



**İSTANBUL UNIVERSITY-CERRAHPAŞA
INSTITUTE OF GRADUATE STUDIES**



M.Sc. THESIS

**ENHANCING A FOOD WASTE ASSESSMENT MODEL BY IMPLEMENTING
AN INTUITIONISTIC FUZZY COGNITIVE MAP APPROACH**

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June, 2022

THESIS ACCEPTANCE AND APPROVAL

This thesis titled **Thesis Title** ", prepared by under the supervision of **Prof. Dr.** , was accepted as a **M.Sc. Thesis** after being **consensus** approved by our jury as a result of the exam held on **08/06/2022**.

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DECLARATION

I hereby declare that this thesis is my own work, I have not had engaged in any unethical behavior at any of the stages from planning to the writing of the thesis, I have obtained all the information in this thesis within the limits of the academic and scientific ethical rules, I have cited all the information and comments being obtained in this thesis study, and I have included these references in the list of references. During the analysis and writing stages of this thesis, I accept that I have abided by the patent and copyright rights and therefore I myself take all kinds of legal responsibility.

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FUNDING

THESIS TITLE

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June, 2022

Oğuz EMİR

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LIST OF SYMBOLS AND ABBREVIATIONS

Abbreviations	Description
BBN	:Bayesian Belief Network
CMs	:Cognitive Maps
EU	:European Union
FAO	:The United Nations Food & Agriculture Organization
FCM	:Fuzzy Cognitive Map
FLI	:Food Loss Index
FWI	:Food Waste Index
GHG	:Greenhouse Gas
iFCM	:Intuitionistic Fuzzy Cognitive Map
IFSs	:Intuitionistic Fuzzy Sets
MFs	:Membership Functions
NGOs	:Non-Governmental Organisations
SDGs	:Sustainable Development Goals
TFNs	:Triangular Fuzzy Numbers
UNEP	:The United Nations Environment Programme
WRAP	:Waste & Resources Action Programme

GENİŞLETİLMİŞ ÖZET

[YÜKSEK LİSANS TEZİ]

[SEZGİSEL BULANIK BİLİŞSEL HARİTA YAKLAŞIMININ UYGULANARAK GIDA İSRAFI DEĞERLENDİRME MODELİNİN GELİŞTİRİLMESİ]

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İsraf yönetimi, günümüz dünyasında her bir birey için önem teşkil eden evrensel bir konudur. Özellikle gıda israfı ve gıda kayıpları, olumsuz çevresel, sosyal ve ekonomik etkiler göz önüne alındığında önemli ölçüde ilgi görmektedir. Birleşmiş Milletler Gıda ve Tarım Örgütü'nün (2011) yayınlamış olduğu raporda gıda kaybı ve israfının yıllık küresel emisyonların yaklaşık %8'inden sorumlu olduğu tahmin edilmektedir. Buna göre, eğer gıda israfı bir ülke olsaydı, dünyadaki ortalama gıda atığı, dünyada en büyük sera gazı yayan üçüncü ülke olarak sıralanırdı. Yetersiz beslenen birçok insanın şu anda dünya çapında mevcut olduğu ve sınırlı doğal kaynakların zamanla tükendiği göz önüne alındığında, sürdürülebilir kalkınma için uygun israf yönetimi stratejilerine son derece ihtiyaç duyulmaktadır. Gıda atığı konusunun ele alınması karmaşık doğrusal olmayan etkileşimler içerdiğinden, etkili bir modelin seçimi son derecede önemlidir. Bu bağlamda, entegre çevresel değerlendirme modelleri, genellikle araştırmacılar tarafından gizli kalıpları ortaya çıkarmak ve karar vericilere yeni içgörüler sunmak için tercih edilmektedir. Ayrıca bu modeller, çok disiplinli bilgi, veri ve modelleri tek bir çerçevede birleştiren analitik yaklaşımları birlikte barındırmaktadır. Bu çalışmada, belge kodlama

yöntemi kullanılarak sezgisel bulanık kümelerle genişletilmiş bir bulanık bilişsel harita geliştirilmiştir. Ardından, bu sezgisel bulanık bilişsel harita modeli gıda israfı faktörleri arasındaki etkileşimleri incelemek, potansiyel sebep olan faktörleri araştırmak, bazı politikalara öncelik vermek ve gıda israfını temel olarak azaltmak için kullanılır. Sezgisel bulanık bilişsel harita modelinin oluşturulmasının ardından, sistemdeki karşılıklı ilişkileri netleştirmek ve politika yapıcılar için karar verme sürecini kolaylaştırmak adına varsayımsal senaryo analizleri yapılır. |

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Anahtar kelimeler: | Gıda İsrafı, Bulanık Bilişsel Harita, Sezgisel Bulanık Kümeler, Sezgisel Bulanık Bilişsel Harita, Belge Kodlama |

ABSTRACT

[M.Sc. THESIS]

**[ENHANCING A FOOD WASTE ASSESSMENT MODEL BY IMPLEMENTING AN
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[Recently, waste management has become a global concern that matters to every human being. In waste management cases, food waste is particularly gaining importance when taking into consideration of the negative social, environmental, and economic impacts. For instance, according to the Food and Agriculture Organization of the United Nations, food waste and loss have been predicted to account for roughly 8% of annual greenhouse gas emissions. This ratio would rank food waste as the third-largest greenhouse gas (GHG) emitting country if food wastage were a country. Given that the global population is rapidly increasing over time and many malnourished people are currently available worldwide, appropriate food waste management procedures are significantly needed for long-term sustainable development. The subject of food waste contains many factors, and these factors have complex interactions. Therefore, a robust model is required to capture these conditions perfectly. In line with this purpose, integrated environmental assessment models have been commonly selected to uncover hidden patterns and present new understandings to decision-makers. Furthermore, these models carry analytical approaches that combine multidisciplinary knowledge, models, and data into a

single framework. This project presents a Fuzzy Cognitive Map (FCM) extended with intuitionistic fuzzy sets using the documentary coding method. Then, this intuitionistic FCM (iFCM) is used to explore the interactions between food waste factors, analyse the primary factors and prioritise some policies to diminish food waste. Eventually, several scenario analyses are generated to review interrelationships of the factors in the developed model and facilitate a decision-making process for researchers. |

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Keywords: | Food Waste, Fuzzy Cognitive Map, Intuitionistic Fuzzy Sets, Intuitionistic Fuzzy Cognitive Map, Document Coding |



1. INTRODUCTION

In today's world, waste management is a global concern that matters to every human being. Especially the subject of food waste and loss has received substantial attention from policymakers, international organisations, non-governmental organisations (NGOs), academics and researchers when considering the negative social, environmental, and economic impacts (Papargyropoulou et al., 2014). While the global population is rapidly increasing over time and is forecasted to reach 8.6 billion in 2030 and 9.8 billion in 2050, reducing food waste and loss is vital to achieving long-term sustainable development (United Nations, 2017). Due to the rapid population growth and changing consumption habits globally, the risk of depletion of limited natural resources may be probable unless shifting toward more sustainable food production and consumption systems. As a result, some efforts, including various methods such as food diaries, qualitative surveys, interviews, and nutrition data analysis, have been applied to explore the extent of food waste and reduce food losses. However, despite the emerging awareness of this subject worldwide, the amount of food thrown away has increased over time (Thyberg et al., 2015). Accordingly, international organisations have started to treat this issue determinedly and collaborated to develop new targets. In 2015, all United Nations (UN) member states jointly accepted the 17 Sustainable Development Goals (SDGs). The UN sustainable development targets on food waste include reducing food losses from production to supply chains at the household, retail, and food service level and principally cutting in half global food waste per capita by 2030.

The subject of food waste has been a prominent and exciting case for researchers in the last years, and publications are primarily intensified in defining and estimating the amount of food waste instead of concentrating on the relations between food waste factors within a holistic approach. This study intends to determine the relations between the concepts influencing food waste and inform policymakers, academics, researchers, and others interested in food waste management. For this aim, initially, the literature on this subject is reviewed in depth to gather factors affecting food waste. Hence, the Document Coding method is employed to record all the possible relationships by coding cause and effect concepts. Due to the lack of crisp numbers and the need for fuzzy logic regarding subjective judgments in cause-effect relationships among

concepts, the Fuzzy Cognitive Map (FCM) method is selected in this project to understand possible food waste drivers and their complex causal interactions. FCMs are fuzzy-graphs structures of belief systems and represent fuzzy relations on causal concepts (Kosko, 1986). The FCM approach is frequently used in environmental science to uncover hidden patterns and present new understandings to decision-makers for real-life problems. This technique offers many advantages as the ability to model uncertain and complex relationships, combine different knowledge sources, generate various policy alternatives, and especially the ease of use compared to other methods (Özesmi & Özesmi, 2004).

Furthermore, in this study, the intuitionistic fuzzy sets theory is deployed due to the lack of information. Thus, an intuitionistic Fuzzy Cognitive Map (iFCM) is developed by introducing hesitancy weight factors to the represent lack of information. iFCMs are the enhanced FCMs and powerful tools to cope with situations where hesitations exist. Since food waste interactions are accompanied by uncertainty and data limitation, it is motivated to apply the iFCM method that captures these conditions perfectly. Finally, scenario analyses are performed to discover changes in system concepts. These analyses are generated to observe the system's dynamic behaviour and understand how the factors react to increasing or decreasing the value of other factors. To the best of our knowledge, this study provides the first attempt to collectively analyse and model the food waste factors by integrating the document coding method with iFCM.

The remainder of this thesis is structured as follows: second section starts with a literature review on food waste and loss. This section discretely defines food waste and loss and discusses the systematic literature review phases. The third section supplies the theoretical foundation of methods employed in this project by elaborating on fuzzy logic and cognitive maps. The fourth section expounds on the implementation steps of each technique introduced in the methodology section. Further, this section illustrates the result of constructed iFCM and discusses the generated scenario analyses. The last section outlines concluding remarks and future research directions.

2. CONCEPTUAL FRAMEWORK

Recently, research interest in waste management has escalated, and concerns about food waste and loss have grown substantially considering the negative consequences of social, environmental, and economic impacts. Preventing food waste and loss provides more benefits than other waste management types. The environmental benefits can be obtained by avoiding excess food production and using resources sustainably. This circumstance also implicitly enables economic and social benefits. For example, money can be saved by not purchasing food which is probably disposed of, and excess food can be redistributed to charities (Schott and Canovas, 2015).

Since there is no universally accepted definition in the earlier literature regarding food waste and loss, quantifying and studying food waste is a challenging issue (Thyberg and Tonjes, 2016). Notably, multiple terms have been used interchangeably for items separated from the food supply chain during harvest to consumption with different meanings. Considering the ambiguity between food waste and loss, the literature commonly debates food loss and waste together (Kibler et al., 2018). For this reason, internationally recognised definitions of food loss and waste are needed (Xue et al., 2017). Recently international organisations have been providing a framework for defining food loss and waste. For instance, The United Nations Food & Agriculture Organization (FAO) defines food loss as a decrease in the quality or quantity of food throughout the supply chain for any reason. When it comes to food waste, it is defined as the food initially produced for consumers, but it is discarded or thrown away due to some mismanagement in the food supply chain or a mindful decision (FAO, 2014). Food waste is also usually seen as a subset of food loss and a preventable food loss. Food waste and loss have been distinguished based on the level at which edible food was discarded from the supply chain, with food losses arising former steps of the supply chain and food waste arising in the subsequent phases, where consumer behaviour is a factor. Figure 2.1 provides various food waste definitions from different organisations worldwide.

Organisation	Definition
FAO	Removal of all food products from the supply chain which is allocated for human consumption that is thrown away
European Commission	Food (including inedible parts) lost from the food supply chain, not including food diverted to material uses such as bio-based products, animal feed, or sent for redistribution
United States Environmental Protection Agency (USEPA)	Uneaten food and food preparation wastes from residences, commercial and institutional establishments
US Department of Agriculture	A subset of food losses; occurs when an item still edible is at the time of disposal which is not consumed

Figure 2.1: Food waste definitions (adapted from Thyberg and Tonjes, 2016).

Food waste is increasingly gaining importance in the evolving waste management field in recent years. The amount of food wastage grown worldwide causes high environmental, economic, and social impacts, such as greenhouse gas emissions, soil erosion, water and air pollution, deforestation, depletion of natural resources, inequality, and poverty (Morone, Falcone and Lopolito, 2019; Schanes, Dobernig and Gözet, 2018). As reported by the FAO (2011), food waste and loss have been predicted to account for roughly 8% of annual greenhouse gas emissions. This ratio would rank food waste as the third-largest greenhouse gas (GHG) emitting country if food wastage were a country. Waste & Resources Action Programme (WRAP) is a United Kingdom (UK) based charity that collaborates with businesses, organisations, and governments to make the world a better place where resources are used sustainably. WRAP has published a report that aggregates evidence on food waste attitudes and behaviours since 2007. In 2011, WRAP reported that the cost of food waste in the UK was around £420 per household per year. Other researchers noted that the cost of food waste in Canada is \$936.52 (von Massow et al., 2019), in Australia \$616 (Baker et al., 2009), and in the US almost \$590 (Jones, 2005) per household per year. Recently, WRAP (2020a) estimated that the cost of food waste in the UK is approximately £500 per household per year, corresponding to £13.8 billion annually. As for the social impact, the quantity of food wasted in developed countries is around 222 million tonnes, equal to Sub-Saharan Africa's whole net food production of roughly 230 million tonnes (Gustavsson et al., 2011).

The increasing population and consumption trend worldwide lead to the depletion of limited natural resources unless shifting toward more sustainable food production and consumption systems. In line with the increasing global demand, sustainable action plans are both essential and urgent to reduce food waste and loss (Thyberg and Tonjes, 2016). Due to the data availability and variability, estimating the amount of food waste is a challenging and interesting

case for researchers. Recently, international organisations have taken this work seriously with the intensified attention to the topic and have been working on measuring food loss and waste. FAO is one of the organisations of the United Nations working in 130 countries worldwide to achieve food security and provide access to enough food for everyone. In 2011, FAO reported that approximately one-third of food produced for consumers is lost or wasted globally, corresponding to a notable amount of the global food supply, roughly 1.3 billion tons per year. FAO (2011) also estimated the regional per capita amount of food waste by consumers for some continents. For example, the per capita amount of food waste for Europe and North America is estimated between 95 to 115 kg/year; on the other hand, Africa and South/Southeast Asia are estimated between 5 to 11 kg/year. According to a technical report published in October 2010 and presented to European Commission by BIO Intelligence Service, 42 per cent of all food produced is wasted in the final consumption phase of the food supply chain in Europe. In this report, it has been estimated that citizens of the European Union (EU) throw away almost 76 kg of food per capita per year (Monier et al., 2011). Stenmarck et al. (2016) measured the food waste for 28 EU countries by employing extrapolation from the available data for eleven countries. The analyses resulted that between 46.7 per cent and 63.5 per cent of the total EU food waste is generated from households.

