UNIVERSITY OF PÉCS
FACULTY OF BUSINESS AND ECONOMICS

DOCTORAL SCHOOL OF BUSINESS ADMINISTRATION

ADEOLU DAIRO

Revenue Optimization Through Digital Marketing and Analytics: A Fuzzy Approach for Consumer Firms with Large Customer Base

Supervisor: Dr. Krisztián SZŰCS

Submitted according to the requirements for the degree of
Doctor of Philosophy of
University of Pecs

Pécs, 2021

DECLARATION OF ORIGINALITY

I, the undersigned, solemnly declare that this doctoral dissertation is the result of my own independent research and was written solely by me using the literature and resources listed in the Reference.

Adeolu O. Dairo 10.04.202

ACKNOWLEDGEMENT

"As complexity rises, precise statements
lose meaning and meaningful statements
lose precision"
(Lofti A. Zadeh, 1965)

In the first quarter of 2016, I made the decision that led to the completion of this dissertation. I was initially wondering how I would cope knowing the sacrifices, time, and resources required to complete a Ph.D. dissertation. However, I received the encouragement and strength that propelled me through this journey from the first person I discussed my intention with – my dear Funmilayo. You gave me that encouragement on that day, as you said – *"Ade, you can do it."* Yes, by the grace of Almighty God, I have done it.

First and foremost, my gratitude goes to Almighty God for His divine support throughout this journey. Several individuals have made this dissertation possible. First, I would like to appreciate my supervisor, Dr. Krisztián Szűcs, who has guided me from the beginning of this journey until the end of this dissertation. You are the one that has made this dissertation a success. For all your support and guidance, through all ups and downs, including the tips you often share about the *hidden and unwritten rules of academia, your succinct and encouraging words with your short but loaded emails propelled me forward in moments of frustrations*. Thank you for everything.

I want to thank my family for bearing with me, considering how this dissertation had eaten dip into the time I would have spent with them; for all their moral support – especially, Funmilayo – I say thank you. Special thanks to my colleague, Elvis, former Director of Brands Communications at Etisalat. You consistently hailing me "Dr. Adeolu" every morning whenever we greeted each other between 2014 to 2018 – you were an inspiration for me to commence this journey – a big thank you to you. Thank you, Yinka Lawal, you have been inspirational, and for your encouraging words at a time I wanted to quit – thank you. Thanks to Temitope Akinwumi – you have been highly supportive.

I owe my gratitude to my CEO in Etisalat, Nigeria, Matthew Wilsher, who has given me the opportunity and access to leverage data of over 23 million mobile customers of Etisalat in this dissertation.

My thanks go to all the Faculty and non-Faculty members of the Business and Economics Faculty of the University of Pecs. Special thanks to Gabriella Kohlmann. Your support at every point of this journey has made this dissertation a reality – thank you.

Finally, I dedicate this dissertation to my late friend, Oluwole Rawa – Former General Manager, Consumer Marketing Segments, MTN Nigeria. We had a great discussion before I commenced this journey, but you couldn't wait to see it to the end – rest on my dear friend.

Sincerely, Adeolu O. Dairo

TABLE OF CONTENTS **PAGES**

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

AMA	American Marketing Association
ASO	App Store Optimization
B2C	Business to Consumer
BTL	Below the Line
CI	Computational Intelligence
DPI	Deep Packet Inspection
EIAA	European Interactive Advertising Association
FA	Fuzzy Analytics
IAB	Interactive Advertising Bureau
KPI	Key Performance Indicator
MCDM	Multiple Criteria Decision Marketing
MMA	Mobile Marketing Association
NPS	Net Promoter Score
OTT	Over the Top
ROI	Return on Investment
SCG	Service Control Gateway
SEO	Search Engine Optimization
SMM	Social Media Marketing
USSD	Unstructured Supplementary Service Data
WA	Web Analytics

ABSTRACT

The recent digital evolution and explosion, which have led to digital marketing growth and its associated channels, have continued to drive the increase in brands' budgetary allocation for these marketing channels. However, questions are beginning to arise from marketing practitioners and brands on the justification of these budgets and their impact on business revenue and performance. Marketing analytics have raised optimism for brands on how embedded opportunities in digital marketing channels can be harnessed. However, research has revealed that firms lack a clear understanding of analytical techniques that can drive brands' business performance across these channels. This dissertation adds to the body of knowledge in this space by investigating how firms with a large customer base can drive and optimize their business performance through digital marketing and analytics using a fuzzy approach as the key analytic method.

Following a thorough literature review coupled with Delphi interview of practitioners, this dissertation's primary data is grounded from seven case studies that investigated how analytics can drive revenue and business performance of firms across digital channels. The first case examines a diagnostic customer experience for digital marketing channels; the second case explores Fuzzy Analytics (FA) for digital video advertising campaign effectiveness and measurement; the third case explores the digital channel performance optimization of mobile money transaction through an analytical approach; the fourth investigates the fuzzy expert pricing systems and optimization techniques within the space of marketing science; the fifth case examines the fuzzy logic expert system for pricing digital services; the sixth case examines the battle for digital customer ownership between the Telco and the Over-the-top (OTT) players; and, the seventh reviews the application of Fuzzy Analytics (FA) in the digital and consumer marketing space.

The findings confirm that Fuzzy Analytics (FA) avails marketers the opportunity of maximizing the rich customer data across the enterprise in real-time to generate incremental revenue for consumer businesses with a large customer base across digital channels. Also, findings reveal that business performance will look promising if analytics techniques are layered on digital marketing channels. However, it was found that digital marketing channels are not optimized because the analytics driving the engagement, marketing activities, and customer presentation are not robust enough. This dissertation supports the claim that a firm, which has developed its analytical capability and leverage the rich customer data across the enterprise through automation will compete favorably and drive the customer base's business performance optimally. And finally, results in profit growth.

CHAPTER ONE: INTRODUCTION

1.1 STUDY BACKGROUND AND RESEARCH QUESTIONS

Firms marketing budget and expenditure are under severe scrutiny due to cost reduction after the economic crisis of 2008 while doing more with less strategy is growing across many industries (Kumar and Shah, 2009; McDonald, 2010; Stewart, 2009). This has tremendously increased the pressure on marketers to justify their spending and be more accountable for the business to allocate an appropriate budget for this critical aspect of the firm (Verhoef and Leeflang; Homburg et al., 2015; Payne, Peltier and Barger, 2017). For a firm with a large customer base, research shows (Verhoef and Leeflang, 2009; O'Sullivan, Abela and Hutchison, 2009) that effective management of the existing base, ability to retain effectively, and strategic recruitment of new additions to the base are the secrets of revenue optimization and firm profitability.

In the context of this study, a *large customer base* is a consumer base of a firm with different segments of customers along the value, location, products and other attributes who repeatedly purchase the goods and services of the firms. (Jerath, Fader and Hardie, 2016; Peker, Kocyigit and Eren, 2017; Hazée, Van Vaerenbergh, Delcourt and Kabadayi, 2020). Example of firms with such a large customer base are found mostly in service and utility sectors such as telecommunication, power, banking and media.

Academic research has advanced in impacting business revenue due to effective marketing activities that can influence business revenue, metrics, and performance measurement. The academic literature has also witnessed robust theoretical frameworks that joined marketing activities and their corresponding impacts on firm value and overall business performance (Ambler and Robert, 2008; Keeling, de Ruyter, Mousavi and Laing, 2019). Despite different cost-cutting initiatives by companies and shrinking marketing budget of firms with a large customer base, organizations still depend on the consumer marketers to optimize the base to generate incremental revenue through a thorough understanding of the customers across all channels and interactions with customers.

Businesses look up to the firms' marketing practitioners to solve revenue challenges by optimizing customer base potential to grow the overall business revenue (O’Sullivan and Abela, 2007; Stewart, 2009). The marketers' inability to demonstrate their ability to generate incremental revenue within the customer base that will translate into revenue growth puts consumer marketers in a difficult position within the firm (Verhoef and Leeflang, 2009; Vomberg, Enke and Grimm, 2015).

Despite the theoretical advancement over the years, empirical evidence does not exist to show that consumer marketers managing a large customer base such as the mobile telecommunication industry has fully optimized revenue and generate optimal incremental revenue from the customer base across their critical touch points (O’Sullivan and Butler, 2010; Gök, Peker and Hacioglu, 2015). Consequently, marketing analytics is one of the research areas with so many theoretical advancements but limited marketing practice to leverage analytics to optimize business revenue (Andrew, Goehring, Hui, Pancras and Thornswood, 2016; Busca and Bertrandias, 2020; Gupta, Leszkiewicz, Kumar, Bijmolt, Bijmolt and Potapov, 2020).

Another challenge is the major shift in the marketing channel landscape, due to fragmented marketing channels resulting from digital evolution. Consumption patterns have changed because of the digital impact on consumer behavior (Lingqvist, Plotkin, and Stanley, 2015; Szabolcs and Erzsébet, 2016; Busca and Bertrandias, 2020; Rekettye and Rekettye, 2019). Digital media has taken a considerable amount of overall media budget across the industries (Raman, Mantrala, Sridhar and Tang, 2012; Hofacker, Golgeci, Pillai, and Gligor, 2020). Attracting and keeping customers, especially in sectors with a large customer base through traditional marketing activities, is now even more difficult (Johnson, Muzellec, Sihi and Zahay, 2019; Rahman, Hossain, Abdel Fattah and Akter, 2020). Hence, marketers need to be more innovative and eventful to manage their customer base across their selected digital channels (Mulder and Vetvik, 2009; Webster and Ksiazek, 2012). While digital analytics provides firms with robust data that complements other data sources, Lavalle et al. (2011) argue that firms' ability to leverage the data into actionable insights is rather an issue than data availability (Gök, Peker and Hacioglu, 2015; Helzlsouer, Meerzaman, Taplin and Dunn, 2020).

For a consumer firm with a large customer base, judgment about a proposition, offerings, and promotions can no longer be made by the rule of thumb. It takes a combination of a robust analytical approach with integrated tools and capabilities. Analytics have opened the opportunity for firms to solve the problem of understanding customer behavior across the digital channel to leverage the available insights to generate incremental revenue (Lavalle, Lesser, Shockley, Hopkins, and Kruschwitz, 2011; Rahman, Hossain, Abdel Fattah and Akter, 2020). The data available across the digital space provides many opportunities for brands to address their customer base's needs and improve their business performance. Hence, the data's availability is no longer the issue, but firms' ability to leverage the data into insights and target the customers with the appropriate offerings along the right channels.

This dissertation is defined within the context of consumer marketing (i.e., Business-to-Consumer or B2C marketing), which is generally termed as the marketing of products and services to consumer markets (i.e., individual customers) (American Marketing Association, 2016). Unlike the business market, consumer markets are noted for many customers and general value proposition that can address many segments (mass, youth, adult, teen, or defined segments); and, challenging to manage due to the large customer base (Lilien, 2016), which is significant to the topic of this study. Generally, managing consumer marketing segment is complex due to the fragmented segments that characterized the entire base (Swani, Brown and Milne, 2014; Leeflang, Verhoef, Dahsltröm and Freundt, 2014). Ensuring that each customer within a large customer base consisting of millions of customers is well served across touch points with propositions that will optimize the derived value from individual customers is a significant challenge for consumer marketers.

However, the technological innovations that have resulted in increasing connected devices and the data networks' underlying technology have drastically changed consumer behavior (Payne, Peltier and Barger 2017; García, Lizcano, Ramos and Matos, 2019; Hollebeek, Sprott, Andreassen, Costley, Klaus, Kuppelwieser, Karahasanovic, Taguchi, Ul Islam and Rather, 2019). These have also changed the way the brands interact with their customer base. The influence of these innovations continues to impact how the customers are served, where they are served, and the methods in which they are served. Digitalization has reshaped the entire customer purchase journey (Ryan, Jones, 2009; Sturiale and Scuderi, 2016; Da Silva, 2020). Once the customer purchase journey is impacted (Nagy, Szűcs, Kemény, Simon and Németh, 2019), there is a direct impact on its bottom line. Therefore, marketing techniques are quickly changing to adjust and leverage new digital marketing techniques. These adaptations have given rise to expanded channels, which are referred to as the digital channels.

As far as consumer marketers are concerned, the expansion of marketing channels along the digital space provides robust opportunities for brands for one-to-one marketing engagement and purchase optimization. Unlike traditional marketing techniques, digital marketing makes data available for brands to better understand and profile their customer base. Due to data availability along these channels, digital marketing and analytics open opportunity for consumer marketers to collect data across the entire touch points and different stages along the customer journey. For this study to attain its goals, this dissertation aims at answering the three research questions, listed below in FIGURE 1.1.

Research questions of the dissertation:

1. To what extent can consumer firms with a large customer base drive and optimize business revenue through digital marketing and analytics?

2. Why do some consumer firms drive and optimize business revenue from digital and marketing analytics while others do not?

3. How can consumer firms deploy digital marketing and analytics in driving and optimization of business revenue?

FIGURE 1.1 Research questions of the dissertation

1.2 DISSERTATION JOURNEY

As mentioned in the previous section, this dissertation's motivation arises from the need for marketers to justify the increasing budget that firms put behind digital marketing initiatives. As a consumer marketing professional with over 16 years of experience in managing a large customer base and driving business performance across many mobile telecommunication operations in Emerging markets and Europe, I have witnessed a consistent year on year decline in the marketing budget of consumer firms in the last decade. By following this trend in the last few years, I am certain that marketing budget that consumer firms are still currently allocating to traditional marketing channels such as TV commercials would not be sustainable over time.

However, while budget for digital marketing channels is growing, marketers must be able to justify this spending through the revenue these channels are generating for their brands. Hence, I began to explore the digital marketing space to understanding its associated channels and methods. While I saw many kinds of literature in this space, I struggle to see how businesses and firms can operationalize several techniques and methods proposed in the literature to optimize these digital channels.

My curiosity led me to the theory of fuzzy, which was theorized in 1965 (Zadeh, 1965). I found the fuzzy theory interesting because of its uniqueness to accommodate unclear and subjective boundaries, such as customer judgment. With fuzzy theory, I found alternative means to accommodate vague, unclear, and subjective boundaries that characterize customer behavior and perception across the digital channels. Therefore, this dissertation leverages the fuzzy linguistic application in different marketing domains of decision making along with several mathematical formulations to address the revenue optimization problems in consumer and digital marketing.

In the literature review phase of this research process, I tried to explore how previous research has leveraged and applied the fuzzy method, theory, and logic on digital marketing problems in a systematic approach. Also, I reviewed other cutting-edge analytic approach such as Machine Learning (ML) techniques in relation to fuzzy. The research gaps that were identified set the tone for all the case studies explored in this dissertation. I found gaps in the application of the fuzzy method on customer experience, pricing, customer selection and innovations in digital ecosystem. Opportunities on how the gaps can be bridged were also identified.

In the first study, I applied the Delphi method to obtain a snapshot from the industries' experts in consumer firms with a large customer base. Four sectors were targeted – they were Mobile Telecommunication, Betting, Financial Technology (FinTech), and Banking. The Delphi survey blended with the gaps in the literature re-shaped my research questions. FIGURE 1.2 shows the framework that links the cases in this dissertation with the research questions along the identified gaps in the literature and the Delphi study.

