

6. The *Neuroscience Information Framework Cell Ontology (NIFCELL)* - it is part of the Neuroscience Information Framework (NIF) project [2]. The NIFCELL ontology, expresses knowledge regarding cells and cell types from the Neuroscience Information Framework Standard Ontology [3].

7. The *Epilepsy Semiology Ontology (EPISEM)* - it was designed to capture the semiology of epilepsy. It models the signs and symptoms of epilepsy, and represents the ictal, postictal, inter-ictal, and aura signs.

8. The *Cognitive Paradigm Ontology (COGPO)* [4] - COGPO was developed to describe the experimental conditions within experiments related to cognition and behavior of humans. The ontology defines the conditions of experiments in a standardized format.

9. The *Cognitive Atlas Ontology (COGAT)* [5] - COGAT models and characterizes the state of current thought in cognitive science through a set of mental concepts and tasks. The ontology represents users' knowledge with expertise in psychology, cognitive science, and neuroscience.

Five quantitative metrics and five qualitative metrics were used. The quantitative metrics used in this study were adopted from the OntoMetrics framework [25], which defines various metrics for evaluating ontologies and provides an online environment for their automatic calculation. Several graph metrics have been defined to evaluate ontologies [8, 25]. Five of these metrics were adopted in this study to demonstrate the effectiveness of the proposed ZPLTS-ELECTRE II method. The graph metrics are calculated from the graph and taxonomy tree of the ontology, thereby providing insights pertaining to the characteristics and attributes of the

[2]http://neuinfo.org
[3]https://bioportal.bioontology.org/ontologies/NIFSTD
[4]http://www.cogpo.org/
[5]https://www.cognitiveatlas.org/

ontology [8]. The 5 graph metrics adopted measure the design complexity of ontologies and include the Absolute Leaf Cardinality (ALC), Absolute Root Cardinality (ARC), Average Depth (AD), Average Breadth (AB), and Average Number of Paths (ANP). The details of the metrics are explained comprehensively in Section 3.2.4.

The 5 qualitative attributes used in this study were adopted from a study by Ma et al. [9] where the authors developed an Ontology Usability Scale (OUS) to evaluate ontologies. Based on the OUS, 5 criteria were adopted in this study. These 5 criteria are elaborated on as follows.

1. *Clarity of Purpose (CoP) -* this criterion addresses the question of how clear is the purpose of the ontology [9]. The CoP criterion pertains to the semantics and documentation of the ontology.

2. *Quality of Subclass Definition (QoSD) -* this criterion addresses the question of how properly the subclasses in the ontology are defined, and whether the class hierarchy needs better organization or not [9]. The QoSD criterion pertains to the syntax and structure of the content of the ontology.

3. *Description of Concepts and Relations in Natural Language (DoCRNL) -* this criterion describes how well the concepts and the relations of an ontology are described using natural language [9]. The DoCRNL criterion is expressive of the semantics and documentation of the ontology.

4. *Understandability of Conceptualization (UoC) -* this criterion expresses how easy it is to comprehend the ontology's conceptualization [9]. The UoC criterion pertains to the semantics and documentation aspects of an ontology.

5. *Description of Concepts using Attributes (DoCA) -* this criterion concerns how well the attributes in the ontology describe its concepts [9]. The DoCA criterion pertains to information content of the ontology.

3.5 Conclusion

In this chapter three applications were presented for aiding the selection of ontologies for reuse. The first application involved the application of ELECTRE for ranking ontologies. The second application involved the ELECTRE Tri model for classifying ontologies, together with the Genetic Algorithm. The third application saw the development of a novel ZPLTS-ELECTRE II method and its application to rank a set of ontologies. In the next chapter, the architecture and design of the software developed is presented.

Chapter 4

System Architecture and Design

4.1 Introduction

This chapter presents an overview of the software that was developed in order to perform the experiments for this study. Unified Modelling Language (UML) class diagrams are presented for each algorithm, along with a process flow diagram demonstrating the logical flow of each algorithm. Specifically, Section 4.2 presents the ELECTRE I, II, III, and IV algorithms, Section 4.3 presents the ELECTRE Tri and genetic algorithms, and Section 4.4 presents the ZPLTS-ELECTRE II algorithm.

4.2 Design of ELECTRE I, II, III, and IV

The ELECTRE I, II, III, and IV models were implemented using the Java programming language. To demonstrate the design of the algorithms, a UML class diagram and a flow diagram is presented for each algorithm.

4.2.1 ELECTRE I

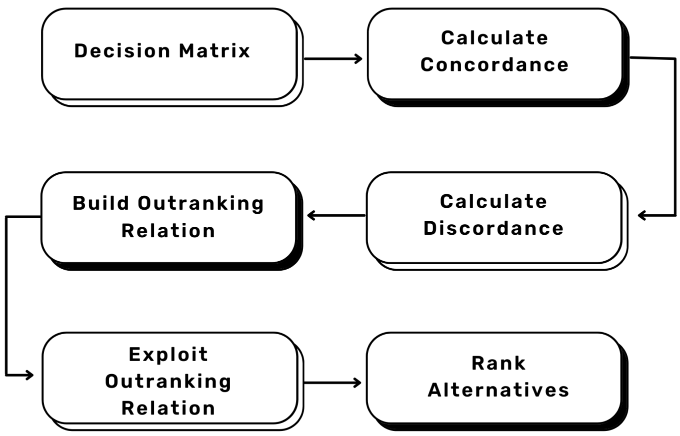


FIGURE 4.1: Process flow diagram for the ELECTRE I method

The process flow diagram for ELECTRE I is shown in Fig. 4.1. As shown in the diagram, firstly, the decision problem is expressed using a decision matrix. Thereafter, the concordance and discordance relations are determined, which is used to build an outranking relation. The outranking relation is then exploited and a ranking of the alternatives is formed.

ElectreI
- decisionMatrix : double[ ] [ ]
- weights : double [ ]
- normalizedMatrix : double[ ] [ ]
- M : int
- N : int
- concordanceMatrix : double[ ] [ ]
- discordanceMatrix : double[ ] [ ]
- aggregateMatrix : double[ ] [ ]
- score : Map$\langle Integer, Integer \rangle$
+ ElectreI(decisionMatrix : double[ ] [ ]) : *constructor*
+ setWeights() : *void*
+ normalizeMatrix() : *void*
+ weightMatrix() : *void*
+ calculateConcordance() : *void*
+ calculateDiscordance() : *void*
+ aggregateMatrix() : *void*
+ rankMatrix() : *void*
+ displayRanking() : List$\langle Map.Entry\langle Integer, Integer \rangle\rangle$
+ runElectreI() : String

FIGURE 4.2: Class diagram for ELECTRE I algorithm

The class diagram for the ELECTRE I software developed is shown in Fig. 4.2 along with the class structure, the variables, and the methods that were used to implement the ELECTRE I algorithm. The constructor method *ElectreI()* takes one parameter, which is the decision matrix. The concordance and discordance values are calculated by applying the *calculateConcordance()* and *calculateDiscordance()* methods. The final ranking can then be obtained by applying the *rankMatrix()* method.

4.2.2 ELECTRE II

The process flow for ELECTRE II is shown in Fig. 4.3. As shown in the diagram, the first step is to express the decision problem in the form of a decision matrix. Thereafter, the concordance and discordance relations are determined in order to build the strong and weak outranking relations. The strong and weak outranking relations are then exploited in order to obtain a first and second pre-order ranking. Finally, the two rankings are combined in order to rank all alternatives from best to worst.

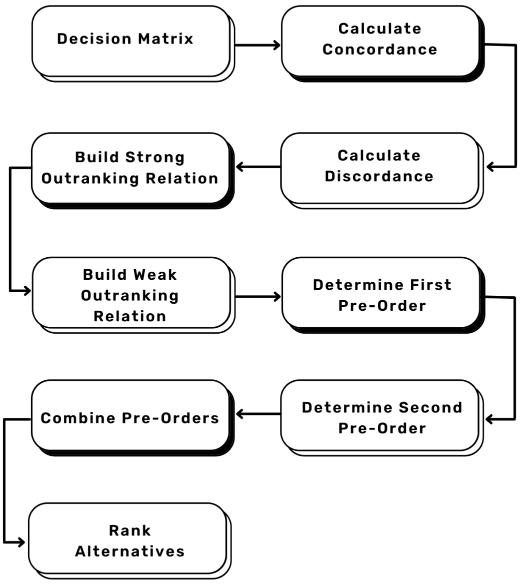


FIGURE 4.3: Process flow diagram for the ELECTRE II method

ELECTRE II was developed in a class called *ElectreII.java*. The class diagram for the ELECTRE II software developed is shown in Fig. 4.4 along with the class structure, the variables, and the methods that were used to implement the ELECTRE II algorithm. The class diagram on the left represents the ELECTRE II method, and the class diagram on the right represents the distillation procedures for the ELECTRE II method. The distillation procedures are used within the ELECTRE II method.

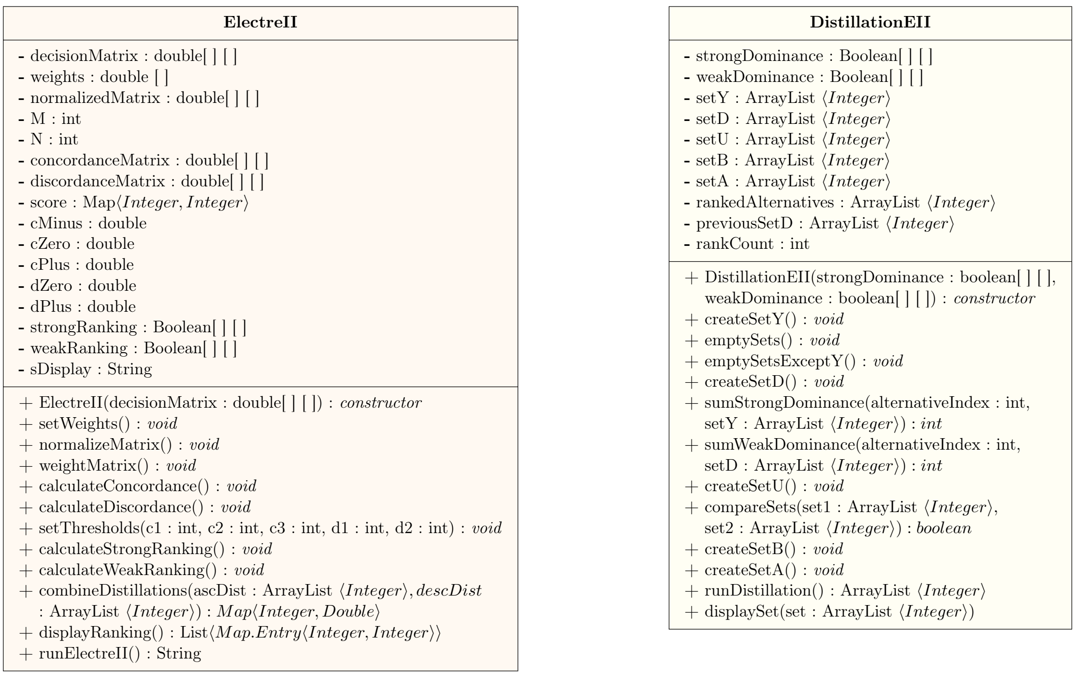


FIGURE 4.4: Class diagram for ELECTRE II and its distillation algorithm

In the *ElectreII.java* class, the constructor method *ElectreII()* takes the decision matrix as a parameter. The weights and thresholds are inputted by calling the *setWeights()* and *setThresholds()* methods, respectively. The concordance and discordance relations can then be determined by applying the *calculateConcordance()* and *calculateDiscordance()* methods, leading to the calculation of the strong and weak outranking relations with the *calculateStrongRanking()* and *calcuateWeakRanking()* methods. The resulting arrays from the strong and weak outranking methods are sent as input to the *DistillationEII.java* class in order to obtain two pre-orders. The pre-orders are then combined using the *combineDistillation()* method to obtain a final ranking.

4.2.3 ELECTRE III

The process flow diagram for the ELECTRE III model is shown in Fig. 4.5. The model begins by obtaining a representation of the decision problem in the form of a decision matrix. Thereafter, the concordance and discordance relations are determined in order to calculate the credibility levels. The credibility levels are then exploited in order to determine an ascending and a descending distillation ranking, which are then combined. The combination of the two rankings yield a final ranking of the alternatives from best to worst.

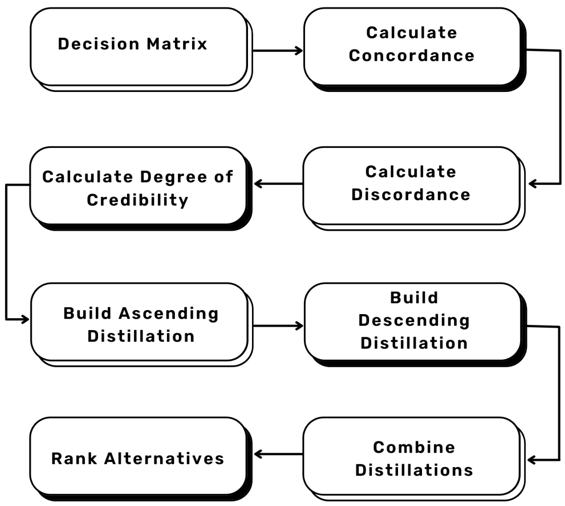


FIGURE 4.5: Process flow diagram for the ELECTRE III method

The class diagram for the ELECTRE III software developed and its distillation procedure are shown in Fig. 4.6 along with the class structure, the variables, and the methods that were used to implement the algorithms. The class diagram on the left depicts the ELECTRE III algorithm, and the class diagram on the right depicts the distillation procedure for the model. The *ElectreIII.java* class has a constructor method named *ElectreIII()* that takes a decision matrix as an argument. The concordance, discordance, and credibility values can be calculated with the methods *calculateConcordance()*, *calculateDiscordance()*, and *calculateCredibility()*, respectively. The credibility values are parsed to the *DistillationEIII.java* class to obtain an ascending and descending ranking. These rankings are then combined with the *combineDistillations()* method to obtain a final ranking.

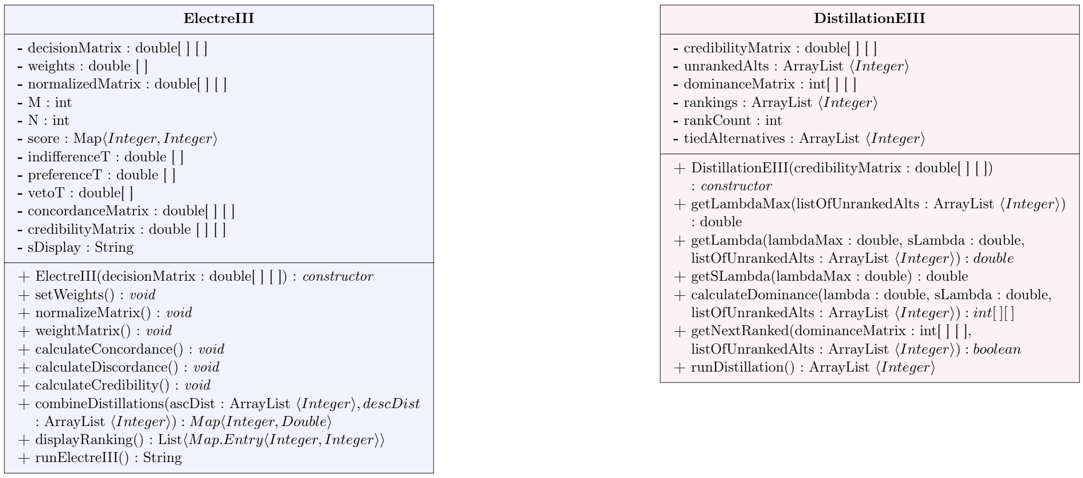


FIGURE 4.6: Class diagram for ELECTRE III algorithm and distillation procedure

4.2.4 ELECTRE IV

The process flow diagram for the ELECTRE IV model is shown in Fig. 4.7. The first step is for the decision problem to be expressed using a decision matrix. Thereafter, the M_p, M_q, M_i, and M_o parameters are determined. These parameters are used to formulate the dominance relations, which are applied to calculate the credibility values. According to the credibility values, an ascending and a descending distillation are performed in order to obtain two rankings. Lastly, the two rankings are combined, yielding a final ranking of the alternatives from best to worst.

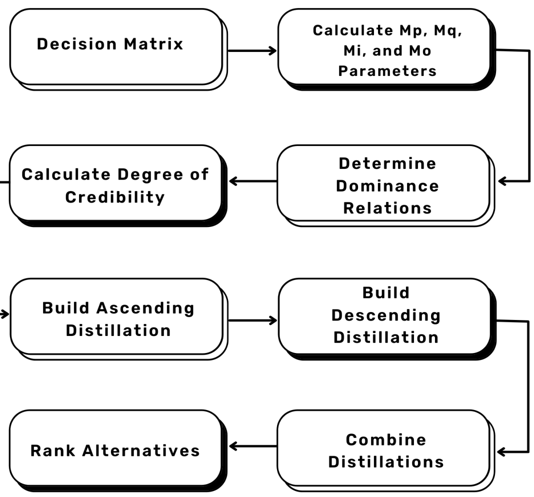


FIGURE 4.7: Process flow diagram for the ELECTRE IV method

ELECTRE IV was developed in a class called *ElectreIV.java*, which is shown in Fig. 4.8 on the left, along with its distillation procedure on the right. The *ElectreIV.java* class has a constructor that takes as input a decision matrix. The parameters are then calculated by applying the methods *calcMp()*, *calcMq()*, *calcMi()*, and *calcMo()*. Thereafter, the credibility values are formed using the *calcOutranking()* method. The credibility values are then parsed into the *DistillationEIV.java* class in order to obtain an ascending and a descending distillation. Finally, the distillations are combined by applying the *combineDistillation()* method to yield a final ranking.

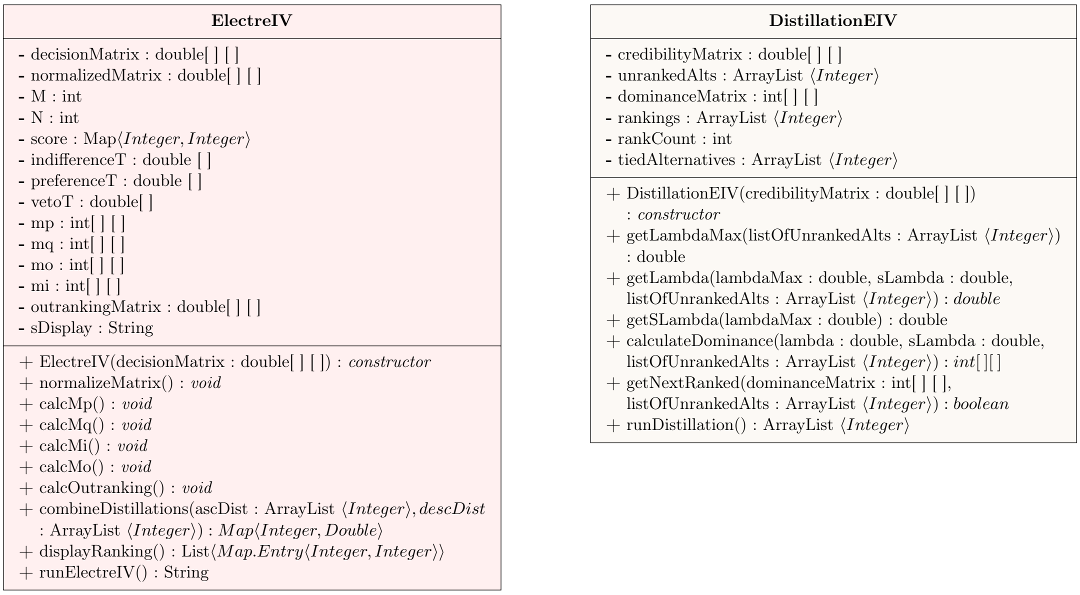


FIGURE 4.8: Class diagram for ELECTRE IV algorithm and distillation procedure

4.3 Design of ELECTRE Tri and the Genetic Algorithm

In this section the design of the software that was developed for the ELECTRE Tri and the genetic algorithms are presented. A UML class diagram and a process flow diagram are presented for each algorithm.

4.3.1 ELECTRE Tri

The process flow diagram for the ELECTRE Tri method is shown in Fig. 4.9. The first step is to express the decision problem in the form of a decision matrix, and thereafter the decision-maker must define a set of classes. The classes must be partitioned with a set of limiting profiles that must also be defined by the decision-maker. The concordance and discordance relations are then determined, which are used to calculate the credibility index. The credibility index is then exploited and finally every alternative is classified into one of the defined classes.

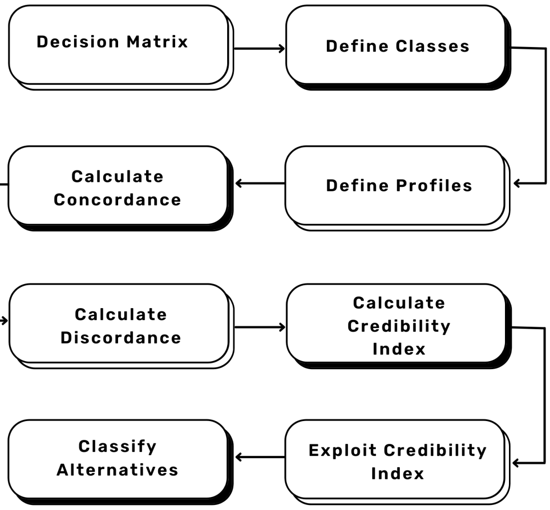


FIGURE 4.9: Process flow diagram for the ELECTRE Tri classification method

The class diagram for ELECTRE Tri is shown in Fig. 4.10 along with the class structure, the variables, and the methods used to implement the ELECTRE Tri algorithm. The class has a constructor method that takes as arguments a decision matrix, a set of thresholds, a set of boundary profiles, and a cut-off level. The concordance values are determined by the *calcGlobalConcXB()* and *calcGlobalConcBX()* methods, and the discordance values are calculated using the *calcDiscXB()* and *calcDiscBX()* methods. Thereafter, the credibility values are determined by applying the *calcCredMatrixXB()* and *calcCredMatrixBX()* methods. Finally, the alternatives are classified by applying the *optimisticClassification()* and *pessimisitcClassification()* methods.

ElectreTri
- decisionMatrix : double[ ] [ ] - normalizedMatrix : double[ ] [ ] - M : int - N : int - score : Map⟨*Integer*, *Integer*⟩ - weights : double[ ] - boundaries : double[ ] [ ] - indifferenceT : double [ ] - preferenceT : double [ ] - vetoT : double[ ] - lambda : double - globalConcXB : double[ ] [ ] - globalConcBX : double[ ] [ ] - credibilityMatrixXB : double[ ] [ ] - credibilityMatrixBX : double[ ] [ ] - preferenceMatrix : int[ ] [ ] - assignedClasses : int[ ] - sDisplay : String
+ ElectreTri(decisionMatrix : double[ ] [ ], q : double[ ] [ ], p : double[ ] [ ], v : double[ ] [ ], boundaries : double[ ] [ ], lambda : double) : *constructor* + updateParams(decisionMatrix : double[ ] [ ], q : double[ ] [ ], p : double[ ] [ ], v : double[ ] [ ], boundaries : double[ ] [ ], lambda : double) : *void* + setWeights() : *void* + normalizeMatrix() : *void* + calcGlobalConcXB() : *void* + calcGlobalConcBX() : *void* + calcDiscXB(i : int, h : int, j : int) : double + calcDiscBX(i : int, h : int, j : int) : double + calcCredMatrixXB() : *void* + calcCredMatrixBX() : *void* + determinePreferences() : *void* + optimisticClassification() : int[ ] + pessimisticClassification() : int[ ] + runElectreTri() : int[ ]

FIGURE 4.10: Class diagram for ELECTRE Tri algorithm

4.3.2 Genetic Algorithm

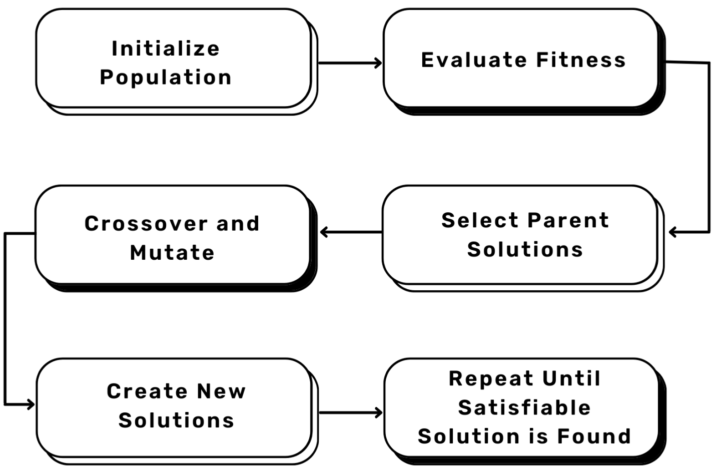


FIGURE 4.11: Process flow diagram for the genetic algorithm

The process flow diagram of the genetic algorithm is shown in Fig. 4.11. The first step is to initialize the population with candidate solutions. Thereafter, the fitness for the candidate solutions are determined and if a suitable solution is not realized then parent solutions are selected. The parent solutions are combined using mutation and crossover operations to develop new solutions. The new solutions form a new population, which is then evaluated. The process continues until a population is formed that contains a desirable solution within it.

GeneticAlgorithm
- numCriteria : Integer - numClasses : Integer - populationSize : Integer - assignments : double[ ] [ ] - classes : Integer[ ] - chromosomeSize : Integer - fitnessScores : double[ ] - classes : Integer[ ]
+ GeneticAlgorithm(numCriteria : Integer, numClasses : Integer, populationSize : Integer, assignments : double[ ] [ ], classes : Integer[ ]) : *constructor* + initializePopulation() : *void* + splitChromosome(chromosome : double[ ]) : double[ ] [ ] + calculateFitness(result : Integer[ ]) : double + populationFitness() : *void* + mutate(solution : double[ ]) : double[ ] + crossover(parent1 : double[ ], parent2 : double[ ]) : double[ ] + elitism(population : double[ ] [ ], numberOfElites : Integer) : double[ ] [ ] + tournamentSelection(numberOfCandidates : Integer) : Integer + runGeneticAlgorithm(numberOfPopulations : Integer) : double[ ]

FIGURE 4.12: Class diagram for the genetic algorithm

The genetic algorithm was implemented in the *GeneticAlgorithm.java* class, the class diagram of which is shown in Fig. 4.12. The class has a constructor method that takes as arguments the number of criteria, the number of classes, the size of the population, a set of assignment examples, and the classes. The population is initialized using the *initializePopulation()* method.

The fitness of each solution is evaluated using the *calculateFitness()* method. In order to select parent solutions, the *tournamentSelection()* and *elitism()* methods are used, and to combine the parent solutions the *mutate()* and *crossover()* methods are used.

4.4 Design of ZPLTS-ELECTRE II

The process flow diagram for the ZPLTS-ELECTRE II model is shown in Fig. 4.13. The first step is to express the decision problem using a decision matrix. The comparative sets are then determined in order to calculate the concordance and discordance relations. Thereafter, the strong and weak outranking relations are formulated, which follows by a forward and backward ranking procedure. The ranking procedures yield two rankings, which are combined to form a final ranking of the alternatives from best to worst.

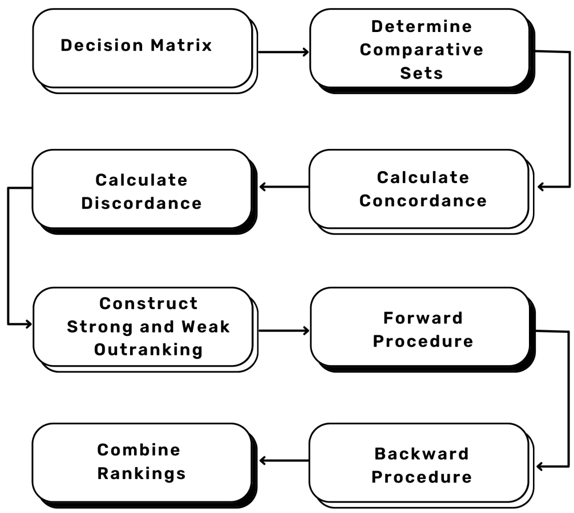


FIGURE 4.13: Process flow diagram for the ZPLTS-ELECTRE II algorithm

The ZPLTS-ELECTRE II algorithm was developed in a class called *ZpltsElectreII.java*, as shown in Fig. 4.14. The class constructor takes as arguments the number of alternatives and criteria, and the number of linguistic terms. The score, deviation, and distance for each ZPLTS is calculated using the *calculateScore()*, *calculateDeviation()*, and *calculateDistances()* methods. These methods are applied to determine the comparative sets with the *fillBMatrices()* method. Thereafter, the concordance and discordances can be calculated using the *getConcordance()* and *fillDiscMatrices()* methods. The ranking procedures and the combining of the rankings to form the final ranking is done within the *runZpltsElectreII()* method.