In September 2015, all United Nations (UN) member states jointly accepted the 17 Sustainable Development Goals (SDGs) for their 2030 agenda. In line with the 17 goals determined, roadmaps have been generated for the most urgent global challenges such as poverty, hunger, climate change, water, and energy for sustainable development. Further, 230 indicators have been established to monitor and track these ambitious goals with support from international agencies, the private sector, civil societies, and other institutions. SDG indicators provide some insights regarding the status of the member states of the UN for the 2030 plan. For example, according to SDG 12.3, it is desired to reduce food losses from manufacturing to consumption at the household, retail, and food service level and cutting in half global food waste per capita by 2030.

The Food Loss Index (FLI) is one of the indicators developed by FAO (2018) that concentrates on food losses and measures losses for critical commodities in a nation across the supply chain except for the retail level. Although limited data is available, it is forecasted that approximately 14 per cent of the world's food is lost globally in the food loss index. In complement to Food Loss Index, The United Nations Environment Programme (UNEP) published the first Food

Waste Index (FWI) report in March 2021 by providing the scale of food waste, measurement methodology and additional information to enable countries to measure their baseline and track progress along with the SDG target. This recently published report estimates that approximately 931 million tonnes of food waste are generated with the distributions of 61 % from households, 26 % from food service, and 13 % from retail respectively.

The initial purpose of the literature review in this study is to examine the existing literature and studies on food waste. Due to the robust research engine, the academic database of Web of Science is used in the literature review. Firstly, the keyword of food waste only in the article titles has been searched since 2011 to check the recent literature. This search shows 4,110 article results from the Web of Science database. Considering the number of articles published by year, figure 2.2 proves that food waste research has gained importance in the last years. When research areas of published articles are checked, most papers can be seen under the environmental science, engineering, and sustainability research categories.

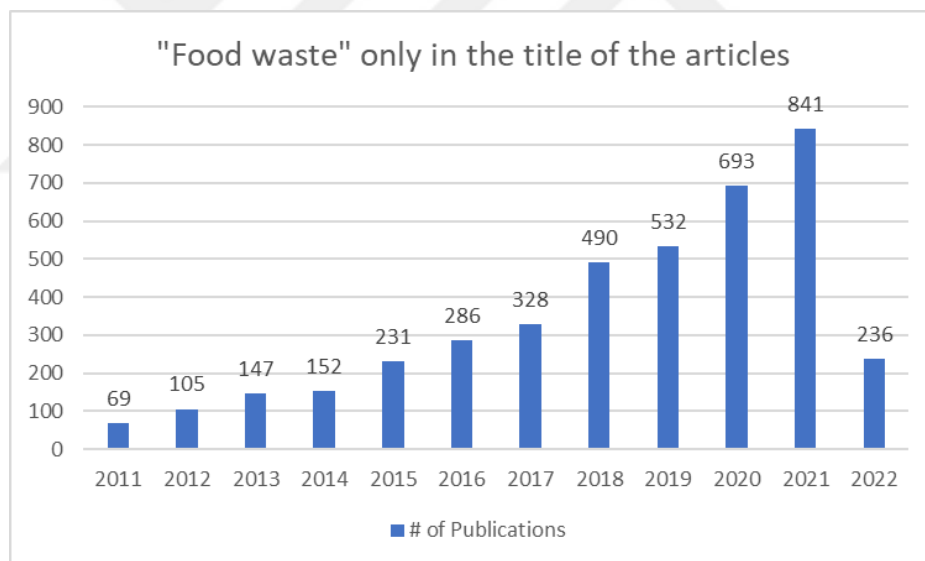


Figure 2.2: Yearly publication numbers of food waste titled articles.

In the initial review of the articles in general, it is realised that it is challenging to find a study that focuses on food waste minimization within a holistic approach. Recently, integrated environmental assessment models have been commonly selected to uncover hidden patterns and present new understandings to decision-makers for complex real-life problems, especially in the field of environmental science. In this regard, integrated environmental assessment models of Bayesian Belief Network (BBN) and Fuzzy Cognitive Map (FCM) are selected for a detailed literature search. These approaches are frequently used in different environmental

applications. Then, these methods are included in literature search combinations within the scope of food waste to understand possible food waste drivers and their complex interactions. However, it is also found that there is not enough study published yet that implements these integrated models for food waste. Due to the scarcity of resources in the field, the literature review is extended by using different search combinations. For instance, a quick filter of "highly cited papers" is applied to review the top food waste papers for the last ten years. The highly cited papers filter shows the papers that received enough citations to be placed in the top 1% of the relevant academic fields. In addition, articles that applied mathematical modelling and decision support system approaches in the food waste area have been searched to elicit more information and gather food waste drivers. Table 2.1 indicates the different search combinations used in the literature review. In the below table, there are some field tags specifically used in the Web of Science. For example, "ALL" stands for all fields and allows to find the search term in any field. "TS" stands for topic and searches title, abstract, author, and keywords in the database. Lastly, "TI" stands for title and searches for article titles. The literature search is also limited to peer-reviewed journal papers published in English in this study.

Table 2.1: Search combinations used in the literature review.

No	Search combinations	Timespan
1	(TI=(food waste)) AND only highly cited articles	2011-2022
2	TS=(mathematical modelling) AND TS=(food waste)	2011-2022
3	TS=(decision support systems) AND TS=(food waste)	2011-2022
4	(TI=(food)) AND ALL=(bayesian network)	1975-2022
5	(ALL=(food)) AND ALL=(fuzzy cognitive map)	1975-2022

In the first phase of the literature flow, 825 papers are found in total from the initial results of each search combination. After that, the obtained articles are checked manually by reading through the abstracts in the second phase. In this phase, papers that primarily deal with food waste and loss reduction are selected for the next phase. In the third phase, selected papers are reviewed in detail. The identified articles are mainly checked by screening the relevance of the introduction, methodology, and conclusion parts. Some exclusion criteria are determined for further reading. Studies that consider food waste recovery programs such as landfilling, and incineration are excluded. In addition, studies that apply biological treatments such as anaerobic digestion and composting are also excluded. In short, food waste disposal studies are excluded from the full paper reading step. Above all, the articles which do not seek to reduce food waste

and analyse the interaction of the driving factors are removed from the article pool. After eliminating articles based on the exclusion criteria, full paper readings for the remaining articles are carried out. At the end of the third phase, 18 articles are selected. Table 2.2 demonstrates the selected number of papers in each phase separately.

Table 2.2: Selected number of papers in each phase.

Search combinations	Phase I # of papers	Phase II # of papers	Phase III # of papers
(TI=(food waste)) AND only highly cited articles	61	19	5
TS=(mathematical modelling) AND TS=(food waste)	325	32	6
TS=(decision support systems) AND TS=(food waste)	287	29	2
(TI=(food)) AND ALL=(bayesian network)	83	13	4
(ALL=(food)) AND ALL=(fuzzy cognitive map)	69	7	1

During this phase, it is noticed that most of the existing studies have intensified on measuring or estimating the amount of food waste. In contrast, a few studies have investigated factors driving food waste and loss. In the next phase, the article pool is further developed by checking the references of selected articles through the snowballing technique. This systematic review resulted in a complete list of 22 articles, including four additional articles. The flow of the literature review phases is illustrated in figure 2.3.

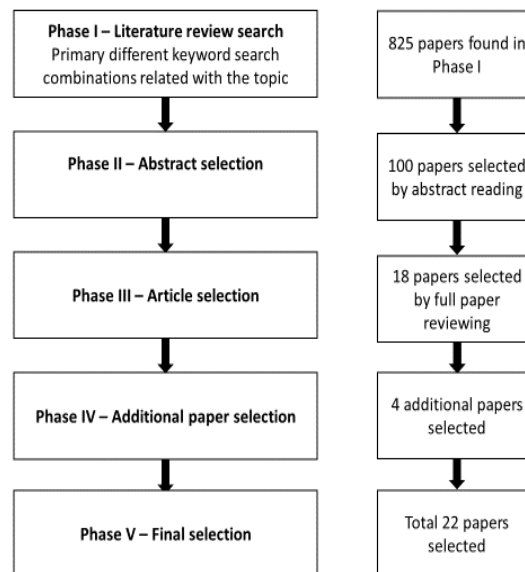


Figure 2.3: Literature review flow.

Figure 2.4 displays the number of papers selected in the literature analysis between 2011- 2022.

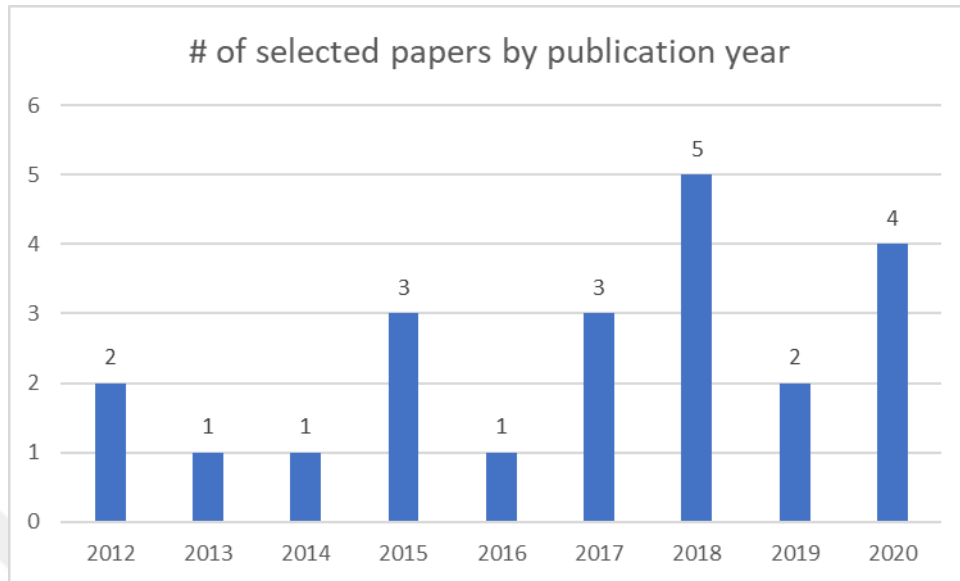


Figure 2.4: Yearly publication numbers of selected papers.

Table 2.3 shows the final selected articles' authors, source titles, concepts, and methods. There are 22 articles from 16 different journals in the final literature review list. This also indicates the variety of sources available in the existing literature focusing on food waste and loss. Further, the "Journal of Cleaner Production" journal stands out with the eight articles from the final list. This situation shows that the journal gives high importance to studies on food waste.

Irani et al. (2018) investigated food waste drivers' relationship to ensure food security through waste reduction. In line with this purpose, the fuzzy cognitive map technique is selected to elucidate the dynamic interrelationships of organisational factors. Furthermore, expert knowledge is used to develop a causal-effect model by conducting workshops with participants from the demand and supply sides of the supply chain. A total of 34 participants have been actively involved in model building and quantifying weights between factors. Simulation results of the developed model have pointed out some factors in a causal sense in reducing food waste, such as food market competition, easiness of market access, and level of bureaucracy.

Table 2.3: Final literature review article list.

Author(s)	Source Title	Concept	Method Used
Song, Semakula, and Palmer (2018)	Journal of Cleaner Production	Household food waste	Bayesian Belief Network
Zhang et al. (2020)	Soft Computing	Fresh food	Bayesian Belief Network
Yang and Zhen (2020)	Environmental Research Letters	Household food consumption	Fuzzy Cognitive Map
Irani et al. (2018)	Computers & Operations Research	Food security	Fuzzy Cognitive Map
Kleemann et al. (2017)	Ecological Complexity	Food security	Bayesian Belief Network
Morone, Falcone and Lopolito (2019)	Journal of Cleaner Production	Food consumption	Fuzzy Cognitive Map
Chai, Shi, Lu and Hu (2020)	Journal of Cleaner Production	Food production & consumption	Bayesian Belief Network
Stancu, Haugaard and Lahteenmaki (2016)	Appetite	Consumer food waste behaviour	Statistical Analysis
Banasik et al. (2017)	Annals of Operations Research	Perishable products	Mathematical Modelling
Iqbal, Kang, and Jeon (2020)	Journal of Cleaner Production	Zero waste for green supply chain	Mathematical Modelling
Sakoda, Takayasu and Takayasu (2019)	Sustainability	Retail food waste	Mathematical Modelling
Stefan et al. (2013)	Food Quality and Preference	Household food waste	Statistical Analysis
Williams et al. (2012)	Journal of Cleaner Production	Household food waste	Statistical Analysis
Secondi, Principato and Laureti (2015)	Food Policy	Household food waste	Statistical Analysis
Katajajuuri et al. (2014)	Journal of Cleaner Production	Food supply chain	Statistical Analysis
Adenso-Díaz, Lozano and Palacio (2017)	Applied Mathematical Modelling	Perishable products	Mathematical Modelling
Janssen et al. (2018)	Computers & Industrial Engineering	Perishable products	Mathematical Modelling
Soysal et al. (2015)	International Journal of Production Economics	Perishable products	Mathematical Modelling
Grainger et al. (2018)	Global Food Security	Household food waste	Bayesian Belief Network
Principato, Secondi and Pratesi (2015)	British Food Journal	Household food waste	Statistical Analysis
Morone et al. (2018)	Journal of Cleaner Production	Food-sharing	Statistical Analysis
Koivupuro et al. (2012)	International Journal of Consumer Studies	Household food waste	Statistical Analysis

Morone, Falcone and Lopolito (2019) focused on factors driving the food waste and followed a three-step methodology to prevent current unsustainable food consumption. Initially, food waste system variables are identified, and causal-effect relationships of each variable are determined to create the influence diagram for the fuzzy cognitive map technique. Next, eighteen concept variables are identified, and the FCM diagram is derived by interviewing eight experts. Then, fuzzy inference simulations reveal the most crucial waste drivers. Among 18 concept variables, public food waste regulations, investment and infrastructure, and small-scale farming variables showed effective results in terms of supporting the sustainable consumption.