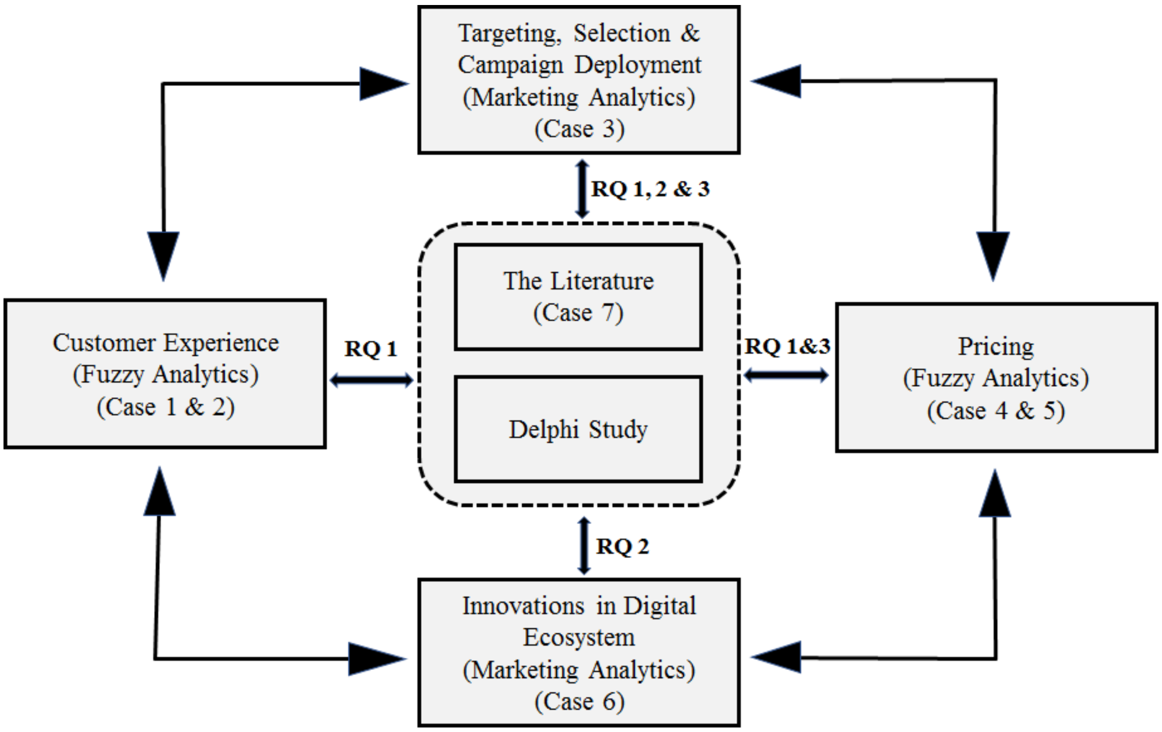

FIGURE 1.2 Dissertation framework

At this stage, I realized a case method would provide more insights into the significant questions surrounding how firms can drive and optimize business performance through digital marketing and analytics. Using the mobile telecommunication industry as a proxy for industries and firms with a large consumer base, all case studies in this dissertation are grounded on mobile telecommunication firms' consumers. Apart from the large customer base that is associated with a typical mobile operator, cellular firm's business model supports and drives digital explosion and evolution (Stone, 2015; Wellmann, 2019). Mobile operators have also devoted time and effort towards leveraging the digital marketing channel and analytics to drive their business performances. Thus, the primary data of six cases in this dissertation came from the real customer data in the mobile industry.

The first case focuses on a diagnostic approach for measuring customer experience of digital services of mobile users. I concluded that if customer experience can be measured in real-time (*moment of truth – at the time of service consumption*), firms can leverage the customer experience in real-time to improve their services and business performance. This, therefore, led to the second case study of this dissertation.

Still, on customer experience, the second case study investigates how Fuzzy Analytics (FA) can be used for measuring digital video advertising campaign effectiveness and customer experience. The outcome of this study shows that the subjective tendency of customer experience is fuzzy. The study, therefore, presents how brands can leverage fuzzy methods for measuring their digital customers' experience in real-time to improve services to their customers.

The third case considers an analytical approach to digital channel performance optimization. In this case study, the focus was on the mobile money customers of the mobile telecommunication industry. I was curious about the power of analytics in targeting, profiling, and selecting the right set of customers for a specific campaign. It was found that the selection output that is driven by the fuzzy analytical model enables appropriate cross-selling and up-selling that can optimize the revenue from customers.

The fourth and fifth case studies leverage insights from a systematic literature review where pricing was identified as a gap under the fuzzy application. Hence, the cases focus on optimizing firms' revenue and performance through pricing adjustment driven by Fuzzy Analytics (FA). Findings in these cases reveal that through fuzzy expert systems, firms can set price points for digital services in a way that will optimize business performance. The sixth case leverages advanced analytics to address the threats and excesses of OTT (over-the-top) players' digital innovative products within the mobile telecommunication ecosystems. (OTT) players distribute video content over a public network. Their activities cut across messaging, voice, digital media, and cloud services.

As linearity characterized many research processes, it is important to note that this dissertation is a product of many iterative processes, in which I have been very transparent. While each case study generates novel ideas and further research questions, they also provoke the research questions evolution throughout the dissertation process.

1.3 RESEARCH SIGNIFICANCE AND CONTRIBUTIONS

This dissertation adds to the body of knowledge in many ways. First, it brings out the usefulness and importance of fuzzy techniques and its analytical capabilities in consumer firms with a large customer base. It contributes both to academics and practice in revealing that fuzzy theory, methods, and associated logic can be adopted and leverage across many digital-related marketing problems.

Secondly, many analytic techniques have been used across firms with a large consumer base in service or utility industries. This dissertation brings out Fuzzy Analytics (FA)'s uniqueness as a cutting-edge subset of Artificial Intelligence (AI).

Third, this dissertation identifies a considerable gap in the application of the fuzzy method across marketing science. Case studies are tailored towards the identified gap in the literature along with the application of Fuzzy Analytics (FA) in customer experience, fuzzy application in pricing and optimization; fuzzy application in targeting and profiling, and analytics towards solving some of the challenges arising from digital evolution and explosion in the consumer space.

In general, all case studies in this dissertation address the opportunities embedded in the digital marketing and analytics for firms to drive and optimize business performance. I have approached this dissertation in a way that makes it significant for both research and practice. This was achieved due to the rich consumer data that serves as the primary data for all the case studies in this dissertation.

Finally, the dissertation would interest researchers, consumer marketers, and businesses, especially firms looking for ways to leverage their customer data to drive and optimize their business performance across the digital and marketing channels.

1.4 KEY CONCEPTS

1.4.1 Digital Marketing

The rapid growth of technology and its advancement have enabled and created a digital economy that is characterized by an intelligence and information space. This digital economy as posited by the France stratégie, has four specific impacting features on brands and consumers: the irrelevance of geographical location, the key role played by platforms, the importance of network effects and the use of big data. These features distinguish it from the traditional economy, particularly as a result of the associated value chain transformations (Charrier and Janin 2015; Valenduc and Vendramin, 2016). The results of these technological growth and innovation have brought about access to information, tools, and communication capabilities through various channels. These channels are the digital channels that consumer marketers are now leveraging to interact with their existing and prospective customers directly (Baye, Santos and Wildenbeest, 2015; Yang, Shi and Wang, 2015).

Digital marketing is the strategic integration that includes the web, methodology and processes, tools, and social media platforms (Leeflang, Verhoef, Dahsltröm and Freundt, 2014; Payne, Peltier and Barger, 2017). Today, consumer behavior has changed due to how they gather and assess the information they leverage for making purchase decisions across the marketing channels due to digital evolution. Therefore, digital marketing can also be described as an integrated process of developing and leveraging online channels to establish the exchange of products and services in the market (Yang, Shi and Wang, 2015; Lengiz, Ibrahim, and Ali; 2016). The underlying strategies of digital marketing are based on marketing goals, and it also opens another stream of channels for marketing strategic goals. While there can be many marketing-related objectives by a firm, the primary marketing objective is for a firm to improve its business performance by generating positive cash flow and net profit (Ambler and Robert, 2008; Busca and Bertrandias, 2020).

One of the most recent and popular trends in digital marketing is Kotler's Marketing 3.0 (Kotler, Kartajaya, Setiawan, 2013), which was later followed by Marketing 4.0 – "the importance of trust fidelity" (Kotler, Kartajaya, Setiawan, 2016). This fueled the marketing strategy studies along the internet channels, including online banners, discounts coupons, and other associated communication and engagement strategies that have not been previously used before this time. Some of these are SEM (Search Engine Marketing), SMM (Social Media Marketing), SEO (Search Engine Optimization), or ASO (App Store Optimization (Payne, Peltier and Barger, 2017; García, Lizcano, Ramos and Matos, 2019).

Many authors have published several articles on the evolution of traditional marketing to digital marketing. Also, institutions such as the Mobile Marketing Association (MMA), Interactive Advertising Bureau (IAB), and European Interactive Advertising Associations (EIAA) have studied this aspect of marketing in a non-academic way to reveal the importance of this space to the business sector (Mavlanova, Benbunan and Lang, 2016; Palos-Sanchez, Saura and Debasa, 2018).

Digital marketing is primarily aimed to promote the brands and increase the customers' reach through targeted advertisements to different segments in an electronic medium (Kelley, Jugenheimer and Sheeham, 2015; Noam, 2019). It leverages digital tools such as personal computers and cell phones. Royle and Lang (2014) simply describe digital marketing as a sub-branch of traditional marketing that uses modern digital channels for the placement of products and services, e.g., downloadable music. When a firm is trying to increase sales in the consumer context, digital marketing can drive potential customers to a firm's website and convert such customers into sales leads (Jarvinen and Karjaluoto, 2015; Welling and While, 2016). Moreover, firms leverage digital marketing to cross-sell and up-sell their products and services. For marketing professionals to maximize the potential of digital marketing, they must truly understand the various techniques that are associated with online social marketing campaigns and programs along with measurement and evaluation indicators to justify their digital spending (Rohm and Hanna, 2011; Felt and Robb, 2016).

Unlike traditional channels such as radio and television, which are mass, digital marketing provides us with personalization that enables brands to personalize communication. Customers can be reached through digital platforms. For example, brands' mobile apps can be integrated with other data sources and empower brands to target individual mobile users following their unique behavior and needs (Megargel, Shankararaman and Reddy, 2018; Hollebeek et al., 2019).

The role of marketing in driving business performance continues to expand. In firms with a large consumer base, the business looks upon the marketing team to develop value propositions and execute them across the channels. However, engaging the market with such propositions has evolved from mass and direct targeting into real-time and personalized targeting through digital evolution and channel expansion (Denecker, Gulati and Niederkorn, 2014; Busca and Bertrandias, 2020).

1.4.2 Fuzzy Analytics

The evolution of digital marketing and social web opportunities have created a situation where consumer marketers are daily searching for new ways to leverage the digital marketing explosion (Hitzler et al., 2010). There are clear opportunities to deploy and implement marketing processes and programs to tap into the customers' needs through digital channels. However, there are associated complexities in customer relationship management with which marketers need to cope. Zadeh Lofti’s work on fuzzy sets first established the concept of fuzzy logic or fuzzy thinking (Zadeh, 1965). In his paper, Zadeh suggests that binary thought simplifies a complex world and is, in most cases, not adequate. According to Zadeh’s, as the complexity of the system increases, it becomes more difficult for us to make more accurate statements about the system until it becomes very difficult, and accuracy becomes impossible (Kosko, 1994; Zimmermann, 1991).

Fuzzy logic can be described as the extension of classical logic with only two truth values, 'true' and 'false'. In fuzzy logic, we are not limited to only two alternatives but varieties of truth values for logical propositions. However, we can view it as an infinite value logic covering the entire interval from true (1) to false (0). In natural languages, fuzzy logic focuses on linguistic variables and a basis for the approximate reasoning with imprecise propositions (Zimmermann, 2001; Donze and Meier, 2012). It is a pure reflection of the correctness and vagueness of human thinking. When considering the nature and concept of revenue optimization from a large customer base, approximate reasoning must be considered (Bojadziev and Bojadziew, 1997; Grint, 1997). Customer behavior, interactions, and purchase decisions are neither 'true' nor 'false.' Still, there is a series of grayscales with which marketing activities can be differentiated and result in an improved outcome on the customer's aspect.

In marketing, the concept of a set of collections of objects or segments is commonly used, especially in customer base management. For example, customer's information such as names, addresses, and customer purchase history are stored in the customer database. The objects within the set are called the elements of the set. Ordinary sets are also called traditional or crisp sets to differentiate them from fuzzy sets. A fundamental notion in set theory is the membership (Kosko, 1994, Zimmermann, 1991, Donze and Meier, 2012). Suppose an element x belongs to a set A, then $x \in A$, otherwise $x \notin A$. Two possibilities exist for each element x of a set A: either x belongs to A, or it does not. The characteristics function is the membership rule that characterizes the element of a set of A.

However, within the marketing space as an illustration, the teen segment's description as a crisp set is unsatisfactory. For example, if a boy is above 12 years but has few minutes before thirteenth year birthday, he is not yet a teenager. However, after a few minutes, he moves into the teen segment. Crisp sets do not allow gradation. The reverse is also true as a teenager slowly says goodbye to the teenage group after the age of nineteen (Zimmermann, 1991; Donze and Meier, 2012). It is inadequate using crisp sets in which the characteristic function can only take two values, 1 or 0, when dealing with linguistic concepts or gradual transitions. Rather than describing the teenagers within the teen segment as a crisp set, the fuzzy set would be a better alternative.

Zadeh (1965) assigns a number to all elements within the universal set; this indicates the degree or grade to which the element belongs to the set. For example, young people of different ages may have a different degree of belonging to the teen segment.

In line with the above, this work aims to critically examine fuzzy logic as an effective and useful method to be applied to consumer digital marketing to optimize customer base management and revenue. The next two chapters systematically review the literature in this regard.

1.5 OUTLINE OF THE DISSERTATION

The dissertation is divided into six Chapters (Table 1.1); the last two Chapters consist of the summary of the dissertation published articles on the dissertation topic and the highlights of their key findings. However, the first four Chapters detailed the theoretical and methodology discussions of the dissertation articles.

Chapters two and three review the literature of the existing works in relation to the topic of the dissertation. In Chapter 2, a systematic review of the literature on the application of fuzzy theory and logic in marketing is conducted with a focus on the fuzzy application in digital and consumer marketing. Other advanced analytics are also briefly reviewed along their applications in marketing. Chapter 3 reviews the fuzzy theory, logic, and method. Chapter 4 is dedicated to the methodology and the research approach. This chapter explains why the case study method was selected for this dissertation and critical realism and the abductive logic approach.

Chapter 5 highlights the dissertation articles, summarizes, and highlights the research findings. Chapter 6 discusses the dissertation results, theoretical contributions, and the implication for practice in line with the research questions. Finally, suggestions and avenues for future research areas are discussed.

Table 1.1: Outline of the dissertation

Outline	
Introduction (Chapter 1)	Discusses study background and research questions, dissertation journey, research significance, contributions, and the dissertation's key concept.
Literature review (Chapter 2 & 3)	The literature review is contained in two chapters: • Chapter 2 systematically reviews the application of the fuzzy method in marketing with a focus on digital marketing and consumer space. Also, a succint review on other advanced analytical methods and their application applications • Chapter 3 reviews the theory, method, and Logic of Fuzzy.

Methodology (Chapter 4)	Details and justifies the use of the case study, critical realism, and abductive logic to approach this study.
Summary of the dissertation (Chapter 5)	It highlights the summary of the dissertation articles, along with their findings.
Discussion (Chapter 6)	Presents findings concerning the research questions, discuss their theoretical contributions, and provide insights into the future research opportunity areas.

1.5.1 Previously Published Articles

This section presents the previously published articles in this dissertation in Table 1.2 below.