ZpltsElectreII
- evaluation : double[ ] [ ] - numAlternatives : Integer - numCriteria : Integer - lenLinguisticTerms : Integer - bMinus : Integer[ ] [ ] - bZero : Integer[ ] [ ] - bPlus : Integer[ ] [ ] - discHigh : Integer[ ] [ ] - discMedium : Integer[ ] [ ] - discLow : Integer[ ] [ ] - decisionMatrix : double[ ] [ ] [ ]
+ ZpltsElectreII(numAlternatives : Integer, numCriteria : Integer, lenLinguisticTerms : Integer) : *constructor* + normalizeMatrix(matrix : double[ ] [ ]) : double[ ] [ ] + calculateScores(evaluationMatrix : double[ ] [ ] [ ], credibilityMatrix[ ] [ ] [ ]) : double[ ] [ ] + calculateDeviation(evaluationMatrix : double[ ] [ ] [ ], credibilityMatrix : double[ ] [ ] [ ]) : double[ ] [ ] + calculateDistances(evaluationMatrixA : double[ ] [ ] [ ], credibilityMatrixA : double[ ] [ ] [ ], evaluationMatrixB : double[ ] [ ] [ ], credibilityMatrixB : double[ ] [ ] [ ]) : double[ ] [ ] [ ] + getMaxCardinality(matrix : double[ ] [ ] [ ]) : Integer + getScore(evaluation : double[ ], crediblity : double[ ]) : double + getDeviation(evaluation : double[ ], credibility : double[ ], cardEval : Integer, cardCred : Integer) : double + getCardinality(matrix : double[ ]) : Integer + getDistance(eval1 : double[ ], cred1 : double[ ], eval2 : double[ ], cred2 : double[ ], cardEval1 : Integer, cardCred1 : Integer) : double + fillBMatricies() : *void* + getConcordance(scores : double[ ] [ ], deviations : double[ ] [ ]) : double[ ] [ ] + fillDiscMatrices() : *void* + runZpltsElectreII() : String

FIGURE 4.14: Class diagram for the ZPLTS-ELECTRE II algorithm

4.5 Conclusion

In this chapter, the design of the software that was developed to implement the ELECTRE models was presented. Each algorithm was expressed using a process flow diagram and a class diagram, providing an overview of the underlying implementation logic and flow. All software was developed in Java using an object-oriented programming approach. The next chapter presents and discusses the experimental results achieved.

Chapter 5

Experimental Results and Discussion

5.1 Introduction

This chapter presents the results of the experiments performed. Three applications of ELECTRE pertaining to ontology ranking were proposed and their results and discussions are presented here. Firstly, the ELECTRE I, II, III, and IV are applied to rank the dataset of 200 ontologies by their 13 complexity metrics. Thereafter, the ELECTRE Tri method is applied to classify the ontologies into 3 classes, in which the genetic algorithm was applied to infer a set of thresholds for ELECTRE Tri. Thirdly, the novel ZPLTS-ELECTRE II algorithm is applied to rank a dataset of mental health ontologies.

5.2 Ranking Ontologies with ELECTRE

The ranking results obtained by applying the ELECTRE algorithms for ranking the dataset of 200 ontologies are presented and analyzed in this section. The 13 complexity metrics used are:

1. Attribute Richness (AR)
2. Inheritance Richness (IR)
3. Relationship Richness (RR)
4. Equivalence Ratio (ER)
5. Average Population (AP)
6. Class Richness (CR)
7. Absolute Root Cardinality (ARC)
8. Absolute Leaf Cardinality (ALC)
9. Average Depth (AD)
10. Maximal Depth (MD)
11. Average Breadth (AB)
12. Maximal Breadth (MB)
13. Average Number of Paths (ANP)

5.2.1 Criteria Importance Weights

Firstly, the criteria importance weights were calculated for each criterion with the use of the CRITIC weighting method. The weights obtained for each criterion are shown in Table 5.1.

TABLE 5.1: Criteria importance weights by CRITIC method

Number	Criterion	Weight
1	Attribute Richness	0.06
2	Inheritance Richness	0.08
3	Relationship Richness	0.14
4	Equivalence Ratio	0.07
5	Average Population	0.07
6	Class Richness	0.10
7	Absolute Root Cardinality	0.05
8	Absolute Leaf Cardinality	0.08
9	Average Depth	0.12
10	Maximal Depth	0.07
11	Average Breadth	0.04
12	Maximal Breadth	0.07
13	Average Number of Paths	0.05

The Relationship Richness metric received the highest importance with a weighting of 0.14. The lowest importance was given to the Average Breadth metric, having a weighting of 0.04. Interestingly, the CRITIC method assigned four metrics with the equal weight of 0.07. These are the Equivalence Ratio, Average Population, Maximal Depth, and the Maximal Breadth metrics.

The ELECTRE I, II, and III methods made use of the criteria weights in Table 5.1, whereas the ELECTRE IV method did not make use of criteria weights.

5.2.2 ELECTRE I Ranking

The thresholds that were set for the ELECTRE I model are shown in Table 5.2. These were then used to determine whether an alternative outranks or is outranked by other alternatives.

TABLE 5.2: Thresholds for ELECTRE I

Threshold	Symbol	Value
Concordance	$\bar{c}$	0.56
Discordance	$\bar{d}$	0.11

After determining the outranking relations, the number of ontologies that each ontology outranks, and the number of ontologies that outrank each ontology were calculated. The difference between these two values provided a score for each ontology, which was ordered in descending order to obtain a ranking of all ontologies. These two values and the ranking are shown in the graph in Fig. 5.1. The green plot signifies the number of ontologies that a particular ontology outranks, with a higher number implying that the ontology is stronger. The red plot signifies the number of ontologies that outrank a particular ontology, with a higher number signifying a weaker ontology. The black plot shows the ranking of ELECTRE I in relation to the other two plots.

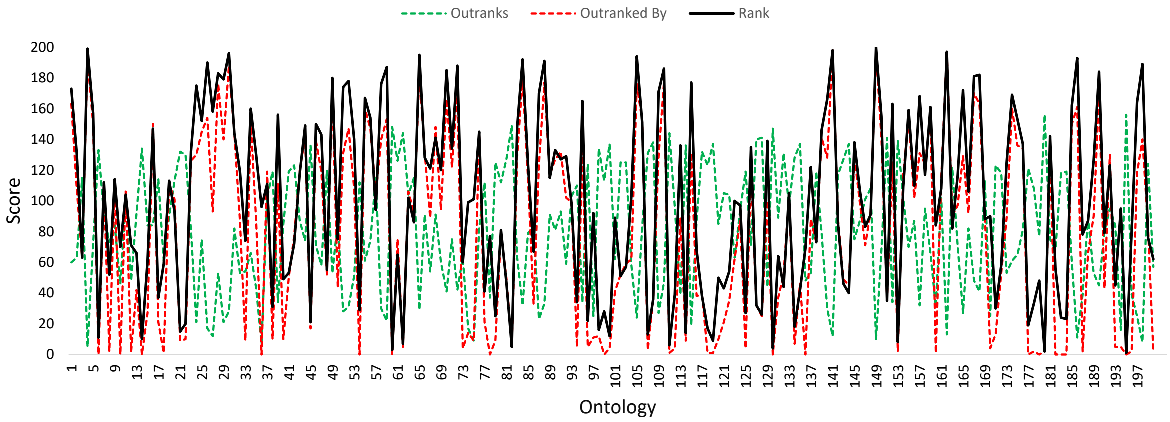


FIGURE 5.1: Graph showing ascending and descending distillations with ranking for ELECTRE I

The ELECTRE I model was able to provide a rank position for all 200 ontologies. The ranking results are depicted in Fig. 5.2. The best ranked ontology was O_{195} and the worst ontology was O_{149}.

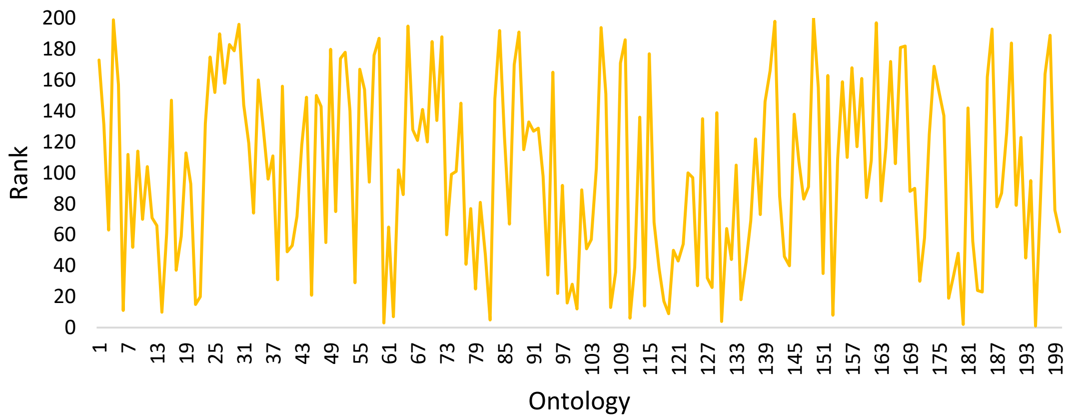


FIGURE 5.2: Ranking results of ELECTRE I

The top 15 ranked ontologies were O_{195}, O_{180}, O_{60}, O_{130}, O_{82}, O_{111}, O_{62}, O_{153}, O_{119}, O_{14}, O_6, O_{100}, O_{107}, O_{114}, and O_{21}, respectively. The bottom 15 ranked ontologies were O_{149}, O_4, O_{141}, O_{162}, O_{30}, O_{65}, O_{105}, O_{186}, O_{84}, O_{88}, O_{26}, O_{198}, O_{72}, O_{59}, and O_{110}, respectively. The names of the top and bottom 15 ranked ontologies are shown in Tables 5.3 and 5.4, where O_i represents the i^{th} ontology with $1 \leq i \leq 200$.

TABLE 5.3: Top 15 ontologies ranked by ELECTRE I

Rank	Ontology	Ontology Name
1	O_{195}	Planarian Phenotype Ontology
2	O_{180}	MHC Restriction Ontology
3	O_{60}	Emergency Care Ontology
4	O_{130}	Cell Line Ontology
5	O_{82}	Cellular Microscopy Phenotype Ontology
6	O_{111}	Ontology of Host-Pathogen Interactions
7	O_{62}	Pathway Terminology System
8	O_{153}	Cognitive Atlas Ontology
9	O_{119}	Parkinson's Disease Ontology
10	O_{14}	The Stroke Ontology
11	O_{6}	NCCN EHR Oncology Categories
12	O_{100}	Ontology of Cardiovascular Drug Adverse Events
13	O_{107}	Ontology of Host-Microbe Interactions
14	O_{114}	Ontology of Adverse Events
15	O_{21}	Ontology of Microbial Phenotypes

The Planarian Phenotype Ontology, MHC Restriction Ontology, and Emergency Care Ontology were ranked as the top 3 ontologies, respectively. The Traditional Medicine Other Factors Value Set was ranked as the lowest ontology. The ISO 19115 Date Type Code and the Loggerhead Nesting Ontology were given the second and third to last rank positions, respectively.

TABLE 5.4: Bottom 15 ontologies ranked by ELECTRE I

Rank	Ontology	Ontology Name
200	O_{149}	Traditional Medicine Other Factors Value Set
199	O_{4}	ISO 19115 Date Type Code
198	O_{141}	Loggerhead Nesting Ontology
197	O_{162}	Physico-Chemical Process
196	O_{30}	Clinical Study Ontology
195	O_{65}	Material Mineral
194	O_{105}	Epigenome Ontology
193	O_{186}	Histological Ontology
192	O_{84}	Consumer Wearable Device
191	O_{88}	Mental Functioning Ontology
190	O_{26}	Phylogenetic Ontology
189	O_{198}	Ontology for Genetic Susceptibility Factor
188	O_{72}	Reproductive Trait and Phenotype Ontology
187	O_{59}	Cardiac Electrophysiology Ontology
186	O_{110}	COPD Ontology

5.2.3 ELECTRE II Ranking

The thresholds that were set for the ELECTRE II model are shown in Table 5.5. These thresholds were then used to determine the outranking relations between the ontologies.

TABLE 5.5: Thresholds for ELECTRE II

Threshold	Symbol	Value
Low Concordance	c^-	0.50
Medium Concordance	c^0	0.60
High Concordance	c^+	0.70
Medium Discordance	d^0	0.20
High Discordance	d^+	0.25

The forward and backward ranking procedures were then determined, each yielding a ranking of the alternatives. The two rankings were then combined to determine their average ranking. The forward, backward, and average rankings are shown in the graph in Fig. 5.3. The green plot signifies the ranking obtained by applying the forward procedure, and the red plot signifies the ranking obtained by applying the backward procedure. The black plot indicates the average ranking obtained. The average ranking was used to order the ontologies from best to worst.

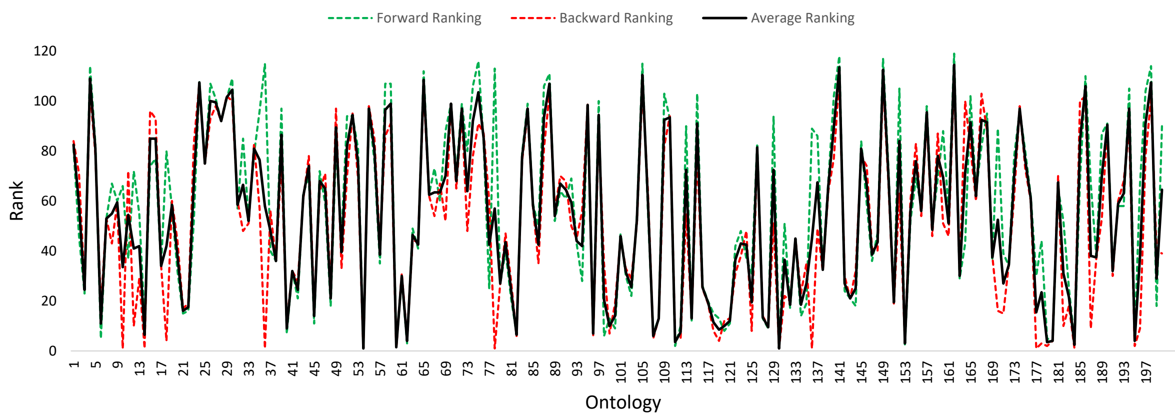


FIGURE 5.3: Graph showing the forward and backward ranking and the average ranking for ELECTRE II

The graph showing the final ranking for each ontology is shown in Fig. 5.4. It can be seen from the graph that all ontologies were successfully ranked by the ELECTRE II method. Tables 5.6 and 5.7 show the names of the top 15 and bottom 15 ontologies, as ranked by the ELECTRE II method, where O_i represents the ith ontology with $1 \leq i \leq 200$. The Ontology of Chinese Medicine for Rheumatism, Cell Line Ontology, and the Emergency Care Ontology were ranked as the top 3 ontologies, respectively. The Physico-Chemical Process was ranked as the lowest ontology. The Loggerhead Nesting Ontology and the Traditional Medicine Other Factors Value Set were given the second and third to last rank positions, respectively.

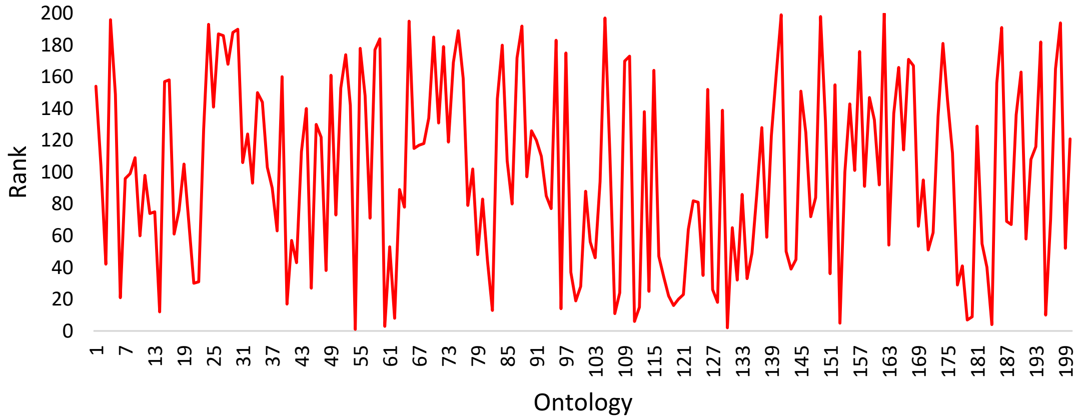


FIGURE 5.4: Ranking results of ELECTRE II

TABLE 5.6: Top 15 ontologies ranked by ELECTRE II

Rank	Ontology	Ontology Name
1	O_{54}	Ontology of Chinese Medicine for Rheumatism
2	O_{130}	Cell Line Ontology
3	O_{60}	Emergency Care Ontology
4	O_{184}	Minimal Standard Terminology of Digestive Endoscopy
5	O_{153}	Cognitive Atlas Ontology
6	O_{111}	Ontology of Host-Pathogen Interactions
7	O_{179}	The Extensible Observation Ontology
8	O_{62}	Pathway Terminology System
9	O_{180}	MHC Restriction Ontology
10	O_{195}	Planarian Phenotype Ontology
11	O_{107}	Ontology of Host-Microbe Interactions
12	O_{14}	The Stroke Ontology
13	O_{82}	Cellular Microscopy Phenotype Ontology
14	O_{96}	Ontology for Biomedical Investigations
15	O_{112}	Brucellosis Ontology

TABLE 5.7: Bottom 15 ontologies ranked by ELECTRE II

Rank	Ontology	Ontology Name
200	O_{162}	Physico-Chemical Process
199	O_{141}	Loggerhead Nesting Ontology
198	O_{149}	Traditional Medicine Other Factors Value Set
197	O_{105}	Epigenome Ontology
196	O_{4}	ISO 19115 Date Type Code
195	O_{65}	Material Mineral
194	O_{198}	Ontology for Genetic Susceptibility Factor
193	O_{24}	Genome Component Ontology
192	O_{88}	Mental Functioning Ontology
191	O_{186}	Histological Ontology
190	O_{30}	Clinical Study Ontology
189	O_{75}	Research Variable Ontology
188	O_{29}	Electronic Care Plan
187	O_{26}	Phylogenetic Ontology
186	O_{27}	Medical Technology Innovation in Healthcare Centers

5.2.4 ELECTRE III Ranking

The indifference (q_j), preference (p_j) and veto (v_j) thresholds for the ELECTRE III model are shown in Table 5.8. The indifference thresholds were set within the range of 0.04 to 0.07. The preference thresholds were set within the range of 0.06 to 0.09. The range for the veto thresholds were between 0.08 and 0.17. The thresholds, along with the concordance and discordance relations were then used to determine the credibility values for all alternative pairs.

TABLE 5.8: Thresholds for ELECTRE III

Criterion	Indifference	Preference	Veto
AR	0.05	0.08	0.14
IR	0.07	0.08	0.10
RR	0.05	0.06	0.08
ER	0.06	0.08	0.12
AP	0.06	0.08	0.12
CR	0.06	0.07	0.10
ARC	0.04	0.07	0.14
ALC	0.05	0.07	0.10
AD	0.06	0.07	0.09
MD	0.04	0.07	0.13
AB	0.04	0.09	0.17
MB	0.04	0.07	0.11
ANP	0.05	0.08	0.13

After determining the credibility values, the ascending and descending distillation procedures were applied, each yielding a ranking of the alternatives. The two rankings were then combined to determine their average ranking. The ascending and descending distillations, and the average rankings are shown in the graph in Fig. 5.5. The green plot signifies the ranking obtained by applying the ascending distillation procedure, and the red plot signifies the ranking obtained by applying the descending distillation procedure. The black plot indicates the average ranking obtained. The average ranking was used to order the ontologies from best to worst. The graph showing the final ranking for each ontology is shown in Fig. 5.6. It can be seen from the graph that all ontologies were successfully ranked by the ELECTRE III method.

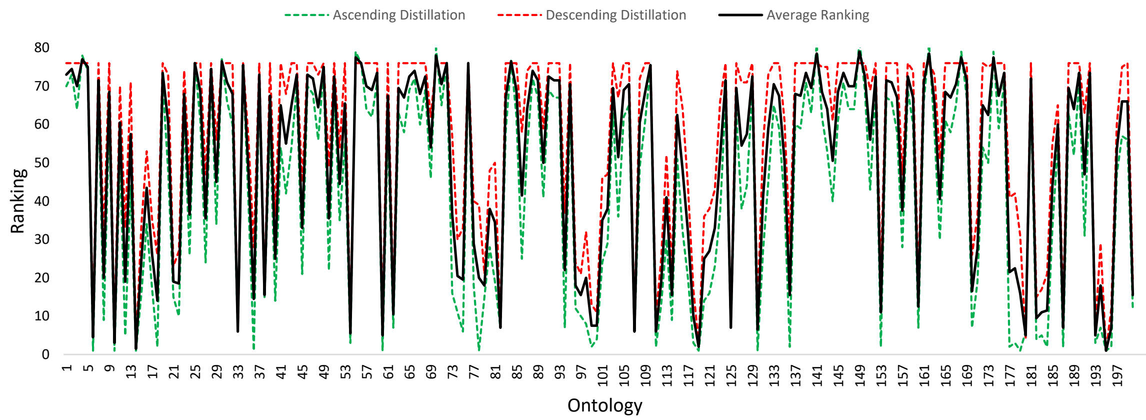


FIGURE 5.5: Graph showing the ascending and descending distillation rankings and the average ranking for ELECTRE III

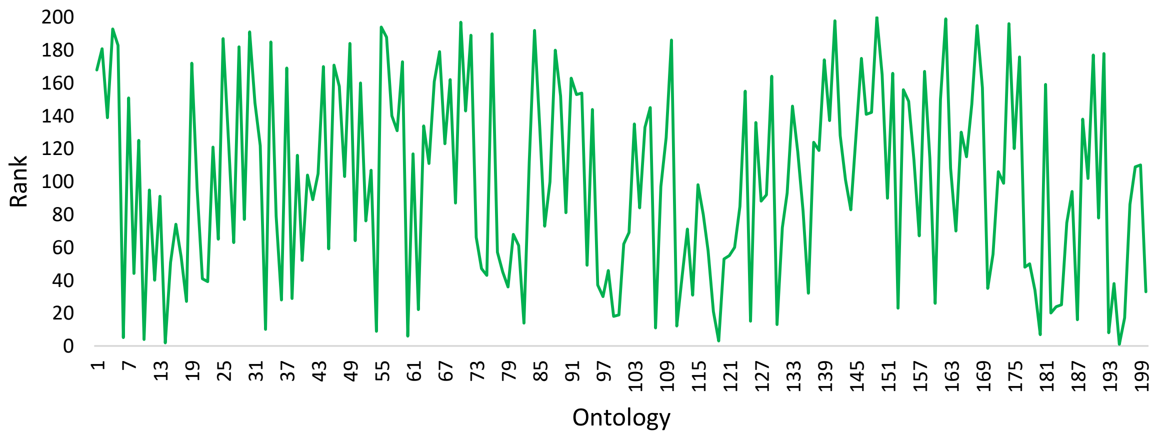


FIGURE 5.6: Ranking results of ELECTRE III

The top and bottom 15 ontologies ranked by ELECTRE III are shown in Tables 5.9 and 5.10, where O_i represents the ith ontology with $1 \leq i \leq 200$. The Planarian Phenotype Ontology, The Stroke Ontology, and Parkinson's Disease Ontology were ranked as the top 3 ontologies, respectively. The Traditional Medicine Other Factors Value Set was ranked as the lowest ontology. The Physico-Chemical Process and the Loggerhead Nesting Ontology were given the second and third to last rank positions, respectively.

TABLE 5.9: Top 15 ontologies ranked by ELECTRE III

Rank	Ontology	Ontology Name
1	O_{195}	Planarian Phenotype Ontology
2	O_{14}	The Stroke Ontology
3	O_{119}	Parkinson's Disease Ontology
4	O_{10}	Allergy Detector II
5	O_{6}	NCCN EHR Oncology Categories
6	O_{60}	Emergency Care Ontology
7	O_{180}	MHC Restriction Ontology
8	O_{193}	Confidence Information Ontology
9	O_{54}	Ontology of Chinese Medicine for Rheumatism
10	O_{33}	Population and Community Ontology
11	O_{107}	Ontology of Host-Microbe Interactions
12	O_{111}	Ontology of Host-Pathogen Interactions
13	O_{130}	Cell Line Ontology
14	O_{82}	Cellular Microscopy Phenotype Ontology
15	O_{125}	Breast Cancer Grading Ontology

TABLE 5.10: Bottom 15 ontologies ranked by ELECTRE III

Rank	Ontology	Ontology Name
200	O_{149}	Traditional Medicine Other Factors Value Set
199	O_{162}	Physico-Chemical Process
198	O_{141}	Loggerhead Nesting Ontology
197	O_{70}	Computer Cluster
196	O_{174}	Apalegal
195	O_{168}	APA Statistical Cluster
194	O_{55}	Legalapa
193	O_{4}	ISO 19115 Date Type Code
192	O_{84}	Consumer Wearable Device
191	O_{30}	Clinical Study Ontology
190	O_{76}	APA Treatment Cluster
189	O_{72}	Reproductive Trait and Phenotype Ontology
188	O_{56}	APA Occupational and Employment Cluster
187	O_{25}	APA Neuro Cluster
186	O_{110}	COPD Ontology

5.2.5 ELECTRE IV Ranking

The indifference (q_j), preference (p_j) and veto (v_j) thresholds that were set for the ELECTRE IV model are shown in Table 5.11. These thresholds are the same as those set for the ELECTRE III model. The thresholds were used to determine the credibility values.

TABLE 5.11: Thresholds for ELECTRE IV

Criterion	Indifference	Preference	Veto
AR	0.05	0.08	0.14
IR	0.07	0.08	0.10
RR	0.05	0.06	0.08
ER	0.06	0.08	0.12
AP	0.06	0.08	0.12
CR	0.06	0.07	0.10
ARC	0.04	0.07	0.14
ALC	0.05	0.07	0.10
AD	0.06	0.07	0.09
MD	0.04	0.07	0.13
AB	0.04	0.09	0.17
MB	0.04	0.07	0.11
ANP	0.05	0.08	0.13

The credibility values were then exploited by applying the ascending and descending distillation procedures to determine two rankings. The two rankings were then combined to determine their average ranking. The two distillations and the average rankings are shown in the graph in Fig. 5.7. The green plot shows the ranking obtained from the ascending distillation, the red plot shows the ranking obtained from the descending distillation, and the black plot shows the average ranking.

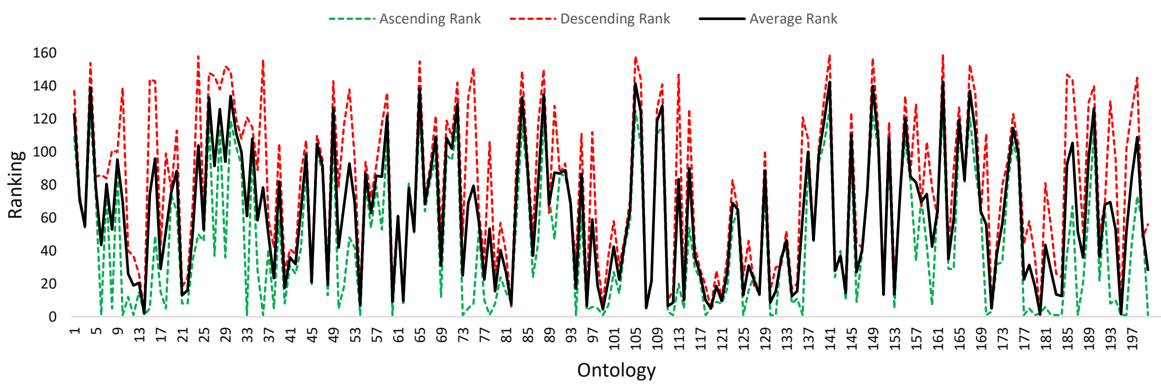


FIGURE 5.7: Graph showing the ascending and descending distillation rankings and the average ranking for ELECTRE IV

The graph showing the final ranking for each ontology is shown in Fig. 5.8. It can be seen from the graph that all ontologies were successfully ranked by the ELECTRE IV method.

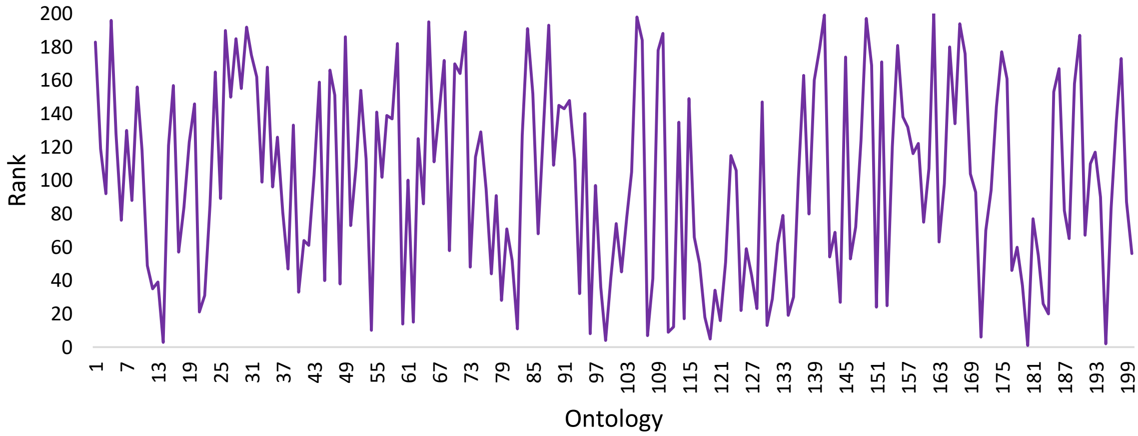


FIGURE 5.8: Ranking results of ELECTRE IV

Tables 5.12 and 5.13 show the top and bottom 15 ranked ontologies by the ELECTRE IV method, where O_i represents the ith ontology with $1 \leq i \leq 200$. The MHC Restriction Ontology, Planarian Phenotype Ontology, and The Stroke Ontology were ranked as the top 3 ontologies, respectively. The Physico-Chemical Process ontology was ranked as the lowest ontology. The Loggerhead Nesting Ontology and the Epigenome Ontology were given the second and third to last rank positions, respectively.