Yang and Zhen (2020) performed a fuzzy cognitive map to quantitatively evaluate the drivers that influence food consumption in the local rural region of households in China. The study's objective is to explore key food consumption factors and reveal hidden relations between these factors among families. Interviews are conducted with residents of Xilin Gol Grassland, one of the country's most extensive grassland areas, and statistical data including gross domestic product, population and income are obtained to provide empirical analysis for future research and policy development. Based on the interviews, 28 various drivers are collected and classified into four groups as ecological, social, economic, and personal drivers. Personal and ecological drivers are the most critical drivers of the four classified groups: consumption habits, age, and livestock numbers. Song, Semakula, and Palmer (2018) estimated the food waste of typical Chinese provinces by combining household survey data and life-cycle assessment datasets. Also, a BBN model is created to establish the critical food waste drivers and predict food waste reduction possibilities by scenario analysis. Seven key variables are determined, and Netica software is used to develop BBN. In total, 21 scenarios are generated to reveal the significant variables, and sensitivity analysis is performed to estimate the overall performance of the model. The developed model resulted in an accuracy of 78% in predicting household food waste possibilities. In the end, refrigerator ownership is found as the top factor contributing to food waste generation.

Katajajuuri et al. (2014) concentrated on establishing the amount of avoidable food waste in the entire Finnish food supply chain. A kitchen diary procedure is performed for households to weigh their daily discarded food in two weeks for household analysis. Based on participant data, it is estimated that there is approximately 23 kilogram of food waste per person or 63 kilogram per household in Finland. The ratio of avoidable food waste to the purchased food amount is measured at almost 4-5%. Also, it is realised that most of the discarded food is

perishable products or leftover foods from cooking. In addition, a questionnaire is designed to discover reasons for food waste in detail in terms of socio-demographic, behavioural and attitudinal factors. According to questionnaire results, food is mainly discarded due to spoilage, mouldy, leftovers from dining, and prepared over needs. Williams et al. (2012) investigated the reasons for household food waste and primarily focused on more packaging related food waste. The kitchen diary method is used to collect data from two distinct groups of participants to explore packaging aspects concerning household food waste. These two groups have similar demographic properties. However, the only difference is that one group received environmental education prior to the kitchen study. This study has indicated that packaging is one of the fundamental factors influencing the amount of food waste in households and relates to 20-25% of food waste.

Stefan, van Herpen, Tudoran and Lahteenmaki (2013) examined food choices and consumer habits and investigated food waste from a food-related behaviour standpoint to identify potential drivers. For this purpose, a web-based questionnaire is designed and sent to Romanian consumers responsible for cooking or shopping in their households. After collecting responses from 244 participants, a two-stage empirical analysis is implemented. Firstly, preliminary confirmatory factor analysis and then a structural equation model are implemented to check the validity of the measurement scales. Based on the results, the model is found consistent. The responses of consumers on their self-reported food waste pointed out that shopping and planning routines are the most significant predictors of food waste behaviour. Secondi, Principata and Laureti (2015) contributed to the literature by proposing a two-level framework considering household food waste behaviour. Researchers explored the behaviour of EU-27 citizens towards food waste according to the survey conducted by European Commission. This framework jointly considers both individual and contextual variables associated with individuals' household food waste behaviour innovatively. Stancu, Haugaard and Lahteenmaki (2016) examined consumers' behaviour and critical factors about consumer food waste. For this purpose, a survey is conducted to 1037 Danes responsible for cooking in their household. The questionnaire is designed to measure food-related routines, household skills, awareness and attitudes toward food waste, and perceived behavioural control of participants. The validity and reliability of the measurement are tested, and it is concluded that the measurement model is valid. Lastly, shopping routines, leftovers reuse routines, and perceived behavioural control are resulted in more significant determinants of food waste.

Chai, Shi, Lu and Hu (2020) explored the interactions between Water-Energy-Food-Economy-Society-Environment Nexus to foresee the vital natural resources in China for sustainable development. Due to the increasing population in China, predicted to reach 1.44 billion by 2030, researchers aim to reveal the causal relationship between nexus variables and predict future demand for water, energy, and food in China by implementing Bayesian networks. In this study, the Document Coding method identifies the causal relationship of the variables and requires an in-depth analysis of relevant literature from similar studies. The Bayesian network is constructed based on expert knowledge and annual data acquired from the China Statistical Yearbook. Three models are built to predict water withdrawal, energy demand and food demand forecasting. Also, interactions between variables are investigated with the developed model to reveal the impacts of changing trends. On the food side, it is concluded that population growth is the most significant factor contributing to the increase of food demand directly proportional.

Kleemann et al. (2017) investigated the regional assessment of food provision in Ghana by developing BBN models to predict food insecurity under different weather and land-use conditions. The models are constructed by using both data-driven and expert knowledge. The developed model demonstrated that extreme weather conditions with high rainfall considerably exacerbate the risk of food insecurity.

Zhang et al. (2020) focused on factors influencing the reliability of perishable products e-commerce logistics systems, and relevant factors are determined based on research and expert knowledge. Bayesian network is used to build a model to investigate the factors to advance the intelligence and reliability of these platforms. The triangular fuzzy number technique is employed to calculate the conditional probabilities due to the finite number of samples collected. This technique can serve as a bridge between numerical values and uncertain fuzzy linguistic variables. The constructed Bayesian network model is used for causal analysis and sensitivity analysis to identify the most significant factors for system reliability. Consequently, the factors of facilities and equipment, external environment, and information technology have the most considerable impact on fresh food e-commerce logistics systems through simulation analysis.

Adenso-Díaz, Lozano and Palacio (2017) investigated the relationship between wasted units and revenue under different dynamic pricing policies. For this, a deterministic mathematical model is developed to examine the influence of some factors under different scenarios. It is

concluded that a dynamic price strategy can remarkably reduce total waste by preventing revenue loss in most cases. Janssen, Sauer, Claus, and Nehls (2018) proposed a new age-based inventory model that considers closing days constraints for perishable items, unlike most models in the literature. Simulation analysis of the developed model achieved an essential amount of waste and cost reduction in grocery stores. It is possible to observe various studies that propose a mathematical model for reducing waste for perishable products (Banasik et al., 2017; Soysal et al., 2015).

Iqbal, Kang, and Jeon (2020) recommended a primary and secondary closed-loop supply chain framework and proposed a nonlinear mathematical model to achieve zero waste for the green supply chain.

Sakoda, Takayasu and Takayasu (2019) concentrated on food waste reduction in the retail. Researchers of the study contributed literature with a practical solution for demand forecasting with non-stationary censored sales data. This solution is combined with the newsvendor problem to establish optimal stock amounts. The numerical analysis of the developed model confirmed that food waste reduction could be achieved by keeping a high profit in the retail sector.

Grainger et al. (2018) used the Eurobarometer dataset conducted by the European Commission in 2014 regarding waste management attitudes of Europeans to establish the drivers of self-assessed food waste. Grainger et al. (2018) used the Eurobarometer dataset conducted by the European Commission in 2014 regarding waste management attitudes of Europeans to determine the drivers of self-assessed food waste. The dataset includes 20 questions about household food waste attitudes and behaviours directed to 26595 households. In addition, a machine learning integrated Bayesian Network method is used to analyse selected fourteen variables to develop a candidate food waste network in the EU. It is concluded that the age of the respondent, the country of the respondent, and the size of the households are significant drivers of food waste.

Principato, Secondi and Pratesi (2015) conducted a questionnaire by addressing 28 questions to 233 university students in Italy to assess youths' knowledge about food waste and identify factors that significantly contribute to changing the behaviours/attitudes toward diminishing food waste. The scope of this study is determined as household food waste which covers food products consumed within the home. The reliability of the survey is tested, and the convenience

sampling design is performed. Responses from university students to the survey reveal that the more educated youths involving food waste, they tend to positively modify their attitudes toward food waste, such as making a shopping list and planning the purchases.

Morone et al. (2018) focused on a different side of food waste reduction: food-sharing practices. Researchers investigated the causal relation between food waste reduction and food-sharing practices by performing framed field experiments on twenty university students living in a private shared flat. The main goal of the experiment is to estimate the effectiveness of food-sharing practices over generated food waste amounts at the household level. The preliminary results showed that households' adoption of food-sharing practices does not directly contribute to reducing food waste amounts. However, this can be achieved by introducing three critical enablers before implementing food-sharing practices. These key enablers are environmental and economic awareness, skills, and collaborative behaviours.

Koivupuro et al. (2012) examined the influences of socio-demographical, attitudinal and behavioural factors on the volume of avoidable food waste by carrying out both a questionnaire and a food waste diary study on 380 Finnish households. After two weeks of food waste diary study accompanied by a questionnaire, statistical analyses are performed to establish the correlation between the possible food waste factors and the amount of avoidable food waste. Consequently, some factors such as household size, gender of the person responsible for shopping, and the respondent's view of food waste emerged by owning high correlation with the amount of avoidable food waste. On the other hand, other prevalent factors did not show a clear correlation, including the age of the respondents, the educational level of the respondents, and the shopping and eating habits of the respondents.

Figure 2.5 indicates the number of methods used in the selected papers of the literature review. The reviewed literature shows that researchers mostly preferred statistical analysis and mathematical modelling methods. However, in recent years, other integrated decision-making methods holding analytical approaches and consolidating multidisciplinary knowledge, data, and models such as BBN and FCM, which also incorporate uncertainty in addressing food waste, have also started to be used.

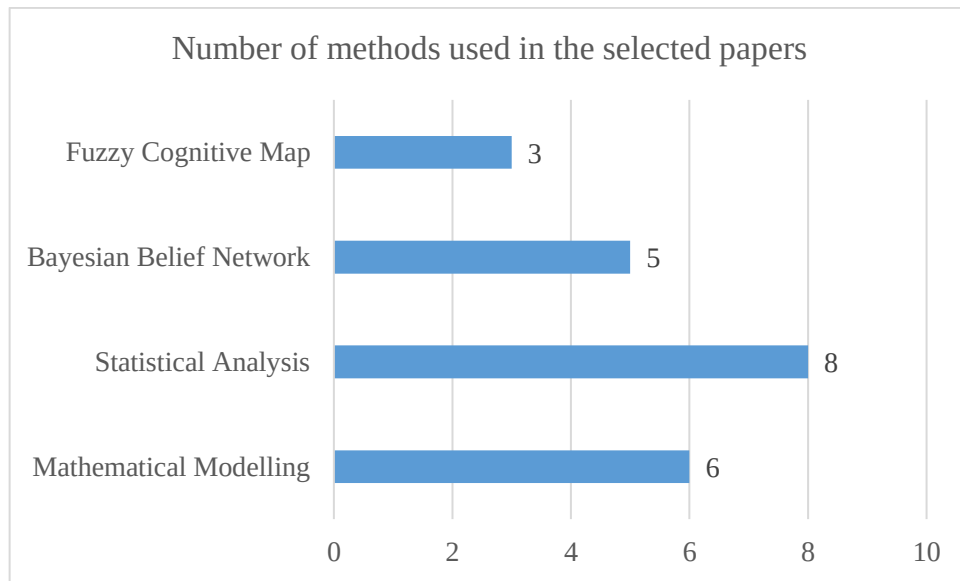


Figure 2.5: Number of methods used in the selected papers.

3. METHOD

This section presents the methods used in this study respectively. The methodology section is divided into two main parts regarding fuzziness and cognitive maps. The first part introduces the theory of fuzzy sets and intuitionistic fuzzy sets. Also, the features and various types of membership functions are clarified. The second part describes the CMs and FCMs by illustrating visual examples. Then, the terminology of the document coding method is shared to build the influence matrix of FCMs. Finally, the FCM tool extended with intuitionistic fuzzy sets is presented.

3.1. BASIC CONCEPT OF FUZZINESS

In the past, the uncertainty has not always been handled enough. As a result, uncertainty was ignored mainly in traditional science and was considered as an undesirable state. Most of the conventional techniques for modelling and computing were crisp and deterministic. Crisp means dichotomous, that is, a statement can be true or false and nothing in between. In set theory, the crisp set is divided into two groups in the given universe of discourse: members (elements that belong to the set) and nonmembers (elements that do not belong to the set). There is a clear distinction between the members and nonmembers of the set (Klir and Yuan, 1995). In conventional dual logic, a statement can be true or false; in optimization, a solution can be feasible or not feasible. Later, scientists realized that methods without uncertainty did not address the problems until the late 19th century. Therefore, new approaches were developed based on a probability theory that captures a form of uncertainty. This new theory, mentioned as random uncertainty, introduced the influence of uncertainty on problems and became popular in science until the late 20th century. However, the statement of uncertainty using probability theory was questioned with the identification of fuzzy sets by Lotfi Zadeh in 1965 (Ross, 2010).

Due to lack of information, real situations are generally uncertain or vague which makes it difficult to know the future state of the system. This situation has been appropriately embraced by probability theory for long years. In this type of probabilistic approach (stochastic character), it is believed that the elements of sets or the statements are well established. However, in fuzziness, the semantic meaning of the events or statements is vague. Fuzziness is frequent in

areas where human judgment, decisions and assessments are considered highly especially in engineering, medicine, manufacturing, and meteorology (Zimmermann, 2001).

3.1.1. Fuzzy Set Theory and Fuzzy Sets

Lotfi Zadeh introduced the first fuzzy set theory in 1965 by introducing the pioneering idea of continuous-valued logic. This set theory provides a mathematical framework to represent fuzziness and vagueness for some situations where fuzzy relations exist. Zadeh also (1965) highlighted that set membership is essential in decision problems where uncertainty exists.

Classical sets hold objects that meet specific membership properties; on the other hand, fuzzy sets hold items that meet the imprecise membership properties. In fuzzy sets, it is possible to observe that the membership of an object can be approximate. For instance, individual elements form a set called A in the universe. In crisp sets, an element x can be either a component of the crisp set A or a nonmember of the crisp set A . This can be shown with the indicator function,

$$\chi_A(x) = \begin{cases} 1, & x \in A \\ 0, & x \notin A \end{cases}$$

where the symbol $\chi_A(x)$ indicates membership of element x in set A .