Table 1.2: Dissertation articles

Title	**Authors**	**Publication outlet**	**Study focus**	**Related research questions**
A diagnostic customer experience measurement for digital marketing channels	Dairo, A.	Proceedings of European Marketing Academy - EMAC (2018)	Diagnostic measurement of customer experience	Research question 1
Towards Fuzzy Analytics for Digital Video Advertising Campaign Effectiveness and Customer Experience	Dairo, A., Szűcs, K.	International Journal of Fuzzy Logic and Intelligent Systems (2019)	Fuzzy analytics application of customer experience of digital customers	Research question 1
Analytical approach to digital channel performance optimization of mobile money	Dairo, A., Szűcs, K	Innovative Marketing Journal (2020)	Analytical approach to digital channel optimization	Research question 1, 2 & 3

transactions in emerging markets				
Fuzzy Expert Pricing Systems and Optimization Techniques in Marketing Science	Dairo, A., Szűcs, K	Frontiers in Artificial Intelligence and Applications (FAIA), (2020)	Fuzzy Expert Pricing System & Optimization	Research question 1 & 3
A Fuzzy Logic Expert System for pricing digital services: the case of price adjustment for a mobile service provider	Dairo, A., Szűcs, K	International Journal of Fuzzy Logic and Intelligent Systems (2020)	Fuzzy Expert Pricing Tools for pricing digital services	Research question 1 & 3
Battle for digital customer ownership between the telco and Over-the-top (OTT) players: Emerging markets perspective	Dairo, A., Szűcs, K	African Journal of Science, Technology, Innovation, and Development (2021)	An innovative and analytical framework for OTT and Telco ecosystems	Research question 2
Fuzzy Analytics Application in Digital and Consumer Marketing: A Literature Review	Dairo, A., Szűcs, K	Smart Innovation, Systems Technology, Springer Book, (2021)	A review	Overview

CHAPTER TWO:

2.1 FUZZY ANALYTICS APPLICATION IN MARKETING

In the following two chapters, a review of this dissertation's conceptual framework is conducted as shown in FIGURE 2.1.

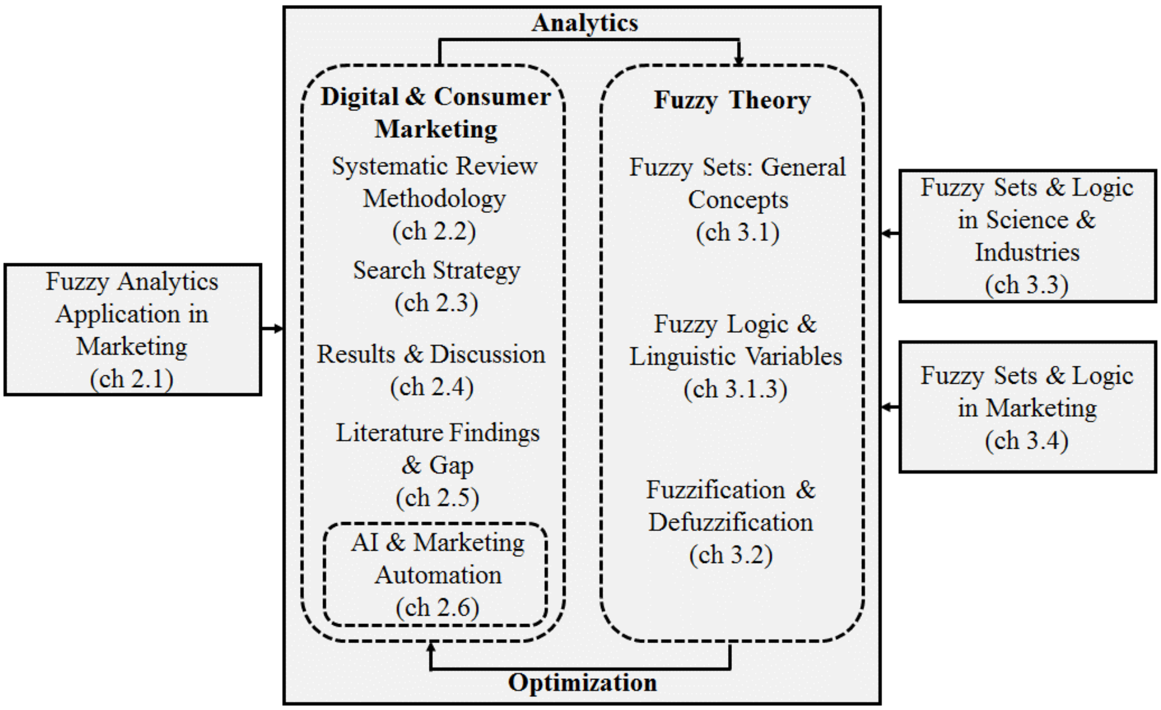

FIGURE 2.1 Conceptual framework of the dissertation

In the dissertation conceptual framework, multiple theoretical streams are integrated under a unified model. The framework starts with a systematic literature review of the application of Fuzzy theory in marketing, specifically, digital marketing and consumer marketing.

2.2 SYSTEMATIC REVIEW METHODOLOGY: PROKNOW-C

A literature review can be approached and conducted in several ways. However, this study has followed the most common, which is the theoretical background review of the literature. According to (Onwuegbuzie, Leech and Collins, 2012), literature regarding a topic can be analyzed using within-study literature analyses or between-study literature studies. Within-study literature analyses involve the analysis of a specific work while between-study literature studies entail a detailed contrasting of the content. A theoretical background literature review is fundamental and beneficial because it highlights how a given area has been explored along with the gap and pending exploration in the area. Key concepts will also be linked along with methodologies that have been previously successfully considered (Okoli, and Schabram, 2010; Onwuegbuzie, Collins, Leech, Dellinger and Jiao, 2010).

A detailed literature review must be systematic and follow a methodological approach (Okoli, and Schabram, 2010). The review methodology in this study follows the Knowledge Development Process-Constructivist (ProKnow-C) (Ensslin, Ensslin, Lacerda and Tasca, 2010), a methodology that follows steps that is similar to a protocol as shown in FIGURE 2.2.

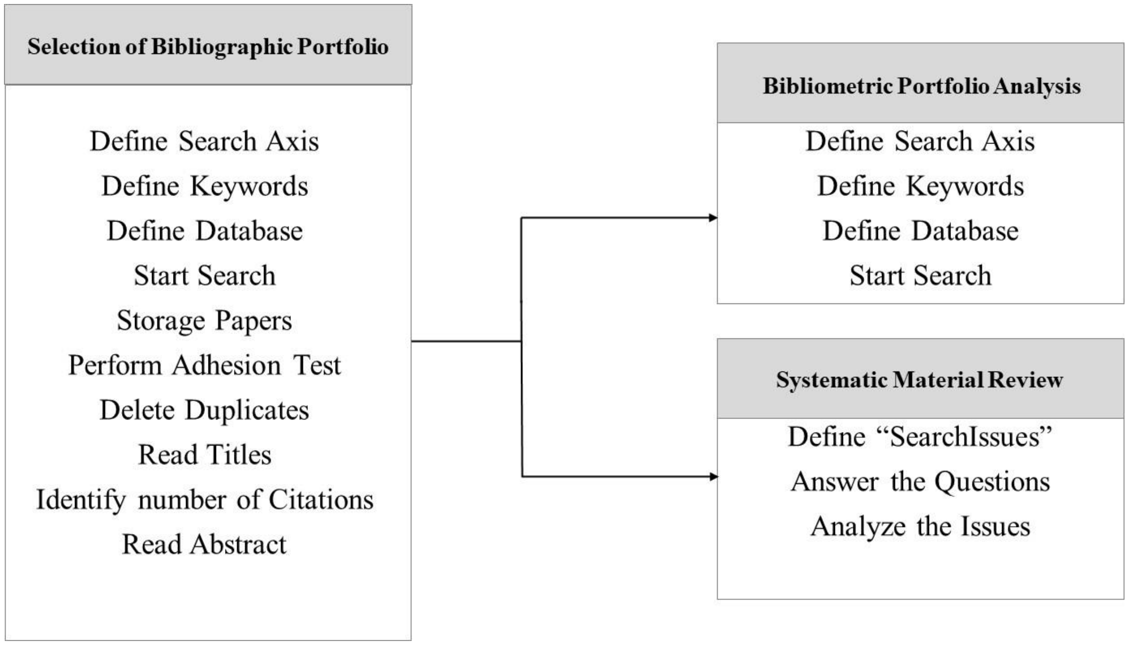

FIGURE 2.2 ProKnow-C - Adapted from Ensslin et al. (2010, p.21)

An extensive search across multiple sources was conducted in this study for the systematic analysis to gather information around the content from different articles that finally make up the portfolio of this review. First, a bibliometric analysis was carried out. This is to ensure that relevant data on published articles, trends, topics of the journals, and most relevant authors are obtained. In recent years, we have seen this method been applied in various reviews of different subjects and topics (Arruda, França and Quelhas, 2014; Ensslin, Mussi, Chaves and Demetrio, 2016; Thiel, Ensslin and Ensslin, 2017). This method's ability to particularly deal with tasks that are descriptive and exploratory motivates the use of this approach in this study. Hence, ProKnow-C is appropriate and useful for theoretical background literature reviews such as the one this study tries to explore.

The criteria for the formation of the articles in the review portfolio are strictly on the relevance of the articles on how fuzzy theory and all its associate methods have been applied to consumer marketing. At this stage, I must again clarify what is meant by consumer marketing. This study's context is consumer marketing (i.e., Business-to-Consumer), which simply means the marketing of products and services to consumer markets (American Marketing Association, 2016). Many customers characterize the consumer market with different micro-segments within the market (Leeflang, Verhoef, Dahsltröm and Freundt, 2014; Lilien, 2016; Felt and Robb, 2016). Since this study investigates how digital marking within the consumer marketing aspect can leverage fuzzy analytics to drive business performance, the literature search is broadened along the line of these topics.

This study focusses on Scopus and Web of Science databases. The motivation for Scopus and Web of Science arises from the acknowledgment of these sources within the academic community as two significant repositories of academic collections (Aghaei, Salehi, Yunus, Farhadi, Fooladi, Farhadi, and Ale, 2013; Mongeon and Paul-hus, 2014). The Boolean combination of keywords around the topic is grouped on two main axes across many combinations, namely "fuzzy theory" and "marketing," "fuzzy sets" and "marketing," "fuzzy logic" and "marketing," "digital marketing" and "fuzzy logic," "digital marketing" and "fuzzy sets," "digital marketing" and "fuzzy theory," "digital marketing" and analytics," "fuzzy marketing" and "analytics," "fuzzy marketing" and "application."

The study selections are positioned to be vague so that the searches can yield the maximum return of results. I applied the defined queries on the selected databases and filter the output by sources, including all documents such as academic journals, books, book chapters, conference papers, and proceedings (Behrens, 1992; Moher, Liberati, Tetzlaff and Altman, 2009). Duplicated records are taken out of the portfolio. A further assessment was carried out on the remaining records manually, starting from the relevance of the title, abstract, and the full text in that order. The full text's direct scanning as this stage was vital as it reduces and eliminates bias at an individual study level.

To control the risk of bias, relevant references from the portfolio's articles were added to the final portfolio. The portfolio was subjected to a Google Scholar test, and articles without citations were excluded from the portfolio as they cannot be classified as relevant studies from the academic point of view. Finally, the final portfolio is depicted in this study to identify areas in this subject where much have been accomplished and methods that have been effective so far within the academic literature.

2.3 SEARCH STRATEGY

This section highlights the results of the study's analysis and the associated characteristics of the bibliometric, along with the content of the 475 final articles in this review's portfolio. First, the analysis of the bibliometric of the portfolio is conducted. Focus is on the yearly trends of publications, most renowned journals, and authors about this study's topic. After that, a section focusing on the content of the articles.

In arriving at a final portfolio, both databases are searched, and all other documents were excluded except academic journals, conference papers, and proceedings. A total of (8,438) records were obtained (3,642) from Scopus and (4,796) from Web of Science. After a duplicate check, a total of (2,435) articles appeared in both databases resulting in the initial bibliographic portfolio of (6,003) records. Manual filtration by title relevance is followed by abstract and then full-text relevance filtration. These steps reduced the portfolio records to 656 records (see Figure 2.3).

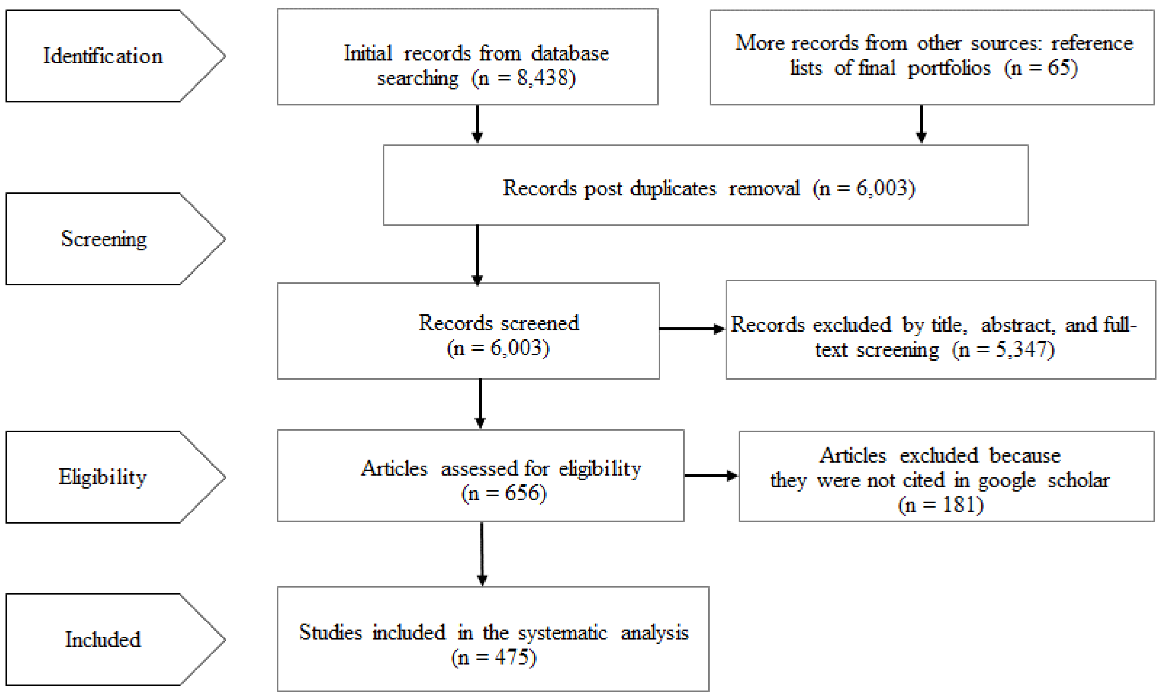

FIGURE 2.3 Flow diagram of the study selection process. PRISMA model (Moher et al., 2009).

These records are subjected to Google Scholars, and all articles that are not cited in Google Scholars are removed. This is because having no citation in the Google Scholars may not be considered academic relevance (Sanchez-Roger et al.,2019; Tawfik et al., 2019). This approach reduces the number of articles to 410. All the 410 articles' references were considered to see which one is relevant to the topic not included in the 410. Additional 65 eligible papers are obtained, and the final portfolio increased to 475 articles. A detailed flow diagram of the selection process is presented above in (Figure 2.3). An analysis of the final article portfolio in this study on the fuzzy application to marketing and its associated concepts became sizeable from the mid of 2005, as presented in (Figure 2.4).