TABLE 5.12: Top 15 ontologies ranked by ELECTRE IV

Rank	Ontology	Ontology Name
1	O_{180}	MHC Restriction Ontology
2	O_{195}	Planarian Phenotype Ontology
3	O_{14}	The Stroke Ontology
4	O_{99}	Vaccine Ontology
5	O_{119}	Parkinson's Disease Ontology
6	O_{171}	Schema.org Core and All Extension Vocabularies
7	O_{107}	Ontology of Host-Microbe Interactions
8	O_{96}	Ontology for Biomedical Investigations
9	O_{111}	Ontology of Host-Pathogen Interactions
10	O_{54}	Ontology of Chinese Medicine for Rheumatism
11	O_{82}	Cellular Microscopy Phenotype Ontology
12	O_{112}	Brucellosis Ontology
13	O_{130}	Cell Line Ontology
14	O_{60}	Emergency Care Ontology
15	O_{62}	Pathway Terminology System

TABLE 5.13: Bottom 15 ontologies ranked by ELECTRE IV

Rank	Ontology	Ontology Name
200	O_{162}	Physico-Chemical Process
199	O_{141}	Loggerhead Nesting Ontology
198	O_{105}	Epigenome Ontology
197	O_{149}	Traditional Medicine Other Factors Value Set
196	O_4	ISO 19115 Date Type Code
195	O_{65}	Material Mineral
194	O_{167}	Material Rock
193	O_{88}	Mental Functioning Ontology
192	O_{30}	Clinical Study Ontology
191	O_{84}	Consumer Wearable Device
190	O_{26}	Phylogenetic Ontology
189	O_{72}	Reproductive Trait and Phenotype Ontology
188	O_{110}	COPD Ontology
187	O_{190}	Cell Ontology for Human Lung Maturation
186	O_{49}	Anatomic Ontology for Mouse Lung Maturation

5.2.6 Comparative Analysis of ELECTRE Rankings

In order to compare the performances of the different ELECTRE algorithms on the dataset, the ranking graphs were combined into a single axis, as shown in Fig. 5.9. The graph shows the ELECTRE I, II, III, and IV ranking results for each ontology. The ELECTRE I ranking is represented by the yellow plot, the ELECTRE II ranking by the red plot, ELECTRE III is represented by the green plot, and the ELECTRE IV ranking is shown by the purple plot. Despite some variations amongst the four plots, it can be observed that all four ELECTRE variants follow a similar ranking trend. By analysing the graph, the green plot appears to have a higher level of deviation from the other plots, particularly in the range of ontologies O_1 to O_{37}.

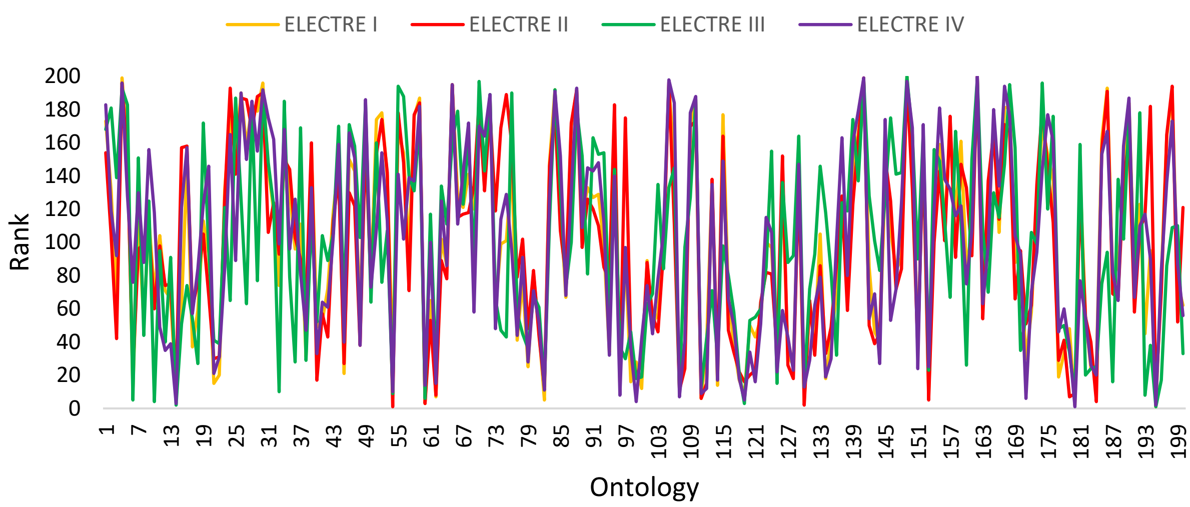


FIGURE 5.9: Comparison of ELECTRE ranking results

A comprehensive review of the top 15 ontologies ranked by the 4 ELECTRE algorithms is presented in Appendix E, and a comprehensive review of the bottom 15 ranked ontologies is presented in Appendix F.

5.2.7 Statistical Analysis of ELECTRE Rankings

In order to understand and quantify the relationships between the ranking results of the different ELECTRE methods, four statistical correlation measures [26–29] were employed to calculate rank correlation. These measures include the Spearman's Rho coefficient, the Weighted Spearman's Rho coefficient, the Top-Down Correlation value, and the WS coefficient. Firstly, the Spearman's Rho correlation coefficient values were calculated for each ELECTRE pair. The calculated coefficients are shown in Fig. 5.10.

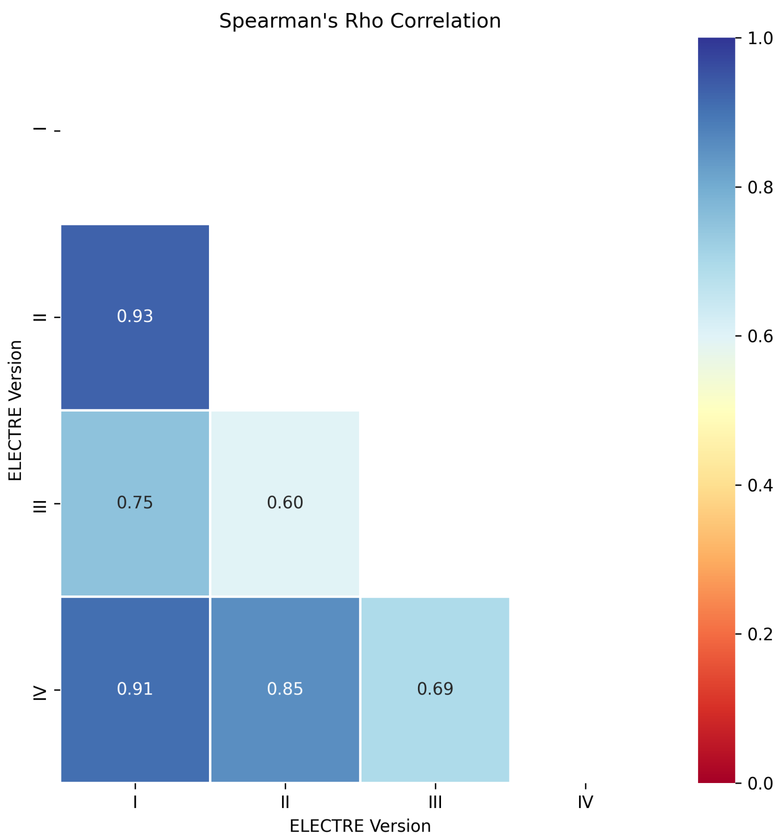


FIGURE 5.10: Spearman's Rho correlation coefficients for the ELECTRE rankings

The Spearman's Rho coefficient [26] is determined according to the differences in the ranks by treating all ranks equally. This means that whether a rank difference between two rankings is at the top or at the bottom is irrelevant when applying the Spearman's Rho measure of correlation. It can be seen from Fig. 5.10 that all ELECTRE pairs have a strong relationship. The lowest coefficient was between the ELECTRE II and III methods, having a value of 0.6. The highest coefficient was between the ELECTRE I and II methods, with a value of 0.93. The ELECTRE I method had the overall highest coefficients for all its pairwise comparisons, that is, ELECTRE I had the highest correlation with ELECTRE II, 0.93, it had the highest correlation with ELECTRE III, 0.75, and it had the highest correlation with ELECTRE IV, 0.91. The ELECTRE III method had the lowest Spearman's Rho coefficient in all its pairwise comparisons. The coefficients in Fig. 5.10 depict a strong relationship between all ELECTRE pairs.

The Weighted Spearman's Rho coefficient was then calculated for all alternative pairs, the results of which are displayed in Fig. 5.11.

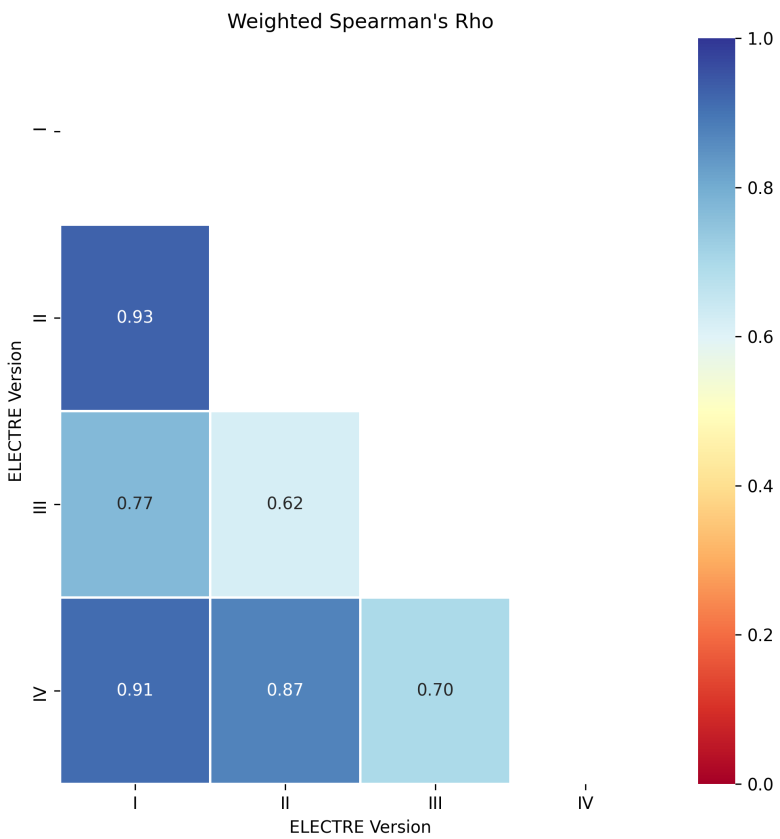


FIGURE 5.11: Weighted Spearman's Rho correlation coefficients for the ELECTRE rankings

The Weighted Spearman's Rho coefficient [27] is a general measure of similarity that places more significance on rank differences that occur in higher ranks, as opposed to differences occurring in lower ranks. The Weighted Spearman's Rho coefficient has a minimum value of -1 when a pair of rankings are inverted, and a maximum value of 1 when a pair of rankings are the same. The strongest correlation was between the ELECTRE I and ELECTRE II rankings, having a coefficient of 0.93. The weakest correlation was between ELECTRE II and ELECTRE III, with a value of 0.62. It can be seen from Fig. 5.11 that all of the blocks are some shades of blue in color, meaning that, apart from the ELECTRE II-III pair, all other ELECTRE pairs had a Weighted Spearman's Rho coefficient of at least 0.7. The ELECTRE I method had the strongest correlation with all other ELECTRE methods, that is, ELECTRE I and II had a stronger correlation than that of ELECTRE III and II, and that of ELECTRE IV and II. The same with the

ELECTRE I and III pair, and the ELECTRE I and IV pair. Similarly, ELECTRE III had the weakest correlation with all other ELECTRE methods. It can be seen that all ELECTRE pairs had coefficients close to 1, signifying strong correlation. The correlation values are also slightly higher than the Spearman's Rho coefficients in Fig. 5.11. This implies that in some ELECTRE pairs, specifically ELECTRE I-III, II-III, II-IV, and III-IV, there exists more rank differences towards the bottom of the rankings as opposed to towards the top of the rankings.

The Top-Down coefficient was then calculated for all alternative pairs. The results are shown in Fig. 5.12.

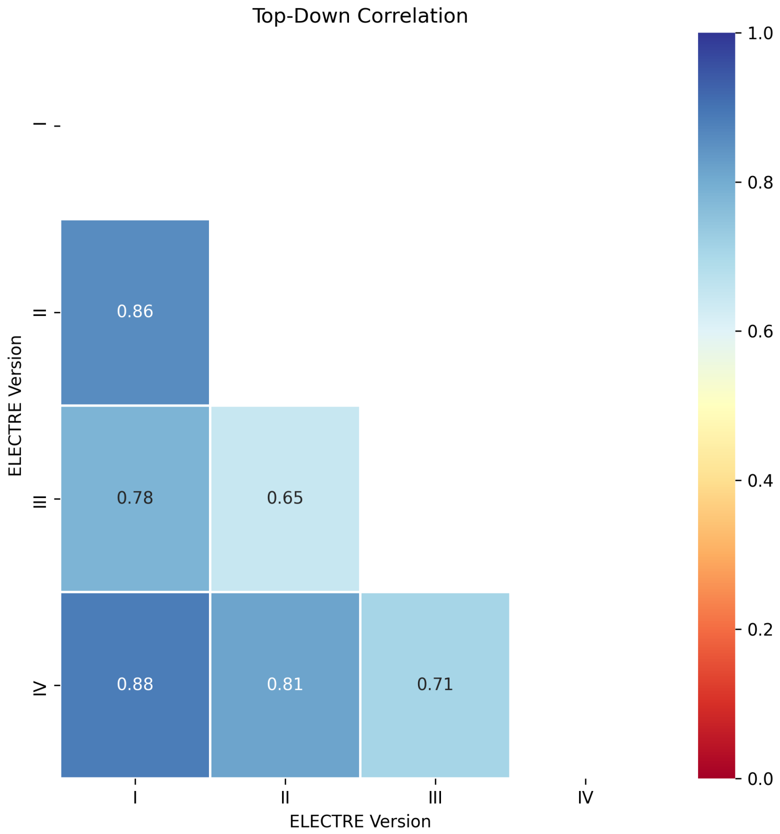


FIGURE 5.12: Top-Down correlation coefficients for the ELECTRE rankings

The Top-Down coefficient [28] was developed in order to quantify the correlation between rankings in a more sensitive manner towards the top ranks. The measure of correlation provides a good indication of the general relationship between rankings, with an emphasis on the topmost ranks. It can be observed from Fig. 5.12 that all blocks are colored in some shade of blue, indicating that all ELECTRE pairs have Top-Down correlation values approaching 1. The highest coefficient was between ELECTRE I and IV, with a value of 0.88. The lowest coefficient was between the ELECTRE II and III methods, having a value of 0.65. ELECTRE I had the strongest correlation with all the other ELECTRE methods. The method that had the lowest correlation with all other ELECTRE methods is ELECTRE III. This implies that the ELECTRE II and III, having the lowest coefficient, have more substantial differences between their ranks at the top as compared to the rankings from all other ELECTRE pairs. Lastly, the WS coefficient was calculated and is shown in Fig. 5.13.

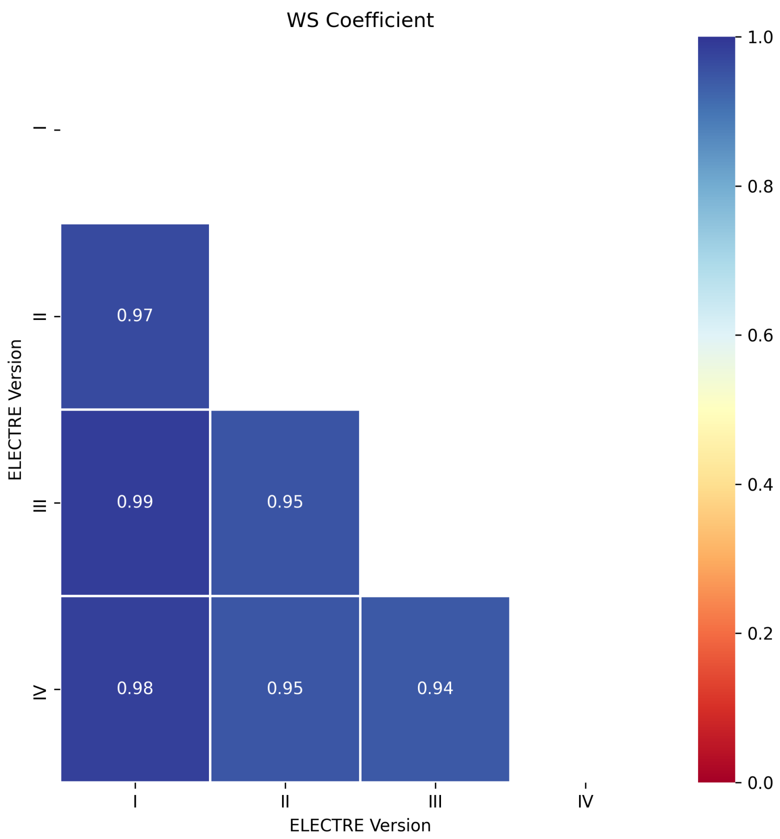


FIGURE 5.13: WS correlation coefficients for the ELECTRE rankings

The WS coefficient [29] takes into account where the difference in ranks occur, placing more emphasis on the top ranks than the bottom ranks. The WS coefficient is also more sensitive to rank differences at the top as compared to the Weighted Spearman's Rho coefficient which is more generalized. It can be observed from Fig. 5.13 that all of the blocks in the heatmap are dark blue in color, signifying that the correlation between all ELECTRE pairs are strongly approaching 1. Every ELECTRE pair had a coefficient of at least 0.94, with the highest coefficient being 0.99. The ELECTRE I and III methods had the strongest correlation of 0.99, whilst the ELECTRE III and IV methods had the weakest correlation of 0.94. ELECTRE I had particularly strong correlations with ELECTRE II, III, and IV, having coefficient values of 0.97, 0.99, and 0.98, respectively. The lowest correlations were between ELECTRE II and III, III and IV, and II and IV, with coefficient values of 0.95, 0.95, and 0.94, respectively. Therefore, the fact that all of the ELECTRE pairs have strong WS coefficients indicates that each pair has more significant differences in their rankings towards the bottom rather than towards the top. This means that there is a strong correlation between the ELECTRE rankings, particularly concerning agreement in the top rankings.

5.3 Classification of Ontologies with ELECTRE Tri

Three classes were defined for the ELECTRE Tri model, that is *Class 1*, *Class 2*, and *Class 3*. The classes were representative of varying levels of quality of the ontologies in respect to the four dimensions, i.e., accuracy, understandability, cohesion, and conciseness defined in Subsection 3.2.4. The characteristics and implications of these three classes are discussed as follows.

Class 1 represents those ontologies that have a high level of accuracy indicating that the ontologies are strongly representative of a real-world domain. The ontologies in this class have a high level of understandability, signifying a vastly comprehensive set of concepts, relations, and properties. These ontologies also have a high level of cohesion and conciseness, which means that the ontologies are highly relevant in the domain they are representative of.

Class 2 represents those ontologies that have a moderate level of accuracy indicating that the ontologies are moderately representative of a real-world domain. The ontologies in this class have a fairly comprehensive set of concepts, relations, and properties. These ontologies also have a moderate level of cohesion and conciseness, which means that they have a considerable amount of importance in relation to their domains.

Class 3 represents the ontologies that have a low level of accuracy, which indicates that the ontologies are only somewhat representative of a real-world domain. The ontologies also have low understandability, meaning that they have a set of concepts, relations, and properties that are not very comprehensive. Ontologies in this class have a minor level of cohesion and conciseness, which means that the ontologies are of lower importance in relation to the domain they are representative of.

In order to infer a set of appropriate thresholds, a set of assignments were made. After analyzing the ontologies along with their classes, properties, and relations, an assignment of 27 ontologies was made. Nine ontologies were assigned to each of the three classes, as shown in Table 5.14 where O_i represents the ith ontology with $1 \leq i \leq 200$. The criteria importance weights were set to the values obtained from the CRITIC method. Since there were 3 classes defined, there was a need to define 2 sets of class boundaries to represent the boundaries of the 3 classes. After analyzing the ontologies and their metrics, the class boundaries were defined. The weights and class boundaries are shown in Table 5.15.

The Genetic Algorithm was applied using the parameters in Table 5.16, in each iteration a candidate solution comprising a set of thresholds was applied to develop an ELECTRE Tri model. The fitness of that particular candidate solution set of thresholds was based on how well the ELECTRE Tri model created was able to assign ontologies according to the original set of assignments in Table 5.14. After 1000 generations a set of thresholds was realized. The thresholds were able to develop an ELECTRE Tri model to fully classify all assignment examples into their correct classes, having an accuracy of 1. The set of thresholds were analysed and were found to be appropriate for use. These thresholds are shown in Table 5.17.

TABLE 5.14: Assignment examples for each class

Class 1	**Class 2**	**Class 3**
O_{14}	O_{13}	O_{4}
O_{36}	O_{16}	O_{26}
O_{60}	O_{20}	O_{30}
O_{78}	O_{80}	O_{49}
O_{136}	O_{102}	O_{58}
O_{153}	O_{151}	O_{59}
O_{179}	O_{157}	O_{72}
O_{184}	O_{159}	O_{140}
O_{195}	O_{173}	O_{152}

TABLE 5.15: Weights and class boundaries for each criterion

Index j	**Criterion c_j**	**Weight ω_j**	**Boundary b_{1j}**	**Boundary b_{2j}**
1	AR	0.06	0.06	0.02
2	IR	0.08	0.12	0.06
3	RR	0.14	0.08	0.04
4	ER	0.07	0.16	0.07
5	AP	0.07	0.09	0.05
6	CR	0.10	0.07	0.03
7	ARC	0.05	0.05	0.03
8	ALC	0.08	0.25	0.10
9	AD	0.12	0.23	0.11
10	MD	0.07	0.08	0.03
11	AB	0.04	0.06	0.04
12	MB	0.07	0.18	0.07
13	ANP	0.05	0.18	0.05

The ELECTRE Tri model was then constructed using the thresholds inferred in Table 5.17 and a cut-off level λ was set to 0.72. The model was then applied to classify the dataset of 200 ontologies. The results are shown in Fig. 5.14.

All assignments were assigned correctly by the inferred thresholds, as can be observed in Fig. 5.14. Most of the ontologies were classified to the third class, denoting lower levels of the four quality dimensions. About one fifth of the the dataset was classified to the second class, and about one quarter was classified to the first class. Out of the 200 ontologies, 109 (54.5%) were assigned to class 3, 43 (21.5%) were assigned to class 2, and 48 (24%) were assigned to class 1. The names of the ontologies for each class can be obtained from Appendix B.

5.3.1 Analysis of Classification

In order to further understand the classification results obtained from ELECTRE Tri, they were compared with the ranking results obtained in Section 5.2. The average rank of each ontology was calculated by summing up the ranks from each of the ELECTRE methods and dividing it by 4. The graph in Fig. 5.15 shows the relationship between the classes assigned to each ontology by ELECTRE Tri and the average rank assigned to each ontology by the four ELECTRE

TABLE 5.16: Parameters of the Genetic Algorithm

Parameter	**Value**
Population size PS	100
Number of generations	1000
Number of elites	$0.04PS$
Number of random candidates	$0.10PS$
Selection type	Tournament selection
Crossover type	Arithmetic crossover
Gene mutated	cut-off level λ
Tournament size	2
Mutation rate	0.04
Mutation range	$[0.50, 1]$

TABLE 5.17: Inferred thresholds by the Genetic Algorithm

Criterion c	**Indifference q**	**Preference p**	**Veto v**
AR	0.01	0.01	0.02
IR	0.01	0.02	0.05
RR	0.02	0.02	0.03
ER	0.04	0.06	0.09
AP	0.01	0.01	0.03
CR	0.01	0.02	0.02
ARC	0.01	0.01	0.10
ALC	0.03	0.06	0.10
AD	0.03	0.05	0.07
MD	0.01	0.01	0.02
AB	0.01	0.01	0.01
MB	0.02	0.05	0.08
ANP	0.02	0.04	0.09

methods. The values on the left y-axis depict the average ranks, and the values on the right y-axis depict the classes. The blue bars represent the class that an ontology was assigned to, and the orange curve represents the average rank for that ontology.

It was found that the 82.4% of ontologies from class 1 had an average rank that was lower than 100, and from that 82.4% a further 50% had an average rank that was less than 50. From the ontologies classified into class 2, 46.5% of them had an average rank of below 100, and the remaining 53.5% had an average rank above 100. Only 29.3% of the ontologies assigned to Class 3 had an average rank of below 100, the remaining 70.7% of ontologies had an average rank above 100. Furthermore, from the 77 ontologies in class 3 that had an average rank of over 100, only 14 had an average rank in the range of 100 to 120, 16 had an average rank in the range of 121 to 140, 20 had an average rank in the range of 141 to 160, 12 had an average rank between 161 and 180, and 15 ontologies had an average rank between 181 and 200.

This shows that the ontologies assigned to class 1 - such as O_6, O_{54}, O_{60}, O_{153} and O_{195} - were generally of higher quality than those assigned to class 2, and those assigned to class 2 - such as O_{11}, O_{35}, O_{80}, O_{102} and O_{131} - were generally of higher quality than those assigned to class 3 - such as O_4, O_{19}, O_{88}, O_{105} and O_{110}. This is observable from Fig. 5.15, when the

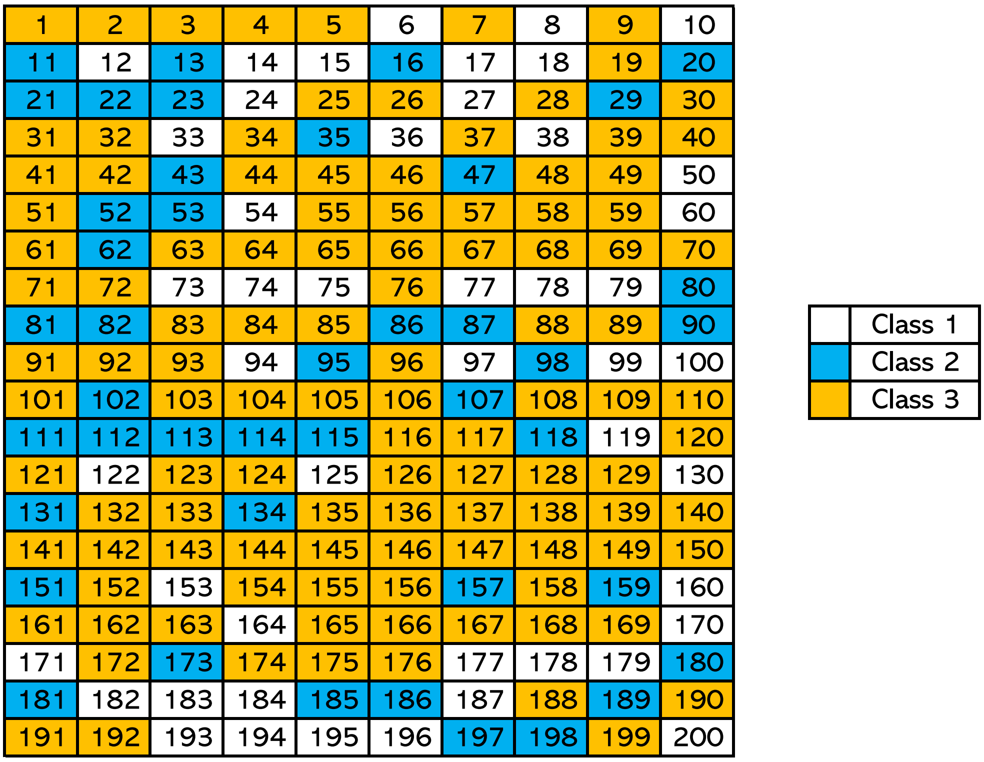


FIGURE 5.14: Diagram showing classification of ontologies

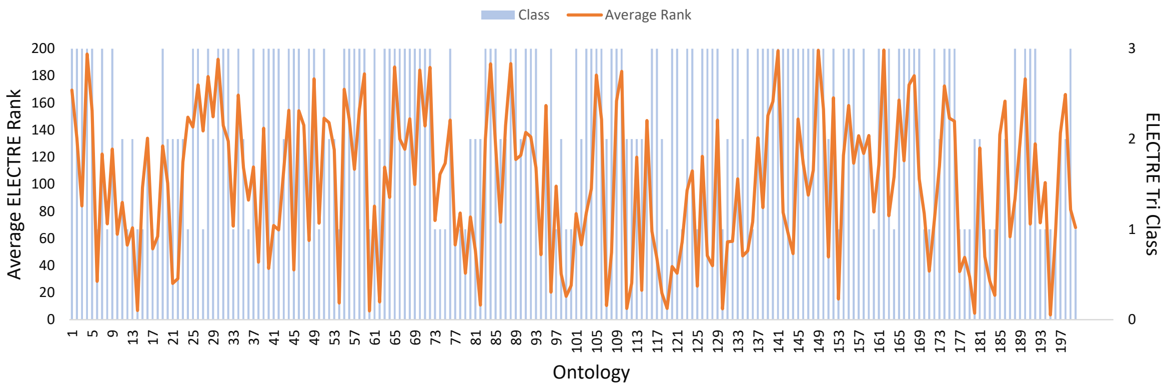


FIGURE 5.15: Comparison between ELECTRE Tri classification and average ELECTRE Ranking

ontology is classified into the third class (highest blue bar) then the average ranking is generally high (higher orange plot value), and accordingly, when the ontology is assigned to class 1 (lowest blue bar), then the average rank is generally low (low orange plot value).