Zadeh similarly set the endpoints "0" for non-membership, and "1" for full membership on an actual continuous interval $[0,1]$, just like the indicator function in crisp sets. In addition, the concept of binary membership is expanded to various degrees of membership where an infinite number of values exist between the interval of 0 and 1. According to Zadeh (1965), the sets in the universe of discourse that hold "degrees of membership" can be defined as fuzzy sets. Eventually, one can observe the sharp distinction between crisp sets and fuzzy sets regarding their membership function. Crisp sets have a constant membership function, while fuzzy sets can take limitless membership function values. In fuzzy sets, the mathematical notation of membership in a set is symbolized with a tilde underscore, $\underline{A}$, which is given as,

$$\mu_{\underline{A}}(x) \in [0, 1]$$

where the symbol $\mu_{\underline{A}}(x)$ is the degree of membership of element x in fuzzy set $\underline{A}$.

If X is a collection of items indicated generically by x , then a fuzzy set $\underline{A}$ in the universe of discourse:

$$\underline{A} = \{ \langle x, \mu_{\underline{A}}(x) \mid x \in X \rangle \}$$

From a two-dimensional perspective, Figure 3.1 demonstrates abstractions of two set examples in the universe of discourse, called X . Figure 3.1(a) exemplifies a crisp set with specific boundaries, and there is no uncertainty in the location of the set members. The right side of the figure 3.1(b) exemplify a fuzzy set with fuzzy boundaries. When the location of the points is examined in figure 3.1(a), the membership of points can be specified easily. Point a is a component of the crisp set; on the other side, point b is unambiguously not. Figure 3.1(b) displays the uncertain boundary of the fuzzy set $\underline{A}$ and the shaded boundary indicates the boundary region of $\underline{A}$. When the location of the points is examined in figure 3.1(b), point a which is in the central part of the fuzzy set belongs to set with a full membership. Point b , which is located outside of the boundary region, is not a component of the fuzzy set. Lastly, point c , which is located on the border partially belongs to the fuzzy set and takes the intermediate value of membership between 0 and 1.

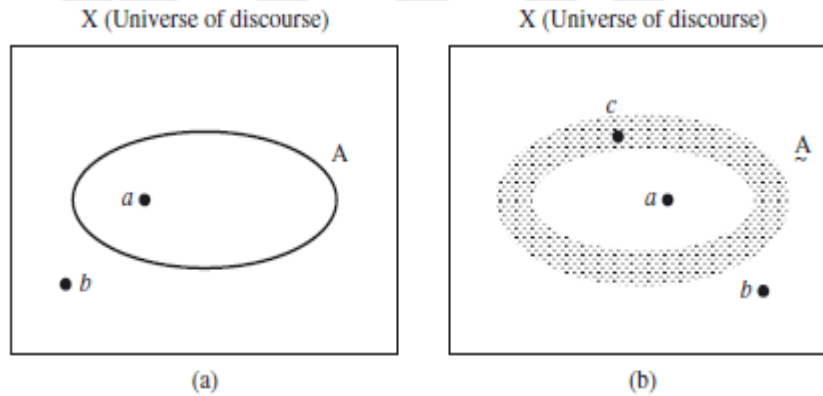


Figure 3.1: (a) crisp set and (b) fuzzy set regions (Ross, 2010).

As mentioned earlier, a fuzzy set can provide a mathematical framework by assigning each element in the universe of discourse a value indicating the grade of membership in the fuzzy set. These individual elements can be represented by real-number values changing in the closed interval of $[0,1]$. Moreover, each element's membership degree can be indicated based on its belongingness in the fuzzy set to a greater or lesser degree. If an element has greater belongingness, this element is indicated by a larger membership degree and vice versa.

A notation rule for fuzzy sets introduced by Zadeh (1965) when the universe of discourse, X , is discrete and finite, the fuzzy set $\underline{A}$ is shown as,

$$\underline{A} = \left\{ \frac{\mu_{\underline{A}}(x_1)}{x_1} + \frac{\mu_{\underline{A}}(x_2)}{x_2} + \dots \right\} = \left\{ \sum_i \frac{\mu_{\underline{A}}(x_i)}{x_i} \right\}$$

When the universe of discourse, X , is continuous and infinite, the fuzzy set $\underline{A}$ is shown as,

$$\underline{A} = \left\{ \int \frac{\mu_{\underline{A}}(x)}{x} \right\}$$

3.1.2. Membership Functions (MFs)

It is better to describe the features of membership functions when dealing with fuzzy sets. There are three main basic characteristics of the membership function. The first one is core, which is the region of the universe characterized by complete membership in the fuzzy set $\underline{A}$. Elements x of the universe positioned in the core have the membership value of one ($\mu_{\underline{A}}(x) = 1$). The second feature is called support, and this is the region of the universe characterized by nonzero membership in the fuzzy set $\underline{A}$. Elements x of the universe positioned in the support have the membership value of greater than zero ($\mu_{\underline{A}}(x) > 0$). The last main feature is boundaries, described as the region of the universe including elements that have a nonzero membership but not full membership in the fuzzy set. Elements x of the universe positioned in the boundaries have the membership value between zero and one ($0 < \mu_{\underline{A}}(x) < 1$). Figure 3.2 illustrates the typical fuzzy set's core, support, and boundaries regions in the universe.

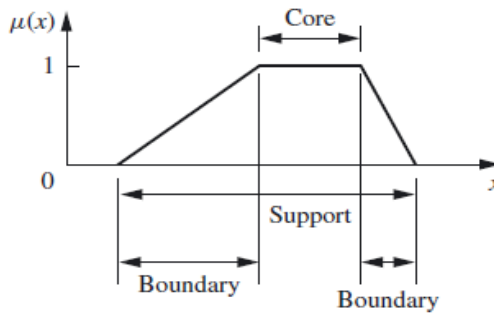


Figure 3.2: Features of a fuzzy set (Ross, 2010).

A fuzzy set that consists of at least one element ' x ' and whose membership value equals unity is called a normal fuzzy set. The height of a fuzzy set $\underline{A}$ is the maximum value of the membership function that can be expressed as $hgt(\underline{A}) = \max\{\mu_{\underline{A}}(x)\}$. If the height of fuzzy

set $\underline{A}$ is less than one, then the fuzzy set is called a subnormal fuzzy set. However, if the height of fuzzy set $\underline{A}$ is equal to one, then it is a normal fuzzy set. The normal and subnormal fuzzy set examples can be seen in figure 3.3.

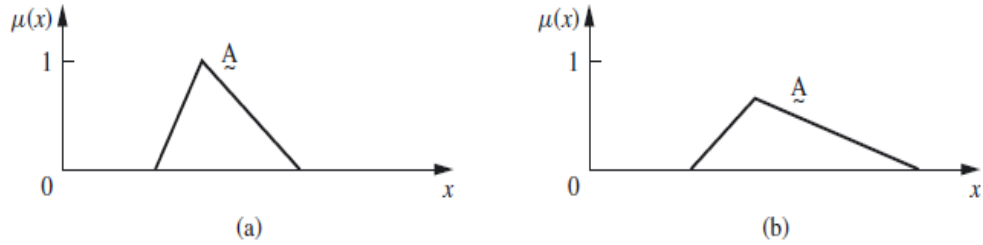
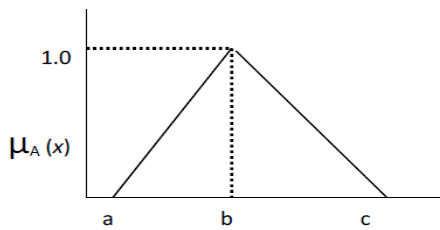


Figure 3.3: (a) normal and (b) subnormal fuzzy sets (Ross, 2010).

The shape of a membership function depends on the application and can be either symmetrical or not. There is not any established and universal rule for assigning a membership function for a particular type of fuzzy subset. There are various types of membership functions such as triangular, trapezoid, gaussian, bell shapes and sigmoid. The selection of membership function mostly depends on the users' experience and knowledge of the problems encountered.

3.1.2.1. Triangular Membership Functions

This is one of the well-known and frequently used membership functions in the fuzzy environment. The triangle which fuzzifies the input can be identified by three parameters a , b , and c . These parameters indicate the x -coordinates of three vertices of $\mu_{\underline{A}}(x)$ in a fuzzy set $\underline{A}$. Parameter a and c represents lower and upper boundary respectively, where the membership degree is zero. Parameter b is the centre of the x -coordinate where membership degree is one. Figure 3.5 demonstrates the triangular membership function diagram.



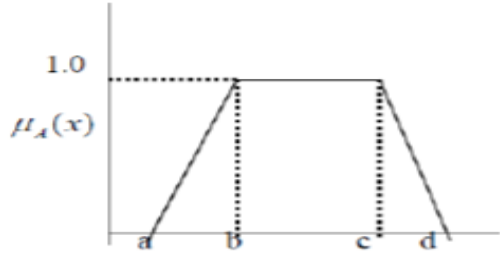
$$\mu_{\underline{A}}(x) = \begin{cases} 0, & \text{if } x \leq a \\ \frac{x-a}{b-a}, & \text{if } a \leq x \leq b \\ \frac{c-x}{c-b}, & \text{if } b \leq x \leq c \\ 0, & \text{if } x \geq c \end{cases}$$

Figure 3.4: Triangular membership function diagram.

$$\mu_{\underline{A}}^{triangular} = \max\left(\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right)$$

3.1.2.2. Trapezoidal Membership Functions

This membership function is identified by four parameters a , b , c , and d . Similarly, parameters represent the x-coordinates of four vertices of $\mu_A(x)$ in a fuzzy set A . Parameters b and c stand for the highest membership value that element can take. And if x is between (a, b) or (c, d) , then a membership value can be assigned between zero and one. Figure 3.6 demonstrates the trapezoidal membership function diagram.



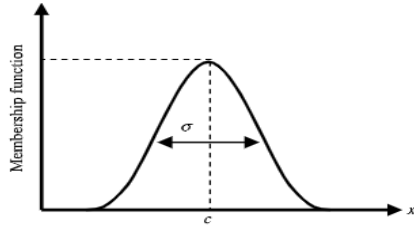
$$\mu_A(x) = \begin{cases} 0, & \text{if } x \leq a \\ \frac{x-a}{b-a}, & \text{if } a \leq x \leq b \\ 1, & \text{if } b \leq x \leq c \\ \frac{d-x}{d-c}, & \text{if } c \leq x \leq d \\ 0, & \text{if } d \leq x \end{cases}$$

Figure 3.5: Trapezoidal membership function diagram.

$$\mu_{A\text{trapezoidal}} = \max\left(\min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right)$$

3.1.2.3. Gaussian Membership Functions

The Gaussian membership function is defined by two parameters, c and σ . Parameter c represents the mean, parameter σ represents the standard deviation. Furthermore, this function is not preferred by researchers a lot due to mathematical complexity. Figure 3.7 shows the gaussian membership function diagram.



$$\mu_{A\text{gaussian}} = \exp\left[-\frac{1}{2}\left|\frac{x-c}{\sigma}\right|^2\right]$$

Figure 3.6: Gaussian membership function diagram.

3.1.2.4. Generalized Bell Membership Functions

A generalized bell membership function is defined by three parameters, a , b , and c . Parameter a is responsible for width, parameter c is responsible for the centre, and lastly, parameter b is responsible for slope. Figure 3.8 shows the generalized bell membership function diagram.

$$\mu_{A\text{gbellmf}} = \frac{1}{1 + \left|\frac{x-c}{b}\right|^{2b}}$$

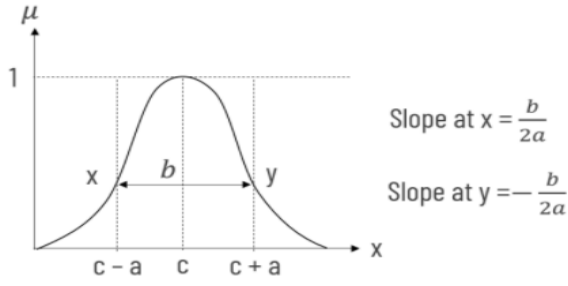


Figure 3.7: Generalized bell membership function diagram.

3.1.2.5. Sigmoid Membership Functions

Sigmoid functions are frequently used in machine learning especially in logistic regression and neural network. A sigmoid membership function is specified by two parameters, a , and m . Parameter a control the slope at the crossover point where $x=m$. Figure 3.9. shows the sigmoid membership function diagram.



Figure 3.8: Sigmoid membership function diagram.

3.1.3. Fuzzy Aggregation Operation

In this study, the graded mean integration will be used to aggregate linguistic variables from different sources represented by triangular fuzzy numbers (Chuo, 2003). This technique can be defined for the triangular fuzzy number $\tilde{N}$ as,

$$\tilde{N} = \frac{1}{6}(a + 4b + c)$$

Let $\tilde{Z} = (a_{ij}, b_{ij}, c_{ij})$ be a triangular fuzzy number representing the influence on concept C_i to C_j . Then representation of the aggregation operation on triangular fuzzy numbers can be defined as,

$$(\tilde{Z}^1 \oplus \tilde{Z}^2 \oplus \dots \oplus \tilde{Z}^p) = \left[\frac{1}{6}(a_{ij}^1 + 4b_{ij}^1 + c_{ij}^1 + a_{ij}^2 + 4b_{ij}^2 + c_{ij}^2 + \dots + a_{ij}^p + 4b_{ij}^p + c_{ij}^p) \right]_{n \times n}$$

$$Z = \left[\frac{1}{P} (\widetilde{Z}^1 \oplus \widetilde{Z}^2 \oplus \dots \oplus \widetilde{Z}^P) \right]_{n \times n}$$

Once the relationships between each concept are determined through the use of the fuzzy linguistic scale, the fuzzy aggregation operator can be employed to create the final influence matrix. This aggregation operator also removes the need for defuzzification and saves the effort of other mathematical operations.