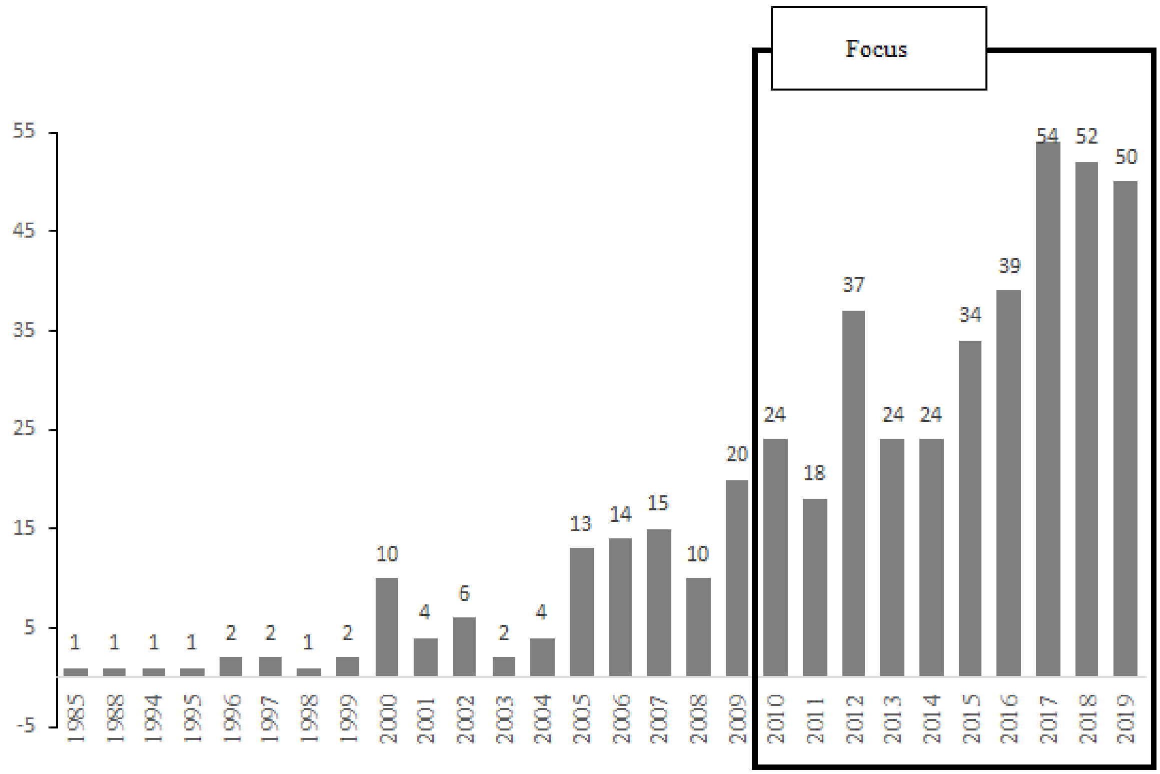

FIGURE 2.4 Number of publications in the dataset (portfolio) per year

2.4 RESULTS AND DISCUSSION

2.4.1 Analysis of the Sample

According to the publication dates and focus in (Figure 2.4), (356) articles were included in the final categorization following the classification. The key top academic journals in the portfolio are Expert Systems with Applications (90 records), Fuzzy Sets and Systems (30 records), Decision Support Systems (29 records), and Applied Soft Computing (25 records). This is followed by the Journal of Computer and Industrial Engineering (20 records), Knowledge-Based Systems (20 records), Journal of Soft Computing (15 records), International Journal of Soft Fuzzy System Applications (6 records), IEEE Transactions on Fuzzy Systems (10 records), and Journal of Intelligent and Fuzzy Systems (6 records).

I identified the top articles by citations they received from publications within the portfolio. The top-ranked journals are Expert Systems with Applications (1,201 citations), Applied Soft Computing (1,025 citations), and Fuzzy Sets and Systems (979 citations). This analysis reveals that leading Expert Systems, Knowledge-based, and Soft Computing, particularly journals, are heavily cited by publications in the application of Fuzzy methods and analytics in the field of marketing. This indicates the importance of these publication outlets as contributors to the intellectual base of Fuzzy marketing.

2.4.2 Analysis of Key Publications

This review conducts a content analysis of key articles in the final portfolio to identify each publication's different research approaches and contributions. Following a thorough exploration of the use and application of Fuzzy sets, Fuzzy logic, and all associated Fuzzy theories on all aspects of marketing, a categorization of articles by topic is proposed. First, the articles are categorized into five categories following their application of FA in the marketing field. These categorizations are Fuzzy modeling, Web analytics, Clustering and Segmentation, Performance Analysis, and Fuzzy Market Analysis. The classification of the article topics into these five categories is shown in Table 2.1.

Fuzzy modeling accounts for 42% of the total portfolio. This includes FA in social networks, expert marketing systems, recommendation systems, and Multi-Criteria Decision Making (MCDM). Also, web analytics and online marketing have seen a lot of Fuzzy application usage in recent years. The use of Fuzzy Analytics (FA) in data mining and clustering within the marketing field aligns with the growing consumer data and the big data evolution. However, research focus has been limited to FA's use in marketing campaigns, measurement, scoring, and portfolio marketing.

Table 2.1 Categorization and classification of the main topics into streams of fuzzy application (FA) in marketing

Categorization	Article Classification	Categorization (%)
Fuzzy Modeling	1. Fuzzy Application in Social Networks 2. Fuzzy Application in Expert Systems 3. Fuzzy Application in Recommendation Engine 4. Fuzzy Optimization and Multi-Criteria Decision Making (MCDM)	42%
Web Analytics	1. Fuzzy Application in Web Analytics 2. Fuzzy Application in Online Marketing	17%
Performance Analysis	1. Fuzzy Application in Performance Measurement 2. Fuzzy Application in Marketing Programs	2%
Fuzzy Clustering	1. Fuzzy Application in Customer Data Mining 2. Fuzzy Segmentation and Clustering	35%
Fuzzy Market Analysis	1. Fuzzy application in Scoring Methods 2. Fuzzy Application in Portfolio Marketing Techniques	4%

The next section explores and provides insights into the most common marketing topics, both in traditional and digital marketing space, in which FA has been used while summarizing the main findings in each field along with the research gaps.

2.4.3 Fuzzy Modeling

An area of Fuzzy modeling that has seen extensive usage in marketing is the Fuzzy expert systems. This aspect of FA application to marketing in this portfolio is 42%. This shows the relevance of this aspect of the Fuzzy application to marketing science. Expert systems took root from the branch of computing, which is now referred to as artificial intelligence

(AI) (Vipul and Gupta, 2001; Hesami et al., 2013). Expert systems are a part of computer science that utilize symbolic and non-algorithm methods to solve tasks that are seemingly difficult to be executed by a human. They are computer programs that use problem-solving knowledge and simulations at the level that can be compared with human experts (Vipul and Gupta, 2001; Keskin, 2015).

The main components which constitute a fuzzy expert system are knowledge base, inference engine, fuzzifier, defuzzier, and user interface (Muriana et al., 2016; Thaker and Nagori, 2018). The inference engine is responsible for bringing decisions based on its understanding and interpretation of the expert knowledge. The major participants in the expert system are the domain expert and are responsible for making decisions.

Multiple Criteria Decision Making (MCDM) refers to a process that leads to making a judgment within multiple and usually conflicting alternatives or criteria (Keskin, 2015; Khatwani and Srivastava, 2015). Marketers face MCDM problems in everyday life. Digital marketing problems are modellable as a fuzzy MCDM problems (see Table 2.2). This is because issues associated with digital marketing include qualitative criteria that can be evaluated by using linguistic terms and some quantitative imprecise and vague data (Kahraman, Yazici and Karaşan, 2018). The fuzzy set theory has the characteristic of accommodating this vagueness along with its associated linguistic evaluations within numerical calculations. Fuzzy MCDM methods have extensively been developed and applied to a large variety of multi-criteria problems (Keskin, 2015). MCDM has been used for the measurement of several aspects of digital marketing channels. In these measurements, many criteria, such as lack of budget, ROI, leads generation, content management, CRM capability, conversion, speed, and innovation, have been used in the literature (Khatwani and Srivastava, 2015; Kahraman, Yazici and Karaşan, 2018). These criteria are critical to the success of any digital marketing channel.

Table 2.2 Fuzzy analytics (FA) application in digital marketing

Authors	**Applications**	**Methods**	**Year**
Liu and Chen [18]	Website prioritization and recruitment	Fuzzy AHP	2009
Lee and Ahn [19]	Consumer e-commerce web system	Fuzzy Cognitive Map	2009
Ramkumar et al. [20]	Product scoring	Fuzzy Logic	2010
Ajayi et al. [21].	Improvement of response time	Fuzzy logic-based information retrieval model	2010
Mohanty and Passi [22]	Firm’s reaction to customers’ feedbacks	Fuzzy Linear Programming	2010
Zumstein [23]	Web metrics analysis	Fuzzy Logic	2010
Yu et al. [24]	Ranking of consumer e-commerce websites in e-alliance	AHP and fuzzy TOPSIS	2011
Kabir and Hasin [25]	Mobile e-commercee success identification factor	Fuzzy AHP	2011
Zandi and Tavana [26]	e-CRM framework development	Fuzzy QFD	2011
Kolomvatsos et al. [27]	Electronic marketplace	Fuzzy Logic	2012
Şengül and Eren [28]	E-market place	Fuzzy AHP -TOPSIS	2015
Kaltenrieder et al. [29]	Digital marketing management improvement	Fuzzy ANP	2015
Naili et al. [30]	E-Commerce	Fuzzy MCDM	2015
Chiang [31]	Digital marketing customer value	Fuzzy MCDM	2017
Murugananthan and Gandhi [32]	Social media analytics	Fuzzy MCDM	2020

Early research in recommender systems grew out of information retrieval and filtering research (Goldberg, Nichols, Oki and Terry, 1992). Also, recommender systems emerged as an independent research area in the mid-1990s. Researchers started to focus on recommendation problems that explicitly rely on computational intelligence (CI) techniques such as Bayesian techniques, artificial neural networks, clustering techniques, genetic algorithms, and fuzzy set techniques (Castrol-Schez et al., 2011). In recommender systems, these computational intelligence techniques are widely used to construct recommendation models with strong relevance in marketing practice (Amatriain, Jaimes, Oliver and Pujol, 2011; Castrol-Schez et al., 2011).

2.4.4 Web Analytics

In the Internet economy, it has become essential for brands to monitor, optimize, and drive traffic to their websites for optimal usage of these digital channels (Järvinen and Karjaluoto, 2015). As the number of connected devices and terminals continue to grow with digital evolution, brands' websites have become a crucial instrument of information, communication, and electronic channel for driving business performance. With this growing importance of the web, the analysis, monitoring, and optimization of a website and online marketing, which is referred to as web analytics (WA), is now an essential issue for business practice and academic research (Kruzslicz, Bagó, Balogh, 2009; Zumstein, 2010). However, in a few cases, we have seen studies devoted to digital marketing performance and measurement with WA to improve marketing actions and programs (Nakatani and Chuang, 2011; Jarvinen and Karjaluoto, 2015).

Online marketing has grown tremendously due to dramatic growth related to the usage proportion of the internet. This will continue to grow as the number of connected devices worldwide continue to grow, along with a wide range of technology platforms (Werro et al., 2005; Abbasimehr et al., 2013). The availability of a wide range of products and services with the ability to compare different offerings by several brands with just a few clicks makes online marketing even more desirable. The advent of online marketing had significantly changed the way brands and marketers design and implement their strategies (Fullam, 2017; Kumar et al., 2018). In a cost-effective manner, online marketing has provided brands with opportunities to enhance their business and grow their business revenue. Online marketing involves a brand putting together several automations across different platforms to deliver the products and services based on specific rules set for the users. The objective is to attract, build, and maintain trust with current and new customers to generate business revenue (Kantrowitz, 2014; Hubspot, 2015).

2.4.5 Performance Analysis

Many studies have explored different performance measurements and associated systems, along with the various levels of marketing automation in digital marketing. These studies have yielded several areas of performance measures, such as data gathering, analysis, interpretation, metrics, and reporting. Their implementations have influenced marketing actions to change the identified metrics' trends for the better (Bourne et al., 2005; Mercanti-Guerin and Bezes, 2017). Deng (2008), study and presents a Fuzzy Neural-based importance-performance analysis (FN-IPA). It integrates Fuzzy set theory, back-propagation neural network, and three-factor theory to effectively and adequately identify critical service attributes worthy of measurement.

A Web-based hybrid system, WebMarP, was created by Li et al. (2013) to evaluate marketing and e-commerce Website performance. The proposed novel approach integrates the analytic hierarchy process strengths, Web-based expert system, fuzzy online rules, and graphical displays (Neely, Greory and Platts, 1995; Li et al., 2011). Sofiyabadi et al. (2015) attempt to focus on the strategic control leverage VIKOR technique to measure the importance and priority of key performance indicators (KPIs) in firms with a large customer base.

All the literature around digital marketing programs for the consumer segment aligns that micro and multiple segments' approaches are the way to go when targeting and rewarding customers within a broad base (Franco-Santos et al., 2007; Şengül and Eren, 2015; Efe, 2016; Garg, 2016).

However, the literature on developing appropriate marketing strategies and programs for digital products in a large consumer base for different segments along business performance enhancement are few. Meanwhile, in practice, going to market with new digital products while focusing on different customers to increase company revenue is critical.

2.4.6 Fuzzy Clustering

Segmentation helps managers to understand the enormous variety of consumers. Marketing managers understand that there are many kinds of customers displaying many different buying patterns. However, market segmentation techniques have not been of much help to these professionals (Yankelovich and Meer, 2006; Chauhan and Kaur, 2014). Market clustering originated from the need for segmentation and profiling of the market (D'Urso and Giordani, 2006; Carrasco et al., 2018).

Clustering and segmentation of the customer base are very crucial to marketers managing firms with a large customer base. The application of FA in this aspect of marketing constitutes 35% of this review's final article portfolio. This reflects the importance of clustering and segmentation to marketers and researchers.

Mathur and Nand (2014) stated that soft computing techniques and their impact and their new emerging trends are changing requirements in data mining. Soft computing methodologies, involving Fuzzy sets, neural networks, genetic algorithms, rough sets, and their hybridizations, have recently been used to solve data mining problems. Newly, several commercial data mining tools have been developed based on soft computing methodologies. These include Data Mining Suite with underlying rules using Fuzzy logic (Wasan, Bhatnagar and Kaur, 2007; Carrasco et al., 2018). Alavijeh (2015) argues that link mining is becoming a very popular research area for data mining and web mining and in the field of social network analysis. Market clustering originated from the need for segmentation and profiling of the market, which Smith (1956) first defined as conceptually heterogeneous (Wasan, Bhatnagar and Kaur, 2007; Liu et al., 2012).

The underlying and driving strategy behind market segmentation is developing a robust, targeted marketing campaign along with a customized offering across segments for effective profiling decisions and marketing development plans (Kotlier, 2009). However, consumer firms with a large customer base have not fully leveraged this in their customer selection and targeting for optimal campaign delivery and returns.

Several market characteristics exist for segmentation. These include demographics or related socioeconomic factors and geographic location. Also, product-related behavioral characteristics, such as purchase and consumption behavior, are included (Hanafizadeh and Mirzazadeh, 2011; Li, Wong and Wu, 2012). Digital marketing associated data such as social media data are confronted with several issues concerning data collection and existing mining and analysis techniques. This is because digital marketing data are generated in large quantities with a dynamic and complex nature. Hence, for marketing managers to make sense of this large amount of data quickly, methods, and techniques that can be easily interpreted and actioned by marketing managers are required for mining such data.

While many Fuzzy methods have been researched and applied to marketing and digital marketing data, literature is silent about their usage within the large customer base environment. How marketing managers can operationalize these techniques such that these models' output can be part of day-to-day marketing actions and revenue optimization programs remains a research opportunity for the future.

2.4.7 Fuzzy Market Analysis

Credit scoring models have been used to evaluate the risks from an applicant or a firm based on five attributes such as ‘the amount of loan requested’, ‘the collateral’, ‘the ability to repay’, ‘the condition of the market’, and ‘the characteristics of the person’ (Najjar and Najjar, 2014; Sohn et al., 2016). Credit scoring for firms handles issues such as the firm risk, profitability, and liquidity (Lee and Hosanagar, 2018; Yang, Ou and Hsu, 2019). Scoring models have been developed with logistic regression (Moon and Sohn, 2010), neural network (Yazdi, Pourreza and Yazdi, 2010; Liu et al., 2017), support vector machine (Huang eta l., 2007), clustering (Tsai and Chen, 2010), and regression tree (Sohn et al., 2014).

However, in the evaluation process, a vague expression can be used and inevitably encompass the evaluators' subjective opinions (Syau, Hsieh and Lee, 2001; Tavana, at., 2013). For the subjective and linguistic evaluation process of credit scoring, fuzzy set analyses have been used as substitutes for traditional statistical methods. Chen and Chio (1999) propose a credit rating model using a fuzzy integral methodology that aggregates credit information in bottom-up based on the hierarchical decision structure.