Thereafter, the classification results of ELECTRE Tri were compared against the actual complexity metrics for each ontology. The comparison of the first 100 ontologies are shown in the graph in Fig. 5.16. The blue bar represents the class that the ontology was assigned to by ELECTRE Tri, and the other bars represent the ratios of the 13 complexity metrics for that particular ontology.

The next 100 ontologies, that is O_{101} to O_{200}, are shown in the graph in Fig. 5.17. It can be observed by the graphs that those ontologies that were assigned to class 1 generally have higher

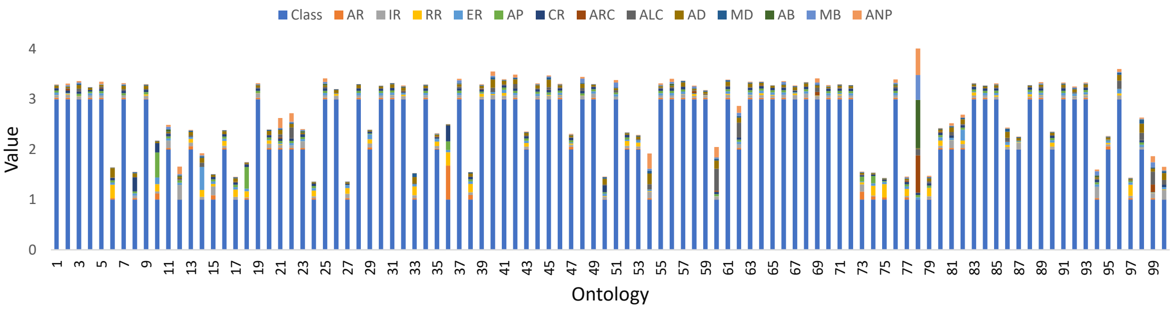


FIGURE 5.16: Comparison between ELECTRE Tri classification and complexity metrics for ontology O_1 to O_{100}

levels of complexity metrics, whereas those ontologies that were assigned to class 3 generally have lower levels of complexity metrics.

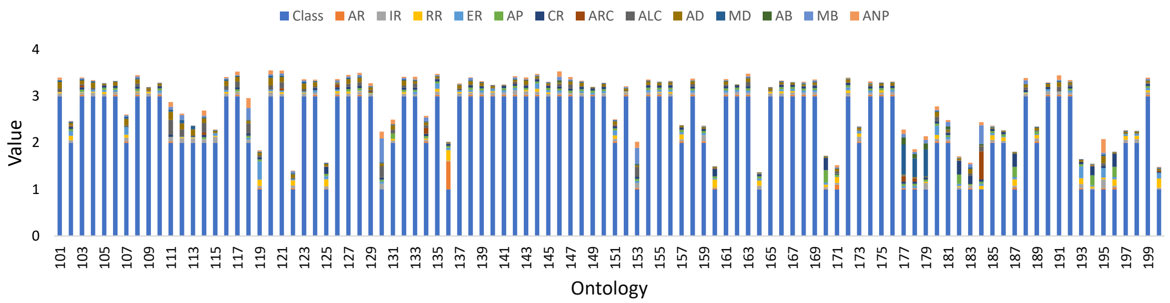


FIGURE 5.17: Comparison between ELECTRE Tri classification and complexity metrics for ontology O_{101} to O_{200}

5.4 Application of the ZPLTS-ELECTRE II Algorithm for Ranking Ontologies

This section presents (1) the description of the results of the application of the ZPLTS-ELECTRE II algorithm for ranking ontologies, (2) the comparative analysis of the performance of the ZPLTS-ELECTRE II method against the traditional ELECTRE II and fuzzy ELECTRE II methods, and (3) the discussion of the overall performance of the proposed ZPLTS-ELECTRE II method. The performance of the ZPLTS-ELECTRE II method is firstly compared against that of the traditional ELECTRE II and the PLTS ELECTRE II methods on the same dataset; thereafter, the ZPLTS-ELECTRE II method is compared against previous studies that have used MCDM methods in ontology ranking as well as the existing fuzzy ELECTRE II methods implemented in related studies. Finally, the strengths and weaknesses of the proposed ZPLTS-ELECTRE II method are described.

Initially, the quantitative matrix, Λ, of the ZPLTS-ELECTRE II algorithm contains the 5 complexity metrics for each of the 9 ontologies of the mental health domain presented in Section 3.4.5, as in Table 5.18. These metrics were calculated by using the OntoMetrics platform. Column O_i represents the ontologies, with $1 \leq i \leq 9$.

TABLE 5.18: Quantitative matrix Λ representing the 5 complexity metrics for the ontologies

Oi	**ALC**	**ARC**	**AD**	**AB**	**ANP**
O_1	26	447	1.97	53.20	532
O_2	7	494	1.98	62.62	250.50
O_3	1	228	3.80	5.28	40
O_4	14	16	1.60	2.15	7
O_5	7	1323	6.82	7.10	156.91
O_6	2	320	5.21	6.80	46.75
O_7	11	1364	4.76	4.04	181.40
O_8	8	181	3.19	10.47	49.75
O_9	6	3508	2.37	27.56	454.87

The qualitative criteria, defined in Section 3.4.5, were evaluated by 4 decision-makers and accordingly, 4 qualitative matrices were formed. These are Γ^b, where $b = \{1, 2, 3, 4\}$. The decision-makers selected a linguistic term for each criterion for every ontology, along with an accompanying linguistic term representing their credibility level for that criterion evaluation. The linguistic term set S was used for the evaluation of criteria, and the linguistic term set S' was used for expressing levels of credibility. S and S' are defined in Tables 5.19 and 5.20.

TABLE 5.19: Linguistic Term Set S for evaluating ontology criteria

Term	s_{-2}	s_{-1}	s_0	s_1	s_2
Evaluation	Very bad	Bad	Average	Good	Very good

There are 5 linguistic terms in S. The worst term is 'Very bad' and the best term is 'Very good'. The middle term is 'Average'. The term 'Bad' lies between 'Average' and 'Very bad', and the term 'Good' lies between 'Average' and 'Very good'.

TABLE 5.20: Linguistic Term Set S' for expressing credibility level for evaluation

Term	s'_{-2}	s'_{-1}	s'_0	s'_1	s'_2
Evaluation	Not at all sure	Not sure	Moderately sure	Sure	Very sure

There are also 5 linguistic terms in S'. The worst term is 'Not at all sure' and the best term is 'Very sure'. The middle term is 'Moderately sure'. The term 'Not sure' lies between 'Moderately sure' and 'Not at all sure', and the term 'Sure' lies between 'Moderately sure' and 'Very sure'. The matrices representing the decision-makers' evaluations, i.e., Γ^1, Γ^2, Γ^3, and Γ^4, are presented in Tables 5.21 to 5.24.

After obtaining the quantitative matrix, Λ, and the qualitative matrices, Γ^1 to Γ^4, the decision matrix, E, is built. Firstly, the 4 qualitative matrices are combined by adding the probabilities of like terms for each criteria, to form a single matrix, Γ. The matrix Γ is then normalized, as shown in Tables 5.25 to 5.29. The Γ matrix prior to normalization is shown in Appendix C. Thereafter, the matrix Λ is concatenated with Γ to form the decision matrix E with dimensions $m \times n$, which can be seen in Appendix C. The criteria importance weightings were obtained

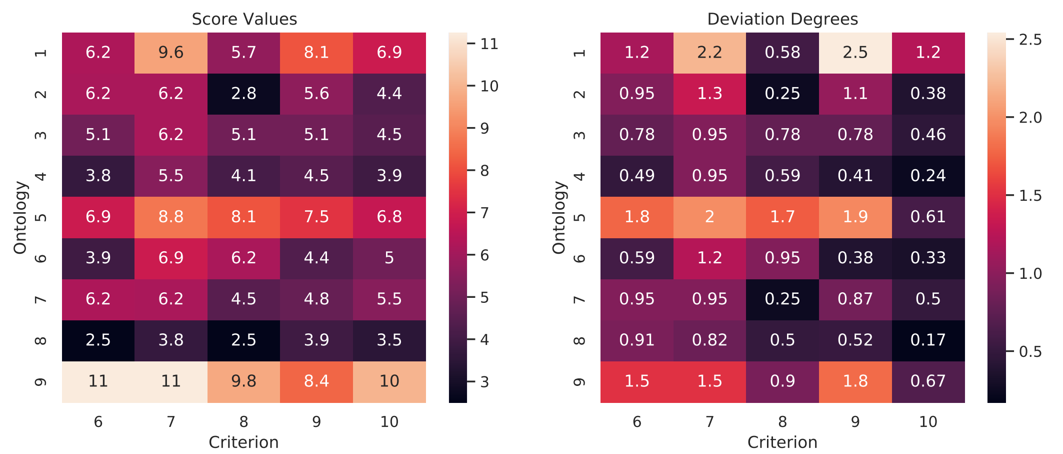
TABLE 5.21: Ontology qualitative criteria evaluation by decision-maker 1 (Γ^1)

Oi	**CoP**	**QoSD**	**DoCRNL**	**UoC**	**DoCA**
O_1	(s_1, s'_1)	(s_1, s'_1)	(s_1, s'_0)	(s_0, s'_1)	(s_1, s'_0)
O_2	(s_0, s'_0)	(s_{-1}, s'_1)	(s_{-1}, s'_1)	(s_0, s'_0)	(s_0, s'_1)
O_3	(s_0, s'_1)	(s_1, s'_1)	(s_0, s'_0)	(s_1, s'_0)	(s_0, s'_0)
O_4	(s_{-1}, s'_0)	(s_0, s'_1)	(s_{-1}, s'_1)	(s_0, s'_0)	(s_0, s'_1)
O_5	(s_2, s'_1)	(s_1, s'_1)	(s_1, s'_1)	(s_0, s'_0)	(s_1, s'_0)
O_6	(s_0, s'_1)	(s_1, s'_1)	(s_0, s'_1)	(s_{-1}, s'_1)	(s_0, s'_1)
O_7	(s_0, s'_0)	(s_0, s'_1)	(s_1, s'_1)	(s_{-1}, s'_0)	(s_0, s'_0)
O_8	(s_{-1}, s'_1)	(s_{-1}, s'_0)	(s_{-1}, s'_0)	(s_0, s'_0)	(s_0, s'_0)
O_9	(s_1, s'_1)	(s_1, s'_1)	(s_1, s'_1)	(s_2, s'_1)	(s_2, s'_1)

TABLE 5.22: Ontology qualitative criteria evaluation by decision-maker 2 (Γ^2)

Oi	**CoP**	**QoSD**	**DoCRNL**	**UoC**	**DoCA**
O_1	(s_1, s'_{-1})	(s_2, s'_0)	(s_2, s'_{-1})	(s_1, s'_{-1})	(s_1, s'_0)
O_2	(s_0, s'_1)	(s_1, s'_0)	(s_{-1}, s'_0)	(s_{-1}, s'_0)	(s_{-1}, s'_1)
O_3	(s_1, s'_{-1})	(s_0, s'_0)	(s_0, s'_{-1})	(s_0, s'_{-1})	(s_0, s'_{-1})
O_4	(s_0, s'_0)	(s_1, s'_0)	(s_0, s'_0)	(s_{-1}, s'_0)	(s_{-1}, s'_0)
O_5	(s_1, s'_{-1})	(s_2, s'_{-1})	(s_2, s'_{-1})	(s_1, s'_0)	(s_1, s'_{-1})
O_6	(s_1, s'_0)	(s_0, s'_1)	(s_0, s'_1)	(s_0, s'_1)	(s_0, s'_1)
O_7	(s_0, s'_0)	(s_1, s'_0)	(s_0, s'_1)	(s_{-1}, s'_1)	(s_0, s'_1)
O_8	$(\mathrm{s}_{-1}, s'_{-1})$	(s_1, s'_0)	(s_0, s'_0)	$(\mathrm{s}_{-1}, s'_{-1})$	(s_{-1}, s'_0)
O_9	(s_2, s'_1)	(s_2, s'_1)	(s_2, s'_1)	(s_2, s'_0)	(s_2, s'_1)

by applying the mean weighting method, that is, all criteria were given equal importance. The weights and the discordance thresholds are shown in Table 5.30. The concordance thresholds are set as $\alpha_1 = 0.55$, $\alpha_2 = 0.70$ and $\alpha_3 = 0.85$.



(a) Score values

(b) Deviation degree values

FIGURE 5.18: Score and deviation values for all alternatives for criteria 6 to 10

The comparative sets, $\mathcal{B}^-(x, y)$, $\mathcal{B}^0(x, y)$, and $\mathcal{B}^+(x, y)$ for comparing alternative x with y are created for all alternatives. To determine the comparative relationships the scores and deviation

TABLE 5.23: Ontology qualitative criteria evaluation by decision-maker 3 (Γ^3)

Oi	**CoP**	**QoSD**	**DoCRNL**	**UoC**	**DoCA**
O_1	(s_0, s'_1)	(s_2, s'_1)	(s_1, s'_0)	(s_2, s'_1)	(s_1, s'_1)
O_2	(s_0, s'_1)	(s_0, s'_1)	(s_{-1}, s'_1)	(s_1, s'_1)	(s_0, s'_0)
O_3	(s_0, s'_1)	(s_0, s'_1)	(s_0, s'_1)	(s_0, s'_1)	(s_0, s'_1)
O_4	(s_{-1}, s'_1)	(s_{-1}, s'_1)	(s_{-1}, s'_1)	(s_1, s'_0)	(s_0, s'_0)
O_5	(s_0, s'_1)	(s_2, s'_1)	(s_1, s'_1)	(s_2, s'_1)	(s_1, s'_1)
O_6	(s_{-1}, s'_0)	(s_1, s'_0)	(s_0, s'_1)	(s_0, s'_0)	(s_0, s'_0)
O_7	(s_1, s'_1)	(s_0, s'_1)	(s_0, s'_1)	(s_0, s'_1)	(s_0, s'_1)
O_8	(s_0, s'_0)	(s_{-1}, s'_1)	(s_{-1}, s'_0)	(s_1, s'_0)	(s_0, s'_0)
O_9	(s_2, s'_1)	(s_2, s'_1)	(s_1, s'_1)	(s_2, s'_0)	(s_2, s'_0)

TABLE 5.24: Ontology qualitative criteria evaluation by decision-maker 4 (Γ^4)

Oi	**CoP**	**QoSD**	**DoCRNL**	**UoC**	**DoCA**
O_1	(s_0, s'_1)	(s_1, s'_1)	(s_1, s'_0)	(s_1, s'_1)	(s_0, s'_1)
O_2	(s_1, s'_1)	(s_1, s'_1)	(s_{-1}, s'_1)	(s_1, s'_1)	(s_0, s'_0)
O_3	(s_0, s'_0)	(s_0, s'_1)	(s_1, s'_1)	(s_0, s'_1)	(s_1, s'_0)
O_4	(s_0, s'_1)	(s_0, s'_1)	(s_0, s'_1)	(s_1, s'_0)	(s_0, s'_0)
O_5	(s_0, s'_1)	(s_1, s'_1)	(s_1, s'_1)	(s_1, s'_1)	(s_1, s'_1)
O_6	(s_{-1}, s'_0)	(s_1, s'_0)	(s_1, s'_0)	(s_0, s'_0)	(s_0, s'_0)
O_7	(s_1, s'_1)	(s_0, s'_1)	(s_0, s'_1)	(s_1, s'_1)	(s_0, s'_1)
O_8	(s_{-1}, s'_0)	(s_{-1}, s'_1)	(s_{-1}, s'_0)	(s_1, s'_0)	(s_0, s'_0)
O_9	(s_1, s'_1)	(s_1, s'_1)	(s_1, s'_1)	(s_1, s'_0)	(s_1, s'_0)

TABLE 5.25: Normalized combined qualitative matrix for criterion 6

O_i	**Criterion 6: CoP**
O_1	$\{s_0(0.5), s_1(0.5), s_1(0)\}, \{s'_{-1}(0.25), s'_1(0.75), s'_1(0)\}$
O_2	$\{s_0(0.75), s_1(0.25), s_1(0)\}, \{s'_0(0.25), s'_1(0.75), s'_1(0)\}$
O_3	$\{s_0(0.75), s_1(0.25), s_1(0)\}, \{s'_{-1}(0.25), s'_0(0.25), s'_1(0.5)\}$
O_4	$\{s_{-1}(0.5), s_0(0.5), s_0(0)\}, \{s'_0(0.5), s'_1(0.5), s'_1(0)\}$
O_5	$\{s_0(0.5), s_1(0.25), s_2(0.25)\}, \{s'_{-1}(0.25), s'_1(0.75), s'_1(0)\}$
O_6	$\{s_{-1}(0.5), s_0(0.25), s_1(0.25)\}, \{s'_0(0.75), s'_1(0.25), s'_1(0)\}$
O_7	$\{s_0(0.5), s_1(0.5), s_1(0)\}, \{s'_0(0.5), s'_1(0.5), s'_1(0)\}$
O_8	$\{s_{-1}(0.75), s_0(0.25), s_0(0)\}, \{s'_{-1}(0.25), s'_0(0.5), s'_1(0.25)\}$
O_9	$\{s_1(0.25), s_2(0.75), s_2(0)\}, \{s'_1(1), s'_1(0), s'_1(0)\}$

degree values are required. These are calculated by applying Eqs. (3.84) and (3.85). The scores and deviation degree values for criteria 6 to 10, that is, the qualitative criteria, are calculated and displayed in the heatmaps in Figure 5.18. As an illustration, when comparing alternative 1 to alternative 2, that is, the Mental State Assessment Ontology and the APA Neuro Cluster Ontology, the comparative sets are formed as follows.

$$\mathcal{B}^+(1,2) = \{1, 5, 6, 7, 8, 9, 10\}$$

Based on the set $\mathcal{B}^+(x, y)$, it can be observed that alternative 1 outperforms alternative 2 for criteria 1, 5, 6, 7, 8, 9, and 10.

TABLE 5.26: Normalized combined qualitative matrix for criterion 7

O_i	Criterion 7: QoSD
O_1	$\{s_1(0.5), s_2(0.5), s_2(0)\}, \{s'_0(0.25), s'_1(0.75), s'_1(0)\}$
O_2	$\{s_{-1}(0.25), s_0(0.25), s_1(0.5)\}, \{s'_0(0.25), s'_1(0.75), s'_1(0)\}$
O_3	$\{s_0(0.75), s_1(0.25), s_1(0)\}, \{s'_0(0.25), s'_1(0.75), s'_1(0)\}$
O_4	$\{s_{-1}(0.25), s_0(0.5), s_1(0.25)\}, \{s'_0(0.25), s'_1(0.75), s'_1(0)\}$
O_5	$\{s_1(0.5), s_2(0.5), s_2(0)\}, \{s'_{-1}(0.25), s'_1(0.75), s'_1(0)\}$
O_6	$\{s_0(0.25), s_1(0.75), s_1(0)\}, \{s'_0(0.5), s'_1(0.5), s'_1(0)\}$
O_7	$\{s_0(0.75), s_1(0.25), s_1(0)\}, \{s'_0(0.25), s'_1(0.75), s'_1(0)\}$
O_8	$\{s_{-1}(0.75), s_1(0.25), s_1(0)\}, \{s'_0(0.5), s'_1(0.5), s'_1(0)\}$
O_9	$\{s_1(0.25), s_2(0.75), s_2(0)\}, \{s'_1(1), s'_1(0), s'_1(0)\}$

TABLE 5.27: Normalized combined qualitative matrix for criterion 8

O_i	Criterion 8: DoCRNL
O_1	$\{s_1(0.75), s_2(0.25), s_2(0)\}, \{s'_{-1}(0.25), s'_0(0.75), s_0(0)\}$
O_2	$\{s_{-1}(1), s_{-1}(0), s_{-1}(0)\}, \{s'_0(0.25), s'_1(0.75), s'_1(0)\}$
O_3	$\{s_0(0.75), s_1(0.25), s_1(0)\}, \{s'_{-1}(0.25), s'_0(0.25), s'_1(0.5)\}$
O_4	$\{s_{-1}(0.5), s_0(0.5), s_0(0)\}, \{s'_0(0.25), s'_1(0.75), s'_1(0)\}$
O_5	$\{s_1(0.75), s_2(0.25), s_2(0)\}, \{s'_{-1}(0.25), s'_1(0.75), s'_1(0)\}$
O_6	$\{s_0(0.75), s_1(0.25), s_1(0)\}, \{s'_0(0.25), s'_1(0.75), s'_1(0)\}$
O_7	$\{s_0(0.75), s_1(0.25), s_1(0)\}, \{s'_1(1), s'_1(0), s'_1(0)\}$
O_8	$\{s_{-1}(0.75), s_0(0.25), s_0(0)\}, \{s'_0(1), s'_0(0), s'_0(0)\}$
O_9	$\{s_1(0.75), s_2(0.25), s_2(0)\}, \{s'_1(1), s'_1(0), s'_1(0)\}$

TABLE 5.28: Normalized combined qualitative matrix for criterion 9

O_i	Criterion 9: UoC
O_1	$\{s_0(0.25), s_1(0.25), s_2(0.5)\}, \{s'_{-1}(0.25), s'_1(0.75), s'_1(0)\}$
O_2	$\{s_{-1}(0.25), s_0(0.25), s_1(0.5)\}, \{s'_0(0.5), s'_1(0.5), s'_1(0)\}$
O_3	$\{s_0(0.75), s_1(0.25), s_1(0)\}, \{s'_{-1}(0.25), s'_0(0.25), s'_1(0.5)\}$
O_4	$\{s_{-1}(0.25), s_0(0.25), s_1(0.5)\}, \{s'_0(1), s'_0(0), s'_0(0)\}$
O_5	$\{s_0(0.25), s_1(0.5), s_2(0.25)\}, \{s'_0(0.5), s'_1(0.5), s'_1(0)\}$
O_6	$\{s_{-1}(0.25), s_0(0.75), s_0(0)\}, \{s'_0(0.5), s'_1(0.5), s'_1(0)\}$
O_7	$\{s_{-1}(0.5), s_0(0.25), s_1(0.25)\}, \{s'_0(0.25), s'_1(0.75), s'_1(0)\}$
O_8	$\{s_{-1}(0.25), s_0(0.25), s_1(0.5)\}, \{s'_{-1}(0.25), s'_0(0.75), s'_0(0)\}$
O_9	$\{s_1(0.25), s_2(0.75), s_2(0)\}, \{s'_0(0.75), s'_1(0.25), s'_1(0)\}$

$$\mathcal{B}^0(1,2) = \{\}$$

Since the set $\mathcal{B}^0(x,y)$ is empty, it can be observed that there exists no criteria for which the performance of alternative 1 is equivalent to the performance of alternative 2.

$$\mathcal{B}^-(1,2) = \{2,3,4\}$$

Based on the set $\mathcal{B}^-(x,y)$, it can be observed that alternative 1 is outperformed by alternative 2 for criteria 2, 3, and 4.

TABLE 5.29: Normalized combined qualitative matrix for criterion 10

O_i	Criterion 10: DoCA
O_1	$\{s_0(0.25), s_1(0.75), s_1(0)\}, \{s'_0(0.5), s'_1(0.5), s'_1(0)\}$
O_2	$\{s_{-1}(0.25), s_0(0.75), s_0(0)\}, \{s'_0(0.5), s'_1(0.5), s'_1(0)\}$
O_3	$\{s_0(0.75), s_1(0.25), s_1(0)\}, \{s'_{-1}(0.25), s'_0(0.5), s'_1(0.25)\}$
O_4	$\{s_{-1}(0.25), s_0(0.75), s_0(0)\}, \{s'_0(0.75), s'_1(0.25), s'_1(0)\}$
O_5	$\{s_1(1), s_1(0), s_1(0)\}, \{s'_{-1}(0.25), s'_0(0.25), s'_1(0.5)\}$
O_6	$\{s_0(1), s_0(0), s_0(0)\}, \{s'_0(0.5), s'_1(0.5), s'_1(0)\}$
O_7	$\{s_0(1), s_0(0), s_0(0)\}, \{s'_0(0.25), s'_1(0.75), s'_1(0)\}$
O_8	$\{s_{-1}(0.25), s_0(0.75), s_0(0)\}, \{s'_0(1), s'_0(0), s'_0(0)\}$
O_9	$\{s_2(1), s_2(0), s_2(0)\}, \{s'_0(0.5), s'_1(0.5), s'_1(0)\}$

TABLE 5.30: Criteria importance weights and discordance thresholds

Index j	Criterion	ω_j	β_j^-	β_j^+
1	ALC	0.10	3	7
2	ARC	0.10	250	700
3	AD	0.10	0.75	3
4	AB	0.10	4.50	15
5	ANP	0.10	35	150
6	CoP	0.10	0.30	1
7	QoSD	0.10	0.50	1.10
8	DoCRNL	0.10	0.70	1.20
9	UoC	0.10	0.30	0.90
10	DoCA	0.10	0.50	1.10

The concordance values between every alternative pair, $C(x, y)$, is calculated by applying Eq. (3.96). The resulting concordance values are shown in the concordance matrix in Table 5.31, where O_i represents the i^{th} ontology alternative, $1 \leq i \leq 9$.

In order to determine the discordance relations between all criteria pairs, the differences in their performance for all 10 criteria are needed to be calculated. When considering quantitative criteria, that is, criteria 1 to 5, the difference between the performance of alternative x and alternative y at criterion j is the difference between x_j and y_j, that is, $x_j - y_j$. The calculated differences between all alternatives at each criterion is presented in the heat-maps in Figure 5.19.

When considering qualitative criteria, that is, criteria 6 to 10, the difference between the performance of alternative x and alternative y at criterion j is the distance between x_j and y_j, as given by Eq. (3.86). The calculated distances between all alternatives at each criterion is presented in the heat-maps in Figure 5.20.

After analyzing the differences and distances between the criteria for all alternatives, the discordance relations are determined. For comparing each alternative pair, x and y, the comparison between their criteria performances are partitioned into 1 of 3 discordance sets, high discordance $\mathcal{Q}^+(x, y)$, medium discordance $\mathcal{Q}^0(x, y)$, or low discordance $\mathcal{Q}^-(x, y)$. To illustrate this, when considering the comparison between alternative 1 and 3, the comparative sets are formed as follows.

TABLE 5.31: Concordance matrix

	O_1	O_2	O_3	O_4	O_5	O_6	O_7	O_8	O_9
O_1	0	0.70	0.90	1.00	0.60	0.80	0.70	0.90	0.30
O_2	0.30	0	0.60	0.80	0.30	0.60	0.30	0.80	0.20
O_3	0.10	0.40	0	0.90	0.00	0.20	0.40	0.70	0.10
O_4	0.00	0.20	0.10	0	0.10	0.20	0.10	0.60	0.10
O_5	0.40	0.80	1.00	0.90	0	1.00	0.70	0.80	0.20
O_6	0.20	0.40	0.80	0.80	0.00	0	0.40	0.70	0.10
O_7	0.30	0.70	0.70	0.90	0.30	0.60	0	0.90	0.20
O_8	0.10	0.20	0.30	0.40	0.20	0.30	0.10	0	0.20
O_9	0.70	0.80	0.90	0.90	0.80	0.90	0.80	0.80	0

$$\mathcal{Q}^{+}(1,3) = \{\}$$

The set $\mathcal{Q}^{+}(1,3)$ is an empty set, which implies that there is no criteria for which the comparison of alternative 1 with 3 yields high discordance.

$$\mathcal{Q}^{0}(1,3) = \{3\}$$

Since the set $\mathcal{Q}^{0}(1,3)$ has 1 element, that is criterion 3, it means that there is medium discordance when comparing alternative 1 and 3 against criterion 3.

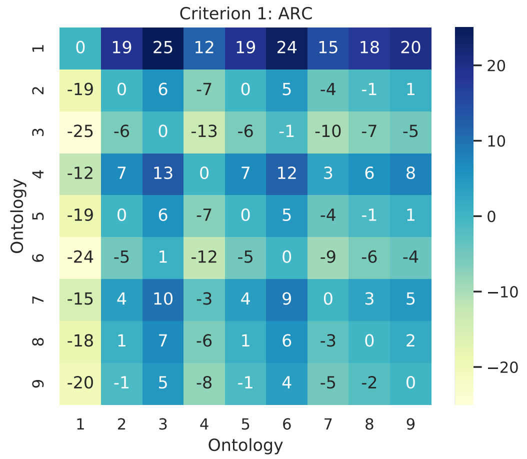
$$\mathcal{Q}^{-}(1,3) = \{1,2,4,5,6,7,8,9,10\}$$

By observing the set $\mathcal{Q}^{-}(1,3)$, it can be seen that comparing alternative 1 with 3 yields the set comprising 9 out of 10 criteria that have low discordance levels.
After determining the concordance and discordance relations, the strong and weak outranking relations are determined by applying Eqs. (3.104) to (3.107). The outranking relations obtained are displayed in Table 5.32, where S^F represents a strong outranking relation, and S^f represents a weak outranking relation.