3.1.4. Intuitionistic Fuzzy Sets

In the fuzzy environment, the generalization and extension of fuzzy sets are developed to overcome the drawbacks of ordinary fuzzy sets. In this regard, a type 2 fuzzy set called intuitionistic fuzzy sets (IFSs) is proposed to model uncertainty and lack of information in a better way (Atanassov, 1999). The fuzzy sets extended by Atanassov consider the membership and non-membership values. The basic definitions of IFS can be seen below.

$$\underline{A} = \{ \langle x, \mu_{\underline{A}}(x), \gamma_{\underline{A}}(x) \mid x \in X \rangle \}$$

where the symbol $\gamma_{\underline{A}}(x)$ is the degree of nonmembership of element x in fuzzy set $\underline{A}$. Both the degree of membership and non-membership should be between zero and one ($\mu_{\underline{A}} : X \rightarrow [0,1]$, $\gamma_{\underline{A}} : X \rightarrow [0,1]$). Also, the following requirement should be satisfied for every $x \in X$.

$$0 \leq \mu_{\underline{A}}(x) + \gamma_{\underline{A}}(x) \leq 1$$

In IFS, the hesitancy factor can be regarded as the uncertainty degree of the membership of the element $x \in X$. The degree of hesitancy represents the lack of information. The hesitancy function can only be a positive number that takes values within zero and one ($\pi_{\underline{A}} : X \rightarrow [0,1]$).

$$\pi_{\underline{A}}(x) = 1 - \mu_{\underline{A}}(x) - \gamma_{\underline{A}}(x)$$

3.2. COGNITIVE MAPS

Cognitive maps (CMs), are directed graphs and, were introduced in the early 1970s, and the tool is appeared in the literature by Robert Axelrod (1976) to help decision making under the notion of causation in political and social sciences. Axelrod used CMs to show causal relationships between variables. The proposed system has only two essential elements: concepts (nodes) and causal beliefs (directed arrows). Nodes represent variables, and directed arrows

represent the relationships between variables. For example, the policy alternatives, different causes and effects, and the ultimate utility of the decision-maker can be considered concept variables, and these concepts are represented as points. Also, concept variables are flexible in cognitive maps, and they may be continuous, ordinal, or dichotomous variables.

The causal beliefs between the concept variables are represented as arrows placed between the points. A plus (+) sign connected to the arrows indicates a positive relationship, that is an increase (decrease) in the cause concept results with an increase (decrease) in the result concept; conversely, a minus (-) sign attached indicates a negative relationship, that is an increase (decrease) in the cause concept results with a decrease (increase) in the result concept. This representation of assertions as a directed graph is called a cognitive map. The complete cognitive map pictured in a diagram allows one to notice how each of the concepts and causal relationships link to each other and the general form of the whole set of portrayed assertions. This simply shows the real power of this tool. Figure 3.10 shows an example of a cognitive map.

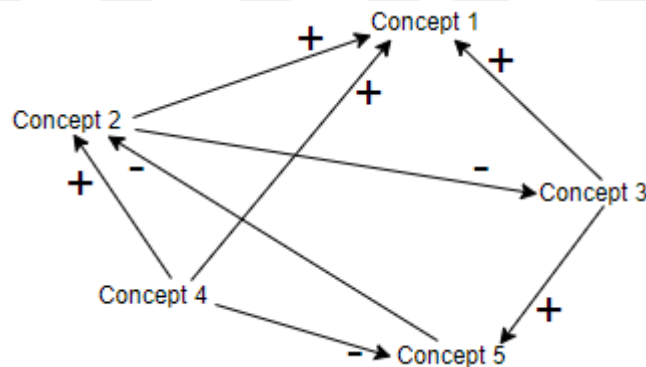


Figure 3.9: Example of a cognitive map.

In CMs, the sign of the causal relationships is attached with arrowheads. Considering the above figure, a positive sign from concept 2 to concept 1 means concept 2 causally increases concept 1. Conversely, a negative edge from concept 2 to concept 3 means concept 2 causally decreases concept 3. When a connection exists between two concepts, decision-makers can assign the relative strength of the relationships between concepts as -1 or 1. In addition, CMs can be transformed into adjacency matrices, as shown in table 3.1 (Kosko, 1986).

Table 3.1: The adjacency matrix of an CM.

	Concept 1	Concept 2	Concept 3	Concept 4	Concept 5
Concept 1	0	0	0	0	0
Concept 2	1	0	-1	0	0
Concept 3	1	0	0	0	1
Concept 4	1	1	0	0	-1
Concept 5	0	-1	0	0	0

CMs are derived from assertions of people's beliefs and used to analyze the relationships between concepts. Most studies determine the concepts for the subject and then create a decision matrix. Further, decision-makers express their opinions on the decision matrix. After implementing some aggregation and analytical techniques, cognitive maps are built as the final product (Axelrod, 1976). Several methods for deriving cognitive maps include survey research techniques, content analysis, questionnaires, documentary coding, and open-ended probing interview. Recently questionnaire and documentary coding methods have been preferred considering the reliability and validity of these methods.

3.2.1. Document Coding

Coding is the first method in constructing a cognitive map. In this step, coders have a great responsibility. The coder's job is to encode the textual documents elaborately and meticulously and, most importantly, not code spurious implications. In addition, the coder should scrutinize all the possible relationships and record the actual cause-effect relationships in resources. The coder can be successful when the texts are reviewed structurally and by content. They should concentrate on the sentences or paragraphs that assert a causal relationship. These sentences frequently unearth the cause-effect concepts and direction of the relationship between concepts.

The basic structure in the coder terminology is “Cause Concept / Linkage / Effect Concept”. The coder should always keep in mind the form when reviewing a textual document to record all the possible relationships. Considering the terminology, the cause-and-effect concepts must be represented as variables that can take different values. The linkages are mainly presented in three types plus sign (+), minus sign (-), and zero (0). Plus sign is used when the relationship is directly proportional; minus sign is used when the connection is inversely proportional; and lastly, zero is stated when there is no association between cause-effect concepts. Some sample sentences might be as follows:

1) The amount of food waste increases with growing household size (Koivupuro et al., 2012).

Cause Concept: Household size

Linkage: +

Effect Concept: Food waste

2) As environmentally friendly behaviour increases, food wastes were reduced (Morone, et al., 2018).

Cause Concept: Environmental attitude

Linkage: -

Effect Concept: Food waste

3) No correlation was found between household income and food waste (Williams et al., 2012).

Cause Concept: Household income

Linkage: 0

Effect Concept: Food waste

3.2.2. Fuzzy Cognitive Maps

Fuzzy Cognitive Maps (FCMs) are a special form of cognitive maps. Kosko (1986) modified Axelrod's cognitive maps by applying fuzzy logic to include vague and qualitative knowledge. In addition to that, Kosko (1987) was also the first to model FCM and evaluate the results of an FCM under several policy options by employing a neural network methods. FCMs are fuzzy-graph structures of belief systems applied mainly in soft knowledge domains such as political, medical, and environmental science, where the system concepts are essentially fuzzy (Özesmi & Özesmi, 2004). FCMs consist of fuzzy nodes and weighted arcs, depicting a model's weighted graph with feedback loops. The nodes symbolize the concepts of the system, and the edges illustrate the causal relationships between concepts (Kok, 2009). The causal relationship between concepts is described as a fuzzy relation, and some weight values are assigned to denote the strength of the influence. The degree of influence is defined by using linguistic variables for every weight (w_{ij}) that represents the cause-and-effect influence of one concept

on another ranging from -1 to 1. The degree of causal relationship between concepts can also be a positive or negative sign. Three types of causal interactions can be seen between concepts (Stylios, 2004):

- $w_{ij} > 0$, stands for the increase (decrease) on the value of the i_{th} concept causes an increase (decrease) of the value of the j_{th} .
- $w_{ij} < 0$, stands for the increase (decrease) on the value of the i_{th} concept causes a decrease (increase) of the value of the j_{th} .
- $w_{ij} = 0$, stands for no relationship between i_{th} and j_{th} concept.

Table 3.2 displays an example of an FCM adjacency matrix. The matrix structure is an $n \times n$ matrix form that indicates the strength of the influence between concepts. The values in the matrix represent the weight of the relationship between the concepts. For instance, concept 2 positively influences concept 1 with a degree of 0.7. This relationship states that an increase in concept 2 will cause a 0.7 increase in the value of concept 1. Similarly, concept 5 negatively influences concept 2 with a degree of 0.8, and this states that an increase in concept 5 will cause a 0.8 decrease in the value of concept 2 or vice versa.

Table 3.2: The adjacency matrix of an FCM.

	Concept 1	Concept 2	Concept 3	Concept 4	Concept 5
Concept 1	0				
Concept 2	0.7	0	-0.5		
Concept 3	0.9		0		0.1
Concept 4	0.7	0.6		0	-0.6
Concept 5		-0.8			0

Figure 3.11 exemplifies a mental representation of the concepts existing within the problem and the relationships between these concepts in an FCM model. For example, if the line between concepts is blue, this shows that the causal relationship is positive, while the red line represents a negative causal relationship. Moreover, concepts in the FCM model can be categorized into different groups, which can be described within colours. Based on the figure below, concepts 1 and 5 are in the same group and coloured with green; on the other side concept, 2 and 4 are in the same group coloured with orange.

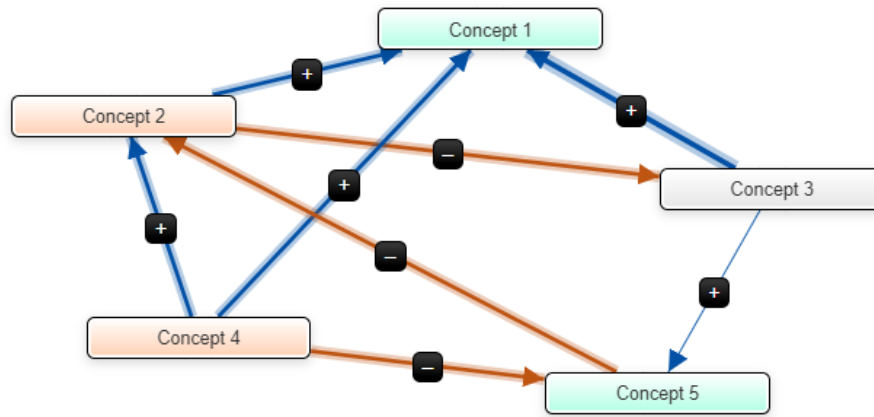


Figure 3.10: Example of fuzzy cognitive map.

The analysis of complex cognitive maps begins by calculating FCM network metrics. Initially, the number of concepts (N) and the number of connections (C) are counted in the map. Next, the clustering coefficient called density index (D) is calculated to see whether the constructed fuzzy cognitive maps are connected or sparse. The number of connections is divided by the maximum number of possible connections for the density calculation. The high-density index indicates that more possible causal relationships exist among the concepts.

$$Density = \frac{C}{N(N-1)}$$

Then concepts in the model are classified into three types: the transmitter (driver), receiver, and ordinary concepts. The class type of each concept is identified by calculating outdegree and indegree values. Outdegree is the degree of influence a concept has on other concepts, and indegree is the degree to which other concepts influence a particular concept. In this regard, transmitter concepts have positive outdegrees and zero indegrees. Transmitter concepts are described as the forcing functions that affect other concepts but are not affected by any concept. Receiver concepts have positive indegrees and zero outdegrees. Receiver concepts are described as receiving functions affected by other concepts but do not affect any concept. Lastly, ordinary concepts have certain outdegree and indegree values. Ordinary concepts can influence and also can be influenced by other concepts in the FCM model. Outdegree is the cumulative sum of absolute weights for the outgoing connections, while indegree is the cumulative sum of absolute weights for the ingoing connections. The centrality, also called total degree, is the summation of outdegree and indegree values. The centrality value is essential because it shows the cumulative strength of the concept connections. The concept with a higher centrality score indicates the significant concept in the model. In the final analysis of FCM, the

complexity score of the model is measured by taking the ratio of the number of receiver variables to transmitter variables (Gray et al., 2015; Gray et al., 2017; Özesmi & Özesmi, 2004). Table 3.3 and 3.4 demonstrates the network metrics of the example FCM illustrated in Figure 3.11.

Table 3.3: Example of an FCM metrics calculation.

FCM Network Metrics	Value
Number of concepts (N)	5
Number of connections (C)	8
Density index	0.4
Number of transmitter concepts	1
Number of receiver concepts	1
Number of ordinary concepts	3
Complexity score	1

Table 3.4: Example of indegree, outdegree and centrality calculation.

Concepts	Indegree	Outdegree	Centrality
Concept 1	2.3	0.0	2.3
Concept 2	1.4	2.2	2.6
Concept 3	0.5	1.0	1.5
Concept 4	0.0	1.9	1.9
Concept 5	0.7	0.8	1.5

After the model is built and metrics are calculated, the FCM equation is processed through an iterative way to determine the system's steady-state until converges to a fixed point. The concept value (C_i) is calculated at each iteration by applying the auto-associative neural network method (Reimann, 1998). The FCM equation used to generate updated values of concepts is given in the below equation.

$$A_i^{k+1} = f \left(A_i^k + \sum_{j=1}^N A_j^k \cdot w_{ji} \right)$$

In this equation, w_{ji} is the weight of connection from concept C_j to C_i , and f is the threshold function incorporated into the equation to restrict the concept values in a specific interval between $[0,1]$ or $[-1,1]$ (Papakostas, 2008). Generally, two threshold functions are preferred in the FCM framework as a sigmoid and hyperbolic tangent. In this study, the sigmoid function

will be used to transform the results into an interval between 0 and 1. Then, the equation repeatedly multiplies the transformed vector with the adjacency matrix of the model until the system approaches a steady-state where it converges to a fixed point.

In FCM methodology, it is also possible to generate scenarios and evaluate the updated concept values under different conditions or policies. In this step, users may decide to run some alternative scenarios to observe the amount of relative changes in the concepts compared to the base model.

3.2.3. Intuitionistic Fuzzy Cognitive Maps

The FCMs are enhanced by using the theory of intuitionistic fuzzy sets (IFSs) to construct Intuitionistic Fuzzy Cognitive Map (iFCM) in 2009. The first application is executed in medical decision making by introducing hesitancy factors in the causal relationships of the concepts (Papageorgiou & Iakovidis, 2009). In the context of IFSs, the hesitancy factor of a weight that takes only positive values between 0 and 1 is integrated into the FCM equation. Furthermore, this enhanced model captures the degree of hesitancy in the relations of the concept considering the missing data and lack of information. Therefore, the FCM equation is reformulated as given in below.

$$A_i^{k+1} = f \left(A_i^k + \sum_{j=1}^N A_j^k (w_{ji}^{\mu} - w_{ji}^{\pi}) \right)$$

w_{ji}^{μ} represents the influence weight, and w_{ji}^{π} represents the hesitancy weight corresponding to the edge directed from concept j to concept i.