The fuzzy set analysis has been combined with other modern techniques, resulting in improved performance compared to traditional statistics models. Examples include the neuro-fuzzy model (Malhotra and Malhotra, 2002; Yang, Ou and Hsu, 2019), the fuzzy support vector machine (Chaudhuri and De, 2011), the Fuzzy rule-based k-nearest neighbors' algorithm (Laha, 2006), and fuzzy clustering (Luo et al., 2003; Chen and Cheng, 2013). Those methods have been applied to credit scoring. Also, for various analyses of markets, fuzzy logic allows geographic, demographic, psychographic and behavioral profiling. Hence, the Fuzzy Analytics (FA) application has proven that it is more successful and realistic for brands with a large customer base to target the market fuzzily if well implemented in marketing space.

2.5 RESEARCH GAP

This review explores the use of Fuzzy Analytics (FA) in marketing, and its growing research focus within the Fuzzy application community. Topics in these areas are consolidated and reviewed to identify critical open questions and possible future research opportunities. The review of the existing literature in the final portfolio of this study reveals that FA has already been applied to a wide range of areas within the marketing field. However, when compared with the use of Fuzzy logic and theory in other fields such as engineering and control systems, its potential in marketing science is still far from being reached (Ramkumar, Rajasekar and Swamynathan, 2010).

One of the main takeout from this review is that FA has demonstrated a useful property in addressing uncertainty and vagueness associated with customer behavior in marketing. From this insight, coupled with the rate at which digital channel is evolving, this dissertation projects an increase that will be significant in the publication of FA application in digital marketing in the coming years.

Many research applications in marketing have emerged using FA as the modeling techniques. The application around fuzzy modeling, which consists of expert marketing systems and recommender systems, will continue to grow along with AI techniques (Kaltenrieder et al, 2015; Chiang, 2017). This growth will move along the digital evolution across many customer touch points. As revealed in this study, another prominent field of marketing is customer behavior and customer satisfaction models. FA offers opportunities in evaluating relations between consumer needs and service attributes. The ability to navigate through the natural language and its statements components has yielded contributions from researchers in product and service areas with quality evaluation and group analysis. However, application in customer experience management is silent in the literature. Marketers have a powerful tool in FA, which can be leveraged in the development of marketing models.

FA model is a new way of carrying out marketing analysis by marketers, which has emerged because of the usage of fuzzy linguistic variables instead of the crisp value. With this new modeling approach, marketers are now endowed with sustainable business tools for driving business performance. Marketers promptly can respond to the dynamic and sophisticated consumer market, along with competition and other market fluctuations. Also, customer profiling, clustering, and segmentation are other marketing fields that have witnessed the significant application of FA application. The marketing mix and strategy are other prominent areas of fuzzy applications in marketing science according to this review's findings – though, application in the pricing side of the marketing mix is scanty.

In all these applications, marketers have seen an increase in marketing analysis because of the use of FA in several aspects of marketing. However, literature has been silent on four key areas critical to marketers on how marketers can leverage fuzzy methods to drive business performance. These are areas of customer experience, pricing, target and customer selection for campaign management, and digital innovation in platforms and over-the-top (OTT) players within the digital ecosystem.

2.6 AI AND MARKETING AUTOMATION

The first part of this chapter focuses on the systematic literature review of the use of fuzzy methods in digital and consumer marketing. However, this section of the literature review focuses on other advanced analytical and automation techniques within the marketing space. Since FA is a subset of Artificial Intelligence (AI) (Freksa, 1994; Downey and Charles, 2015), it is important this dissertation discusses another cutting-edge subset of AI such as Machine Learning (ML) and the relationships between marketing automation and analytics within a large consumer firm.

2.6.1 State-of-the-Art in Research and Practice

Marketing automation facilitates the orchestration and integration of tools, people, and processes through automated workflows (Gans, Agrawal and Goldfarb, 2017; Huang and Rust, 2018). It is software or platforms that follow a pre-programmed rule (Shankar, 2018). However, AI is the theory and development of computer systems to perform tasks that normally require human intelligence, such as visual perception, product preference, and decision-making between two offer acceptance (Ghahramani 2015; Mnih et al., 2015;

Pederson, Reid and Aspevig, 2018; Lashinky, 2019;). ML techniques have attributes that make it a robust application for solving marketing issues in consumer firms with a large customer base, such as mobile telecommunication (Wang and Kosinski, 2018)

Marketing automation has a single purpose: to let machines perform repetitive, monotonous tasks (Longoni et al., 2019; Ghnemat and Jaser, 2014). In marketing operations, automated machines such as campaign management solutions are all driven by manual configuration. An example is a case of *'If X, then Y'*. Essentially, the marketer defines the *'X'*, which drives the automated system to perform *the 'Y'* – "If he is a male adult, propose him this particular product". Generally, the result is a more efficient, cost-effective approach and workforce that is more productive for a business (Huang and Rust, 2018; Reid and Aspevig, 2018). This approach frees up time for marketing professionals to focus on more important tasks that require the personal touch and ability to reach out to millions of customers. While marketing automated solutions collate data, AI systems "understand" it (Baum et al., 2011; Reese, 2018; Kaplan and Haenlein, 2019).

ML is a subset of AI in the field of computer science that often uses underlying statistical techniques to empower computers with the ability to "learn" (i.e., progressively improve performance on a specific task) with data without explicitly programmed (Shankar 2018; Powell et al., 2018). Consumer businesses with a large customer base invest in AI-driven technologies to maximize the potential of rich customer data in their possession. While there exists associated risk (Solon and Laughland, 2018), the embedded opportunities are enormous for marketers to drive business performance through targeted campaigns across channels (Petro, 2018 Davenport and Ronanki, 2018).

ML tasks are usually classified into four broad types, depending on the nature of the learning ‘signal’ or ‘feedback’ available to a learning system. These classifications are supervised learning, unsupervised learning, reinforcement learning, and semi-supervised learning (Kong et al., 1995; Cotter et al., 2011; Hochman et al., 2018; Huang et al., 2018). The developed recommendation engine approach for many digital marketing channels follows semi-supervised learning. They are semi-supervised because part of the customer data used in developing the recommendation engines are prepared beforehand, while part of the data is also generated in real-time (Ghnemat and Jaser, 2014). Some customer events are considered real-time, while some historical customer data are also leveraged.

Apart from the fact that AI is designed to simulate human thinking, the whole point of AI in marketing applications is to create technologies that ably mimic what a human can say, think, and do. Several applications in AI and ML exist in solving customer issues and marketing challenges in consumer firms with millions of customers (Wilson, 2016; Longoni et al., 2019).

Marketing literature related to the usage and implementation of ML in the consumer environment with a large consumer base to drive business revenue is relatively sparse (Gans, Agrawal and Goldfarb, 2017; Davenport et al., 2020). While researchers have described how artificial intelligent (AI) and ML are used in carrying out various marketing analytics and automation in several industries, application and implementation from the marketing perspectives on how consumer businesses can drive business revenue with AI and ML is limited (PwC, 2017, Columbus 2019, Mende et al., 2019; Rahwan et al., 2019).

However, many marketing solutions and analytical models have been deployed using AI and ML to improve customer experience and support via chatbots (Kietzman et al., 2018; Luo et al., 2019). Chatbots are used to attend to customers' queries and requests. Chatbots are designed to seek patterns just as humans, learn from experience constantly, and self-reflect the appropriate responses in situations just like humans would do. Firms use chatbots so that their customers can get a real-time response and resolve any issues with the help of the ticketing system that is leveraging ML technology (French, 2018). Chatbot algorithms can identify faults in the context of historical information, server ticket data, and network logs.

ML has also been applied in the telecommunication environment. In the fine-tuning of propensity models for persona-specific strategies, risk prediction, and intervention models to reduce churn, dynamic price optimization, and real-time personalized advertising (Luo et al., 2019). Generally, AI and ML have a transformational impact on marketing and other functions that drive business performance. In customer service, it is creating a better customer experience by proactively identifying and servicing needs. In sales, it is optimizing sales using AI-empowered predictive analytics. Also, in marketing, it enhances hyper-personalization and allows communication to sync with customer behavior (Antonio 2018).

ML's motivation as a branch of AI is its concern with the design and development of algorithms that allow computers to evolve behavior based on empirical data. It allows marketers to leverage systems that can learn from experience concerning assigned tasks and specified performance measures within a specified time (Power 2017). As the performance measure improves, the experience also improves. These ML attributes of self-learning and management of low event rates have shifted marketing analytics from the traditional statistical models that are highly static and dependent on the sample's quality (Wilson et al., 2016).

AI and ML are helping the consumer firms with a large customer base in driving revenues, enhancing digital transformation and functions (Syam and Sharma, 2018; Davenport et al., 2020). ML is helping to build more revenues and stronger customer relationships. By leveraging AI and ML, consumer firms can leverage the huge complex and customer-generated data to deliver faster, precise, and more accurate results. Through AI and ML technologies, they have started to get into the digital transformation era's core, and many large consumer firms are living it (Parekh, 2018; Longoni et al., 2019; Davenport et al., 2020). These technologies find their way into many functions of work, like business process, network automation, customer relations, new digital services, and the channels with which these products are taken to the market (Soegoto and Simbolon, 2018; French, 2018).

Many consumer firms are shifting their focus from revenue growth to margins enhancement across corporate margins and customer-related margins. Therefore, ML presents brands the opportunity to leverage real-time and historical data of the customers, social links, and purchase patterns to propose offers to their customers (Goodwin, 2013; Wang et al., 2017). By combining this big data with other network elements across their enterprise, they can build high-granular and multi-dimensional insights into potential customer margins (Syam and Sharma, 2018; Mehta et al., 2018).

The evolution of digital channels resulting from increasing connected devices, sophistication, and engaging applications is transforming the way brands are connecting their customers. Digital marketing is quickly taking a considerable market share among several go-to-market channels such as other traditional channels (Wang and Feng, 2012; Holliman and Rowley, 2014; Gray and Rumpe, 2015).

However, despite the associated advantages of marketing channel expansion due to digital evolution, brands can only maximize these channels when marketing campaigns are automated with the right marketing campaign tools and capabilities (Vernuccio & Ceccotti, 2015; Opreana and Vinerean, 2015; Patrutiu-Baltes, 2016). When a brand has the right campaign and marketing tool that is well integrated with other customer-related applications or CRM, then such a brand can leverage the full potential of digital marketing and marketing analytics (Halligan and Shah, 2014; Handley and Chapman, 2010; Soegoto and Simbolon, 2018).

For marketers tasked with driving the business revenue performance through analytics, robust and integrated campaign management would be required before any analytical output can be optimally leveraged from any source of analytics, be it fuzzy, ML or any other models (André et al., 2018). In this modern age, it is difficult for consumer businesses to survive without leveraging their customers' information and behavior in their enterprise through analytics. Also, access to good and quality data for ML and other analytical projects is critical for success. No algorithmic sophistication level will make up for a poor set of data (Wilson, 2016; Longoni et al., 2019). Therefore, the implementation of analytical models by marketers to drive business revenue performance depends on data availability and a well- integrated system with the relevant digital channels of a large consumer base. The next chapter of this dissertation focuses on the theory of fuzzy analytics and all the relevant concepts that are used in the cases of this dissertation following the identified gaps as detailed in this current chapter.

3.1 FUZZY SETS: GENERAL CONCEPTS

To understand the idea of a fuzzy set, note that a subset A of a set X can be described by its membership function $\chi_A : X \to \{0,1\}$:

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

Hence, χ_A characterizes the degree to which an element x belongs to a set A. This degree can only be either 0 or 1. When this degree is between 0 and 1, we arrive at Zadeh's concept (Zadeh, 1965) of a fuzzy subset A of a set X, represented as $A \tilde{\subset} X$ and characterized by its membership function $\mu_A : X \to [0,1]$. The value $\mu_A(x)$ is interpreted as the degree of belongness of a point $x \in X$ to a fuzzy set A (Sostaks, 2010).

3.1.1 Characteristics of the Membership Function

All the information that is contained within a fuzzy set is described by its membership function. It is important to describe some terms to describe various special features of this function. For simplicity purpose, Figure 3.1 clarifies the description.

Definition 1 The *core* of a membership function for some fuzzy set $\underset{\sim}{A}$ is defined as that region of the universe characterized by complete and full membership in the set $\underset{\sim}{A}$. That is, the *core* comprises those elements x of the universe such that $\mu_{\underset{\sim}{A}}(x) = 1$.

Definition 2 The *support* of a membership function for some fuzzy set $\underset{\sim}{A}$ is defined as that region of the universe that is characterized by nonzero x membership in that set $\underset{\sim}{A}$. That is, the support comprises those elements x of the universe such that $\mu_{\underset{\sim}{A}}(x) > 0.$

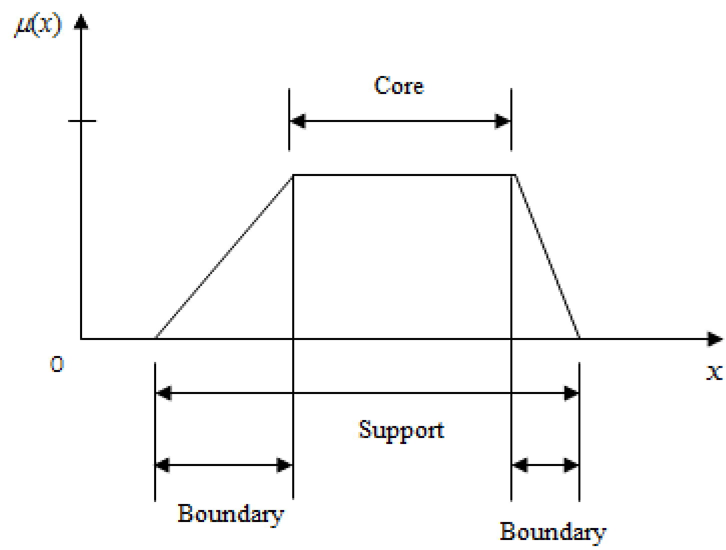

FIGURE 3.1 Core, support, and boundary of a Fuzzy set

Definition 3 The *boundaries* of a membership function for some fuzzy set $\underset{\sim}{A}$ are defined as that region of the universe containing elements that have a nonzero membership but not complete membership. That is, the boundaries comprise those elements x of the universe such that $0 < \mu_{\underset{\sim}{A}}(x) < 1.$ These elements of the universe are those with some degree of fuzziness, or only partial membership in the fuzzy set $\underset{\sim}{A}$. FIGURE 3.1 shows the region in the universe comprising the core, support, and boundaries of a typical fuzzy set.

Definition 4 The *normal* fuzzy set is one whose membership function has at least one element x in the universe whose membership value is unity. For fuzzy sets where one and only one element has a membership equal to one, this element is typically referred to as the prototype of the set, or the prototypical element. FIGURE 3.2 shows typical normal and subnormal fuzzy sets.

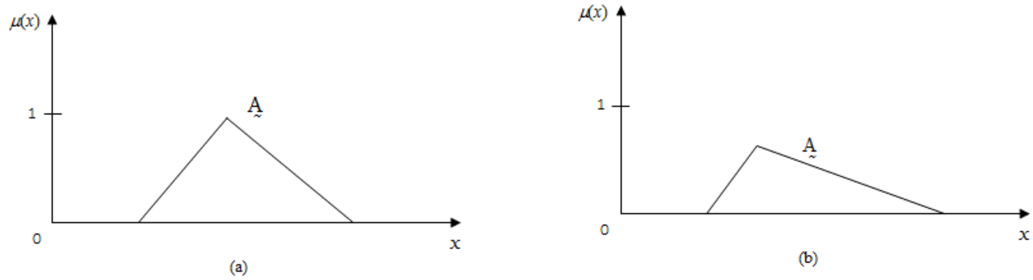

FIGURE 3.2 Fuzzy sets that are normal (a) and subnormal (b)

Definition 5 A *convex* fuzzy set is described by a membership function whose membership values are strictly monotonically increasing, or whose membership values are strictly monotonically decreasing, or whose membership values are strictly monotonically increasing then strictly monotonically decreasing with increasing values for elements in the universe. To be put in another way, if, for any elements x, y, and z in a fuzzy set $\underset{\sim}{A}$, the relation $x < y < z$ implies that

$$\mu_{\underset{\sim}{A}}(y) \geq \sim \min\left[\mu_{\underset{\sim}{A}}(x), \mu_{\underset{\sim}{A}}(z)\right] \qquad 3.1$$

then $\underset{\sim}{A}$ is said to be a convex fuzzy set (Ross, 1995). Typical convex fuzzy set and nonconvex fuzzy set is illustrated in (Figure 3.3).