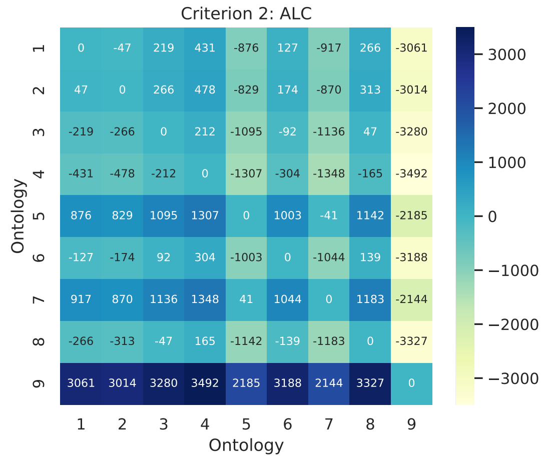
TABLE 5.32: Strong and weak outranking relationships

	O_1	O_2	O_3	O_4	O_5	O_6	O_7	O_8	O_9
O_1			S^F	S^F				S^F	
O_2			S^f					S^F	
O_3									
O_4								S^f	
O_5			S^F			S^f	S^F	S^F	
O_6									
O_7									
O_8									
O_9			S^F			S^F	S^F	S^F	

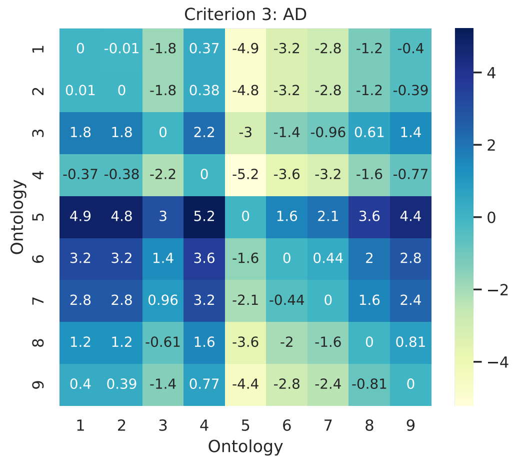
Based on Table 5.32, the strong and weak outranking graphs can be constructed. The constructed graphs are shown in Figure 5.21. Each node, O_i, represents the i^{th} ontology alternative,



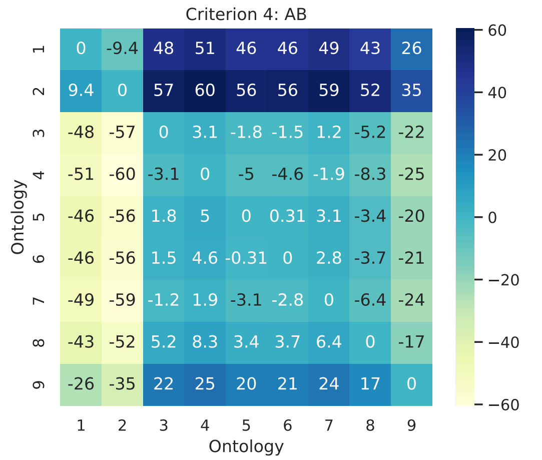
(a) Difference in criterion performance for ARC



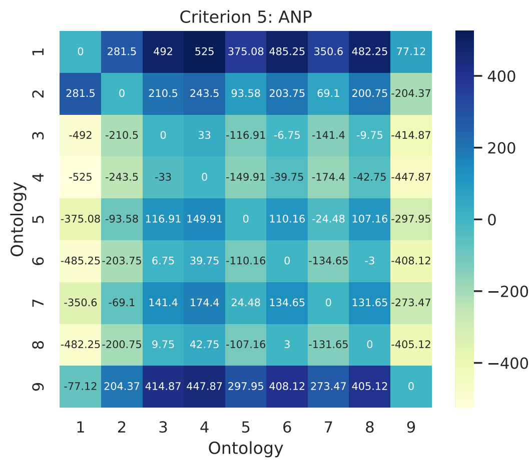
(b) Difference in criterion performance for ALC



(c) Difference in criterion performance for AD

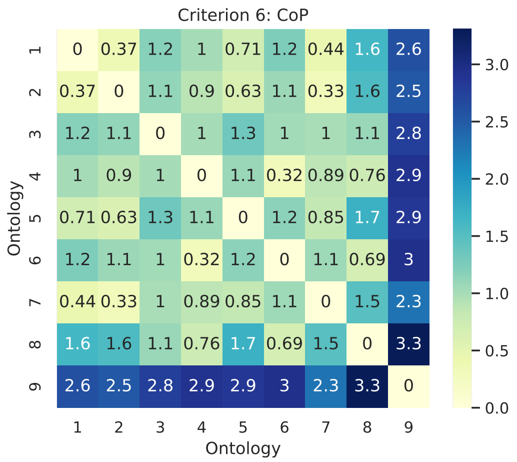


(d) Difference in criterion performance for AB

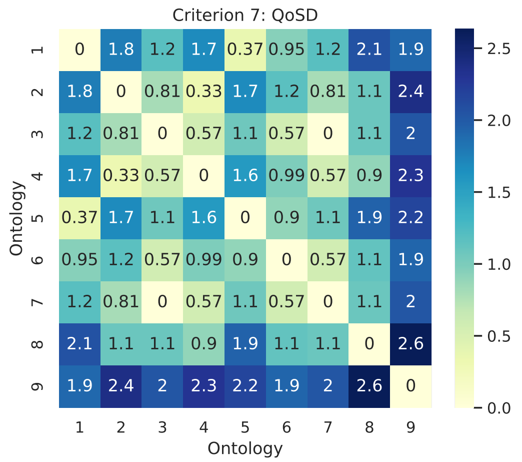


(e) Difference in criterion performance for ANP

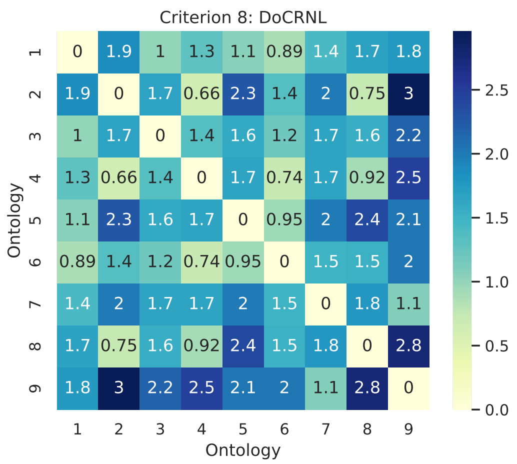
FIGURE 5.19: Differences in quantitative criterion performance for all alternative pairs



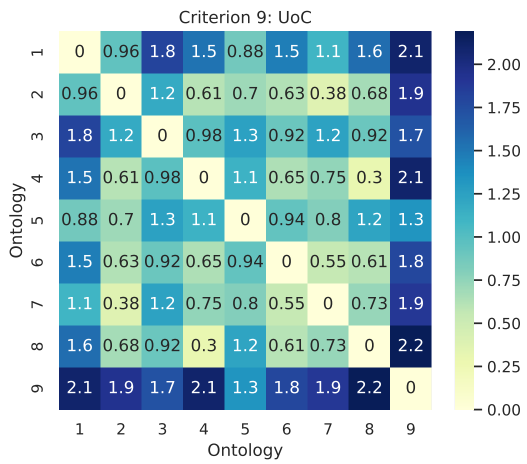
(a) Distances in criterion performance for CoP



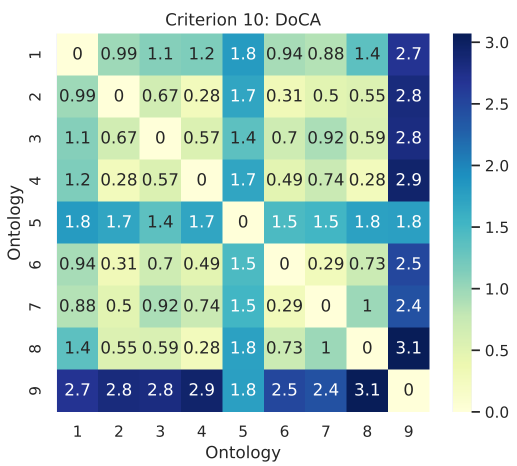
(b) Distances in criterion performance for QoSD



(c) Distances in criterion performance for DoCRNL

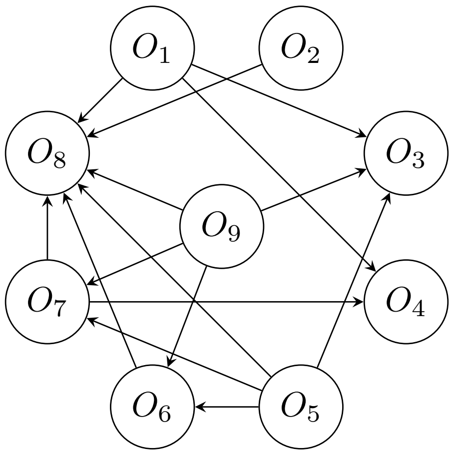


(d) Distances in criterion performance for UoC

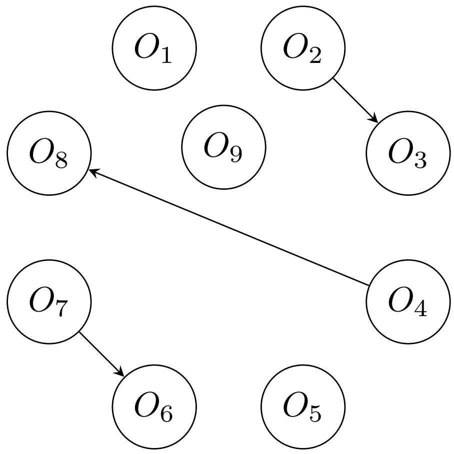


(e) Distances in criterion performance for DoCA

FIGURE 5.20: Differences in qualitative criterion performance for all alternative pairs



(a) Strong outranking graph S^F



(b) Weak outranking graph S^f

FIGURE 5.21: Strong and weak outranking graphs

where $1 \le i \le 9$. A directed edge from one node to another signifies that the node from which the edge begins outranks the node to which the edge points to.

After constructing the outranking graphs, the outranking relations are exploited by applying the forward and reverse procedures, as in Section 3.4.4. Firstly, the forward procedure is performed as follows. In the first iteration the strong and weak outranking graphs, G_1^F and G_1^f, are observed and the sets N_1^F and N_1^f are formed. The elements in these sets represent the non-dominate alternatives in G_1^F and G_1^f. N_1^F is formed as:

$$N_1^F = \{1, 2, 5, 9\}$$

and N_1^f is formed as:

$$N_1^f = \{1, 2, 4, 5, 7, 9\}$$

Thereafter, the intersection between the non-dominate sets are formed as N_1:

$$N_1 = \{1, 2, 5, 9\}$$

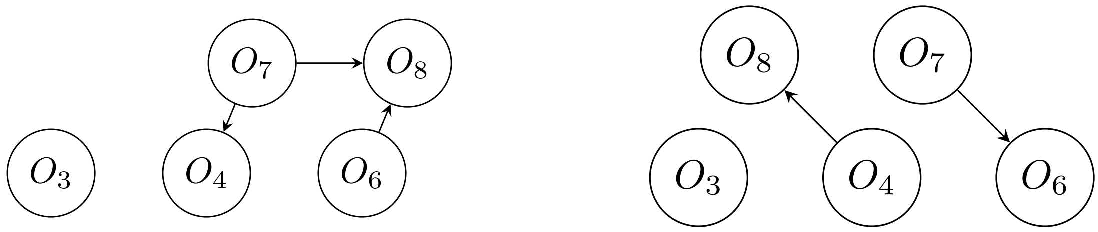
After determining the intersection N_1, the alternatives in N_1 are assigned a rank, that is, $\psi_1(1) = 1$, $\psi_1(2) = 1$, $\psi_1(5) = 1$, and $\psi_1(9) = 1$. All alternatives assigned a rank are then removed from the graphs, along with their associated edges. The new graphs are then constructed, as in Figure 5.22. The non-dominate sets and their intersection are then formed for the second iteration as follows:

$$N_2^F = \{3, 6, 7\}$$

and N_2^f is formed as:

$$N_2^f = \{3, 4, 7\}$$

Thereafter, the intersection between the non-dominate sets are formed as N_2:



(a) Strong outranking graph G_2^F

(b) Weak outranking graph G_2^f

FIGURE 5.22: Strong and weak outranking graphs for the second iteration in the forward procedure

(a) Strong outranking graph G_3^F

(b) Weak outranking graph G_3^f

FIGURE 5.23: Strong and weak outranking graphs for the third iteration in the forward procedure

$$N_2 = \{3, 7\}$$

The alternatives in the intersection are assigned the rank position of 2, that is, $\psi_1(3) = 2$ and $\psi_1(7) = 2$. The third iteration then proceeds with the new graphs in Figure 5.23.
The non-dominate sets and their intersection is then formed for the third iteration as follows:

$$N_3^F = \{4, 6\}$$

and N_3^f is formed as:

$$N_3^f = \{4, 6\}$$

Thereafter, the intersection between the non-dominate sets are formed as N_3:

$$N_3 = \{4, 6\}$$

The alternatives in the intersection are assigned the rank position of 3, that is, $\psi_1(4) = 3$ and $\psi_1(6) = 3$. Since there are still nodes in the graph, the fourth iteration then proceeds with the new graphs in Figure 5.24.
Since both the graphs in Figure 5.24 have only 1 node which is not dominated by any other nodes, their intersection will be equal and hence the alternative O_8 is assigned the 4^{th} rank position, that is, $\psi_1(8) = 4$. All alternatives in the graphs have been ranked and the forward procedure is completed.

After performing the forward procedure, the reverse procedure is performed. The first step in the reverse procedure is to construct the mirror image of the strong and weak outranking

(a) Strong outranking graph G_4^F **(b)** Weak outranking graph G_4^f

FIGURE 5.24: Strong and weak outranking graphs for the fourth iteration in the forward procedure

graphs by reversing the direction of the edges. Thereafter, the same steps follow as performed in the forward procedure. The resulting ranking is then transformed by applying Equation (3.108). Finally, to generate the final ranking of the alternatives, the forward rankings and the transformed reverse rankings are combined by applying Eq. (3.109). The rankings obtained from the reverse procedure, $\psi_2(O_i)$, the transformed rankings, $\psi_3(O_i)$, and the final rankings, $\bar{\psi}(O_i)$, are shown in Table 5.33.

TABLE 5.33: Final ranking results of the ontology alternatives

Alternative O_i	$\psi_1(O_i)$	$\psi_2(O_i)$	$\psi_3(O_i)$	$\bar{\psi}(O_i)$
O_1	1	3	2	1.5
O_2	1	2	3	2
O_3	2	1	4	3
O_4	3	2	3	3
O_5	1	4	1	1
O_6	3	2	3	3
O_7	2	3	2	2
O_8	4	1	4	4
O_9	1	4	1	1

The final ranking for the 9 ontologies is determined as follows, with $\succ$ representing outranking:

$$O_5, O_9 \succ O_1 \succ O_2, O_7 \succ O_3, O_4, O_6 \succ O_8$$

Accordingly, ontologies 5 and 9 are the best, and the worst ontology is ontology 8.

5.4.1 Comparison with Traditional ELECTRE II

Here the performance of the ZPLTS-ELECTRE II method is compared with the traditional ELECTRE II method [14]. Since the traditional ELECTRE II cannot model linguistic criteria, only the quantitative criteria were used, that is, ALC, ARC, AD, AB, and ANP. Firstly, the alternatives and criteria form a decision matrix, which is the same as the matrix in Table 5.18. The decision matrix (Table 5.18) was then normalized to form the matrix in Table 5.34.

The criteria were assigned equal weights, as done with the application of ZPLTS-ELECTRE II. Since there were 5 criteria, each criterion received a weight of 0.20. The concordance thresholds were set as $c_1 = 0.85$, $c_2 = 0.70$, and $c_3 = 0.55$. However, since the traditional ELECTRE II does not allow separate discordance thresholds to be specified for each criterion like the ZPLTS-ELECTRE II, the discordance thresholds, d_1 and d_2, were set as $d_1 = 0.40$ and $d_2 = 0.25$.

TABLE 5.34: Decision matrix for traditional ELECTRE II

Oi	**ALC**	**ARC**	**AD**	**AB**	**ANP**
O_1	1.00	0.13	0.29	0.85	1.00
O_2	0.27	0.14	0.29	1.00	0.47
O_3	0.04	0.06	0.56	0.08	0.08
O_4	0.54	0.00	0.24	0.03	0.01
O_5	0.27	0.38	1.00	0.11	0.29
O_6	0.08	0.09	0.76	0.11	0.09
O_7	0.42	0.39	0.70	0.06	0.34
O_8	0.31	0.05	0.47	0.17	0.09
O_9	0.23	1.00	0.35	0.44	0.86

The next step was to calculate the concordance values between all alternative pairs, as shown in Table 5.35.

TABLE 5.35: Concordance matrix for traditional ELECTRE II

	$\boldsymbol{O_1}$	$\boldsymbol{O_2}$	$\boldsymbol{O_3}$	$\boldsymbol{O_4}$	$\boldsymbol{O_5}$	$\boldsymbol{O_6}$	$\boldsymbol{O_7}$	$\boldsymbol{O_8}$	$\boldsymbol{O_9}$
$\boldsymbol{O_1}$	0.00	0.60	0.80	1.00	0.60	0.80	0.60	0.80	0.60
$\boldsymbol{O_2}$	0.60	0.00	0.80	0.80	0.60	0.80	0.40	0.60	0.40
$\boldsymbol{O_3}$	0.20	0.20	0.00	0.80	0.00	0.00	0.20	0.40	0.20
$\boldsymbol{O_4}$	0.00	0.20	0.20	0.00	0.20	0.20	0.20	0.20	0.20
$\boldsymbol{O_5}$	0.40	0.60	1.00	0.80	0.00	1.00	0.40	0.60	0.40
$\boldsymbol{O_6}$	0.20	0.20	1.00	0.80	0.20	0.00	0.40	0.60	0.20
$\boldsymbol{O_7}$	0.40	0.60	0.80	0.80	0.60	0.60	0.00	0.80	0.40
$\boldsymbol{O_8}$	0.20	0.40	0.60	0.80	0.40	0.60	0.20	0.00	0.40
$\boldsymbol{O_9}$	0.40	0.60	0.80	0.80	0.60	0.80	0.60	0.60	0.00

Thereafter, the discordance values were determined for every alternative pair, as shown in Table 5.36.

Thereafter, the strong and weak outranking graphs were constructed by considering the concordance and discordance matrices. The strong and weak outranking relations are shown in Table 5.37.

This follows by the ontologies being ranked using the forward and reverse ranking procedures, and finally they were combined [13]. The final ranking was as follows:

$$O_9 \succ O_1 \succ O_7 \succ O_2 \succ O_5 \succ O_6, O_8 \succ O_3, O_4$$

The graph in Fig. 5.25 compares the ranking obtained by the ZPLTS-ELECTRE II to that of the traditional ELECTRE II. The blue plot shows the ZPLTS-ELECTRE II and the orange plot shows the traditional ELECTRE II.

It can be observed that there are some differences in the ranking by the ZPLTS-ELECTRE II with that of the traditional ELECTRE II, due to the fact that, the traditional ELECTRE II does not model the qualitative linguistic criteria and the decision-makers credibility levels, and only

TABLE 5.36: Discordance matrix for traditional ELECTRE II

	O_1	O_2	O_3	O_4	O_5	O_6	O_7	O_8	O_9
O_1	0	0.15	0.27	0.00	0.71	0.47	0.41	0.18	0.87
O_2	0.73	0	0.27	0.27	0.71	0.47	0.41	0.18	0.86
O_3	0.96	0.92	0	0.50	0.43	0.19	0.38	0.27	0.94
O_4	0.99	0.97	0.32	0	0.76	0.52	0.45	0.22	1.00
O_5	0.74	0.89	0.00	0.27	0	0.00	0.14	0.06	0.62
O_6	0.92	0.89	0.00	0.46	0.29	0	0.33	0.22	0.91
O_7	0.79	0.94	0.02	0.12	0.30	0.06	0	0.11	0.61
O_8	0.91	0.83	0.09	0.23	0.53	0.29	0.34	0	0.95
O_9	0.77	0.56	0.21	0.31	0.65	0.41	0.35	0.12	0

TABLE 5.37: Strong and weak outranking relations for traditional ELECTRE II

	O_1	O_2	O_3	O_4	O_5	O_6	O_7	O_8	O_9
O_1		S^f	S^f	S^F				S^F	
O_2			S^f	S^f				S^f	
O_3									
O_4									
O_5			S^F	S^f		S^F		S^f	
O_6			S^F					S^f	
O_7			S^F	S^F	S^f	S^f		S^F	
O_8			S^f	S^F		S^f			
O_9			S^F	S^f			S^f	S^f	

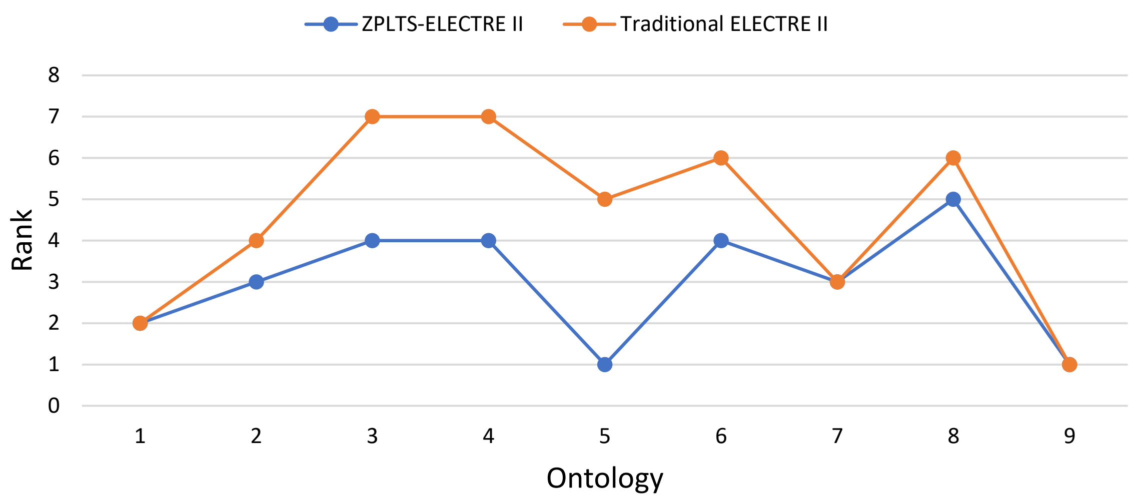


FIGURE 5.25: Graph showing ranking from ZPLTS-ELECTRE II and traditional ELECTRE II

allows the definition of two discordance thresholds. Therefore, the traditional ELECTRE II method offers limited modelling capabilities in decision-making problems compared to the proposed ZPLTS-ELECTRE II method.

5.4.2 Comparison with PLTS ELECTRE II

The performance of the ZPLTS-ELECTRE II method was also compared with the PLTS ELECTRE II method [30] for the task of evaluating and ranking mental health ontologies. In the case of the PLTS ELECTRE II, only PLTS data can be modelled, therefore, the decision matrix only comprises the qualitative linguistic criteria as in Table 5.38. Furthermore, the PLTS ELECTRE II method cannot model credibility values and therefore the credibility aspect was omitted. The mathematical details of the PLTS ELECTRE II model is presented in Appendix D

TABLE 5.38: Decision matrix for PLTS ELECTRE II

O_i	CoP	QoSD	DoCRNL	UoC	DoCA
O_1	$\{s_0(0.5), s_1(0.5), s_1(0)\}$	$\{s_1(0.5), s_2(0.5), s_2(0)\}$	$\{s_1(0.75), s_2(0.25), s_2(0)\}$	$\{s_0(0.25), s_1(0.25), s_2(0.5)\}$	$\{s_0(0.25), s_1(0.75), s_1(0)\}$
O_2	$\{s_0(0.75), s_1(0.25), s_1(0)\}$	$\{s_{-1}(0.25), s_0(0.25), s_1(0.5)\}$	$\{s_{-1}(1), s_{-1}(0), s_{-1}(0)\}$	$\{s_{-1}(0.25), s_0(0.25), s_1(0.5)\}$	$\{s_{-1}(0.25), s_0(0.75), s_0(0)\}$
O_3	$\{s_0(0.75), s_1(0.25), s_1(0)\}$	$\{s_0(0.75), s_1(0.25), s_1(0)\}$	$\{s_0(0.75), s_1(0.25), s_1(0)\}$	$\{s_0(0.75), s_1(0.25), s_1(0)\}$	$\{s_0(0.75), s_1(0.25), s_1(0)\}$
O_4	$\{s_{-1}(0.5), s_0(0.5), s_0(0)\}$	$\{s_{-1}(0.25), s_0(0.5), s_1(0.25)\}$	$\{s_{-1}(0.5), s_0(0.5), s_0(0)\}$	$\{s_{-1}(0.25), s_0(0.25), s_1(0.5)\}$	$\{s_{-1}(0.25), s_0(0.75), s_0(0)\}$
O_5	$\{s_0(0.5), s_1(0.25), s_2(0.25)\}$	$\{s_1(0.5), s_2(0.5), s_2(0)\}$	$\{s_1(0.75), s_2(0.25), s_2(0)\}$	$\{s_0(0.25), s_1(0.5), s_2(0.25)\}$	$\{s_1(1), s_1(0), s_1(0)\}$
O_6	$\{s_{-1}(0.5), s_0(0.25), s_1(0.25)\}$	$\{s_0(0.25), s_1(0.75), s_1(0)\}$	$\{s_0(0.75), s_1(0.25), s_1(0)\}$	$\{s_{-1}(0.25), s_0(0.75), s_0(0)\}$	$\{s_0(1), s_0(0), s_0(0)\}$
O_7	$\{s_0(0.5), s_1(0.5), s_1(0)\}$	$\{s_0(0.75), s_1(0.25), s_1(0)\}$	$\{s_0(0.75), s_1(0.25), s_1(0)\}$	$\{s_{-1}(0.5), s_0(0.25), s_1(0.25)\}$	$\{s_0(1), s_0(0), s_0(0)\}$
O_8	$\{s_{-1}(0.75), s_0(0.25), s_0(0)\}$	$\{s_{-1}(0.75), s_1(0.25), s_1(0)\}$	$\{s_{-1}(0.75), s_0(0.25), s_0(0)\}$	$\{s_{-1}(0.25), s_0(0.25), s_1(0.5)\}$	$\{s_{-1}(0.25), s_0(0.75), s_0(0)\}$
O_9	$\{s_1(0.25), s_2(0.75), s_2(0)\}$	$\{s_1(0.25), s_2(0.75), s_2(0)\}$	$\{s_1(0.75), s_2(0.25), s_2(0)\}$	$\{s_1(0.25), s_2(0.75), s_2(0)\}$	$\{s_2(1), s_2(0), s_2(0)\}$

The criteria importance weights were set as 0.2 for all 5 criteria. Since the PLTS ELECTRE II makes use of strong, medium, and weak concordances and discordances, as well as indifference sets, the corresponding weights are also required. The strong, medium, and weak concordance weights were set as $\omega_C = 1$, $\omega'_C = 0.9$, and $\omega''_C = 0.8$, respectively. The strong, medium, and weak discordance weights were set as $\omega_D = 1$, $\omega'_D = 0.9$, and $\omega''_D = 0.8$, respectively. The indifference weight was set as $\omega_J^{=} = 0.7$. The score values for all ontologies at each criterion is shown in Table 5.39, and the deviation values for all ontologies at each criterion is shown in Table 5.40.

TABLE 5.39: Score values for PLTS ELECTRE II

	CoP	QoSD	DoCRNL	UoC	DoCA
O_1	0.50	1.50	1.25	1.25	0.75
O_2	0.25	0.25	-1.00	0.25	-0.25
O_3	0.25	0.25	0.25	0.25	0.25
O_4	-0.50	0.00	-0.50	0.25	-0.25
O_5	0.75	1.50	1.25	1.00	1.00
O_6	-0.25	0.75	0.25	-0.25	0.00
O_7	0.50	0.25	0.25	-0.25	0.00
O_8	-0.75	-0.50	-0.75	0.25	-0.25
O_9	1.75	1.75	1.25	1.75	2.00

Thereafter, the concordance matrix was formulated, as shown in Table 5.41. The next step was to formulate the discordance matrix. This is shown in Table 5.42.

TABLE 5.40: Deviation values for PLTS ELECTRE II

	CoP	QoSD	DoCRNL	UoC	DoCA
O_1	0.35	0.35	0.27	0.49	0.27
O_2	0.27	0.49	0.00	0.49	0.27
O_3	0.27	0.27	0.27	0.27	0.27
O_4	0.35	0.35	0.35	0.49	0.27
O_5	0.49	0.35	0.27	0.35	0.00
O_6	0.49	0.27	0.27	0.27	0.00
O_7	0.35	0.27	0.27	0.49	0.00
O_8	0.27	0.53	0.27	0.49	0.27
O_9	0.27	0.27	0.27	0.27	0.00

TABLE 5.41: Concordance matrix for PLTS ELECTRE II

	O_1	O_2	O_3	O_4	O_5	O_6	O_7	O_8	O_9
O_1	0	0.92	0.90	0.92	0.46	0.92	0.86	0.92	0.14
O_2	0.00	0	0.14	0.66	0.00	0.38	0.18	0.66	0.00
O_3	0.00	0.82	0	0.94	0.00	0.70	0.66	0.90	0.00
O_4	0.00	0.46	0.00	0	0.00	0.18	0.18	0.84	0.00
O_5	0.66	0.96	0.92	0.96	0	0.90	0.92	0.96	0.14
O_6	0.00	0.58	0.32	0.78	0.00	0	0.62	0.76	0.00
O_7	0.14	0.72	0.46	0.78	0.00	0.48	0	0.76	0.00
O_8	0.00	0.46	0.00	0.28	0.00	0.18	0.18	0	0.00
O_9	0.94	0.96	0.92	1.00	0.92	0.92	0.94	0.96	0

TABLE 5.42: Discordance matrix for PLTS ELECTRE II

	O_1	O_2	O_3	O_4	O_5	O_6	O_7	O_8	O_9
O_1	0	0.00	0.00	0.00	0.41	0.00	0.00	0.00	0.92
O_2	0.90	0	0.75	0.32	0.90	0.75	0.75	0.22	0.92
O_3	0.63	0.00	0	0.00	0.64	0.22	0.11	0.00	0.92
O_4	1.00	0.58	0.58	0	1.00	0.58	0.58	0.00	1.00
O_5	0.12	0.00	0.00	0.00	0	0.00	0.00	0.00	0.75
O_6	0.65	0.54	0.54	0.39	0.75	0	0.53	0.39	0.90
O_7	0.63	0.12	0.54	0.12	0.75	0.29	0	0.12	0.90
O_8	0.90	0.60	0.66	0.49	0.90	0.60	0.66	0	0.92
O_9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0

The concordance thresholds, c^-, c^0, c^*, and the discordance thresholds, d^0, d^*, were set to $c^- = 0.55, c^0 = 0.70, c^* = 0.85$ and $d^0 = 0.25, d^* = 0.40$. Thereafter, the strong and weak outranking relations were built, as shown in Table 5.43.