4. IMPLEMENTATION AND RESULTS

This section covers the implementation and results of the methods mentioned in the previous section. The Document Coding method is initially employed to record all the possible relationships by coding cause concepts, linkages, and effect concepts based on the terminology. However, causal relationships between concepts can include vague or imprecise judgments during document coding. Due to that, the idea of linguistic variable is introduced under the fuzzy set theory to handle ambiguity arising from fuzziness in subjective judgements (Tzeng and Huang, 2011). Next, linguistic variables are converted to triangular fuzzy numbers, and the membership region of each linguistic term is designated. Then, linguistic terms are transformed into numerical values. After that, an aggregation operation is performed to identify the weight matrix for building the FCM model. Following that, the model is enhanced by introducing a hesitancy factor in the context of IFSs. Finally, some scenarios are generated, and comparative results are discussed. The implementation flow of the study is illustrated in figure 4.1.

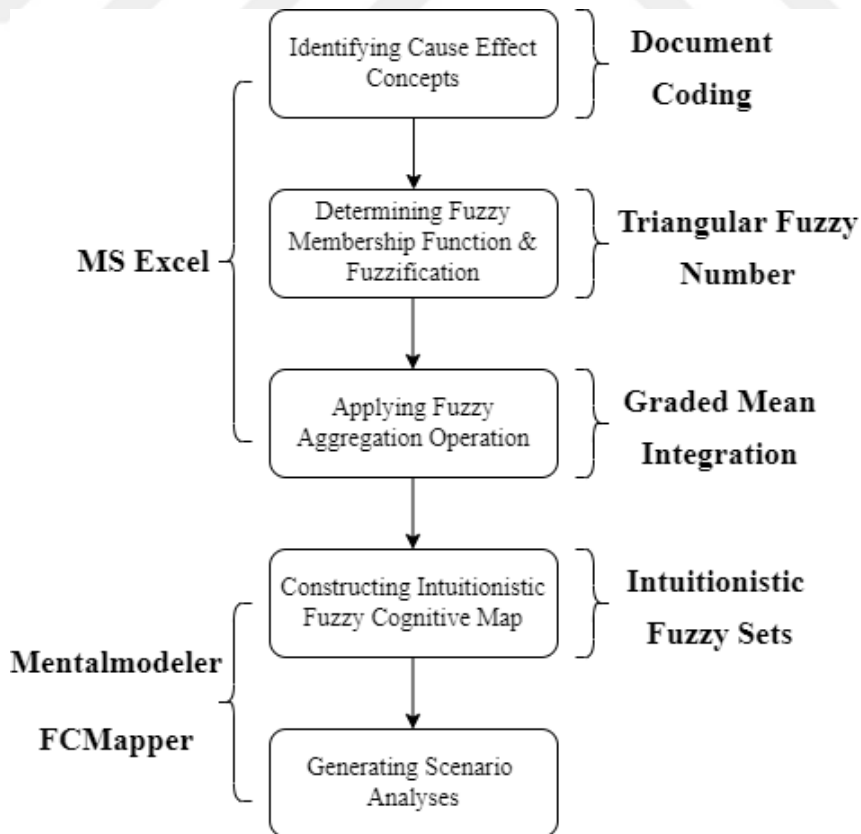


Figure 4.1: Implementation flow of the study.

4.1. IDENTIFYING CAUSE EFFECT CONCEPTS BY DOCUMENT CODING

The first step in this section is coding the cause-effect relationships of possible food waste drivers in the literature. This qualitative research technique holds a simple structure. The coder takes notes of possible relationships according to the conducted literature review by including the cause concept, linkage, and effect concept. In this study, the weight of linkage is also coded additionally. For example, Secondi et al. (2015) claimed that attitudes and food waste are strongly associated and highlighted that individuals with a higher sense of attitudes are more likely to waste less. Therefore, this sentence can be coded as follows:

Cause Concept: Attitudes

Linkage: -

Weight of Linkage: More likely to occur

Effect Concept: Food waste

Another example can also be provided. Chai et al. (2020) stated that as the population grows at high speed, the growth rate of food demand is also high. The second example can be coded as follows:

Cause Concept: Population growth

Linkage: +

Weight of Linkage: High

Effect Concept: Food demand

In line with the abovementioned examples, 83 cause-effect concepts in total are identified by following the documentary coding terminology. Table 4.1 displays the representative part of the complete list. The whole coded cause-effect concepts are listed in Appendix 1.

After finalising the list of document coding, 57 unique concept variables are gathered. Next, all concept variables are counted in the pivot table to identify the most recurrent concepts. Then a threshold value is set as four. Based on the count of concept variables in the final list, concepts

that are repeated four times or more are filtered. This way of filtering results in 13 concepts. Table 4.2 shows these concepts and their counts in the final list.

Table 4.1: Sample list of cause-effect concepts.

No	References	Cause Concept	Linkage	Weight of linkage	Effect Concept
1	Irani et al. (2018)	Food recycling	-	Very low	Food waste
2	Irani et al. (2018)	Demand planning	-	Very low	Food waste
3	Kleemann et al. (2017)	Population growth	+	Strong driving force	Food insecurity
4	Yang and Zhen (2020)	Household income	+	Most important impact	Food consumption
5	Yang and Zhen (2020)	Age of family members	-	Most important impact	Food consumption
6	Chai, Shi, Lu and Hu (2020)	Population growth	+	High	Food demand
7	Stancu et al. (2016)	Shopping routines	+	Most important determinant	Food waste
8	Koivupuro et al. (2012)	Household size	+	Significant effect	Food waste
...	...	...	...	...	...
82	Grainger et al. (2018)	Age of family members	-	Strong impact	Food waste
83	Katajajuuri et al. (2012)	Household size	+	Significant effect	Food waste

Table 4.2: Filtered cause effect concepts and counts of these concepts (4 and more).

Cause or effect concept	Count of concepts in the final list
Food waste	43
Attitudes (moral & environmental)	8
Age of family members	7
Household size	6
Household income	6
Shopping routines	5
Biorefinery	5
Environment, socio-economic system, and ethical system	5
Public food waste rules	4
Intention not to food waste	4
Perceived behavioural control	4
Planning routines	4

Following this filtering, the resources of the selected concepts are examined, and it is noticed that some concepts have only one source. This means that the cause-effect relationship of these concepts is only discussed in one article. Therefore, these concepts are eliminated to avoid biases for the next steps. Eventually, nine concepts are selected, and the following concepts are excluded: food consumption, biorefinery, environment, socio-economic and ethical system, and public food waste rules.

A brief definition of the selected concepts is shared below.

Food waste: It is the main concept, refers to the food that is discarded or thrown away.

Attitudes (moral & environmental): It refers to the attitudes towards food waste concerning moral and environmental ethics.

Age of family members: It denotes the age of family members in a household.

Household size: It denotes the number of people living in a household.

Household income: It indicates the income level of a household.

Shopping routines: It refers to purchase routines of larger amounts of food than needed while going shopping.

Intention not to food waste: It signifies a more ordinary way of expressing intentions toward food waste.

Perceived behavioural control: It associates with the degree to which consumers believe reducing food waste is under their control.

Planning routines: It represents the effort of checking the inventory levels before purchasing foods already in stock at home.

4.2. DETERMINING FUZZY MEMBERSHIP FUNCTION & FUZZIFICATION

In most cases, real-world problems contain a mixture of crisp and fuzzy data. Some variables or attributes can be difficult to estimate by exact numerical values. This situation requires the usage of fuzzy logic for problems holding ambiguity. The fuzzy set theory introduced by Zadeh (1965) is used to solve problems comprising imprecise expressions. Instead of numerical values, linguistic variables are used to describe quantitative expressions. Linguistic variables are linguistic terms that can be symbolized by fuzzy numbers (Zadeh, 1975; von Altrock, 1996).

In this study, a 5-point linguistic scale is designed to express the causality among concepts from very high influence to very low influence. Further, the most commonly used fuzzy number is selected as triangular fuzzy numbers. Figure 4.2 shows the triangular membership functions of linguistic terms in a graph.

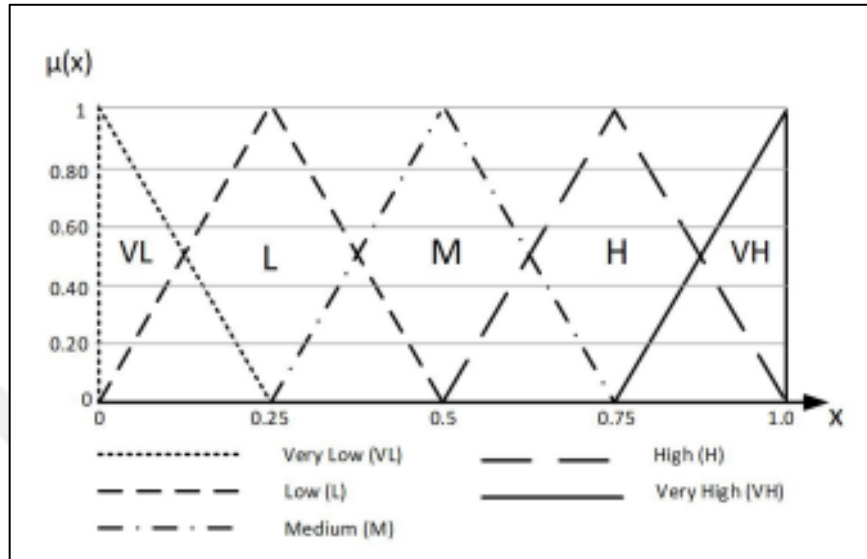


Figure 4.2: Triangular membership functions of linguistic terms.

The triangular fuzzy numbers for the linguistic terms can also be demonstrated in table 4.3.

Table 4.3: Triangular fuzzy numbers (TFNs) for the linguistic terms.

Linguistic terms	Triangular Fuzzy Numbers (TFNs)		
	lower	medium	upper
Very low influence	0.00	0.00	0.25
Low influence	0.00	0.25	0.50
Medium influence	0.25	0.50	0.75
High influence	0.50	0.75	1.00
Very high influence	0.75	1.00	1.00

The final list of the selected concepts and their cause-effect relationships, including the linkage and linguistic term information, is presented in the below table 4.4. This table will be an input for the construction of the FCM model.

Table 4.4: Cause-effect relationships of selected concepts.

References	Cause Concept	Linkage	Linguistic Scale (5MFs)	Triangular FN	Effect Concept
Stancu et al. (2016)	Age of family members	-	Low influence	(0.00, 0.25, 0.50)	Food waste
Stefan et al. (2013)	Age of family members	-	Low influence	(0.00, 0.25, 0.50)	Food waste
Secondi et al. (2015)	Age of family members	-	Very high influence	(0.75, 1.00, 1.00)	Food waste
Grainger et al. (2018)	Age of family members	-	High influence	(0.50, 0.75, 1.00)	Food waste
Secondi et al. (2015)	Attitudes (moral & environmental)	-	Very high influence	(0.75, 1.00, 1.00)	Food waste
Morone et al. (2018)	Attitudes (moral & environmental)	-	Very high influence	(0.75, 1.00, 1.00)	Food waste
Stefan et al. (2013)	Attitudes (moral & environmental)	+	High influence	(0.50, 0.75, 1.00)	Intention not to food waste
Stancu et al. (2016)	Attitudes (moral & environmental)	+	Low influence	(0.00, 0.25, 0.50)	Intention not to food waste
Stefan et al. (2013)	Attitudes (moral & environmental)	-	Medium influence	(0.25, 0.50, 0.75)	Shopping routines
Stancu et al. (2016)	Household income	+	Low influence	(0.00, 0.25, 0.50)	Food waste
Stefan et al. (2013)	Household income	+	Low influence	(0.00, 0.25, 0.50)	Food waste
Song et al. (2018)	Household size	+	High influence	(0.50, 0.75, 1.00)	Food waste
Stancu et al. (2016)	Household size	+	Low influence	(0.00, 0.25, 0.50)	Food waste
Katajajuuri et al. (2012)	Household size	+	Very high influence	(0.75, 1.00, 1.00)	Food waste
Koivupuro et al. (2012)	Household size	+	Very high influence	(0.75, 1.00, 1.00)	Food waste
Grainger et al. (2018)	Household size	+	Very high influence	(0.75, 1.00, 1.00)	Food waste
Stancu et al. (2016)	Intention not to food waste	-	Low influence	(0.00, 0.25, 0.50)	Food waste
Stancu et al. (2016)	Perceived behavioural control	-	Very high influence	(0.75, 1.00, 1.00)	Food waste
Stefan et al. (2013)	Perceived behavioural control	-	Medium influence	(0.25, 0.50, 0.75)	Food waste
Stefan et al. (2013)	Perceived behavioural control	+	Medium influence	(0.25, 0.50, 0.75)	Planning routines
Stefan et al. (2013)	Perceived behavioural control	-	Medium influence	(0.25, 0.50, 0.75)	Shopping routines
Stefan et al. (2013)	Planning routines	-	Medium influence	(0.25, 0.50, 0.75)	Food waste
Stancu et al. (2016)	Planning routines	-	Medium influence	(0.25, 0.50, 0.75)	Shopping routines
Stancu et al. (2016)	Shopping routines	+	Very high influence	(0.75, 1.00, 1.00)	Food waste
Stefan et al. (2013)	Shopping routines	+	High influence	(0.50, 0.75, 1.00)	Food waste

4.3. APPLYING FUZZY AGGREGATION OPERATION

The graded mean integration technique is selected as an aggregation operation on triangular fuzzy numbers in the third step. Although there are many arithmetical aggregation operators, this technique is easy to interpret and removes the need for defuzzification. Thus it reduces the computation time and saves the effort of applying other mathematical operations. In this study, once the relationships between each concept are determined by document coding and fuzzified through triangular fuzzy numbers, the fuzzy aggregation operator can be employed to create the final influence matrix.

For example, the influence weight calculation of cause concept (shopping routines) and effect concept (food waste) is given below considering the equation denoted in the methodology section. According to the document coding list, Stancu et al. (2016) state a positive very high influence and Stefan et al. (2013) state a positive high influence between shopping routines and food waste. These linguistic terms are converted into triangular fuzzy numbers respectively ($\widetilde{Z}^1 = (0.75, 1.00, 1.00)$ and $\widetilde{Z}^2 = (0.50, 0.75, 1.00)$) representing the influence of the shopping routines on food waste. Then fuzzy aggregation operation is applied as follows. Table 4.5 shows the influence weight calculation as an example.

Table 4.5: Influence weight calculation of example 1.