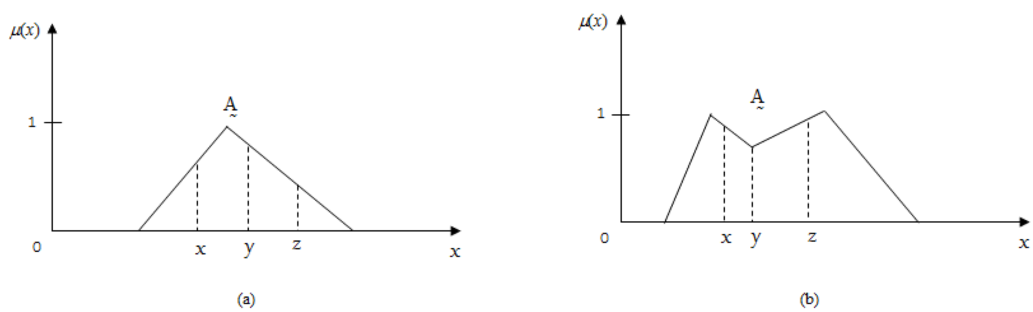

FIGURE 3.3 Convex, normal fuzzy set (a) and nonconvex, normal fuzzy set (b)

A special property of two convex fuzzy sets, say $\underset{\sim}{A}$ $\underset{\sim}{B}$, is that the intersection of these two convex fuzzy sets is also a convex fuzzy set, as depicted in FIGURE. 3.4. That is , for $\underset{\sim}{A}$ and $\underset{\sim}{B}$, which are both convex, $\underset{\sim}{A} \cap \underset{\sim}{B}$ is also convex.

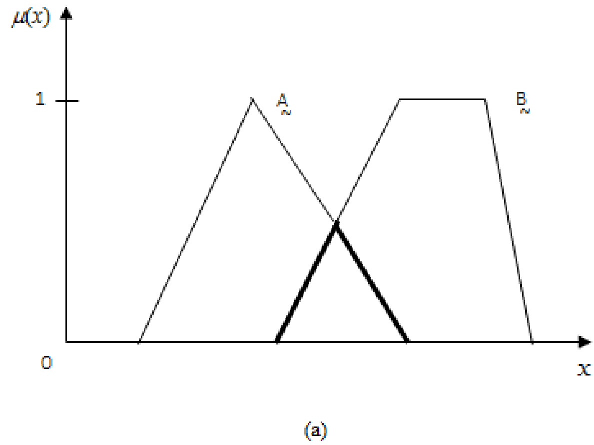

FIGURE 3.4 The intersection of two fuzzy convex sets produces a convex fuzzy set

Definition 5 The *crossover points* of a membership function are defined as the elements in the universe for which a fuzzy set $\underset{\sim}{A}$ has values equal to 0.5, i.e., for which $\mu_{\underset{\sim}{A}}(x) = 0.5$.

Definition 6 The *height* of a fuzzy set $\underset{\sim}{A}$ is the maximum value of the membership function, i.e., $hgt(\underset{\sim}{A}) = \max\{\mu_{\underset{\sim}{A}}(x)\}$. If the $hgt(\underset{\sim}{A}) < 1$, the fuzzy set is said to subnormal.

The $hgt(\underset{\sim}{A})$ may be viewed as the degree of validity or credibility of information expressed by $\underset{\sim}{A}$. If $\underset{\sim}{A}$ is a convex single-point normal fuzzy set defined on the real line, then $\underset{\sim}{A}$ is often termed a *fuzzy number* (Klir and Yuan, 1995; Ross, 2010).

3.1.2 Fuzzy Numbers

Two essential different approaches are available in the literature to the problems of a fuzzy real number (Sostaks, 2010). The first is based on the understanding of fuzzy real number as a generalized interval in R, the second one views a fuzzy number as a certain distribution-type function $z : R \to [0,1]$. With regards to the definition of arithmetic operations with fuzzy real numbers, both approaches align on a definition following the Zadeh's extension principle (Dubois, 1987).

In Zadeh's early works, which was later expanded by other authors, especially by Lee and Takagi (1993), the first approach (internal-type approach) views fuzzy numbers as intervals with blurred borders. According to this approach, a fuzzy number is a fuzzy set $A \tilde{\subset} R$ which is defined by a convex membership function $\mu_A : R \to I$ where the convexity means

$$\min\{\mu_A(x_1), \mu_A(x_3)\} \le \mu_A(x_2) \quad \text{whenever} \quad x_1 \le x_2 \le x_3, \qquad 3.2$$

(and hence the levels A_α are intervals, probably unbounded, in R) (Engelking, 1977).

Among several special classes of fuzzy numbers, I mention fuzzy triangular numbers $A := (a,b,c)$. These numbers are characterized by membership functions defined as follows

$$\mu_A(x) = \begin{cases} 0 & if \;\; x \le a, \\ \dfrac{x-a}{b-a} & if \;\; a < x \le b \\ \dfrac{x-c}{b-c} & if \;\; b \le x < c \\ 0, & if \;\; c \le x \end{cases} \qquad 3.3$$

To consider the case when some of the equalities $a = b = c$ hold, we have to make specification that also in this case $b - a/b - a = 1$, $b - c/b - c = 1$. Hence, if $a = b = c$, then the fuzzy number (a, a, a) can be identified with a real number $a \in R$ (Zadeh, 1965).

3.1.3 Fuzzy Logic and Linguistic Variables

Zadeh (1965) describes a linguistic variable as a natural or artificial language whose values are words or sentences. *"Age"* is an example of a linguistic variable. Suppose its values are also linguistic, i.e., very young, quite young, old and not very old, etc. rather than 20, 21, 22, 23.... (Zimmermann, 2001).

One of the fundamentals of marketing science is that customer behavior cannot be claimed to be well understood until it can be detailed into quantitative terms (Kaymak and Zetnes 2000). Fuzzy logic set effectively handles vague, inexact, stochastic input variables, and treat the dynamic nature of such variables (Zimmermann, 1999). Classical or two-valued logic has to do with propositions that are either true or false. Fuzzy logic is an extension of many classical logic with proposition more than two truth values. It incorporates fuzzy sets and relations, deals with linguistic variables, and defines modifiers such as very, mostly, and not, and so on (Kaymak and Zetnes, 2000; Bag and Samanta, 2008).

Without any questions, algorithms and models through computers have proved to be very effective in dealing with the mechanistic system, where behavior is governed by mechanics, physics, and chemistry (Zimmermann, 2001). On the other hand, humanistic systems such as customer behavior have proved to be somewhat impervious to mathematical analysis and computer simulation (Zadeh, 1975; Zimmermann, 1999). Fuzzy logic allows us to make significant assertions about humanistic systems' behavior and help us tolerate analyses mathematically to approaches that are approximate in nature (Zadeh, 1965). Linguistic variables are a variable whose values are word in a natural or artificial language. For example, when defining a segment within the customer base (see Fig 3.5), a series of linguistic terms can be derived, such as a child, teenager, youngster, middle-aged, senior and other. We then defined each customer segment approximately by these different linguistic terms. Marketers determine the linguistic terms and determine the appropriate membership functions along the data mining process (Donze and Meier, 2012). Triangular, Trapezoidal, S-shaped or a combination of these are well-known membership functions.

For example, when considering the age and we say, *"Customer A"* is *"young"*, this is less precise than when we say, *"A is 25"*. In this sense, the label *"young"* may be regarded as a linguistic value of the variable Age. We can have the same understanding that this plays the same role as the numerical value 25 but less precise and hence less informative. For linguistic values such as very young, not young, extremely young, not very young, etc, this is also fine compared to the numerical values 20, 21, 22, 23 and so on. The totality of values of a linguistic variable form its term set, which could be an infinite number of elements. For example, the term set of the linguistic variable age might read T (Age) = {young + not young + very young + not very young, very very young + …… + old + not old + very old + ... + middle-aged + old and not middle-age + ……. In which *"+"*} represents the union rather than arithmetic. (Appearance) = beautiful + pretty + cute + handsome + attractive + not beautiful + very pretty + quite pretty + quite handsome + ... + not very attractive and not very unattractive + …,. Regarding the linguistic variable *Age*, a linguistic value such as young may be interpreted as a label for a fuzzy restriction on the base variable's value. This fuzzy restriction is what we take to be the meaning of young (Zimmermann, 2001; Kaymak and Setnes, 2000).

Formally, Zadeh (1975) defines a linguistic variable as a quintuple $(X, T(X), U, G, M)$, where:

- X is the name of the base variable, which is a variable in the classical sense (e.g., Age);
- $T(X)$ represents the set of linguistic terms of X (e.g. $T(X)$ = {young, old});
- U is the universe of discourse of the base variable;
- G stands for the syntactic rule for generating the linguistic terms based on the primary term (e.g., very young, not old);
- M is the semantic rule for associating a meaning to each linguistic term, i.e., a corresponding fuzzy set to represent X the term itself.

In marketing, the linguistic variable can play an important role. Apart from age and appearance, which we have defined above, other linguistic variables such as customer experience, price, profit, customer value, customer satisfaction, net promoter score, loyalty, etc. can be defined (Donze and Meier, 2012). When pre-defined, these linguistic variables and terms can then be used in mathematical modeling or algorithm to control marketing and business problems (Chamberlain, 1976; Donze and Meier, 2012).

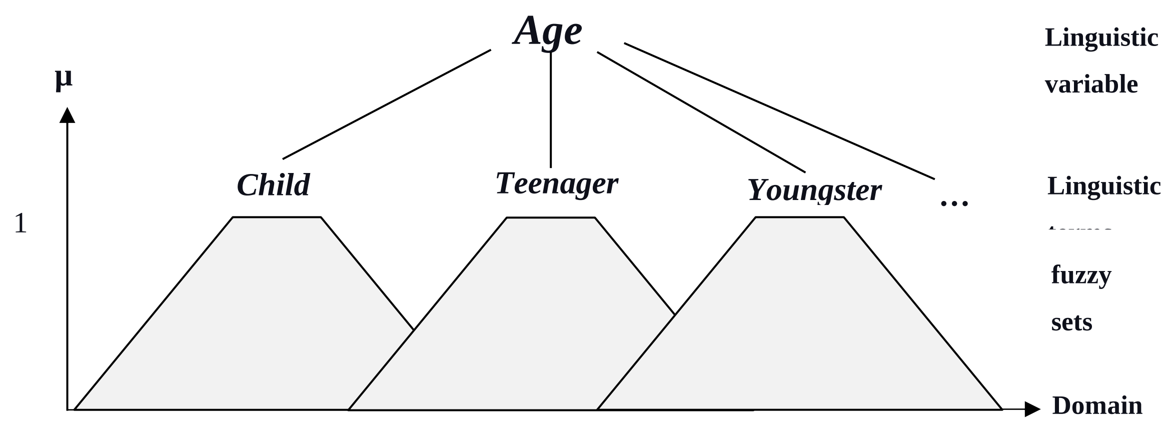

FIGURE 3.5 Linguistic variable and terms defined over fuzzy sets (based on Meier, 2008)

3.2 FUZZIFICATION AND DEFUZZIFICATION

3.2.1 Fuzzification

Fuzzification is the process of converting crisp quantity to fuzzy. This is achieved by recognizing that many crisp and deterministic quantities are not deterministic at all. They come with a considerable level of uncertainty. When such uncertainty occurs, due to ambiguity, vagueness, and imprecision, the variable is probably fuzzy and can take the form of a membership function (Mamdani, 1997; Corchado, Abraham, Ponce and Ferreira de Carvalho, 2010)

The fuzzification process takes the input variables and compares them along with membership functions of the antecedent part of the fuzzy rule to assign membership values to each linguistic label (Kecman, 2001; Buckley, 2003).

3.2.2 Defuzzification

There are situations where the output of a fuzzy process needs to be a singular scalar quantity for it to be used and interpreted. Defuzzification is the conversion of a fuzzy quantity to a crisp quantity. It is the exact opposite of fuzzification. The result of a fuzzy process can be the logical union of two or more fuzzy membership functions that are defined within the universe of discourse of the output variable. Suppose a fuzzy output is comprised of two parts: the first part, C_1, a trapezoidal shape FIGURE 3.6a, and the second part $\underset{\sim}{C}_2$, a triangular membership shape FIGURE 3.6b. The union of these two membership functions, i.e., $\underset{\sim}{C} = \underset{\sim}{C}_1 \cup \underset{\sim}{C}_2$, involves the max operator, which graphically is the outer envelope of the two shapes shown in FIGURE 3.6a and b; the out of the combined shape is in FIGURE 3.6c. In some cases, the general output may involve many output parts that are more than two, and their shapes can be outside triangle or trapezoids. It is possible that the membership functions may not be normal. In general, we can have

$$\underset{\sim}{C}_k = \bigcup_{i=1}^{k} \underset{\sim}{C}_i = \underset{\sim}{C} \qquad 3.4$$

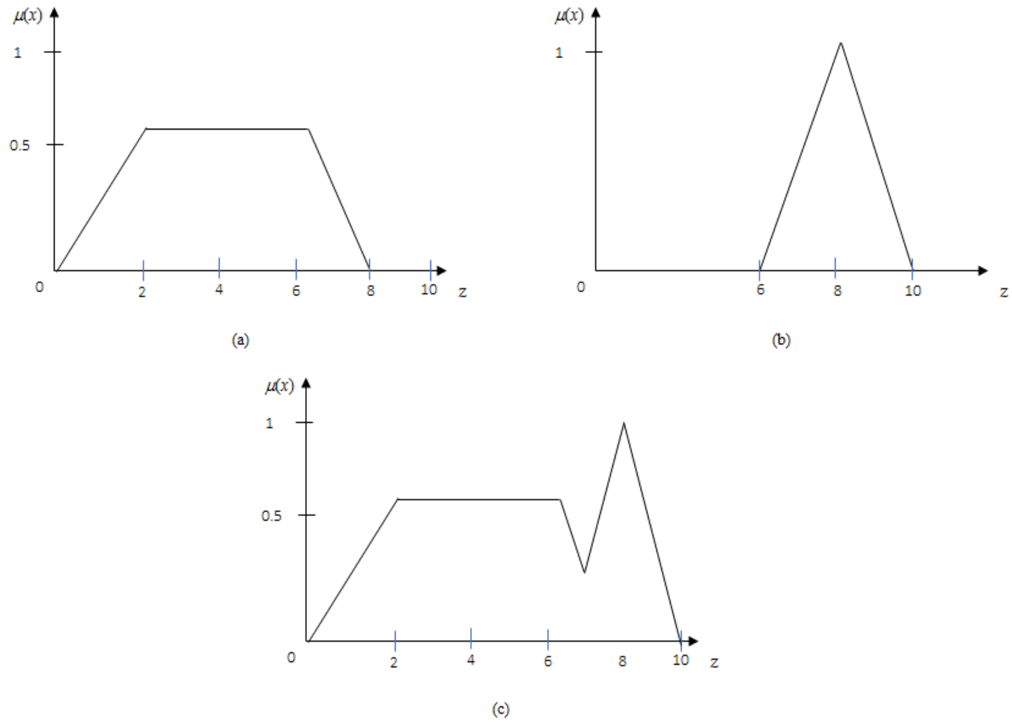

FIGURE 3.6 Typical fuzzy process output: (a) first part of fuzzy output; (b) second part of fuzzy output; (c) union of both parts.