TABLE 5.43: Strong and weak outranking relationships for PLTS ELECTRE II

	O_1	O_2	O_3	O_4	O_5	O_6	O_7	O_8	O_9
O_1		S^F	S^F	S^F		S^F	S^F	S^F	
O_2		S^f						S^f	
O_3		S^F		S^F		S^F	S^f	S^F	
O_4								S^F	
O_5	S^f	S^F	S^F	S^F		S^F	S^F	S^F	
O_6				S^f				S^f	
O_7		S^F		S^F				S^F	
O_8									
O_9	S^F	S^F	S^F	S^F	S^F	S^F	S^F	S^F	

The strong and weak outranking relations were then exploited using the forward and backward ranking procedures. The final ranking obtained was:

$$O_9 \succ O_5 \succ O_1 \succ O_3 \succ O_7 \succ O_6 \succ O_2 \succ O_4 \succ O_8$$

The graph in Fig. 5.26 compares the ranking obtained by the ZPLTS-ELECTRE II to that of the traditional ELECTRE II. The blue plot shows the ZPLTS-ELECTRE II and the orange plot shows the PLTS ELECTRE II.

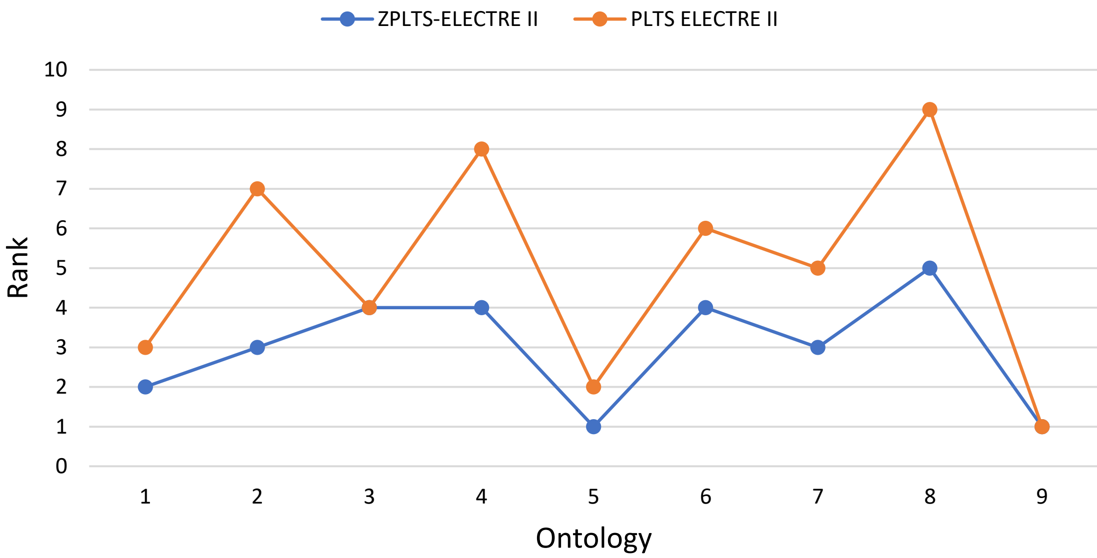


FIGURE 5.26: Graph showing ranking from ZPLTS-ELECTRE II and PLTS ELECTRE II

It can be observed that the ranking from the PLTS ELECTRE II was similar to the ranking from ZPLTS-ELECTRE II. In both rankings, ontology O_9 was ranked first, O_3 was ranked fourth, and the last ontology was O_8. However, the ZPLTS-ELECTRE II method produced more tied rankings than that of the PLTS ELECTRE II method. The difference in rankings are expected due to the following issues. (1) The PLTS ELECTRE II only modelled the 5 qualitative linguistic criteria and was not able to combine numerical and linguistic data. (2) The PLTS

ELECTRE II method was not able to model the credibility aspects of the decision-makers, and (3) the PLTS ELECTRE II method did not allow for individual discordance thresholds to be specified for each criterion like the ZPLTS-ELECTRE II method did. In light of the above, the proposed ZPLTS-ELECTRE II offers better modelling capabilities in decision-making problems than the PLTS ELECTRE II method.

5.4.3 Comparison with Existing MCDM Methods for Ontology Ranking

The ZPLTS-ELECTRE II method is compared with other studies that have applied MCDM methods to rank ontologies. The comparison can be seen in Table 5.44.

TABLE 5.44: Comparison of ZPLTS-ELECTRE II with other MCDM methods for ontology ranking

Method	**Quantitative Criteria**	**Qualitative Criteria**	**No. of Criteria**	**No. of Ontologies**
ELECTRE I [22]	Yes	No	8	70
ELECTRE I/III [23]	Yes	No	5	12
WLCRT [20]	Yes	No	8	70
TOPSIS/WSM/WPM [21]	Yes	No	8	70
ZPLTS-ELECTRE II [*this study*]	Yes	Yes	10	9

It can be observed from Table 5.44 that from all the studies that have applied MCDM methods to rank ontologies, this study has used the largest number of criteria and both the qualitative and quantitative criteria as well as the complexity and usability metrics to perform ontology ranking. Therefore, this study extends the existing literature with the development of the ZPLTS-ELECTRE II method that (1) uses both the quantitative and qualitative criteria, (2) both the complexity and usability metrics, and (3) the largest number of criteria in the task of ontology ranking.

Furthermore, it is shown in Table 5.44 that 9 ontologies were used in this study compared to more ontologies in related studies. The ontology alternatives (9) were chosen to demonstrate the effectiveness of the proposed ZPLTS-ELECTRE II method. Future applications of the ZPLTS-ELECTRE II method may effectively use more alternatives.

5.4.4 Comparison with Existing Fuzzy ELECTRE II Methods

The ZPLTS-ELECTRE II method is compared with other recent developments of ELECTRE II that make use of fuzzy set theory. The comparison can be seen in Table 5.45.

TABLE 5.45: Comparison of ZPLTS-ELECTRE II with other ELECTRE II enhancements

Method	**Enhancement**	**Credibility**	**Structure**
PL-ELECTRE II [106]	PLTS	No	Possibility Degree
PLTS-ELECTRE II [107]	PLTS	No	Score & Deviation
PLTS ELECTRE II [30]	PLTS	No	Score & Deviation
HF-ELECTRE II [99]	HFLTS	No	Score & Deviation
ZPLTS-ELECTRE II [*this study*]	ZPLTS	Yes	Score & Deviation

Table 5.45 compares the ZPLTS-ELECTRE II method with existing enhanced ELECTRE II methods. It is shown in Table 5.45 that some of these methods share some similar [30, 107] and dissimilar [99, 106] features with the ZPLTS-ELECTRE II method. In particular, Table 5.45 shows that none of the existing enhanced ELECTRE II methods enables the measurement of the credibility level of a decision-maker's evaluation as the proposed ZPLTS-ELECTRE II method does. The differences between the ZPLTS-ELECTRE II method and the other enhancements of ELECTRE II are that, (1) the ZPLTS-ELECTRE II method offers better modelling capabilities in decision-making problems through the ability of decision-makers to better express their credibility and confidence levels with the use of Z-numbers as well as the ability of decision-makers to specify an individual discordance level for each criterion, and (2) the ZPLTS-ELECTRE II method provides the capability to model both quantitative numerical criteria as well as qualitative linguistic criteria, unlike the existing enhancements of ELECTRE II methods.

5.4.5 Strengths and Weaknesses of ZPLTS-ELECTRE II

The advantages and strengths of the proposed ZPLTS-ELECTRE II method that make it superior to existing ELECTRE II enhancement methods are as follows:

1. The method can model both quantitative numerical and qualitative linguistic criteria thereby providing decision-makers with more flexible and realistic expression of their preferences.
2. Individual discordance thresholds can be specified for each criterion. This provides the decision-makers with more flexibility in expressing their preferences.
3. Decision-makers are able to express their level of confidence or credibility when providing their evaluations, thereby improving the ability of the model to capture the cognitive nature of the decision-making process.
4. The applications of the ZPLTS-ELECTRE II method are not constrained to ontology ranking, but rather it can be applied to any decision-making problem in any domain.

The ZPLTS-ELECTRE II method has some weaknesses and limitations as follows:

1. The different decision-makers are assigned equal weighting and the final decision matrix is composed by combining the individual decision-makers' evaluation matrices with equal importance given to all decision-makers. This may not be desirable in some decision-making problems.
2. The ZPLTS-ELECTRE II method is dependent on the decision-makers for the specifications of the thresholds and parameters, such as the criteria importance weights, the concordance thresholds, and the discordance thresholds. This may be challenging to some decision-makers.
3. The ability of the ZPLTS-ELECTRE II method to model both linguistic and numerical data has the implication of individual discordance thresholds for each criterion. This is an advantage as it expands the methods capability of modelling decision-problems. However,

when comparing the method to other ELECTRE II methods, ZPLTS-ELECTRE II has the disadvantage of having a larger number of discordance thresholds to be analysed and defined as opposed to other methods that may only require a smaller number of discordance thresholds.

5.5 Conclusion

In this chapter the results of the 3 proposed applications of ELECTRE were presented. The first section presented the ranking of ontologies by applying ELECTRE I, II, III, and IV. The second section presented the classification of ontologies by applying the Genetic Algorithm with the ELECTRE Tri method. The final section presented the application of the novel ZPLTS-ELECTRE II method for ranking ontologies, together with a comprehensive analysis of the results. The next chapter discusses the strengths and limitations of this study, the achievement of the objectives, the recommendations for selecting an ELECTRE model, the future research directions, and the conclusion.

Chapter 6

Conclusion and Future Work

6.1 Summary of Research

In this study, the complexity associated with selecting appropriate ontologies for reuse was identified and some solutions were proposed in order to reduce this complexity. The problem of ontology selection for reuse was categorized as a Multi-Criteria Decision-Making problem, as there are multiple ontologies to choose from, each having multiple characteristics. Accordingly, a prominent branch of the MCDM family, namely, the ELECTRE algorithms, were studied and applied for the task of ranking and classifying ontologies for selection.

Three applications of ELECTRE were proposed. Firstly, the ELECTRE I, II, III, and IV algorithms were implemented and applied to rank a dataset of 200 biomedical ontologies. The ontologies had 13 of their complexity metrics computed, which were then used as attributes for guiding the decision-making process. The rankings obtained were then analyzed and many of the ontologies were ranked in the top positions by more than one ELECTRE method. Four statistical rank correlation coefficients were also calculated for each ELECTRE ranking pair, all of which reaffirmed the strong relationship between the results as well as the ability of ELECTRE to rank ontologies. A part of these results was published in [140] and the full results has been accepted for publication in [141].

The second application was focused on classifying ontologies according to their 13 complexity metrics. Three ordinal classes were defined and the ELECTRE Tri model was used to classify the 200 ontologies into the classes. In order to reduce the complexity associated with specifying thresholds and parameters for ELECTRE Tri, a set of 27 ontology assignments were made and thereafter a genetic algorithm was designed and implemented to infer a set of appropriate thresholds from the 27 ontology assignment examples. The ELECTRE Tri model was successfully built and was able to classify all ontologies into one of three classes. The classification results were then analyzed and compared with the ranking results obtained from ELECTRE I to IV in order to further validate the results. These results have been accepted for publication in [142].

The third application identified the need for ranking ontologies by considering not only their complexity metrics, but also the extent to which they meet the decision-makers needs and requirements. To accomplish this, a novel ELECTRE model was developed by combining ELECTRE II with the concept of Z-Probabilistic Linguistic Term Sets, named as ZPLTS-ELECTRE II . The model was then applied to rank a dataset of 9 ontologies pertaining to the mental health domain. Rather than using only complexity metrics, a mixture of complexity and usability metrics were used as attributes. Five complexity metrics were used, and five usability metrics were extracted from the Ontology Usability Scale, which were then evaluated by 4 decision-makers. The ZPLTS-ELECTRE II model was able to successfully rank the ontologies from best to worst. Thereafter, the results were compared with the traditional ELECTRE II and the PLTS ELECTRE II methods, which reaffirmed the superiority of the novel ZPLTS-ELECTRE II method over existing ELECTRE enhancements for modeling ontology selection problems. These results have been published in [143].

6.2 Achievement of Dissertation Objectives

All of the research aims and objectives that were defined in Section 1.4 were successfully accomplished. The research aims and objectives, along with the degree to which they have been satisfied, are elaborated on as follows.

1. To investigate existing ELECTRE algorithms. The history of the ELECTRE algorithms and their main variations were presented in Section 2.3. A *state-of-the-art* review of the ELECTRE algorithms and their recent extensions was presented in Section 2.3.2. The various applications of the ELECTRE algorithms were also surveyed in Section 2.3. A comparison of the performances of the ELECTRE algorithms was presented in Section 5.2.

2. To investigate existing studies that have implemented ELECTRE algorithms to rank ontologies to aid their selection. The existing studies that made use of the ELECTRE family of decision making methods to rank ontologies were studied and presented in Section 2.4.4. A further comparison was performed with the novel ZPLTS-ELECTRE II model and other ELECTRE methods that have been applied to rank ontologies in Section 5.4.3.

3. To gather the complexity metrics of existing ontologies. 13 complexity metrics were studied and computed for the 200 ontologies used in this study via the OntoMetrics platform [25]. The complexity metrics were selected to express 4 dimensions of ontology evaluation, namely, *accuracy*, *understandability*, *cohesion*, and *conciseness*. The computed complexity metrics are presented in Appendix A.

4. To implement and compare the performances of existing ELECTRE algorithms in ontology selection. The ELECTRE I, II, III, and IV algorithms were implemented using the Java programming language and were applied to rank the dataset of 200 ontologies. The class diagrams showing the software implementation are shown in Section 4.1. The rankings obtained were analyzed and compared using statistical analysis techniques, as in Section 5.2.7. The ELECTRE Tri classification algorithm was implemented, along with a genetic algorithm for preference disaggregation. ELECTRE Tri was then applied to classify the dataset of ontologies, the results of which were analyzed and compared with the rankings obtained in Section 5.2. This can be seen in Section 5.3. Finally, an analysis was presented in Section 6.3 wherein some guidelines were expressed to assist prospective users in selecting an appropriate ELECTRE algorithm variant to solve their decision making problems.

5. To experiment the use of ELECTRE in the task of ontology classification. The ELECTRE Tri algorithm was applied for the task of classifying ontologies according to their 13 complexity metrics in Section 5.3. Furthermore, to reduce the complexity associated with building the ELECTRE Tri model, a genetic algorithm was designed and implemented to infer a set of thresholds. The results of the ELECTRE Tri model were analyzed and compared with the rankings in Section 5.2.

6. To investigate the use of both quantitative and qualitative metrics in ontology ranking and selection. A novel ZPLTS-ELECTRE II algorithm was developed to provide the capability of ranking ontologies using both quantitative and qualitative metrics. The Ontology Usability Scale [9] was studied and 5 metrics were adopted from the study. The ZPLTS-ELECTRE II algorithm was then successfully applied to rank a set of 9 mental health ontologies using 5 complexity metrics and five usability metrics, as in Section 5.4.

Overall, the study provides a new perspective for selecting and ranking ontologies.

6.3 Recommendations for Selecting an ELECTRE Model

In this study 6 different ELECTRE models were studied, that is, the ELECTRE I, II, III, IV, Tri, and ZPLTS-ELECTRE II. In real-world decision-making problems a decision-maker would most likely only require a single model. The process of selecting an appropriate ELECTRE model is complex as they each have their own advantages and disadvantages, and essentially were built to solve different types of problems. To overcome this challenge, some guidelines, based on this research, are provided to differentiate the different use-cases of the ELECTRE models.

1. *ELECTRE I* has the advantage of being easier to comprehend compared to other ELECTRE versions. It is therefore easier to implement, as well as to integrate into larger systems, such as recommender and decision support systems. However, the method makes use of only two thresholds, which reduces its modelling capability. ELECTRE I could be ideal for eliminating poor-performing alternatives by selecting a non-dominated kernel from all alternatives.

2. *ELECTRE II* is, in some sense, an improvement to ELECTRE I, granted that it is able to better identify differences in performance due to its five thresholds, as opposed to the two thresholds in ELECTRE I. However, this method may also have lower modelling capability than ELECTRE III and IV. Furthermore, ELECTRE II may be less intuitive than ELECTRE I, thereby decreasing its comprehensibility and making it harder to implement.

3. *ELECTRE III* allows a decision-maker to define thresholds for the different criteria separately, as opposed to ELECTRE I and II. This enables a richer form of decision modelling and expressiveness. One concern may be the complexity involved in the distillation procedure, which can be less intuitive than the exploitation procedures for ELECTRE I and II. ELECTRE III should be considered for ranking as it is quite expressive and flexible.

4. *ELECTRE IV* follows a similar approach to ELECTRE III, but the major difference lies in its ability to function without weights. This may be an advantage and a disadvantage depending on the use case. It is an advantage if a decision-maker is not able to specify weights for the problem, in which case ELECTRE IV would be the only applicable method. However, if a user requires to specify criteria importance weights then ELECTRE IV cannot be used in that instance. The ELECTRE IV method could be applied as a component of a larger system, such as a decision support system, whereby ranking is required without weighted criteria importance.

5. *ELECTRE Tri* is one of the most widely-used MCDM classification methods. However, the profiles and thresholds may be difficult for some decision-makers to specify, but that issue could be resolved with the use of optimization models such as the genetic algorithm used in this study. The ELECTRE Tri does have some advantages over other classification models, such as machine learning (ML), being that it does not need to be trained like ML models do, and it does not require large amounts of data. A significant drawback of ELECTRE Tri is that it only performs ordinal classification.

6. *ZPLTS-ELECTRE II* is different from the other 5 ELECTRE variants as it enables a decision-maker to model both numerical and linguistic attributes. It also enables multiple decision-makers to participate in the decision-making process. The credibility aspect of the model further aligns to the complex and intricate nature of human cognition. The ZPLTS-ELECTRE II model should be used when there are multiple decision-makers, and when it is more appropriate for the decision-makers to express their views using natural language as opposed to numerical values.

6.4 Limitations of Research

The limitations of this research study are enumerated and elaborated on as follows.

1. The ontologies comprising the dataset used in this study were limited to those that have less than 20000 classes. This was due to the inability of the OntoMetrics platform to compute metrics for ontologies with their number of classes larger than 20000.

2. The ontologies used in this study were representative of only a single domain of knowledge, that is, knowledge from the biomedical domain, despite the myriad ontologies available representing other knowledge domains.

3. This study made use of only 13 complexity metrics for ranking ontologies. There is still a wider range of other metrics that may be applied for the task of evaluating and ranking ontologies.

4. The study extracted 5 usability metrics from the Ontology Usability Scale for ranking ontologies with the ZPLTS-ELECTRE II model. There are however, various other usability metrics that exist.

6.5 Future Directions of Research

The future directions of research that could be undertaken are elaborated on as follows.

1. The scalability of the ELECTRE methods for ranking ontologies may be analyzed in future works. As such, larger datasets and a more extensive selection of features may be used. These may include ontologies from various domains other than the biomedical domain, as well as other complexity and usability metrics. The ZPLTS-ELECTRE II may also be applied to real-world decision-making problems from various domains.

2. The rapid increase in the amount of ontologies available, coupled with the myriad of available metrics for evaluating ontologies may sometimes require techniques and models that are able to handle high-dimensional data and features. MCDM models may sometimes be inadequate for extremely large, high-dimensional datasets. In future work it would interesting to study and apply techniques from the field of mathematical topology, specifically Topological Data Analysis, for analysing and evaluating ontologies for reuse.

3. Apart from MCDM models, machine learning techniques may be applied for ranking ontologies. The Learning-to-Rank branch of machine learning focuses specifically on ranking data. However, these models may require a large amount of labeled data to train. Accordingly, MCDM methods like ELECTRE may be integrated with Learning-to-Rank models in order to provide labeled data to train the machine learning rankers.

4. This research applied the ELECTRE Tri method for classifying ontologies into ordinal classes. It would be useful to classify ontologies into non-ordinal classes (nominal classes) as well. This could be achieved with the use of machine learning classification models, such as the k-Nearest Neighbors, Support Vector Machine, Naive Bayes Classifier, and Decision Trees.

5. The ZPLTS-ELECTRE II model made use of the ZPLTS structure. However, the fuzzy logic and set theory domain is widely-studied and as such future developments may incorporate and extend the ZPLTS-ELECTRE II model with other types of fuzzy sets, such as Hesitant Fuzzy Sets, Pythagorean Fuzzy Sets, Fermatean Fuzzy Sets, q-Rung Orthopair Fuzzy Sets, and the Neutrosophic Sets.

6.6 Conclusion

This dissertation explored and investigated the applications of the ELECTRE algorithms for the task of ontology ranking and selection. Three applications were studied, one of which saw the development of the novel ZPLTS-ELECTRE II model. All three applications provided solutions to the problem of ontology selection for reuse. In essence, the usefulness of ELECTRE for ontology selection, and essentially ontology engineering is demonstrated clearly. This research shows the applicability of ELECTRE in advancing the field of ontology engineering.

"...research on ELECTRE methods is not a dead field. Rather the opposite, it is still evolving and gains acceptance thanks to new application areas, new methodological and theoretical developments, as well as user-friendly software implementations. Figueira et al. (2013)"

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Appendix A

Dataset - Complexity Metrics

TABLE A.1: Ontologies O_1 to O_{40}

O_i	AR	IR	RR	ER	AP	CR	ARC	ALC	AD	MD	AB	MB	ANP
O_1	.23	1.03	.02	.12	1.13	.15	1	66	3.15	5	3.46	31	19.40
O_2	.23	1.36	.06	.03	.06	.15	86	301	2.09	4	4.04	86	113
O_3	.03	1.06	.04	0	1.13	.15	11	829	5.27	12	4.17	109	10.83
O_4	.23	.95	0	.12	.84	.11	1	17	2.79	3	6.33	16	6.33
O_5	.23	.90	0	.12	1.10	.15	27	483	2.24	3	1.50	27	177.70
O_6	.23	0	1	.12	1.13	.15	14	14	14	1	14	14	14
O_7	.23	1	0	0	1.13	.15	1	496	5.11	8	4.51	53	79.50
O_8	.23	1	0	.12	1.09	.88	1	84	5.30	8	3.53	37	15
O_9	.08	1.28	.10	.01	1.13	.15	3	212	4.73	8	3.79	16	36
O_{10}	1	.83	.55	.33	13.42	.58	2	7	2.58	4	2	3	3
O_{11}	.23	2.97	.01	.12	1.13	.15	3	243	1.99	2	85.33	242	128
O_{12}	.01	6.02	0	.12	1.23	.02	26	447	1.98	2	53.20	119	532
O_{13}	.52	1.50	.28	.10	.03	.01	16	298	5.20	11	3.57	35	38.64
O_{14}	0	1.15	.51	1.17	.04	.01	1	1328	7.24	14	4.81	74	155
O_{15}	.71	3.71	.19	.12	1.13	.15	6	9	2.63	4	2.08	6	6.75
O_{16}	.23	.97	.35	.12	1.13	.15	1	21	4.31	6	2.33	4	5.83
O_{17}	.03	1.10	.54	.14	1.13	.15	17	80	5.14	8	3.46	17	26.38
O_{18}	.23	.41	.45	.12	11.59	.17	24	24	1.41	2	2.28	24	2.50
O_{19}	.23	1.96	.01	0	1.13	.15	9	218	3.50	5	4.53	35	73.40
O_{20}	.23	1.78	.26	.04	1.13	.15	2	42	5.79	10	2.05	15	8
O_{21}	.23	1.25	.06	.06	1.13	.15	59	1058	6.56	10	2.08	59	707.30
O_{22}	.23	1.10	0	.12	1.13	.15	7	3626	5.28	10	5.28	80	606.50
O_{23}	.23	2.69	.01	.12	1.13	.15	5	112	1.96	2	56.50	108	56.50
O_{24}	.23	.80	.43	.12	1.13	.15	1	3	2	3	1.67	3	1.67
O_{25}	.23	.99	0	.12	1.13	.15	7	494	1.99	2	62.63	170	25.50
O_{26}	.05	1.40	.14	.01	.01	.01	5	81	4.43	6	3.35	15	19
O_{27}	.22	1.86	.42	.16	.06	.07	6	18	2	4	3.83	6	5.75
O_{28}	.23	.99	0	.12	1.13	.15	1	87	4.63	6	3.46	9	2.17
O_{29}	.31	1.66	.32	.25	.41	.13	6	11	1.50	2	6	6	6
O_{30}	.23	.97	0	.12	1.13	.15	1	31	2.81	3	5.29	11	12.33
O_{31}	.23	1.06	.02	.12	1.13	.15	1	95	5.09	8	2.72	15	22.75
O_{32}	0	1.28	.11	.09	.12	.05	21	262	4.79	8	3.18	25	56.13
O_{33}	.23	1.25	.65	.12	.08	.02	2	100	9.34	37	1.80	9	8.30
O_{34}	.23	1.03	0	.12	1.13	.15	6	102	3.37	7	4.32	18	22.86
O_{35}	.10	1.15	.33	.14	.15	.09	36	74	2.54	5	2.75	36	3.20
O_{36}	5.50	0	1	.12	4.50	1	2	2	1	2	2	2	2
O_{37}	.23	1.05	0	.12	1.13	.15	1	545	3.60	6	19	240	101.33
O_{38}	.74	1.13	.64	.12	1.13	.15	2	78	4.68	9	3.85	22	11.56
O_{39}	.05	.91	.24	.03	.70	.14	32	220	3.26	7	3.74	32	42.71
O_{40}	0	1.78	.08	.10	.02	0	1	1418	12.19	20	2.52	129	306.60