References	Cause Concept	Linkage	Effect Concept	Linguistic Scale (5MFs)	Triangular FN	Graded mean integration
Stancu et al. (2016)	Shopping routines	+	Food waste	Very high influence	(0.75, 1.00, 1.00)	0.85
Stefan et al. (2013)	Shopping routines	+	Food waste	High influence	(0.50, 0.75, 1.00)	

$$(\widetilde{Z}^1 \oplus \widetilde{Z}^2) = \left[\frac{1}{6} (1.25 + 4 * (1.75) + 2) \right]_{2 \times 2}$$

$$Z = \left[\frac{1}{2} (\widetilde{Z}^1 \oplus \widetilde{Z}^2) \right]_{2 \times 2} = 0.85$$

The influence weight between shopping routines and food waste is computed as 0.85. Another aggregation example is given between the concepts of the age of family members and food waste. This aggregation operation is computed with an influence weight of 0.55 between

concepts. Table 4.6 shows another example calculation by following the graded mean integration technique.

Table 4.6: Influence weight calculation of example 2.

References	Cause Concept	Linkage	Effect Concept	Linguistic Scale (5MFs)	Triangular FN	Graded mean integration
Stancu et al. (2016)	Age of family members	-	Food waste	Low influence	(0.00, 0.25, 0.50)	0.55
Stefan et al. (2013)	Age of family members	-	Food waste	Low influence	(0.00, 0.25, 0.50)	
Secondi et al. (2015)	Age of family members	-	Food waste	Very high influence	(0.75, 1.00, 1.00)	
Grainger et al. (2018)	Age of family members	-	Food waste	High influence	(0.50, 0.75, 1.00)	

$$(\tilde{Z}^1 \oplus \tilde{Z}^2 \oplus \tilde{Z}^3 \oplus \tilde{Z}^4) = \left[\frac{1}{6} (1.25 + 4 * (2.25) + 3) \right]_{4 \times 4}$$

$$Z = \left[\frac{1}{4} (\tilde{Z}^1 \oplus \tilde{Z}^2 \oplus \tilde{Z}^3 \oplus \tilde{Z}^4) \right]_{4 \times 4} = 0.55$$

4.4. CONSTRUCTING INTUITIONISTIC FUZZY COGNITIVE MAP BY IFSS

This study intends to determine the relations between the factors influencing food waste and inform policymakers, academics, researchers, and others interested in food waste management about the complex causal relationship of these factors. Due to the lack of crisp numbers and the need for fuzzy logic regarding subjective judgments in cause-effect relationships among concepts, iFCM method is chosen. iFCMs are the enhanced FCMs with the identification of hesitancy factors and especially powerful tools to cope with situations where hesitations exist.

This study deploys the intuitionistic fuzzy sets (IFSSs) theory due to the lack of information and the hesitancy weight factor is introduced to represent the lack of information. When the current document coding list is examined, it is realised that multiple resources refer to cause-effect relationships of specific concepts. On the other hand, cause-effect relationships of some concepts are cited by only a few resources. Therefore, a scale is designed based on the number of cause-effect relations among concepts in the final document coding list. According to this scale, the hesitancy weight factor is assigned zero when three or more cause-effect relationships are recorded in document coding. Moreover, the hesitancy weight is given 0.02 when there are two cause-effect relationships and 0.04 when only one cause-effect relationship is recorded. These degrees of hesitancy values are assigned considering the IFS equation denoted in the

methodology, which can only take a positive value between zero and one. Also, the summation of the degree of hesitancy and membership should be less than or equal to one. Table 4.7 shows the developed scale for hesitancy weight factors.

Table 4.7: Hesitancy weight factors.

# of the cause-effect relations	Hesitancy weight factor
≥ 3	0.00
2	0.02
1	0.04

After that, the influence weights are calculated based on the equation given in methodology part for iFCM. Table 4.8 demonstrates the influence weight calculations of each cause-effect relationship concept and figure 4.3 indicates final adjacency matrix.

	Food waste	Age of family members	Household size	Household income	Shopping routines	Intention not to food waste	Perceived behavioural control	Planning routines	Attitudes (moral & environmental)
Intuitionistic FCM									
Food waste	0.00								
Age of family members	-0.55	0.00							
Household size	0.78		0.00						
Household income	0.23			0.00					
Shopping routines	0.83				0.00				
Intention not to food waste	-0.21					0.00			
Perceived behavioural control	-0.71				-0.46		0.00	0.46	
Planning routines	-0.46				-0.46			0.00	
Attitudes (moral & environmental)	-0.94				-0.46	0.48			0.00

Figure 4.3: Final adjacency matrix for iFCM.

In this study, Mentalmodeler modelling software is used to visualise the iFCM graph, and FCMapper modelling software is used for computational operations. Figure 4.4 indicates the diagram of the developed iFCM model. Blue lines symbolise the positive causal relationship, and red lines symbolise the negative causal relationship between concepts. Furthermore, the concepts are categorized into three groups and highlighted in different colours. For example, factors highlighted with orange represent household-related factors, greens represent food routine related factors, and purples represent psycho-social factors.

Table 4.8: Influence weight calculation for iFCM.

Cause Concept	Linkage	Linguistic Scale (5MFs)	Effect Concept	Influence weight		
				Graded mean integration	Hesitancy weight	Excluded hesitancy weight
Age of family members	-	Low influence	Food waste	0.55	0.00	0.55
Age of family members	-	Low influence	Food waste			
Age of family members	-	Very high influence	Food waste			
Age of family members	-	High influence	Food waste			
Attitudes	-	Very high influence	Food waste	0.96	0.02	0.94
Attitudes	-	Very high influence	Food waste			
Attitudes	+	High influence	Intention not to food waste	0.50	0.02	0.48
Attitudes	+	Low influence	Intention not to food waste			
Attitudes	-	Medium influence	Shopping routines	0.50	0.04	0.46
Household income	+	Low influence	Food waste	0.25	0.02	0.23
Household income	+	Low influence	Food waste			
Household size	+	High influence	Food waste	0.78	0.00	0.78
Household size	+	Low influence	Food waste			
Household size	+	Very high influence	Food waste			
Household size	+	Very high influence	Food waste			
Household size	+	Very high influence	Food waste			
Intention not to food waste	-	Low influence	Food waste	0.25	0.04	0.21
Perceived behavioural control	-	Very high influence	Food waste	0.73	0.02	0.71
Perceived behavioural control	-	Medium influence	Food waste			
Perceived behavioural control	+	Medium influence	Planning routines	0.50	0.04	0.46
Perceived behavioural control	-	Medium influence	Shopping routines	0.50	0.04	0.46
Planning routines	-	Medium influence	Food waste	0.50	0.04	0.46
Planning routines	-	Medium influence	Shopping routines	0.50	0.04	0.46
Shopping routines	+	Very high influence	Food waste	0.85	0.02	0.83
Shopping routines	+	High influence	Food waste			

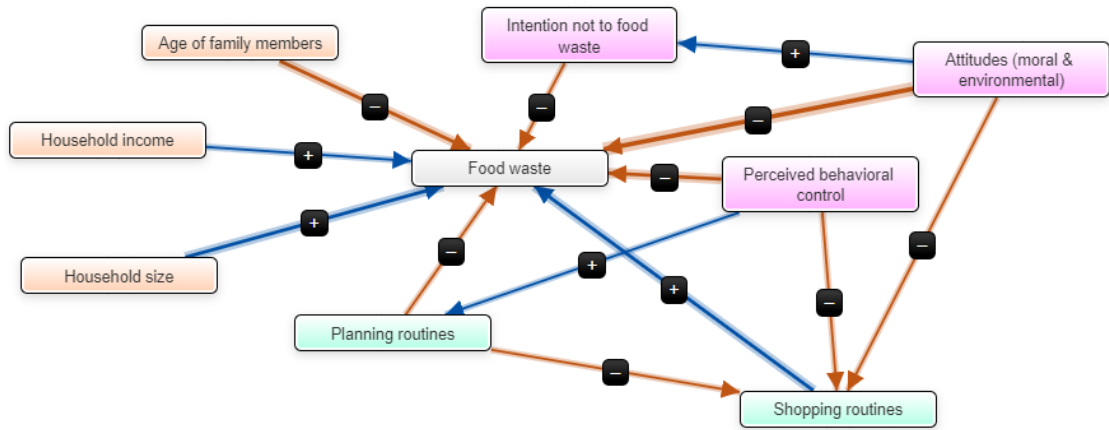


Figure 4.4: The network diagram of iFCM.

In FCMapper, the simulation process is initiated until the developed iFCM converges to a steady-state, in other words, until the value of the updated vector will become steady. The sigmoid function is used as a threshold function since it limits the function values belonging to the interval of $[0, 1]$. The FCM indices can be calculated as follows. There are 9 concepts and 13 connections available in the model. The density index is calculated as 0.181, which is not high. However, the high-density index indicates that more possible causal relationships exist among the concepts. Concepts are classified depending on the outdegree and indegree values. Transmitter concepts have positive outdegree values. There are five transmitter concepts affecting other concepts in the model, and these concepts are not affected by any concept. On the other hand, only one receiver concept is available with positive indegree values, and other concepts influence the receiver concept, but the receiver concept does not affect any concept. The food waste concept is the receiver concept in the developed model. And the rest of the concepts are classified as ordinary concepts. There are three ordinary concepts, and these concepts have both indegree and outdegree values. Lastly, the ratio of receiver concepts to transmitter concepts gives a complexity score of 0.2. Table 4.9 shows iFCM indices.

Table 4.9: Calculations of indices for iFCM.

iFCM Network Metrics	Value
Number of concepts (N)	9
Number of connections (C)	13
Density index (D)	0.181
Number of transmitter concepts	5
Number of receiver concepts	1
Number of ordinary concepts	3
Complexity score	0.2

The summation of outdegree and indegree values returns the total degree value called centrality. The concept with a higher centrality score indicates a significant concept in the model. In this case, food waste with a 4.71 total degree is the most critical concept by far. Next, the concepts of shopping routines and attitudes (moral & environmental) follow the food waste concept with their centrality value, respectively. Table 4.10 displays the indegree, outdegree and centrality value of each concept in the iFCM.

Table 4.10: Indegree, outdegree and centrality of iFCM.

Concepts	Type	Indegree	Outdegree	Centrality
Food waste	Receiver	4.71	0	4.71
Age of family members	Transmitter	0	0.55	0.55
Household size	Transmitter	0	0.78	0.78
Household income	Transmitter	0	0.23	0.23
Shopping routines	Ordinary	1.38	0.83	2.21
Intention not to food waste	Ordinary	0.48	0.21	0.69
Perceived behavioral control	Transmitter	0	1.63	1.63
Planning routines	Ordinary	0.46	0.92	1.38
Attitudes (moral & environmental)	Transmitter	0	1.88	1.88

The simulation process is terminated after 28 iterations when all factor weights remain stable and converge to a fixed point. The figure 4.5 shows the number of iterations until no change is established.

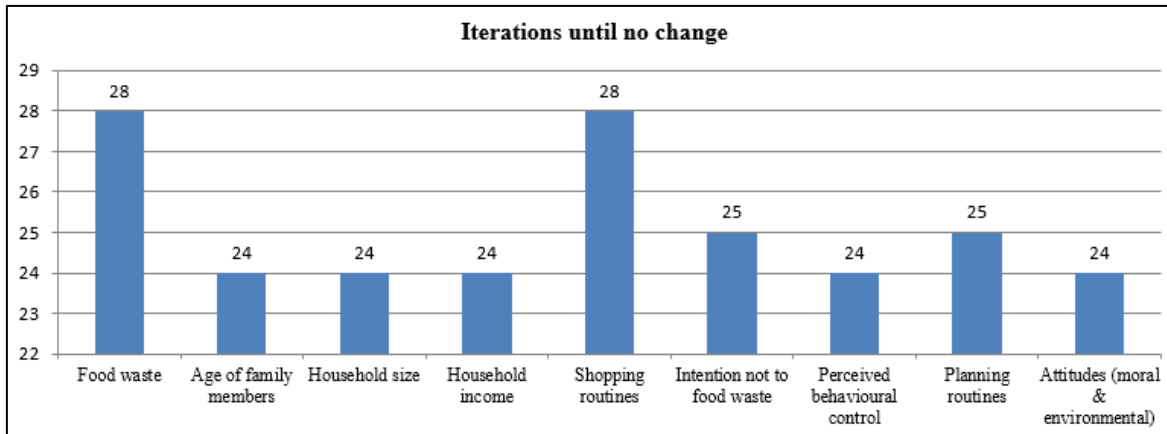


Figure 4.5: Number of iterations until no change.

4.5. GENERATING SCENARIO ANALYSES

Scenario analysis is one of the crucial features of cognitive maps. This feature allows discovering the dynamical behaviour of the model to observe the influence of each interaction between concepts. Once the map is built, and the steady-state is reached, one or more concepts can be altered to gather additional observations and insights regarding the underlying system. This analysis is called what-if analysis, and scenarios are generated by performing several simulations. This ability of the technique helps the policymakers and researchers in terms of predicting and discussing about what happens if some components of the system have been changed. The concepts' values when the system converges are listed in Table 4.10. This concept's values in the equilibrium state can be used to produce different scenarios. Therefore, it is feasible to evaluate which policies would reduce food waste through alternative policy simulations.

Table 4.11: The concepts' values of the model.

Concepts	Concept's value
Food waste	0.3455
Age of family members	0.6590
Household size	0.6590
Household income	0.6590
Shopping routines	0.3567
Intention not to food waste	0.7425
Perceived behavioural control	0.6590
Planning routines	0.7393
Attitudes (moral & environmental)	0.6590

Scenario 1: The first scenario is designed based on the highest value of the concepts in the equilibrium state. Accordingly, intention not to food waste (0.7425) has the highest and planning routines (0.7393) has the second highest importance compared to other concepts. Then these concepts' values are modified to 0.95 to simulate how the concept of food waste responds to an increase in both factors (Drakaki and Tzionas, 2021). As a result, a 0.20 increase in both factors leads to an approximately 0.05 decrease in the food waste concept. And also, a 0.03 reduction can be achieved in the shopping routines concepts.

Table 4.12: The concepts' values for scenario 1.

Concepts	Results - No Changes	Results - Scenario 1
Food waste	0.3455	0.2998
Age of family members	0.6590	0.6590
Household size	0.6590	0.6590
Household income	0.6590	0.6590
Shopping routines	0.3567	0.3285
Intention not to food waste	0.7425	0.9500
Perceived behavioural control	0.6590	0.6590
Planning routines	0.7393	0.9500
Attitudes (moral & environmental)	0.6590	0.6590

Scenario 2: The second scenario is created by considering the centrality value of the model concepts. Followed by the food waste concept (centrality: 4.71), the concept of shopping routines (centrality: 2.21) is the second significant concept (Özesmi & Özesmi, 2004). Therefore, the concept value of shopping routines is diminished from 0.36 to 0.15 to monitor the effects on the existing system (Rodoplu, 2016). However, this only resulted in a change of about 0.05 decrease in the concept value of food waste.