3.2.3 Methods of Defuzzification

Several methods have been proposed in the literature in recent years for the defuzzifying output functions (membership functions); the most common seven methods are described in this dissertation (Hellendoorm and Thomas, 1993).

Max membership principle: This is also known as the height method; this scheme is limited to peaked output functions. It is represented by an algebraic expression

$$\mu_{\underset{\sim}{c}}(z^*) \geq \mu_{\underset{\sim}{c}}(z) \qquad \text{for all } z \in Z \qquad 3.5$$

where z^* is the defuzzified value.

Centroid method: This is also sometimes referred to as the center area or center of gravity. It is the most prevalent and physically appealing method of all (Sugeno, 1985; Lee, 1990). Its algebraic expression is as follows

$$z^* = \frac{\int \mu_{\underset{\sim}{C}}(z) \cdot z\, dz}{\int \mu_{\underset{\sim}{C}}(z)\, dz} \qquad 3.6$$

Weighted average method: The weighted average method is the most frequently used in fuzzy applications since it is one of the more computationally efficient methods. However, it is normally restricted to symmetrical output membership functions. Its algebraic expression is as follows

$$z^* = \frac{\sum \mu_{\underset{\sim}{C}}(\bar{z}) \cdot \bar{z}}{\sum \mu_{\underset{\sim}{C}}(\bar{z})} \qquad 3.7$$

Where $\sum$ denotes the algebraic sum and where $\bar{z}$ is the centroid of each symmetric membership function.

Mean max membership: This method is also called the middle-of-maxima, and it is closely related to the first method, save that the locations of the maximum membership can be nonunique (i.e., the maximum membership can be a plateau rather than a single point). The expression of the method is as follows (Sugeno, 1985; Lee 1990; Ross, 2004).

$$z^* = \frac{a+b}{2} \qquad 3.8$$

Center of sums: This method is adjudged to be faster than any other defuzzification methods that are presently in use, and the method is not restricted to systemmetric membership functions. This process involves the algebraic sum of individual output fuzzy sets, say $\underset{\sim}{C}_1$ and $\underset{\sim}{C}_2$, instead of their union. This method has two drawbacks. The intersecting areas are added twice, and the method also involves finding the centroids of the individual membership functions. The defuzzied value z^* is represented by the following equation:

$$z^* = \frac{\int_Z \bar{z} \sum_{k=1}^{n} \mu_{\underset{\sim}{C}_k}(z)\, dz}{\int_z \sum_{k=1}^{n} \mu_{\underset{\sim}{C}_k}(z)\, dz} \tag{3.9}$$

Where the symbol $\bar{z}$ is the distance to the centroid of each of the respective membership functions.

Center of largest area: If the output fuzzy set has at least two convex subregions, then the center of gravity z^* is calculated using the centroid method of the convex fuzzy subregion with the largest area is used to obtain the defuzzied value z^* of the output. It is algebraically represented as:

$$z^* = \frac{\int \mu_{\underset{\sim}{C}m}(z) z\, dz}{\int \mu_{\underset{\sim}{C}m}(z)\, dz} \tag{3.10}$$

Where $\underset{\sim}{C}_m$ is the convex subregion that has the largest making up $\underset{\sim}{C}_k$. This condition applies in the case when all $\underset{\sim}{C}_k$ is nonconvex; and in the case when $\underset{\sim}{C}_k$ is convex, z^* is the same quantity as determined by the centroid method or the center of largest area method since at this time, there is only one convex region.

First (or last) maxima: This method leverages the overall output or union of all individual output fuzzy sets $\underset{\sim}{C}_k$ to determine the smallest value of the domain with maximized membership degree in $\underset{\sim}{C}_k$. The equations for z^* are as follows. Firstly, the largest height in the union (denoted $hgt(\underset{\sim}{C}_k)$) is determined,

$$hgt(\underset{\sim}{C}_k) = \sup_{z \in Z} \mu_{Ck}(z) \tag{3.11}$$

Then the first of the maxima is found,

$$z^* = \inf_{z \in Z} \left\{ z \in Z \mid \mu_{\underset{\sim}{C}k}(z) = hgt(\underset{\sim}{C}_k) \right\} \tag{3.12}$$

An alternative to this method is called the last maxima, and it is given by

$$z^* = \sup_{z \in Z} \left\{ z \in Z \mid \mu_{\underset{\sim}{C}k}(z) = hgt(\underset{\sim}{C}_k) \right\} \quad 3.13$$

In this section, various types and forms of a membership function along the idea of fuzzification of scalar quantities to make them fuzzy sets are highlighted. This section explains the conversion process from fuzzy membership functions to crisp formats – a process called defuzzification. From the seven defuzzification method described, while we have some popular ones among them, the nature of the problem at hand (Hellendoorn and Thomas, 1993) determines the choice and usage. Five criteria are given by (Hellendoorn and Thomas, 1993) as a guide to know which of the method is good for a problem. First is the ***continuity***. A small change in the input of a fuzzy process should not yield a large change in the output. Second is a criterion known as ***disambiguity***, which simply indicates that a defuzzification method should always result in a unique value for z^*, this means that there is ambiguity in the defuzzied value. Center of largest area method does not meet this criterion. ***Plausibility*** is the third criterion. For this criterion to hold, z^* should lie approximately in the middle of the support region of C_k and have a high degree of membership in C_k. Also, this condition does not hold for the centroid method. The fourth criterion is ***computational simplicity***, which suggests that the more time consuming a technique is, the less value it should have in a computation system. The height method, the mean max method, and the first of the maxima method are faster than the centroid or center of sum methods. The fifth criterion is called the ***weighting method***, which weights the output fuzzy sets. This criterion constitutes the difference between the centroid method, the weighted average method, and center of sum method. The problem with the fifth criterion is that it is problem dependent, as there is little by which to judge the best weighting method; the weighted average method involves less computation than the center of sums, but that attribute falls under the fourth criterion, ***computational simplicity***. As with many issues in fuzzy logic, the method of defuzzification needs to be assessed in terms of the goodness of the answer in the context of the data available (Hellendoorn and Thomas, 1993).

3.3 FUZZY SETS AND LOGIC IN SCIENCE AND INDUSTRIES

From the monograph *"Fuzzy modeling: paradigms and practice"*, which was edited by Pedricz (1996), an American scientist who was actively working in this field., two citations are noted in this dissertation that substantiates the precise knowledge in this field.

> *"The essence of fuzzy modeling is concerned with constructing models that flexibly core heterogeneous data, including those of linguistic and numerical characters."*

> *"Briefly speaking, fuzzy models are modeling constructs, flattering two main properties:*
>
> *- they operate at the level of linguistic terms (fuzzy sets); similarly, all system dependencies can be portrayed in the same linguistic format;*
>
> *- they represent the process of uncertainty."*

Fuzzy Logic has witnessed tremendous growth through the application of fuzzy sets and reasonings in so many works in the last two decades (Sostaks, 2010). Several areas across the humanities and sciences have witnessed applications of Fuzzy Logic. Fuzzy logic applications in earth and geological sciences have been well documented (Demicco, 2004; Novak and Perfilieva, 2000). Within the life sciences, fuzzy sets and rules have been widely applied, especially in biology and medicine. There are several uncertainties that are associated with the level of information that is available to the physicians about their patients. Nevertheless, approximate, acceptable judgments and conclusions can still be achieved by the medical experts. This can be achieved through the theory of fuzzy set as it leverages inexact information to make a robust and acceptable judgment by the medical experts.

According to Adlassing (1986), certain properties of fuzzy theory allows medical diagnosis with uncertain information possible. Through a linguistic approach, inexact medical diagnosis is approximated to crisp information. They provide a reasoning method for the diagnostic system, equipment, and processes (Adlassing, 1986; Akay, Cohen and Hudson, 1997). Many rules-based following the laws of Fuzzy Logic are successfully used and implemented in the industry. Manufacturing firms like Mitsubishi manufactures air-conditioners using fuzzy rules to prevent overshoot-undershoot temperature oscillation and consume less on-off power. The Rice cooker was produced and regulated by fuzzy rules cooking time with respect to steam temperature and the control of the volume of the rice. Fuzzy rules are applied in the production of the washing machine to adjust washing strategy following the level of dirt, fabric material, load size, and the level of water (Sostaks, 2010).

Also, fuzzy rules are applied to shower systems to moderate the variation of water temperature. The autofocus and lighting adjustment of the camera have been made possible by fuzzy rules, while LG and Samsung have leveraged fuzzy rules for the development of television systems along with color and texture adjustment (Sugeno, 1974, Sostaks, 2010).

3.4 FUZZY SETS AND LOGIC IN MARKETING

The advancement and advantages of working with the membership function against crisp values brought to light the importance of fuzzy logic in marketing science (Enache, 2015). The aspect of marketing models has mostly seen the use of fuzzy logic and reasoning. Models are important to marketing science (Lilien, Kotler and Sridhar, 1992). They help marketers to understand consumer behavior and what an ordinary human observation cannot detect from a wide and complex customer database. This understanding allows marketers to respond to the needs of the customers, competition and enhance consumer customer experience toward an acceptable level of profitability.

Marketers have a powerful tool when they leverage fuzzy logic in the development of marketing models. Fuzzy logic marketing model is a new way of carrying out marketing analysis by marketers, which has emerged due to the usage of *if-then* rules instead of the crisp value. With this new modeling approach, marketers are now endowed with business tools that are sustainable for driving business performance. Marketers can now respond to the dynamic and complex consumer market and competitive forces, and other market fluctuations.

A novel perspective emerged, which provided a better view of the classical crisp theory as an extension as soon as Zadeh (1965) presented the fuzzy sets theory in 1965. The ease of use of *if-then* rules resulting from a linguistic formulation that fuzzy sets provide forms the background for the main advantage of fuzzy sets (Jantzen, 2007). Fuzzified variables and membership functions constitute the idea behind the *if-then* rules. Triangular, trapezoidal, singleton and gaussian are common shapes in which membership function can be presented (Mamdani, 1977; Enache, 2012; Enache, 2015).

Many research applications in marketing have emerged using fuzzy logic as modeling techniques. A prominent field of marketing in this regard is customer behavior and customer satisfaction models (Martinez-Lopez, Casillas, 2009; Casillas, Martinez-Lopez, 2009). According to Ertay and Kahraman (2007), fuzzy logic models offer opportunities in evaluating relations between consumer needs and service attributes. The ability to deal through the natural language and its statements components has yielded contributions from researchers in the product, service with a quality evaluation, and group analysis (Temponi, Yen and Tiao,1999; Maruvada and Bellamkonda, 2010). Customer segmentation is another marketing field that has witnessed the significant application of fuzzy logic (Ou, Shuo-Yan and Yao-Hui, 2009). The marketing mix, save for pricing, is another prominent area of fuzzy applications in marketing science (Li, Barry, John, Russell and Yanging, 2002; Susanto, Vasant, Bhattacharya and Fransiscus, 2006; Aly and Vrana, 2005; Xiong, 2010). In all these applications, marketers have seen an increase in marketing analysis due to the use of fuzzy logic in several aspects of marketing science.

CHAPTER FOUR: METHODOLOGY AND RESEARCH DESIGN

Research paradigms are a critical component of research, detailing what is to be investigated by the researcher and the procedure the study will follow. Philosophically debates have been ongoing among marketing researchers over the years on which paradigm is suitable for marketing science. This section discusses the choice of ontology, epistemology and methodology that this dissertation employed in this study.

The primary research strategy of this study is a case study approach. This methodology choice was motivated as a result of its suitability towards the research questions. Case study research has seen a reputational growth as a research methodology, suitable for investigating complex issues within the real-world settings (Harrison, Birks, Franklin and Mills 2017). This dissertation adopts a research paradigm that follows critical realism (Bhaskar, 1978; Easton, 2010; Sayer, 1992).

This section also justifies and details the Delphi methodology for the first result of the qualitative survey study that follows a different research paradigm and logic. The survey study's objective and goal were for a clear overview of how organizations see digital analytics and analytics in driving the business performance within a large consumer base setting. The survey results revealed the use of analytics and digital marketing by consumer firms, which raised questions that required a case study approach that led to this study's primary research strategy. This chapter focuses on the case study research approach, while the Delphi survey results are considered in the last section of this chapter – section 4.3.1.

4.1 RESEARCH PARADIGM – CRITICAL REALISM

Critical realist methodology objectives are to unravel the causally effectual mechanism and formation that underlie perceived events (Dobson, 2002; Sayer, 2000), and suitable for a wide range of research methods. Epistemologically, positivist researchers within the marketing space emphasize research with an underlying scientific protocol involving identifying a conceptually framed framework with results that can be generalized (Szmigin and Foxall, 2000; Boateng and Boateng, 2014).

As for critical realism, the reality is totally independent of our representation of it; both the reality and the interpretation play in different domains (Sayer, 1992). From FIGURE 4.1 below, reality lies in the intransitive along a strong dimension, which relatively subject to transitive and changing dimensions (Downward and Mearman, 2007). The observable events are embedded in the transitive domain, while real causes trigger real events within the intransitive domain (Smith, 2006; Eason, 2002).

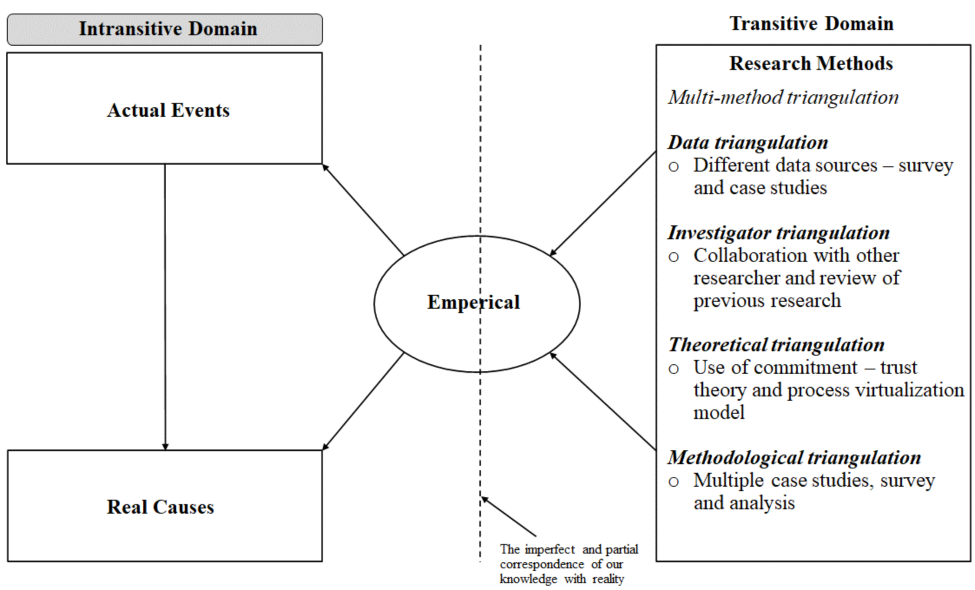

FIGURE 4.1 Critical realism and triangulation in this study. Source: Adapted from Downward and Mearman, 2007).

It has been posited by critical realists within the marketing discipline that questions that are important for marketing researchers should be "what are the necessary key relationships that are crucial to the understanding of marketing phenomena? (Easton, 2002; Boateng and Boateng, 2014). In this dissertation, the marketing phenomenon is digital marketing and analytics. The objects (anything with causal power) in this study are consumer and business performance. In consumer marketing, the nature of the marketing channel can influence both the consumer and the business performance and vice versa. The objective of this dissertation, therefore, is to show how consumer firms can drive and optimize their revenue through digital marketing and analytics. The study obtained answers to how the consumer firm with a large consumer base can optimize business revenue through digital marketing and analytics. The study provoked many questions that are later fine-tuned to the final research questions.