TABLE A.2: Ontologies O_{41} to O_{101}

O_i	AR	IR	RR	ER	AP	CR	ARC	ALC	AD	MD	AB	MB	ANP
O_{41}	.07	1.31	.21	.16	1.13	.15	3	214	5.23	7	5.21	23	38.71
O_{42}	.23	1.04	0	.12	1.13	.15	2	1462	7.08	12	3.36	35	199.25
O_{43}	.07	.99	.27	.12	1.13	.15	2	180	3.74	6	3.67	14	41
O_{44}	.11	1	0	.12	1.13	.15	1	255	4.74	5	4.74	29	64.40
O_{45}	0	1.34	.07	.04	1.13	.15	11	831	11.12	21	2.74	80	75.33
O_{46}	.23	.98	.02	.12	1.13	.15	7	130	3.40	7	2.13	20	34.71
O_{47}	.39	.96	.09	.05	1.13	.15	10	171	2.45	4	7.07	29	49.50
O_{48}	0	1.46	.01	.01	1.13	.15	3	937	6.09	9	8.80	360	117.33
O_{49}	.23	1.61	.01	.12	1.13	.15	8	34	2.47	4	3.44	8	13.75
O_{50}	.08	1	.06	.12	.71	.44	1	214	8.67	13	3.80	22	22.23
O_{51}	.01	.99	.01	.12	.93	0	9	789	2.67	6	4.43	429	169.67
O_{52}	.19	1.07	.36	.07	1.13	.15	15	17	2.12	4	2.83	15	8.50
O_{53}	.11	1	.28	.12	.08	.01	1	228	3.80	7	5.28	19	40
O_{54}	.23	2.77	.04	.09	0	0	1	1716	15.70	27	2.21	165	1068.07
O_{55}	.23	.96	0	.12	1.13	.15	8	219	1.96	2	25.22	57	113.50
O_{56}	.23	.99	0	.12	1.13	.15	5	443	1.99	2	74.67	155	224
O_{57}	.23	1.46	.03	.12	1.13	.15	3	157	5.93	12	2.82	13	24
O_{58}	.23	.81	.14	.04	.01	0	119	262	2.25	6	3.94	119	59.17
O_{59}	.23	.92	.03	.02	0	0	21	183	3.23	7	4.81	25	33
O_{60}	0	1.19	.02	.01	1.13	.15	64	7369	11.85	18	3.87	115	738.06
O_{61}	.23	1.23	.08	.12	1.13	.15	1	287	6.21	12	3.15	26	42.83
O_{62}	.23	1.56	0	.12	1.13	.15	2	4903	7.44	16	3.83	258	495.25
O_{63}	.23	1.08	.03	.12	1.13	.15	1	256	5.12	8	3.09	26	52.88
O_{64}	.23	1.13	.15	.12	1.13	.15	37	102	3.20	6	5.77	37	21.17
O_{65}	.23	.88	.07	.12	1.13	.15	2	13	2.63	3	4	12	5.33
O_{66}	.23	1.25	0	.12	1.13	.15	1	230	3.01	7	4.68	204	58.14
O_{67}	.01	1.76	.12	.04	.26	.08	10	186	4.27	6	5.82	38	37.83
O_{68}	.23	1.62	.01	.12	1.13	.15	1	58	4.66	7	4.17	12	2.86
O_{69}	0	1.42	.03	.01	.03	0	176	1471	3.26	7	5.96	176	289.57
O_{70}	.23	.93	0	.12	1.13	.15	8	106	1.93	2	12.67	36	57
O_{71}	.23	1.05	.09	.05	1.13	.15	20	93	3.30	7	3.07	20	25
O_{72}	.23	.95	0	.12	1.13	.15	5	67	3.20	6	3.20	14	16
O_{73}	1.30	3.01	.16	.04	2.56	.10	16	98	2.29	4	3.94	34	32.50
O_{74}	.52	.36	.73	.12	4	.08	16	20	1.44	3	4.17	16	8.33
O_{75}	.33	0	1	.12	.42	.08	12	12	1	1	12	12	12
O_{76}	.23	.98	0	.12	1.13	.15	9	471	1.98	2	48	123	240
O_{77}	.34	.61	.54	.12	1.13	.15	75	169	1.67	3	9.45	75	63
O_{78}	0	0	0	.12	1.13	.15	2082	2082	1	1	2082	2082	2082
O_{79}	.06	1.24	.64	.01	1.13	.15	14	488	4.51	8	2.96	34	92
O_{80}	.23	.96	.39	.17	1.13	.15	31	65	3.37	8	2.65	31	17.88
O_{81}	.23	3.22	.01	.12	.01	.15	1	1141	6.48	12	3.85	34	172.75
O_{82}	.23	1.64	.27	.55	1.13	.15	7	325	6.92	13	1.65	22	216.46
O_{83}	.23	.98	.23	.04	1.13	.15	18	113	2.96	5	3.95	18	30
O_{84}	.23	.98	0	.12	1.13	.15	9	29	2.69	5	2.22	9	14.20
O_{85}	.01	1.04	.10	.12	1.13	.15	6	220	3.41	5	4.12	23	62.60
O_{86}	0	.99	.16	.15	.05	.01	21	1199	8.64	31	2.87	25	59.42
O_{87}	0	2.73	.06	.04	.18	.01	11	144	3.16	8	3.65	18	24.63
O_{88}	.23	.57	.16	.12	1.13	.15	14	16	1.61	4	2.15	14	7
O_{89}	.23	.98	.02	.12	1.13	.15	8	355	3.01	5	7.68	76	81.40
O_{90}	.01	1.13	.31	.12	1.13	.15	3	65	3.71	7	2.68	8	14.57
O_{91}	.23	1	0	.12	1.13	.15	1	310	4.21	9	3.92	31	46.11
O_{92}	.07	1.02	.03	.12	.11	0	8	388	4.13	8	5.13	65	69.25
O_{93}	.23	1.09	.04	.12	1.13	.15	11	184	3.52	6	3.90	35	66.33
O_{94}	.23	4.77	0	.12	1.13	.15	3	370	2.01	3	62.50	365	125
O_{95}	.48	.94	.10	.12	.27	.02	7	105	2.57	5	5.95	50	25
O_{96}	0	1.60	.14	.23	.09	.01	1	2617	8.75	18	4.48	78	21.78
O_{97}	.23	.99	.83	.12	.86	.01	3	44	1.93	2	15.33	41	23
O_{98}	0	1	0	.12	1.13	.15	8	2362	13.50	41	2.94	66	87.32
O_{99}	.23	2.16	.02	.03	.01	0	420	4315	4.56	12	6.06	420	43.67
O_{100}	.01	4.05	.04	.12	.03	.15	1	1575	1.12	18	2.40	58	254.89
O_{101}	.01	1.24	.10	.01	.06	.01	1	1147	1.53	17	3.83	36	171.41

TABLE A.3: Ontologies O_{102} to O_{161}

O_i	AR	IR	RR	ER	AP	CR	ARC	ALC	AD	MD	AB	MB	ANP
O_{102}	0	1.21	.35	.26	1.13	.15	64	202	3.43	11	2.79	64	28.91
O_{103}	.23	.91	.05	.04	1.13	.15	109	505	5.85	10	5.18	109	63.20
O_{104}	.01	1.53	.09	.11	.03	.01	1	564	8.54	12	3.78	27	70
O_{105}	.04	.87	.17	.12	1.13	.15	8	12	2.35	5	1.92	8	4.60
O_{106}	.23	1.04	.04	.12	1.13	.15	1	66	5.48	8	2.89	7	12.63
O_{107}	.23	1.70	.23	.42	.01	0	2	624	1.20	19	3.20	153	64.58
O_{108}	.23	1.11	.07	.04	1.13	.15	8	1003	6.83	12	5.04	123	115.50
O_{109}	.03	1.17	.13	.02	.02	.01	23	97	3.69	6	4.10	23	21.17
O_{110}	.23	1	0	.12	1.13	.15	1	76	3.72	5	3.26	10	21.80
O_{111}	.23	2.06	.01	0	0	.15	1	5338	12.76	21	3.91	266	361.95
O_{112}	0	2.07	.08	.04	.01	0	4	2539	9.70	36	5.14	441	104.31
O_{113}	.01	1.98	.06	.03	.15	.05	1	131	9.83	35	2.33	34	6.51
O_{114}	0	1.48	.01	.01	1.13	.15	142	3517	7.03	12	4.39	142	381.50
O_{115}	0	2.70	.08	.14	.01	0	13	82	3.05	7	2.37	15	20
O_{116}	0	1.22	.13	.10	.14	.02	1	1292	7.74	17	4.87	93	98.82
O_{117}	.23	1.11	.04	.03	1.13	.15	5	2022	7.09	12	3.21	65	266.25
O_{118}	0	1.23	0	.12	1.13	.15	8	3626	4.32	10	5.52	1044	754.10
O_{119}	.23	.98	.51	1	1.13	.15	10	515	4.46	8	5.36	43	79
O_{120}	0	1.78	.08	.10	.02	0	1	1418	12.19	20	2.52	129	306.60
O_{121}	0	1.08	.13	.10	.01	0	130	2168	8.33	14	4.08	187	215.50
O_{122}	.23	1.15	.42	.06	.04	.01	1	410	5.75	11	4.74	173	48.27
O_{123}	0	1.21	.07	.06	.03	.01	1	908	8.60	17	3.71	119	91.24
O_{124}	.23	1.05	0	.12	0	.15	22	422	7.03	11	2.88	26	69.09
O_{125}	.09	1.12	.57	.17	1.29	.47	33	81	3.47	8	2.67	33	16
O_{126}	.23	.71	.17	.09	0	.15	152	327	1.60	3	11.97	152	119.67
O_{127}	0	1.24	.15	.03	1.13	.15	9	1032	7.40	13	3.02	118	124
O_{128}	.23	1.45	.05	.05	1.13	.15	7	1323	6.83	12	7.11	147	156.92
O_{129}	0	1.07	.02	.01	.45	0	57	651	3.80	7	5.06	69	203.71
O_{130}	0	2.45	.01	.12	1.13	.15	4	4095	4.30	10	4.71	2155	519.70
O_{131}	.02	1	.15	0	3.01	.01	4	1313	6.65	9	5.62	20	343.56
O_{132}	0	1.08	.14	.01	1.13	.15	5	691	7.84	12	3.45	118	104.33
O_{133}	0	.99	0	.12	1.13	.15	11	1353	4.35	9	4.23	50	196.78
O_{134}	.23	.81	.09	.04	1.13	.15	348	943	4.45	11	4.40	348	114.45
O_{135}	.23	1.45	.24	.28	1.13	.15	3	336	3	4	7.31	69	97
O_{136}	4.91	.27	.85	.12	1.13	.15	16	20	1.27	2	7.33	16	11
O_{137}	0	1.28	.11	.09	.12	.05	21	262	4.79	8	3.18	25	56.13
O_{138}	.23	.99	.07	.12	1.13	.15	2	320	5.21	8	6.80	206	46.75
O_{139}	.23	.98	.01	.12	1.13	.15	3	113	4.46	8	3.24	14	62.50
O_{140}	.13	1.31	.10	.12	.19	.03	8	103	2.96	5	3.49	18	28.60
O_{141}	.23	1.13	.01	.12	1.13	.15	1	1	1	1	1	1	1
O_{142}	.23	2.10	.01	.12	1.13	.15	47	409	2.99	5	14.94	158	95.60
O_{143}	.23	1.60	.11	.01	1.13	.15	6	393	6.12	9	4.56	40	144.78
O_{144}	.23	1.45	.24	.28	1.13	.15	3	336	3	4	7.32	69	97
O_{145}	.01	.95	.15	.12	1.13	.15	41	70	2.54	8	2.44	41	14.63
O_{146}	.23	.99	0	.12	1.13	.15	8	814	1.99	2	91.33	324	411
O_{147}	.23	1	0	0	1.13	.15	11	1364	4.77	10	4.04	98	181.40
O_{148}	.02	1.01	.04	.12	1.13	.15	4	297	5.12	11	3.05	36	41.91
O_{149}	.23	0	0	.12	1.13	.15	12	12	1	1	12	12	12
O_{150}	.04	.99	.04	.12	1.13	.15	1	113	4.04	6	5.31	28	23
O_{151}	.23	1.22	.27	.28	1.13	.15	48	265	5.01	10	3.85	48	5.50
O_{152}	.23	1.20	.05	.01	.02	.02	8	181	3.19	4	1.47	81	49.75
O_{153}	.23	2.25	0	.12	1.13	.15	6	3508	2.38	8	27.57	1467	454.88
O_{154}	.23	1.29	0	.12	1.13	.15	4	207	5.35	8	3.90	17	84.75
O_{155}	.23	1.01	.06	.12	1.13	.15	4	59	4.03	6	3.52	8	14.67
O_{156}	.02	1.11	.14	.12	1.13	.15	8	193	3.67	7	3.31	15	4.71
O_{157}	.28	.83	.41	.12	1.37	.15	8	35	2.35	4	3.83	8	11.50
O_{158}	.23	.99	0	.12	1.13	.15	9	767	4.04	8	3.32	18	137.25
O_{159}	.23	2.69	.02	.12	1.13	.15	1	53	1.98	2	27	53	27
O_{160}	.20	.35	.65	.06	1.14	.51	34	44	1.54	3	7.14	34	16.67
O_{161}	.23	1.01	0	.12	1.13	.15	5	553	4.89	8	3.75	28	96

TABLE A.4: Ontologies O_{162} to O_{200}

O_i	AR	IR	RR	ER	AP	CR	ARC	ALC	AD	MD	AB	MB	ANP
O_{162}	.23	1.33	.01	.12	1.13	.15	1	1	1	1	1	1	1
O_{163}	.23	1	0	.12	1.13	.15	1	1556	5.83	9	5.55	79	21.78
O_{164}	.04	1.52	.42	.12	1.13	.15	21	21	1	1	21	21	21
O_{165}	.03	1.17	.13	.02	.02	.01	23	97	3.69	6	4.10	23	21.17
O_{166}	.01	1.23	.18	.11	1.13	.15	33	156	3	7	3.44	33	31.43
O_{167}	.23	1.05	.12	.12	1.13	.15	5	11	2.76	5	1.94	5	6.60
O_{168}	.23	.98	0	.12	1.13	.15	3	137	1.98	2	35	87	70
O_{169}	.23	1.06	.02	.12	1.13	.15	4	369	3.93	9	3.24	90	63.44
O_{170}	.09	.78	.19	.12	7.13	.81	7	31	1.78	2	16	25	16
O_{171}	.78	1.02	.45	.02	1.20	.06	26	665	4.12	6	5.78	56	17.50
O_{172}	.07	1.32	.21	.16	1.13	.15	2	213	5.16	7	5.19	23	38.57
O_{173}	.22	2.27	.24	.12	.13	.03	28	94	3.38	6	3.17	28	37.50
O_{174}	.23	.96	0	.12	1.13	.15	8	219	1.96	2	25.22	57	113.50
O_{175}	.23	1.02	.19	.01	1.13	.15	3	90	3.58	5	3.79	13	25.80
O_{176}	.23	1.32	.01	.12	.80	.15	1	155	4.12	7	5.54	20	27.71
O_{177}	.23	0	0	.12	1.13	.15	325	325	1	325	325	325	325
O_{178}	.23	0	0	.12	1.13	.15	201	201	1	201	201	201	201
O_{179}	.02	2.86	.09	.02	1.13	.15	0	0	1	292	292	292	292
O_{180}	.23	1.27	.29	.52	1.13	.15	1	1631	7.50	10	4.51	101	271.70
O_{181}	.23	1	0	.12	1.13	.15	1	416	2.99	3	139.33	416	139.33
O_{182}	0	.97	.09	.12	5.42	.91	4	223	2.86	3	14.35	48	81.33
O_{183}	.23	1.19	.03	0	.59	.55	2	908	7.09	16	2.31	293	10.81
O_{184}	0	.07	.28	.12	1	.15	1701	1781	1.25	8	39.80	1706	228.88
O_{185}	.12	1	.38	.12	1.13	.15	1	2	1.03	2	39	76	39
O_{186}	.03	.76	.29	.05	1.13	.15	22	22	1.08	2	8	22	12
O_{187}	.33	.83	.52	.12	5.89	.89	3	17	1.83	2	9	15	9
O_{188}	.02	1.09	.04	.02	.38	.15	20	768	4.63	5	1.03	321	172.60
O_{189}	.23	1.45	.26	.06	1.59	.03	5	38	4.44	8	2.18	8	9
O_{190}	.23	1.59	0	.12	.01	.15	1	49	4.65	7	3.65	10	19.29
O_{191}	.23	1.27	.02	.01	.01	.01	3	1647	7.40	14	3.35	79	35.64
O_{192}	.23	1	0	.12	1.13	.15	6	521	3.20	6	5	39	108.83
O_{193}	.23	1.86	.46	.66	1.13	.15	1	9	3.07	5	2.14	3	3
O_{194}	.04	.39	.14	.07	5.74	.61	28	45	1.39	2	23	28	23
O_{195}	.23	3.99	.13	.52	0	.15	1	973	11.20	17	1.92	148	1047.24
O_{196}	.33	.83	.52	.12	5.89	.89	3	17	1.83	2	9	15	9
O_{197}	.05	1.28	.30	.09	.16	.02	5	64	2.85	5	4.88	38	25.40
O_{198}	.02	1.61	.26	.10	.15	.03	10	29	2.09	4	3.67	21	13.75
O_{199}	.23	1.18	.17	.12	1.13	.15	1	362	3.30	6	3.97	93	101.17
O_{200}	0	.75	.75	.30	.05	.05	68	203	2.46	6	6.45	68	43

Appendix B

Dataset - Ontology Names

TABLE B.1: Ontologies O_1 to O_{40}

O_i	Ontology
O_1	EDDA Publication Types Taxonomy
O_2	Cephalopod Ontology
O_3	Electrocardiography Ontology
O_4	ISO 19115 Date Type Code
O_5	PhenX Phenotypic Terms
O_6	NCCN EHR Oncology Categories
O_7	Prostate Cancer Ontology
O_8	insectH
O_9	Just Enough Results Model Ontology
O_{10}	Allergy Detector II
O_{11}	Human Developmental Stages Ontology
O_{12}	Mental State Assessment
O_{13}	VIVO-Integrated Semantic Framework
O_{14}	The Stroke Ontology
O_{15}	ISO 19108 Temporal Objects
O_{16}	Basic Formal Ontology
O_{17}	Major Histocompatibility Complex Ontology
O_{18}	BioLink Model
O_{19}	Dependency Layered Ontology for Radiation Oncology
O_{20}	Vaccine Investigation Ontology
O_{21}	Ontology of Microbial Phenotypes
O_{22}	Fanconi Anemia Ontology
O_{23}	Mouse Developmental Stages
O_{24}	Genome Component Ontology
O_{25}	APA Neuro Cluster
O_{26}	Phylogenetic Ontology
O_{27}	Medical Technology Innovation in healthcare centers
O_{28}	International Classification of Wellness
O_{29}	Electronic Care Plan
O_{30}	Clinical Study Ontology
O_{31}	Zebrafish Experimental Conditions Ontology
O_{32}	Proteomics Data and Process Provenance Ontology
O_{33}	Population and Community Ontology
O_{34}	Data Science Education Ontology
O_{35}	Suggested Ontology for Pharmacogenomics
O_{36}	PAV Provenance, Authoring and Versioning
O_{37}	Human Ancestry Ontology
O_{38}	Systems Chemical Biology and Chemogenomics Ontology
O_{39}	Spinal Cord Injury Ontology
O_{40}	Beta Cell Genomics Ontology

TABLE B.2: Ontologies O_{41} to O_{101}

O_i	**Ontology**
O_{41}	Adherence and Integrated Care in Spanish
O_{42}	Animal Trait Ontology for Livestock
O_{43}	Cell Behavior Ontology
O_{44}	Content Archive Resource Exchange Lexicon
O_{45}	Early Pregnancy Ontology
O_{46}	Host Pathogen Interactions Ontology
O_{47}	Devices, Experimental scaffolds and Biomaterials Ontology
O_{48}	Collembola Anatomy Ontology
O_{49}	Anatomic Ontology for Mouse Lung Maturation
O_{50}	Food Ontology
O_{51}	Growth Medium Ontology
O_{52}	Orthology Ontology
O_{53}	Ontologia de Saúde Mental
O_{54}	Ontology of Chinese Medicine for Rheumatism
O_{55}	legalapa
O_{56}	APA Occupational and Employment cluster
O_{57}	Anatomical Entity Ontology
O_{58}	Obstetric and Neonatal Ontology
O_{59}	Cardiac Electrophysiology Ontology
O_{60}	Emergency care ontology
O_{61}	Hearing Impairment Ontology
O_{62}	Pathway Terminology System
O_{63}	Pathogenic Disease Ontology
O_{64}	Dataset Processing
O_{65}	Material Mineral
O_{66}	Rheumatoid Arthritis ontology
O_{67}	Physical Activity Ontology
O_{68}	Cell Ontology for Mouse Lung Maturation
O_{69}	GenEpiO
O_{70}	Computer Cluster
O_{71}	Santa Barbara Coastal Observation Ontology
O_{72}	Reproductive Trait and Phenotype Ontology
O_{73}	GBOL
O_{74}	DC Terms
O_{75}	Research Variable Ontology
O_{76}	APA Treatment Cluster
O_{77}	BIBFRAME 2.0
O_{78}	Portfolio Management Application
O_{79}	Subcellular Anatomy Ontology
O_{80}	Common Anatomy Reference Ontology
O_{81}	Sickle Cell Disease Ontology
O_{82}	Cellular microscopy phenotype ontology
O_{83}	Enzyme Mechanism Ontology
O_{84}	Consumer Wearable Device
O_{85}	Student Health Record Ontology
O_{86}	Newborn Screening Follow-up & Translational Research
O_{87}	Vaccination Informed Consent Ontology
O_{88}	Mental Functioning Ontology
O_{89}	Inherited Retinal Dystrophy
O_{90}	Genomic Feature and Variation Ontology
O_{91}	Prostate Cancer Life Style Ontology
O_{92}	BioMedical Resource Ontology
O_{93}	BioMedical Topics
O_{94}	BioMedBridges Diabetes Ontology
O_{95}	Biomedical Image Ontology
O_{96}	Ontology for Biomedical Investigations
O_{97}	Biomedical Research Integrated Domain Group Model
O_{98}	Biomedical Informatics Research Network Project Lexicon
O_{99}	Vaccine Ontology
O_{100}	Ontology of Cardiovascular Drug Adverse Events
O_{101}	HIVOntologymain

TABLE B.3: Ontologies O_{102} to O_{161}

O_i	**Ontology**
O_{102}	BioTop Ontology
O_{103}	Biological Imaging Methods Ontology
O_{104}	Ontology of Biological and Clinical Statistics
O_{105}	Epigenome Ontology
O_{106}	Bionutrition Ontology
O_{107}	Ontology of Host-Microbe Interactions
O_{108}	Pre-eclampsia Ontology
O_{109}	Ontology for Drug Discovery Investigations
O_{110}	COPD Ontology
O_{111}	Ontology of Host-Pathogen Interactions
O_{112}	Brucellosis Ontology
O_{113}	Bioinformatics Web Service Ontology
O_{114}	Ontology of Adverse Events
O_{115}	Ontology of Vaccine Adverse Events
O_{116}	Ontology for Biobanking
O_{117}	Chemical Methods Ontology
O_{118}	Software Ontology
O_{119}	Parkinson's Disease Ontology
O_{120}	Beta Cell Genomics Ontology
O_{121}	Human Physiology Simulation Ontology
O_{122}	Infectious Disease Ontology
O_{123}	EuPath Ontology
O_{124}	Systems Biology Ontology
O_{125}	Breast Cancer Grading Ontology
O_{126}	BioAssay Ontology
O_{127}	Semanticscience Integrated Ontology
O_{128}	Alzheimer's disease ontology
O_{129}	Children's Health Exposure Analysis Resource Ontology
O_{130}	Cell Line Ontology [by Maphaven] Ontology
O_{131}	International Classification of Functioning, Disability and Health
O_{132}	Radiation Oncology Ontology
O_{133}	Pediatric Terminology
O_{134}	FoodOn Ontology
O_{135}	Genomic Clinical Decision Support Ontology
O_{136}	Enzyme Structure Function Ontology
O_{137}	Proteomics Data and Process Provenance Ontology
O_{138}	Neuroscience Information Framework (NIF) Cell Ontology
O_{139}	Food Matrix for Predictive Microbiology
O_{140}	Parasite Experiment Ontology
O_{141}	Loggerhead Nesting Ontology
O_{142}	Social Inset Behavior Ontology
O_{143}	PatientSafetyOntology
O_{144}	Genomic Clinical Decision Support Ontology
O_{145}	Viral Disease Ontology Trunk
O_{146}	Disorders cluster
O_{147}	Epilepsy Semiology
O_{148}	RegenBase ontology
O_{149}	Traditional Medicine Other Factors Value Set
O_{150}	Epilepsy Ontology
O_{151}	Ontological Knowledge Base Model for Cystic Fibrosis
O_{152}	Cognitive Paradigm Ontology
O_{153}	Cognitive Atlas Ontology
O_{154}	Nutritional Epidemiological Standards
O_{155}	Mouse Experimental Design Ontology
O_{156}	Presence Ontology
O_{157}	Nurse Transitional
O_{158}	Nurse Transitional
O_{159}	Zebrafish Developmental Stages
O_{160}	MyOntoServiceFull_FallDetection
O_{161}	NMR-Controlled Vocabulary

TABLE B.4: Ontologies O_{162} to O_{200}

O_i	**Ontology**
O_{162}	Physico-Chemical Process
O_{163}	GoMapMan
O_{164}	ISO 19115 Metadata Information
O_{165}	Ontology for Drug Discovery Investigations
O_{166}	Ontology of Medically Related Social Entities
O_{167}	Material Rock
O_{168}	APA Statistical Cluster
O_{169}	Precision Medicine Ontology
O_{170}	Medical Web Lifestyle Aggregator
O_{171}	Schema.org core and all extension vocabularies
O_{172}	Adherence and Integrated Care
O_{173}	Ontology for Geography Markup Language (GML3.0)
O_{174}	apalegal
O_{175}	Phylogenetics Ontology
O_{176}	Clinical MetaData Ontology
O_{177}	Traditional Medicine Signs and Symptoms Value Set
O_{178}	ISO-15926-2_2003_annotations
O_{179}	The Extensible Observation Ontology
O_{180}	MHC Restriction Ontology
O_{181}	IDG gene list
O_{182}	Surgical Secondary Events
O_{183}	Physical Medicine and Rehabilitation
O_{184}	Minimal Standard Terminology of Digestive Endoscopy, French
O_{185}	GeoSPARQL
O_{186}	Histological Ontology
O_{187}	National Institutes of Health Stroke Scale Ontology
O_{188}	G Protein-Coupled Receptor BioAssays Ontology
O_{189}	Cerrado concepts and plant community dynamics
O_{190}	Cell Ontology for Human Lung Maturation
O_{191}	Ontology of Amyotrophic Lateral Sclerosis, all modules
O_{192}	Ontology of Nuclear Toxicity
O_{193}	Confidence Information Ontology
O_{194}	ISO 19115 Codelists
O_{195}	Planarian Phenotype Ontology
O_{196}	Biologie Hors Nomenclature
O_{197}	Comparative Data Analysis Ontology
O_{198}	Ontology for Genetic Susceptibility Factor
O_{199}	EDDA Study Designs Taxonomyv
O_{200}	Family Health History Ontology

Appendix C

Γ and *E* Matrices

TABLE C.1: The Γ matrix before normalization

O_i	CoP	QoSD	DoCRNL	UoC	DoCA
O_1	$\{s_0(0.5), s_1(0.5)\}, \{s'_{-1}(0.25), s'_1(0.75)\}$	$\{s_1(0.5), s_2(0.5)\}, \{s'_0(0.25), s'_1(0.75)\}$	$\{s_1(0.75), s_2(0.25)\}, \{s'_{-1}(0.25), s'_0(0.75)\}$	$\{s_0(0.25), s_1(0.25), s_2(0.5)\}, \{s'_{-1}(0.25), s'_1(0.75)\}$	$\{s_0(0.25), s_1(0.75)\}, \{s'_0(0.5), s'_1(0.5)\}$
O_2	$\{s_0(0.75), s_1(0.25)\}, \{s'_0(0.25), s'_1(0.75)\}$	$\{s_{-1}(0.25), s_0(0.25), s_1(0.5)\}, \{s'_0(0.25), s'_1(0.75)\}$	$\{s_{-1}(1)\}, \{s'_0(0.25), s'_1(0.75)\}$	$\{s_{-1}(0.25), s_0(0.25), s_1(0.5)\}, \{s'_0(0.5), s'_1(0.5)\}$	$\{s_{-1}(0.25), s_0(0.75)\}, \{s'_0(0.5), s'_1(0.5)\}$
O_3	$\{s_0(0.75), s_1(0.25)\}, \{s'_{-1}(0.25), s'_0(0.25), s'_1(0.5)\}$	$\{s_0(0.75), s_1(0.25)\}, \{s'_0(0.25), s'_1(0.75)\}$	$\{s_0(0.75), s_1(0.25)\}, \{s'_{-1}(0.25), s'_0(0.25), s'_1(0.5)\}$	$\{s_0(0.75), s_1(0.25)\}, \{s'_{-1}(0.25), s'_0(0.25), s'_1(0.5)\}$	$\{s_0(0.75), s_1(0.25)\}, \{s'_{-1}(0.25), s'_0(0.5), s'_1(0.25)\}$
O_4	$\{s_{-1}(0.5), s_0(0.5)\}, \{s'_0(0.5), s'_1(0.5)\}$	$\{s_{-1}(0.25), s_0(0.5), s_1(0.25)\}, \{s'_0(0.25), s'_1(0.75)\}$	$\{s_{-1}(0.5), s_0(0.5)\}, \{s'_0(0.25), s'_1(0.75)\}$	$\{s_{-1}(0.25), s_0(0.25), s_1(0.5)\}, \{s'_0(1)\}$	$\{s_{-1}(0.25), s_0(0.75)\}, \{s'_0(0.75), s'_1(0.25)\}$
O_5	$\{s_0(0.5), s_1(0.25), s_2(0.25)\}, \{s'_{-1}(0.25), s'_1(0.75)\}$	$\{s_1(0.5), s_2(0.5)\}, \{s'_{-1}(0.25), s'_1(0.75)\}$	$\{s_1(0.75), s_2(0.25)\}, \{s'_{-1}(0.25), s'_1(0.75)\}$	$\{s_0(0.25), s_1(0.5), s_2(0.25)\}, \{s'_0(0.5), s'_1(0.5)\}$	$\{s_1(1)\}, \{s'_{-1}(0.25), s'_0(0.25), s'_1(0.5)\}$
O_6	$\{s_{-1}(0.5), s_0(0.25), s_1(0.25)\}, \{s'_0(0.75), s'_1(0.25)\}$	$\{s_0(0.25), s_1(0.75)\}, \{s'_0(0.5), s'_1(0.5)\}$	$\{s_0(0.75), s_1(0.25)\}, \{s'_0(0.25), s'_1(0.75)\}$	$\{s_{-1}(0.25), s_0(0.75)\}, \{s'_0(0.5), s'_1(0.5)\}$	$\{s_0(1)\}, \{s'_0(0.5), s'_1(0.5)\}$
O_7	$\{s_0(0.5), s_1(0.5)\}, \{s'_0(0.5), s'_1(0.5)\}$	$\{s_0(0.75), s_1(0.25)\}, \{s'_0(0.25), s'_1(0.75)\}$	$\{s_0(0.75), s_1(0.25)\}, \{s'_1(1)\}$	$\{s_{-1}(0.5), s_0(0.25), s_1(0.25)\}, \{s'_0(0.25), s'_1(0.75)\}$	$\{s_0(1)\}, \{s'_0(0.25), s'_1(0.75)\}$
O_8	$\{s_{-1}(0.75), s_0(0.25)\}, \{s'_{-1}(0.25), s'_0(0.5), s'_1(0.25)\}$	$\{s_{-1}(0.75), s_1(0.25)\}, \{s'_0(0.5), s'_1(0.5)\}$	$\{s_{-1}(0.75), s_0(0.25)\}, \{s'_0(1)\}$	$\{s_{-1}(0.25), s_0(0.25), s_1(0.5)\}, \{s'_{-1}(0.25), s'_0(0.75)\}$	$\{s_{-1}(0.25), s_0(0.75)\}, \{s'_0(1)\}$
O_9	$\{s_1(0.25), s_2(0.75)\}, \{s'_1(1)\}$	$\{s_1(0.25), s_2(0.75)\}, \{s'_1(1)\}$	$\{s_1(0.75), s_2(0.25)\}, \{s'_1(1)\}$	$\{s_1(0.25), s_2(0.75)\}, \{s'_0(0.75), s'_1(0.25)\}$	$\{s_2(1)\}, \{s'_0(0.5), s'_1(0.5)\}$