Scenario 3: The third scenario is generated considering the negative consequences of food waste on economic, environmental, and social impacts. Recently, it has been possible to notice the effects of food waste from the different sources in the literature (Morone, Falcone and Lopolito, 2019; Schanes, Dobernig and Gözet, 2018). Organisations can take advantage of this situation in a proactive way. For instance, awareness can be boosted with information campaigns about food waste. In this case, it is believed that this positively leads to an increase in some psycho-social factors.

Table 4.13: The concepts' values for scenario 2.

Concepts	Results - No Changes	Results - Scenario 2
Food waste	0.3455	0.2978
Age of family members	0.6590	0.6590
Household size	0.6590	0.6590
Household income	0.6590	0.6590
Shopping routines	0.3567	0.1500
Intention not to food waste	0.7425	0.7425
Perceived behavioural control	0.6590	0.6590
Planning routines	0.7393	0.7393
Attitudes (moral & environmental)	0.6590	0.6590

Then the concept value of attitudes and perceived behavioural control is raised from 0.66 to 0.85 to simulate how the other concepts respond in the system. Consequently, a slight increase yield to nearly 0.10 decrease in the food waste concept. In addition, this triggers a 0.05 reduction in the shopping routines and about 0.02 increase in both intention not to food waste and planning routines concepts.

Table 4.14: The concepts' values for scenario 3.

Concepts	Results - No Changes	Results - Scenario 3
Food waste	0.3455	0.2482
Age of family members	0.6590	0.6590
Household size	0.6590	0.6590
Household income	0.6590	0.6590
Shopping routines	0.3567	0.3042
Intention not to food waste	0.7425	0.7634
Perceived behavioural control	0.6590	0.8500
Planning routines	0.7393	0.7596
Attitudes (moral & environmental)	0.6590	0.8500

Scenario 4: Food-related routines can be improved by emphasizing food waste as a problem more and encouraging people with purposeful campaigns. (Thyberg and Tonjes, 2016). The concept of shopping routines is about purchasing routines of larger amounts of food than required while going shopping. And the concept of planning routines is about checking the inventory levels before purchasing foods already in stock at home (Stefan et al., 2013). Therefore, the concept value of shopping routines is reduced from 0.36 to 0.15, and the concept

value of planning routines is increased from 0.74 to 0.95 to comprehend how the factors react to changing the value of other factors. As a consequence, the value of food waste concept is decreased almost 0.07.

Table 4.15: The concepts' values for scenario 4.

Concepts	Results - No Changes	Results - Scenario 4
Food waste	0.3455	0.2729
Age of family members	0.6590	0.6590
Household size	0.6590	0.6590
Household income	0.6590	0.6590
Shopping routines	0.3567	0.1500
Intention not to food waste	0.7425	0.7425
Perceived behavioural control	0.6590	0.6590
Planning routines	0.7393	0.9500
Attitudes (moral & environmental)	0.6590	0.6590

When scenario results are investigated, all scenarios contribute to reducing food waste in some ratio. However, the best result is obtained from the third scenario. This scenario provided the best food waste reduction ratio by 0.10 compared to other alternative scenarios. Also, this scenario improves the value of other concepts such as shopping routines, intention not to food waste, and planning routines.

5. CONCLUSION AND RECOMMENDATIONS

In recent years, the importance of the waste management field has received substantial attention with the increasing possibility of facing adverse effects, including depletion of natural resources, a variety of health issues and economic problems. Therefore, the tendency of research interest, especially in food waste, has escalated among policymakers, organizations, academics and researchers. Because the amount of food wastage grown out at the global level causes high environmental, social, and economic consequences. As reported by the FAO (2011), food waste has been accountable for approximately 8% of annual global emissions. This ratio would rank food waste as the third-largest greenhouse gas (GHG) emitting country in the world if food wastage were a country. Also, FAO reported that approximately one-third of food produced for consumers is wasted globally, corresponding to a notable amount of the global food supply, roughly 1.3 billion tons per year. Given that the global population is rapidly increasing over time and many malnourished people are currently available throughout the world, appropriate food waste management strategies are highly required for long-term sustainable development.

The literature on this subject generally emerges in defining and quantifying food waste rather than holistically investigating the relations between the concepts that influence food waste. Since there is not enough study concentrating on the connections between food waste factors, this study attempts to enhance an environmental assessment model to identify driving food waste factors and reveal their hidden patterns. In this regard, the recent literature and empirical studies on food waste have initially been reviewed systematically. However, due to the scarcity of resources in the field, the Document Coding method is employed to record all the possible cause and effect concepts concerning food waste. In total, 83 different cause and effect concepts are identified by following the documentary coding terminology. Then, the most recurrent concepts are filtered, and some concepts are eliminated based on the determined exclusion criteria. Following that, nine food waste driving factors and 25 cause-effect relationships are specified, and it is noticed that causal relationships between concepts include vague or imprecise judgments. Therefore, the idea of linguistic variable is introduced under the fuzzy set theory to handle ambiguity arising from fuzziness in subjective judgements. In this respect, a

5-point linguistic scale represented by triangular fuzzy numbers is designed to express the causality among concepts from very high influence to very low influence. Next, the graded mean integration technique is applied as a fuzzy aggregation operator to create the final influence matrix. The influence matrix is used as an input for FCM later, but before that, the intuitionistic fuzzy sets theory is deployed. In this regard, the hesitancy weight factor is introduced to represent the lack of information. Then, the iFCM approach incorporated by IFSs is implemented in this project to model the complex causal interactions of food waste concepts. The developed iFCM model is simulated, and the sigmoid function is used as a threshold function. The simulation process is terminated after 28 iterations until all factors reach a steady-state. Then FCM indices are calculated, and model parameters are evaluated. Finally, what-if analysis scenario analyses are performed to observe the dynamical behaviour of the model and understand how the factors react to increasing or decreasing the value of other factors. Therefore, four alternative scenarios have been generated that focus on mainly food waste reduction. Based on the results, it is probable to observe food waste reduction in some ratios. The third scenario particularly gives the best result in terms of both food waste reduction amount and improvement in other concepts. Accordingly, the ratio of food waste concept is reduced by almost 0.10 in the third scenario. The other improvements are observed in the following concepts as shopping routines, intention not to food waste, and planning routines. Therefore, policymakers, researchers and organisations interested in food waste management can review the scenario analyses and check the interactions between food waste concepts in the developed model.

This study attempts to collectively analyse and model the food waste factors by integrating the document coding method with iFCM. The data collection period can be extended for future studies, and researchers can enhance data size to observe more complex causal interactions of various factors. Also, this effective tool can be implemented in other environmental science projects to uncover hidden patterns and presents new insights to decision-makers for real-life problems.

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APPENDICES

APPENDIX-1: The final list of cause-effect concepts

No	References	Cause Concept	Linkage	Weight of linkage	Effect Concept
1	Song et al. (2018)	Refrigerator ownership	-	Very high influence	Food waste
2	Song et al. (2018)	Household income	-	High influence	Food waste
3	Song et al. (2018)	Education level	-	High influence	Food waste
4	Song et al. (2018)	Household size	+	High influence	Food waste
5	Song et al. (2018)	Urbanization level	-	High influence	Food waste
6	Song et al. (2018)	Age of family members	+	Very low influence	Food waste
7	Aschemann-Witzel et al. (2015)	Packaging factors	+	Low influence	Food waste
8	Irani et al. (2018)	Food recycling	-	Very low influence	Food waste
9	Irani et al. (2018)	Food market competition	+	Very high influence	Food waste
10	Irani et al. (2018)	Demand planning	-	Very low influence	Food waste
11	Irani et al. (2018)	Easiness of market access	+	High influence	Food waste
12	Irani et al. (2018)	Time to market	+	Very low influence	Food waste
13	Moronea et al. (2019)	Public food waste rules	-	High influence	Over purchase behaviour
14	Moronea et al. (2019)	Public food waste rules	+	Medium influence	Consumer attitude
15	Moronea et al. (2019)	Information campaigns	-	Medium influence	Environment, socio-economic system, and ethical system
16	Moronea et al. (2019)	Investment and infrastructural subsidies	-	Medium influence	Environment, socio-economic system, and ethical system
17	Moronea et al. (2019)	Cooperation	-	Medium influence	Environment, socio-economic system, and ethical system

APPENDIX-1 (continued):

18	Moronea et al. (2019)	Public food waste rules	-	Medium influence	Environment, socio-economic system, and ethical system
19	Moronea et al. (2019)	Small scale farming	-	Medium influence	Environment, socio-economic system, and ethical system
20	Moronea et al. (2019)	Investment and infrastructural subsidies	+	High influence	Biorefinery
21	Moronea et al. (2019)	Cooperation	+	Medium influence	Biorefinery
22	Moronea et al. (2019)	Public food waste rules	+	Medium influence	Biorefinery
23	Moronea et al. (2019)	Investment and infrastructural subsidies	+	High influence	Supply chain inefficiency
24	Moronea et al. (2019)	Cooperation	+	High influence	Supply chain inefficiency
25	Moronea et al. (2019)	Biorefinery	-	Very high influence	Over purchase behaviour
26	Moronea et al. (2019)	Biorefinery	-	Very high influence	Environment, socio-economic system
27	Moronea et al. (2019)	Food banks and food sharing	-	Medium influence	Food waste
28	Kleemann et al. (2017)	High rainfall	+	High influence	Food insecurity
29	Kleemann et al. (2017)	Improving agricultural programs	-	High influence	Post-harvest loss
30	Kleemann et al. (2017)	Improving agricultural programs	+	High influence	Irrigation
31	Kleemann et al. (2017)	Population growth	+	High influence	Food insecurity
32	Yang and Zhen (2020)	Livestock number	+	Very high influence	Food consumption
33	Yang and Zhen (2020)	Household income	+	Very high influence	Food consumption
34	Yang and Zhen (2020)	Regional economic development	+	Very high influence	Food consumption
35	Yang and Zhen (2020)	Consumption habits	+	Very high influence	Food consumption
36	Yang and Zhen (2020)	Age of family members	-	Very high influence	Food consumption

APPENDIX-1 (continued):

37	Yang and Zhen (2020)	Food price	-	Medium influence	Food consumption
38	Zhang et al. (2020)	Facility and equipment problems	+	High influence	Fresh food logistics failure
39	Chai, Shi, Lu and Hu (2020)	Population growth	+	High influence	Food demand
40	Chai, Shi, Lu and Hu (2020)	Energy consumption growth	+	Very high influence	Food production growth
41	Chai, Shi, Lu and Hu (2020)	Annual rainfall	-	Very high influence	Food production growth
42	Chai, Shi, Lu and Hu (2020)	Water intake	+	Very high influence	Food production growth
43	Stancu et al. (2016)	Injunctive norms	+	Medium influence	Intention not to food waste
44	Stancu et al. (2016)	Attitudes	+	Low influence	Intention not to food waste
45	Stancu et al. (2016)	Perceived behavioural control	-	Very high influence	Food waste
46	Stancu et al. (2016)	Intention not to food waste	-	Low influence	Food waste
47	Stancu et al. (2016)	Household skills	+	Medium influence	Planning routines
48	Stancu et al. (2016)	Household skills	+	Medium influence	Leftovers reuse routines
49	Stancu et al. (2016)	Planning routines	-	Medium influence	Shopping routines
50	Stancu et al. (2016)	Shopping routines	+	Very high influence	Food waste
51	Stancu et al. (2016)	Leftovers reuse routines	-	Very high influence	Food waste
52	Stancu et al. (2016)	Household size	+	Low influence	Food waste
53	Stancu et al. (2016)	Household income	+	Low influence	Food waste
54	Stancu et al. (2016)	Age of family members	-	Low influence	Food waste
55	Katajajuuri et al. (2012)	Household size	+	Very high influence	Food waste
56	Williams et al. (2012)	Packaging factors	+	Low influence	Food waste
57	Williams et al. (2012)	Household size	-	Medium influence	Food waste
58	Williams et al. (2012)	Household income	No correlation	No correlation	Food waste

APPENDIX-1 (continued):

59	Adenso-Díaz, et al. (2017)	Dynamic price strategy	-	Very high influence	Food waste
60	Stefan et al. (2013)	Moral attitudes	+	High influence	Intention not to food waste
61	Stefan et al. (2013)	Planning routines	-	Medium influence	Food waste
62	Stefan et al. (2013)	Shopping routines	+	High influence	Food waste
63	Stefan et al. (2013)	Perceived behavioural control	-	Medium influence	Food waste
64	Stefan et al. (2013)	Moral attitudes	-	Medium influence	Shopping routines
65	Stefan et al. (2013)	Lack of concern	-	Medium influence	Intention not to food waste
66	Stefan et al. (2013)	Lack of concern	-	Medium influence	Moral attitudes
67	Stefan et al. (2013)	Subjective norms	+	Low influence	Moral attitudes
68	Stefan et al. (2013)	Subjective norms	-	Medium influence	Lack of concern
69	Stefan et al. (2013)	Perceived behavioural control	+	Medium influence	Planning routines
70	Stefan et al. (2013)	Perceived behavioural control	-	Medium influence	Shopping routines
71	Stefan et al. (2013)	Awareness	-	Low influence	Food waste
72	Stefan et al. (2013)	Age of family members	-	Low influence	Food waste
73	Stefan et al. (2013)	Household income	+	Low influence	Food waste
74	Secondi et al. (2015)	Age of family members	-	Very high influence	Food waste
75	Secondi et al. (2015)	Urbanization level	-	Very low influence	Food waste
76	Secondi et al. (2015)	Attitudes	-	Very high influence	Food waste
77	Secondi et al. (2015)	Food recycling	-	Very low influence	Food waste
78	Secondi et al. (2015)	Public food waste rules	-	Very high influence	Food waste
79	Morone et al. (2018)	Environmental attitude	-	Very high influence	Food waste

APPENDIX-1 (continued):

80	Koivupuro et al. (2012)	Household size	+	Very high influence	Food waste
81	Koivupuro et al. (2012)	Packaging factors	+	No correlation	Food waste
82	Grainger et al. (2018)	Age of family members	-	High influence	Food waste
83	Grainger et al. (2018)	Household size	+	Very high influence	Food waste

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