TABLE C.2: The final decision matrix *E*

O_i	ALC	ARC	AD	AB	ANP	CoP	QoSD	DoCRNL	UoC	DoCA
O_1	26	447	1.97	53.2	532	$\{s_0(0.5), s_1(0.5), s_1(0)\}, \{s'_{-1}(0.25), s'_1(0.75), s'_1(0)\}$	$\{s_1(0.5), s_2(0.5), s_2(0)\}, \{s'_0(0.25), s'_1(0.75), s'_1(0)\}$	$\{s_1(0.75), s_2(0.25), s_2(0)\}, \{s'_{-1}(0.25), s'_0(0.75), s'_0(0)\}$	$\{s_0(0.25), s_1(0.25), s_2(0.5)\}, \{s'_{-1}(0.25), s'_1(0.75), s'_1(0)\}$	$\{s_0(0.25), s_1(0.75), s_1(0)\}, \{s'_0(0.5), s'_1(0.5), s'_1(0)\}$
O_2	7	494	1.98	62.62	250.5	$\{s_0(0.75), s_1(0.25), s_1(0)\}, \{s'_0(0.25), s'_1(0.75), s'_1(0)\}$	$\{s_{-1}(0.25), s_0(0.25), s_1(0.5)\}, \{s'_0(0.25), s'_1(0.75), s'_1(0)\}$	$\{s_{-1}(1), s_{-1}(0), s_{-1}(0)\}, \{s'_0(0.25), s'_1(0.75), s'_1(0)\}$	$\{s_{-1}(0.25), s_0(0.25), s_1(0.5)\}, \{s'_0(0.5), s'_1(0.5), s'_1(0)\}$	$\{s_{-1}(0.25), s_0(0.75), s_0(0)\}, \{s'_0(0.5), s'_1(0.5), s'_1(0)\}$
O_3	1	228	3.80	5.28	40	$\{s_0(0.75), s_1(0.25), s_1(0)\}, \{s'_{-1}(0.25), s'_0(0.25), s'_1(0.5)\}$	$\{s_0(0.75), s_1(0.25), s_1(0)\}, \{s'_0(0.25), s'_1(0.75), s'_1(0)\}$	$\{s_0(0.75), s_1(0.25), s_1(0)\}, \{s'_{-1}(0.25), s'_0(0.25), s'_1(0.5)\}$	$\{s_0(0.75), s_1(0.25), s_1(0)\}, \{s'_{-1}(0.25), s'_0(0.25), s'_1(0.5)\}$	$\{s_0(0.75), s_1(0.25), s_1(0)\}, \{s'_{-1}(0.25), s'_0(0.5), s'_1(0.25)\}$
O_4	14	16	1.60	2.15	7	$\{s_{-1}(0.5), s_0(0.5), s_0(0)\}, \{s'_0(0.5), s'_1(0.5)\}$	$\{s_{-1}(0.25), s_0(0.5), s_1(0.25)\}, \{s'_0(0.25), s'_1(0.75), s'_1(0)\}$	$\{s_{-1}(0.5), s_0(0.5), s_0(0)\}, \{s'_0(0.25), s'_1(0.75), s'_1(0)\}$	$\{s_{-1}(0.25), s_0(0.25), s_1(0.5)\}, \{s'_0(1), s'_0(0), s'_0(0)\}$	$\{s_{-1}(0.25), s_0(0.75), s_0(0)\}, \{s'_0(0.75), s'_1(0.25), s'_1(0)\}$
O_5	7	1323	6.82	7.10	156.91	$\{s_0(0.5), s_1(0.25), s_2(0.25)\}, \{s'_{-1}(0.25), s'_1(0.75), s'_1(0)\}$	$\{s_1(0.5), s_2(0.5), s_2(0)\}, \{s'_{-1}(0.25), s'_1(0.75), s'_1(0)\}$	$\{s_1(0.75), s_2(0.25), s_2(0)\}, \{s'_{-1}(0.25), s'_1(0.75), s'_1(0)\}$	$\{s_0(0.25), s_1(0.5), s_2(0.25)\}, \{s'_0(0.5), s'_1(0.5), s'_1(0)\}$	$\{s_1(1), s_1(0), s_1(0)\}, \{s'_{-1}(0.25), s'_0(0.25), s'_1(0.5)\}$
O_6	2	320	5.21	6.8	46.75	$\{s_{-1}(0.5), s_0(0.25), s_1(0.25)\}, \{s'_0(0.75), s'_1(0.25), s'_1(0)\}$	$\{s_0(0.25), s_1(0.75), s_1(0)\}, \{s'_0(0.5), s'_1(0.5), s'_1(0)\}$	$\{s_0(0.75), s_1(0.25), s_1(0)\}, \{s'_0(0.25), s'_1(0.75), s'_1(0)\}$	$\{s_{-1}(0.25), s_0(0.75), s_0(0)\}, \{s'_0(0.5), s'_1(0.5), s'_1(0)\}$	$\{s_0(1), s_0(0), s_0(0)\}, \{s'_0(0.5), s'_1(0.5), s'_1(0)\}$
O_7	11	1364	4.76	4.04	181.4	$\{s_0(0.5), s_1(0.5), s_1(0)\}, \{s'_0(0.5), s'_1(0.5), s'_1(0)\}$	$\{s_0(0.75), s_1(0.25), s_1(0)\}, \{s'_0(0.25), s'_1(0.75), s'_1(0)\}$	$\{s_0(0.75), s_1(0.25), s_1(0)\}, \{s'_1(1), s'_1(0), s'_1(0)\}$	$\{s_{-1}(0.5), s_0(0.25), s_1(0.25)\}, \{s'_0(0.25), s'_1(0.75), s'_1(0)\}$	$\{s_0(1), s_0(0), s_0(0)\}, \{s'_0(0.25), s'_1(0.75), s'_1(0)\}$
O_8	8	181	3.19	10.47	49.75	$\{s_{-1}(0.75), s_0(0.25), s_0(0)\}, \{s'_{-1}(0.25), s'_0(0.5), s'_1(0.25)\}$	$\{s_{-1}(0.75), s_1(0.25), s_1(0)\}, \{s'_0(0.5), s'_1(0.5), s'_1(0)\}$	$\{s_{-1}(0.75), s_0(0.25), s_0(0)\}, \{s'_0(1), s'_0(0), s'_0(0)\}$	$\{s_{-1}(0.25), s_0(0.25), s_1(0.5)\}, \{s'_{-1}(0.25), s'_0(0.75), s'_0(0)\}$	$\{s_{-1}(0.25), s_0(0.75), s_0(0)\}, \{s'_0(1), s'_0(0), s'_0(0)\}$
O_9	6	3508	2.37	27.56	454.87	$\{s_1(0.25), s_2(0.75), s_2(0)\}, \{s'_1(1), s'_1(0), s'_1(0)\}$	$\{s_1(0.25), s_2(0.75), s_2(0)\}, \{s'_1(1), s'_1(0), s'_1(0)\}$	$\{s_1(0.75), s_2(0.25), s_2(0)\}, \{s'_1(1), s'_1(0), s'_1(0)\}$	$\{s_1(0.25), s_2(0.75), s_2(0)\}, \{s'_0(0.75), s'_1(0.25), s'_1(0)\}$	$\{s_2(1), s_2(0), s_2(0)\}, \{s'_0(0.5), s'_1(0.5), s'_1(0)\}$

Appendix D

PLTS ELECTRE II

The PLTS ELECTRE II method was developed by He et al. in 2020 [30] and is based on the concept of Probabilistic Linguistic Term Sets (PLTSs). The method is modeled as follows.

Decision Matrix

A decision matrix is defined to represent the alternatives and the criteria, in the form of $M' = [L(p)_{xy}]_{m\times n}$, where $L(p)$ represents a PLTS, m represents the number of alternatives, and n represents the number of criteria.

Criteria Importance Weights

The criteria importance weights for each criterion is defined as ω_j, where the importance weight for the j^{th} criterion is represented by ω_j, and $j = 1, 2, \ldots, n$.

Comparison of Alternatives

All alternative pairs , (x, y), are compared by calculating their score and deviation values. The score is denoted as $E(L(p)_{ij})$ and is given by Eq. (D.1), where $\#L(p)$ is the number of terms in the PLTS $L(p)$, p^k represents the probability value of the k^{th} term, and r^k represents the subscript of the k^{th} term.

$$E(L(p)) = \frac{\sum_{k=1}^{\#L(p)} r^k p^k}{\sum_{k=1}^{\#L(p)} p^k} \tag{D.1}$$

The score value can be used to compare LPTSs, but in the case that the scores are equal then deviation degree is required to further compare PLTSs. The deviation degree for a PLTS is given by Eq. (D.2), where $\sigma(L(p))$ represents the deviation of the PLTS $L(p)$.

$$\sigma(L(p)) = \frac{\sum_{k=1}^{\#L(p)} \sqrt{(p^k(r^k - E(L(p))))^2}}{\sum_{k=1}^{\#L(p)} p^k} \tag{D.2}$$

The score and deviation values can be used to compare two PLTSs as follows:

1. If $E(L_1(p)) > E(L_2(p))$ then $L_1(p) > L_2(p)$.
2. If $E(L_1(p)) < E(L_2(p))$ then $L_1(p) < L_2(p)$.
3. If $E(L_1(p)) = E(L_2(p))$ then:

(a) If $\sigma(L_1(p)) > \sigma(L_2(p))$ then $L_1(p) < L_2(p)$.

(b) If $\sigma(L_1(p)) < \sigma(L_2(p))$ then $L_1(p) > L_2(p)$.

(c) If $\sigma(L_1(p)) = \sigma(L_2(p))$ then $L_1(p) = L_2(p)$.

Concordance Sets

Using the score and deviation values three concordance sets are determined. The first concordance set is the strong concordance set given by Eq. (D.6).

$$J_{C_{kl}} = \{j \mid E(L(p)_{kj}) > E(L(p)_{lj})\ and\ \sigma(L(p)_{kj}) < \sigma(L(p)_{lj})\} \tag{D.3}$$

The second concordance set is the medium concordance set given by Eq. (D.4).

$$J_{C'_{kl}} = \{j \mid E(L(p)_{kj}) > E(L(p)_{lj})\ and\ \sigma(L(p)_{kj}) \geq \sigma(L(p)_{lj})\} \tag{D.4}$$

The third concordance set is the weak concordance set given by Eq. (D.5).

$$J_{C''_{kl}} = \{j \mid E(L(p)_{kj}) = E(L(p)_{lj})\ and\ \sigma(L(p)_{kj}) < \sigma(L(p)_{lj})\} \tag{D.5}$$

Indifference Sets

Using the score and deviation values the indifference set is determined, as in Eq. (D.6).

$$J_{kl}^{=} = \{j \mid E(L(p)_{kj}) = E(L(p)_{lj})\ and\ \sigma(L(p)_{kj}) = \sigma(L(p)_{lj})\} \tag{D.6}$$

Discordance Sets

Using the score and deviation values three discordance sets are determined. The first discordance set is the strong discordance set given by Eq. (D.7).

$$J_{D_{kl}} = \{j \mid E(L(p)_{kj}) < E(L(p)_{lj})\ and\ \sigma(L(p)_{kj}) > \sigma(L(p)_{lj})\} \tag{D.7}$$

The second discordance set is the medium discordance set given by Eq. (D.8).

$$J_{D'_{kl}} = \{j \mid E(L(p)_{kj}) < E(L(p)_{lj})\ and\ \sigma(L(p)_{kj}) \leq \sigma(L(p)_{lj})\} \tag{D.8}$$

The third discordance set is the weak discordance set given by Eq. (D.9).

$$J_{D''_{kl}} = \{j \mid E(L(p)_{kj}) = E(L(p)_{lj})\ and\ \sigma(L(p)_{kj}) > \sigma(L(p)_{lj})\} \tag{D.9}$$

Concordance Matrix

The concordance matrix, C, is determined by considering the three concordance sets, $J_{C_{kl}}$, $J_{C'_{kl}}$, and $J_{C''_{kl}}$, as well as the indifference set $J^{=}_{kl}$. Each element of C, denoted as c_{kl}, is determined by Eq. (D.10), where ω_C, ω'_C, ω''_C, and $\omega^{=}_J$ are weights that must be defined to represent the importance of the strong concordance, medium concordance, weak concordance, and indifference sets, respectively.

$$c_{kl} = \frac{\omega_C \times \sum_{j \in J_{C_{kl}}} \omega_j + \omega'_C \times \sum_{j \in J_{C'_{kl}}} \omega_j + \omega''_C \times \sum_{j \in J_{C''_{kl}}} \omega_j + \omega^{=}_J \times \sum_{j \in J^{=}_{kl}} \omega_j}{\sum_{j=1}^{n} \omega_j} \tag{D.10}$$

Discordance Matrix

The Discordance matrix, D, is determined by considering the three discordance sets, $J_{D_{kl}}$, $J_{D'_{kl}}$, and $J_{D''_{kl}}$. Each element of D, denoted as d_{kl}, is determined by Eq. (D.11), where ω_D, ω'_D, and ω''_D are weights that must be defined to represent the importance of the strong discordance, medium discordance, and weak discordance sets, respectively.

$$d_{kl} = \frac{\max\limits_{j \in J_{D_{kl}} \cup J_{D'_{kl}} \cup J_{D''_{kl}}} \{\omega_D \times d(\omega_j L(p)_{kj}, \omega_j L(p)_{lj}), \omega'_D \times d(\omega_j L(p)_{kj}, \omega_j L(p)_{lj}), \omega''_D \times d(\omega_j L(p)_{kj}, \omega_j L(p)_{lj})\}}{\max\limits_{j \in J} d(\omega_j L(p)_{kj}, \omega_j L(p)_{lj})} \tag{D.11}$$

The distance between two PLTSs, $d(L^a(p), L^b(p))$, is given by Eq. (D.12), where θ is a parameter defined by the decision-maker, $\#l$ denotes the maximum number of terms in the sets $L^a(p)$ and $L^b(p)$, $g(s_\rho)$ is a function such that $g : [-\tau, \tau] \to [0, 1]$, $g(s_\rho) = \frac{\rho}{2\tau} + \frac{1}{2}$ and τ is the subscript of the maximum linguistic term.

$$d(L^a(p), L^b(p)) = \theta \frac{1}{\#l} \sum_{i=1}^{\#l} \left| g(s^a_{\rho(i)}) - g(s^b_{\rho(i)}) \right| + (1-\theta) \sqrt{\frac{1}{2} \sum_{t=-\tau}^{\tau} \left(\sqrt{s^a_t(p)} - \sqrt{s^b_t(p)} \right)^2} \tag{D.12}$$

Outranking Relations

Finally, the concordance and discordance matrices are exploited to build the outranking relations. Three concordance thresholds are required, that is, c^-, c^0, and c^*, such that $0 < c^- < c^0 < c^* < 1$. Two discordance thresholds are required, that is, d^0 and d^*, such that $0 < d^0 < d^* < 1$. Two outranking relations can be formed, the strong outranking relation S^F and the weak outranking relation S^f. In order for alternative k to strongly outrank alternative l Eqs. (D.13) and (D.14) must hold.

$$kS^F l \iff \begin{cases} C_{kl} \geq c^*, \\ D_{kl} \leq d^*, \\ C_{kl} \geq C_{lk} \end{cases} \tag{D.13}$$

$$kS^F l \iff \begin{cases} C_{kl} \geq c^0, \\ D_{kl} \leq d^0, \\ C_{kl} \geq C_{lk} \end{cases} \tag{D.14}$$

In order for alternative k to weakly outrank alternative l Eq. (D.15) must hold.

$$kS^f l \iff \begin{cases} C_{kl} \geq c^-, \\ D_{kl} \leq d^*, \\ C_{kl} \geq C_{lk} \end{cases} \tag{D.15}$$

Rank Alternatives

To rank the alternatives the strong and weak outranking relation graphs must be drawn and they must be exploited. If an alternative k strongly outranks an alternative l then a directed edge is drawn from node k to node l in the strong outranking graph. If k weakly outranks l then a directed edge is drawn from node k to node l in the weak outranking graph. The graphs can be exploited according to the decision-maker to determine a forward and backward ranking, ν_1 and ν_2. The rankings can then be combined to determine the final ranking, $\bar{\nu} = \frac{\nu_1+\nu_2}{2}$.

Appendix E

Top 15 Ontologies by Different ELECTRE Algorithms

The top 15 ontologies ranked by the 4 ELECTRE algorithms are explored in this Appendix. The first column represents the index of the ontology, where $1 \leq i \leq 200$. The second column represents the abbreviated ontology name. The next 4 columns signify the rank given by the ELECTRE I, II, III, and IV algorithms, respectively. If the algorithm assigned a rank that was not in the top 15 then the column is marked with a -. The last column provides a brief summary of each ontology.

TABLE E.1: Ontologies O_6 to O_{96}

Index	Name	E I	E II	E III	E IV	Summary
O_6	NCCN EHR	11	-	5	-	Provides the public with an oncology history categories list, and their synonyms.
O_{10}	ALLERGY	-	-	4	-	Defines concepts that aim to enable detection of allergies.
O_{14}	STO	10	12	2	3	Comprises stroke related knowledge obtained from experts and research.
O_{21}	OMP	15	-	-	-	Comprises phenotypes observed in microbes (viruses, protists, fungi, bacteria).
O_{33}	PCO	-	-	10	-	Contains knowledge related to collections of interacting organisms, such as communities and populations.
O_{54}	OCMR	-	1	9	10	Represents medical information related to anti-rheumatism Chinese medicines.
O_{60}	URGENCES	3	3	6	14	A health ontology containing knowledge regarding emergency care.
O_{62}	PTS	7	8	-	15	Comprises integrated knowledge between various pathway types and biological events.
O_{82}	CMPO	5	13	14	11	Contains phenotypic descriptions for cellular microscopy.
O_{96}	OBI	-	14	-	8	Comprises knowledge regarding biological and medical investigations.

TABLE E.2: Ontologies O_{99} to O_{195}

Index	Name	E I	E II	E III	E IV	Summary
O_{99}	VO	-	-	-	4	Enable integration and standardization amongst vaccines and their components, mechanisms, and data types.
O_{100}	OCVDAE	12	-	-	-	Centered around adversaries associated with drugs, in relation to cardiovascular diseases.
O_{107}	OHMI	13	11	11	7	Composed of host-microbiome interactions, along with their entities and relations.
O_{111}	OHPI	6	6	12	9	Models knowledge pertaining to the interactions of host-pathogens.
O_{112}	IDOBRU	-	15	-	12	Contains knowledge related to brucellosis, the most common bacterial zoonotic disease.
O_{114}	OAE	14	-	-	-	Made up of knowledge pertaining to adverse events due to medical intervention.
O_{119}	PDO	9	-	3	5	Made up of knowledge regarding the Parkinson's domain from a molecular and clinical perspective.
O_{125}	BCGO	-	-	15	-	Is based on breast cancer diagnostics and allocates a grading to a tumor.
O_{130}	CLO	4	2	13	13	Models knowledge pertaining to biological cell lines, with an emphasis on those cell lines that are permanent and from culture collections.
O_{153}	COGAT	8	5	-	-	Models knowledge pertaining to cognitive science with the aim of characterizing the state of current thought.
O_{171}	SCHEMA	-	-	-	6	Enables webmasters to markup HTML pages in ways recognizable to most search providers, eliciting data interoperability.
O_{179}	OBOE	-	7	-	-	Based on representing scientific measure and observations, with the intention of eliciting clarification among observations.
O_{180}	MHCRO	2	9	7	1	Defines the Major Histocompatibility Complex restriction in experiments.
O_{184}	MSTDE-FRE	-	4	-	-	Knowledge of digestive endoscopy, particularly the Minimal Standard Terminology for digestive endoscopy.
O_{193}	CIO	-	-	8	-	Has the purpose of assessing the confidence of annotations in order to enhance analyses in biology.
O_{195}	PLANP	1	10	1	2	Comprises phenotypes from the planarian Schmidtea Mediterranean.

The top 15 ontologies from each ELECTRE algorithm can be downloaded from the following locations.

TABLE E.3: Location of Top 15 Ontologies

Index	Location
O_6	https://bioportal.bioontology.org/ontologies/NCCNEHR
O_{10}	https://bioportal.bioontology.org/ontologies/ALLERGYDETECTOR
O_{14}	https://bioportal.bioontology.org/ontologies/STO-DRAFT
O_{21}	https://bioportal.bioontology.org/ontologies/OMP
O_{33}	https://bioportal.bioontology.org/ontologies/PCO
O_{54}	https://bioportal.bioontology.org/ontologies/OCMR
O_{60}	https://bioportal.bioontology.org/ontologies/ONTOLURGENCES
O_{62}	https://bioportal.bioontology.org/ontologies/PTS
O_{82}	https://bioportal.bioontology.org/ontologies/CMPO
O_{96}	https://bioportal.bioontology.org/ontologies/OBI
O_{99}	https://bioportal.bioontology.org/ontologies/VO
O_{100}	https://bioportal.bioontology.org/ontologies/OCVDAE
O_{107}	https://bioportal.bioontology.org/ontologies/OHMI
O_{111}	https://bioportal.bioontology.org/ontologies/OHPI
O_{112}	https://bioportal.bioontology.org/ontologies/IDOBRU
O_{114}	https://bioportal.bioontology.org/ontologies/OAE
O_{119}	https://bioportal.bioontology.org/ontologies/PDON
O_{125}	https://bioportal.bioontology.org/ontologies/BCGO
O_{130}	https://bioportal.bioontology.org/ontologies/CLO
O_{153}	https://bioportal.bioontology.org/ontologies/COGAT
O_{171}	https://bioportal.bioontology.org/ontologies/SCHEMA
O_{179}	https://bioportal.bioontology.org/ontologies/OBOE
O_{180}	https://bioportal.bioontology.org/ontologies/MHCRO
O_{184}	https://bioportal.bioontology.org/ontologies/MSTDE-FRE
O_{193}	https://bioportal.bioontology.org/ontologies/CIO
O_{195}	https://bioportal.bioontology.org/ontologies/PLANP

Appendix F

Bottom 15 Ontologies by Different ELECTRE Algorithms

The bottom 15 ontologies ranked by the 4 ELECTRE algorithms are explored in this Appendix. The first column represents the index of the ontology, where $1 \leq i \leq 200$. The second column represents the abbreviated ontology name. The next 4 columns signify the rank given by the ELECTRE I, II, III, and IV algorithms, respectively. If the algorithm assigned a rank that was not in the top 15 then the column is marked with a -. The last column provides a brief summary of each ontology.

TABLE F.1: Ontologies O_4 to O_{49}

Index	Name	E I	E II	E III	E IV	Summary
O_4	ISO19115DTC	199	196	193	196	Models knowledge pertaining to the Date Type Codes for the ISO 19115 standards.
O_{24}	GCO	-	-	193	-	Made up of knowledge regarding the division of an organism's genetic information according to its physical partitioning into various components.
O_{25}	APANEURO	-	-	187	-	Comprises knowledge related to the fields of both neuropsychology and neurology.
O_{26}	PHAGE	190	187	-	190	Is made up of knowledge related to the analysis of phylogenetics and related activity.
O_{27}	ITEMAS	-	186	-	-	Is concerned with innovative medical technology within the public healthcare domain.
O_{29}	ECP	-	188	-	-	Represents data regarding care plans, along with the relationships between those care plans.
O_{30}	CSO	196	190	191	192	CSO comprises knowledge describing general clinical studies.
O_{49}	LMMA	-	-	-	186	Represents knowledge related to mouse lungs, including cells, such as, endothelial cells, connective tissue cells, and subendothelial tissue cells.

TABLE F.2: Ontologies O_{55} to O_{149}

Index	Name	E I	E II	E III	E IV	Summary
O_{55}	LEGALAPA	-	-	194	-	Represents knowledge regarding a test with the APA ontology legal cluster.
O_{56}	OCUMPLOY	-	-	188	-	Models employee, occupational and organizational knowledge, such as career areas, job characteristics, and occupational groups.
O_{59}	EP	187	-	-	-	Comprises knowledge representing single-channel electrophysiological experiments and data.
O_{65}	MINERAL	195	195	-	195	Contains knowledge related to minerals and materials, including classes related to solid substances and substance forms.
O_{70}	COMPUTER	-	-	197	-	Made up of knowledge regarding computers and systems related aspects, such as computer applications, computer media, education training.
O_{72}	REPO	188	-	189	189	REPO models knowledge in relation to the productive traits of livestock and phenotypes.
O_{75}	RVO	-	189	-	-	RVO comprises research variables and can be applied to record research regarding empirical data analytics.
O_{76}	APATREAT	-	-	190	-	Relates to treatment and rehabilitation concepts within the healthcare domain.
O_{84}	CWD	192	-	192	191	Comprises knowledge regarding health behavior, human performance, and biometrics, with the aims of tailored public health.
O_{88}	MF	191	192	-	194	Represents knowledge related to the mental functions and functionalities.
O_{105}	EGO	194	197	-	198	A biomedical ontology that represents data analysis knowledge regarding integrative epigenomes.
O_{110}	COPD	186	-	186	188	Contains knowledge regarding chronic obstructive pulmonary disease in routine clinical databases.
O_{141}	LHN	198	199	198	199	Made up of knowledge regarding the nesting behavior of the Loggerhead sea turtle, known as the Caretta caretta.
O_{149}	FACTORS	200	198	200	197	Comprises the value set of the International Classification of Traditional Medicine, specifically the Other Factors property.

TABLE F.3: Ontologies O_{162} to O_{198}

Index	Name	E I	E II	E III	E IV	Summary
O_{162}	REX	197	200	199	200	Made up of knowledge related to microscopic and macroscopic physico-chemical processes.
O_{167}	MATRROCK	194	-	-	-	Models knowledge regarding the materials composing rocks.
O_{168}	STATISTIC	-	-	195	-	An ontology that comprises statistical analysis and design related aspects, such as statistical reliability, validity and statistical theory.
O_{174}	LEGALAPA	-	-	196	-	Includes classes regarding legal personnel, legal issues, and criminal offenses.
O_{186}	HO	193	191	-	-	Contains histological knowledge regarding the human cardiovascular system, relating to issues such as fundamental tissues, organs, and cells.
O_{190}	LMHA	-	-	-	187	Related to aspects concerning the human lungs and its associated concepts.
O_{198}	OGSF	189	194	-	-	A genetic epidemiology ontology that models the genetic susceptibility of diseases and adverse events .

The bottom 15 ontologies from each ELECTRE algorithm can be downloaded from the following locations.

TABLE F.4: Location of Bottom 15 Ontologies

Index	Location
O_4	https://bioportal.bioontology.org/ontologies/ISO19115DTC
O_{24}	https://bioportal.bioontology.org/ontologies/GCO
O_{25}	https://bioportal.bioontology.org/ontologies/APANEUROCLUSTER
O_{26}	https://bioportal.bioontology.org/ontologies/PHAGE
O_{27}	https://bioportal.bioontology.org/ontologies/ITEMAS
O_{29}	https://bioportal.bioontology.org/ontologies/ECP
O_{30}	https://bioportal.bioontology.org/ontologies/CSO
O_{49}	https://bioportal.bioontology.org/ontologies/LUNGMAP-MOUSE
O_{55}	https://bioportal.bioontology.org/ontologies/LEGALAPA
O_{56}	https://bioportal.bioontology.org/ontologies/APAOCUEMPLOY
O_{59}	https://bioportal.bioontology.org/ontologies/EP
O_{65}	https://bioportal.bioontology.org/ontologies/MINERAL
O_{70}	https://bioportal.bioontology.org/ontologies/APACOMPUTER
O_{72}	https://bioportal.bioontology.org/ontologies/REPO
O_{75}	https://bioportal.bioontology.org/ontologies/RVO
O_{76}	https://bioportal.bioontology.org/ontologies/APATREATMENT
O_{84}	https://bioportal.bioontology.org/ontologies/CWD
O_{88}	https://bioportal.bioontology.org/ontologies/MF
O_{105}	https://bioportal.bioontology.org/ontologies/EGO
O_{110}	https://bioportal.bioontology.org/ontologies/COPDO
O_{141}	https://bioportal.bioontology.org/ontologies/LHN
O_{149}	https://bioportal.bioontology.org/ontologies/TM-OTHER-FACTORS
O_{162}	https://bioportal.bioontology.org/ontologies/REX
O_{167}	https://bioportal.bioontology.org/ontologies/MATRROCK
O_{168}	https://bioportal.bioontology.org/ontologies/APASTATISTICAL
O_{174}	https://bioportal.bioontology.org/ontologies/LEGALAPATEST2
O_{186}	https://bioportal.bioontology.org/ontologies/HO
O_{190}	54https://bioportal.bioontology.org/ontologies/LUNGMAP_H_CELL
O_{198}	https://bioportal.bioontology.org/ontologies/OGSF