4.2 CASE STUDY AS A RESEARCH METHOD

Several disciplines have leveraged case study designs, especially in business, social sciences, law, health, and education, with a view of addressing a wide range of evolving research questions (Taylor and Berridge, 2006). Moreover, case study research methodology has witnessed a rapid and rigorous development due to different approaches in which this method has been used over the last few decades (Johnson, 2006).

The unique and fundamental factor towards the evolution of case study research is the ontological and epistemology formation of the researchers through which case study research has evolved. These researchers have emanated from diverse backgrounds and disciplines. Their contributions towards case study research have developed this methodology and its approach in a variety and diversified ways. As a result, proposed designs, preparation, and planning towards successful results of case study research in the way it is conducted are different (Gulsecen and Kubat, 2006).

The case study method helps researchers to critically and closely explore the available data within a context. A case study method often identifies and selects a sample size and a specific geographical location along a subject area of study. In most cases, a case study method selects a small geographical area or a minimal number of individuals as the subjects of study. Through a limited number of events or conditions with respect to interplay relationships, case studies investigate true, real-life phenomena along with a contextual analysis (Yin, 1984). It is defined by Yin (1984) as “an empirical inquiry that explores a contemporary phenomenon within the space of its real-life context in a scenario that has an unclear boundary between the phenomenon and the context while leveraging multiple sources of evidence.”

According to Flyvbjerg (2011), a case study research methodology has been around for a very long period. Its origin, along with its contemporary, has its origin in qualitative approaches to various disciplines (Merriam, 1998; Steward, 2014). According to the biography of Charles Darwin, one can trace the historical examples of the case study to the early nineteenth century (Steward, 2014). However, quantitative methods gained popularity in social sciences due to the dominance of positivism in science towards the late 1940s and 1950s through statistical methods and survey experiments (Johansson, 2003).

However, researchers considered second-generation case study researchers emerged with the grounded theory methodology (Glaser and Strausss, 1967). Qualitative field of study methods was merged with the quantitative methods of data analysis by the Grounded theory

(Johansson, 2003). This merger yielded an inductive methodology that analyzes data through a thorough and systematic step procedures. This led to the revival of the case study within several disciplines (Johansson, 2003; Merriam, 2009; Anthony and Jack, 2009).

In nature, the case study research method is complex, but it is simple in theory. Across its planning, preparation, and execution procedures, it has developed over time. Such a case study research application across several disciplines have provided credible research result and endeavors. Due to its growth and recorded success, it is considered a valid and robust form of inquiry to explore and detail a wide scope of issues that are considered complex (Anthony and Jack, 2009; Merriam, 2009; Yin, 2014).

It was suggested by Brinberg and McGrath (1985) that, for research paths, three different domains exist along a path: a substantive 'real-world' domain (S), a conceptual domain (C), and a methodological domain (M), see FIGURE 4.2. The starting point of conducting any research can fall into any of these domains, while these three domains are covered by any research.

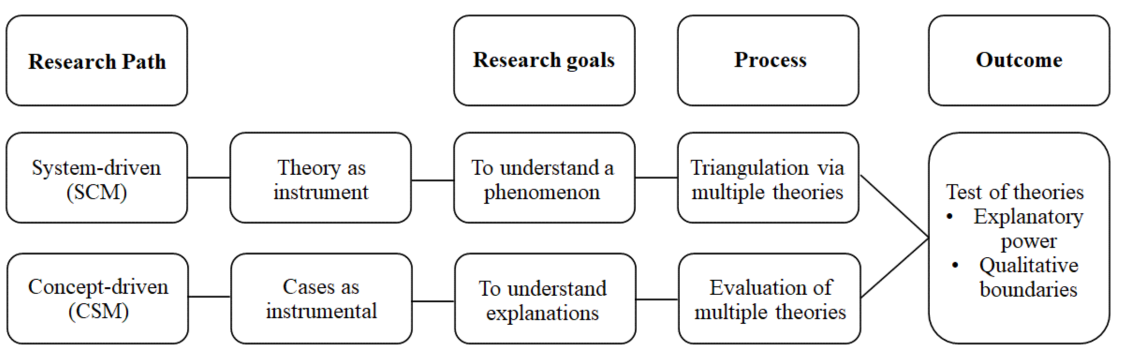

FIGURE 4.2 Theoretical path guiding a case study (Source: Brinberg and McGrath, 1985)

Though many case studies begin in the substantive domain, a theoretical research path also describes a scenario where a study focuses on the conceptual domain. The cases are instrumental to the theoretical contribution. System-driven theoretical paths focus on understanding an empirical system (Brinberg and McGrath 1985). For a system-driven theoretical path, a matching theory-testing case study research design using multiple theories to examine the system from different angles is suggested (triangulation) (Patton 2002; Yin 2014).

Also, the Abductive research process is an intermediary between inductive and deductive approaches, which emphasizes the continuous interaction and interplay between theory and data to develop a theory (Dubois and Gadde, 2002). However, general case studies in marketing reflect a positivistic research paradigm which tilt towards deductive logic (Glaser and Strauss, 1967; Piekkari et al., 2010). Though, in its purest form, the usage is rarely seen. Conducting research with a view to wholly abandoned the theoretical knowledge that has been acquired by the researcher over the years or a preconception is difficult, according to one of the founders of the grounded theory (Strauss and Corbin, 1990). Hence, we see an alternative in abductive logic against deduction and induction through a lea way that shows that a rigid theoretical proposition is not necessarily needed to be developed by a researcher before data collection. However, researchers cannot also afford to collect and analyze data "theory-free", see FIGURE 4.3 (Dubois and Gadde, 2002). Hence, considering a phenomenon, alongside empirical observations, the researcher deepens the theoretical understanding.

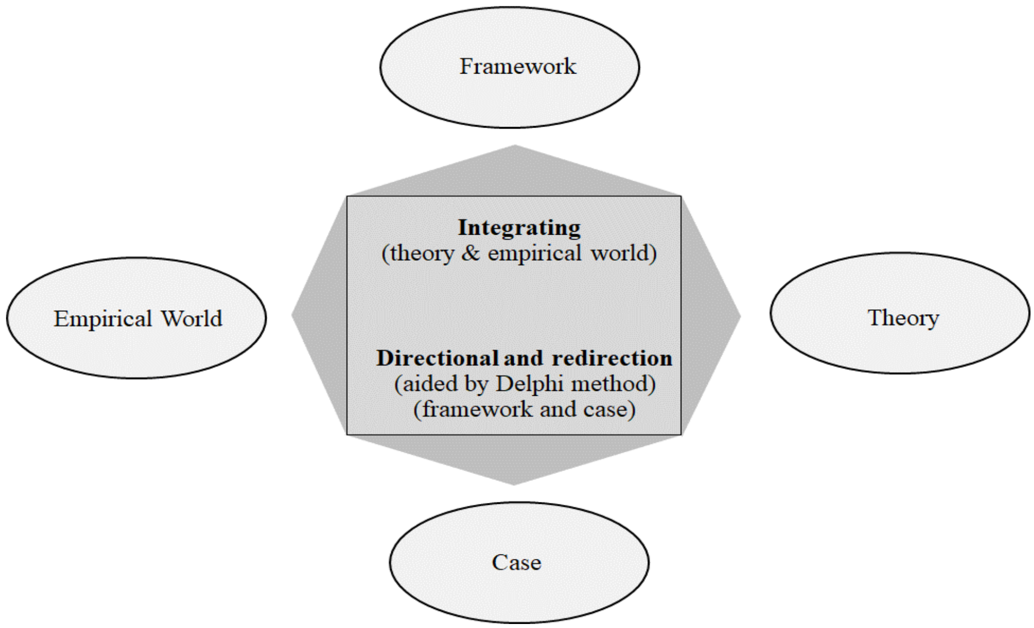

FIGURE 4.3 Systematic methodology combination (adapted from Dubois & Gadde, 2002)

In this dissertation, the research process discussion goes along the direction of abductive logic and aligns the characteristics systematically. This study's goal is to develop theories through continuous alignment and interplay between theory and empirical evidence.

Overall, I put in mind the preliminary theoretical framework throughout this dissertation's development while approaching each case study, which evolves with the data collection and analysis. Consequently, this dissertation's journey took a research process that is iterative because each study serves as a preliminary study for the others.

4.2.1 Common Characteristics of Case Study Research

Certain characteristics are common to different approaches that have been adopted by researchers in carrying out case study research. Consistently, case study research is a versatile way of carrying out an inquiry in qualitative form, which often suits in-depth investigation of issues, phenomena, or situations that are seemingly complex in context.

These contexts usually contain many variables with unclear boundaries between the issues and the context (Stake, 2006; Merriam, 2009; Swanborn, 2010; Yin, 2014).

Case study research fits a wide range of topics and purposes (Simons, 2009; Stewart, 2014). However, one fundamental pre-requisite for the case study as a choice is the researcher's need to shed light on a complex phenomenon (Yin, 2014). It is also used to understand real-life situations to primarily answer both exploratorily and explanatorily type of research questions (Stewart, 2014; Yin, 2014).

To effectively establish the research design elements, developing research questions, and identifying the focus along a refined boundary is highly recommended (Stake, 2006). This requires a precise selection method and identification of parameters of the case and time establishment of the framework for the investigation of the case (Yin, 2014).

The case study method also encourages the use of multiple methods for collecting and analyzing data as they provide informative and synergistic views of the investigating issue (Stake, 2006; Yin, 2014). Also, when a case study is used by the researcher to test a theory, this has an impact on all associated elements of the research design, as shown in Table 4.1 (Løkke and Sørensen, 2014). Hence, in this study, I spent a considerable amount of time preparing data collection and analysis and to make extant theories explicit while setting up an analytical framework.

Table 4.1 Case study design and theory testing (Adapted from George and Bennett, 2005)

Paths of research design affected	**Purpose**	**Research action**	**Outcome**
Research goals	State the point of departure: System-driven or Concept-driven	Specify conceptual context-theoretical analysis	Framework for designing study: e.g., case selection, analytic strategy, etc.
Pre-data collection work on theories	Prepare for empirical phase and analysis	Expand clarification of theories. "Operationalize theories" propositions.	Minimum data requirements
Analysis	Link theories and data	Data reduction and expansion. Develop displays, tables, and other documentation. Examine potential paradoxes/anomalies relative to theories within the case and/or cross-case analysis.	Findings are relative to theories - theory testing.
Internal validity	Support finding's credibility	Check alternative rivals not covered by theories. Comparing minimum data requirements to actual data collected.	Credibility of analysis
External validity	Theory - testing	Extend previous results to the current context.	Evaluation of theories' explanatory power or boundaries

This dissertation has research questions characterized along with the phenomena that are well appropriate for case study research strategy. What this dissertation explored is rare and, at the same time, contemporary due to the traction of the use of Fuzzy Analytics and digital analytics in consumer space that is just gaining academic attention and momentum. In the real world, little research has been seen in how Fuzzy Analytics have been leveraged to drive consumer business performance.

4.2.2 Mobile Telecommunication - A Case for Firms with a Large Consumer Base

The mobile telecommunication choice as the service industry where this dissertation derived its cases is due to the large customer base that characterizes the mobile industry. In answering the research questions in this study, the dissertation articles leverage the mobile telecommunication broad consumer characteristics in developing cases to arrive at the research findings. Due to the rapid technological changes and digital explosion, the mobile telecommunication industry has evolved, thereby benefiting its large consumer base while destroying the boundaries between industries (Stone, 2015).

Recent developments and advancement in technology have enabled some firms with a large customer base to link many digital touch points to enterprise databases. This data availability across the enterprise has accelerated Customer Value Management (CVM) practice in some large consumer firms. Customer Value Management (CVM) is the art and science by which brands manage large customer base through optimization and elongation of customer lifetime using advanced data analytics and robust channel management towards one-to-one marketing approach (Rigby, Reichheld and Schefter, 2002.; Rigby and Ledingham, 2004; Bohling, Bowman, LaValle, Mittal, Narayandas, Ramani and Varadarajan, R; Kim and Mukhopadhyay, 2011; Lemon and Verhoef, 2015).

In the last decade's management and marketing practice, the growth of CVM has been regarded as one of the critical developments (Verhoef and Lemon 2013; Santonino 2020).

Brands' engagement channels are rapidly converging towards digital as a result of digital transformation and innovations. Hence, it has become vital for brands to understand how to optimize the opportunities in the digital space to drive effective and profitable one-to-one marketing (Gallino and Moreno 2014). However, many consumer firms are still struggling to leverage CVM in maximizing business revenue. Telecommunication firms such as MTN, Dutch Mobile, Vodafone, Telefonica, and others have invested and developed their digital CVM capability (Kim and Mukhopadhyay 2011).

However, while some mobile service providers, service and utility firms have expanded their CVM capabilities across all its pillars such as people, analytics, and systems, harnessing embedded CVM opportunities in the robust management of consumer base by many consumer firms with a large customer base remains a challenge. Hence, the choice of this dissertation of the mobile telecommunication industry as the industry of choice where the articles' cases are derived.

4.2.3 **Data Collection**

The primary data for this dissertation is from a mobile operator in Nigeria. All the case studies sourced data from the Business Intelligence (BI) system across the mobile operator's network elements. Table 4.2 summarizes the type of data that was collected for each of the cases in this dissertation.

Table 4.2 Data collection summary

Case	Case Focus	Collected Data
Case 1	Customer experience	Mobile customers data across the digital channels *(n=1200)* • Real-time video usage data • Data usage and consumption data • Customer location and periodical spend • Device types
Case 2	Customer experience	A broad characteristics cross-section of mobile users with different types of mobile devices (n=150). • Video ad view (time, length, traffic, and usage) for 14 days • A real-time survey on the mobile app also captured • Customer data on usage movement across digital products and services
Case 3	Digital channel optimization	Usage logs of mobile money customers across all transaction channels for 90 days, *(n=300).* • Usage across the digital channel and non-digital channel • Activities data across all other cellular behavior (usage, traffic for data and voice)
Case 4	Review	
Case 5	Digital service pricing and Pricing Adjustment	The entire data user and non-data user on the customer base *(N=20.2 million)* • Data users; Non-data users • New customers • Product purchase history, customer usage, and lifetime on the network
Case 6	Digital customer ownership – Telco & OTT rivalry	OTT (over-the-top) protocols and traffic of all smartphone users *(n=10.2 million)* • Protocol traffic at the customer level • Data usage; overall base traffic; data usage and consumption; voice traffic and consumption at the protocol level
Case 7	Review	

4.3 DELPHI METHOD

This dissertation used the Delphi method to gather insights from the experts across consumer firms with a large customer base as the basis for exploration and investigation into the other cases conducted in this study. Delphi technique stands as one of the research methods that are used for prospective inquiries. It is widely considered suitable for analyzing and exploring opinions regarding a specific topic. These opinions are opinions that are made without influence or pressure from the experts within the group. The implication of this is that one can validate any consensual study's output in the near future (Kaushik, 2009; Helmer, 1998; Kovács, 2012).

Regarding the topic or subject under consideration, the Delphi technique is a flexible method that relies on expert consensual decision-making capability. In obtaining information from experts on a subject, the Delphi method uses a structured process and a range of selected questions to validate responses from a previously selected expert group.

For experts not to influence each other, they never exchange opinions about responses. Delphi's method, which I used in this study to harness the experts' view to guide other cases in this dissertation, systematically harness opinions later analyzed (Goder, 1996). This technique focusses on a carefully selected group of digital and analytics specialists from different consumer firms with a large customer base. It uses their answers from successive questionnaires to arrive at a consensus answer on a subject. My objectives were to find a consensus on the experts' opinions regarding this study's research questions (Linsone and Turoff, 1975). Further discussion on how the Delphi method was administered in this dissertation is found in the next section.

4.3.1 Delphi Survey Study: Digital and Marketing Analytics in Large Consumer Firms

This section details the Delphi survey study, which was conducted to establish the experts' view in various service organizations on the impact and use of digital marketing and analytics in business performance. The study follows the stages, as shown below in (FIGURE 4.4).

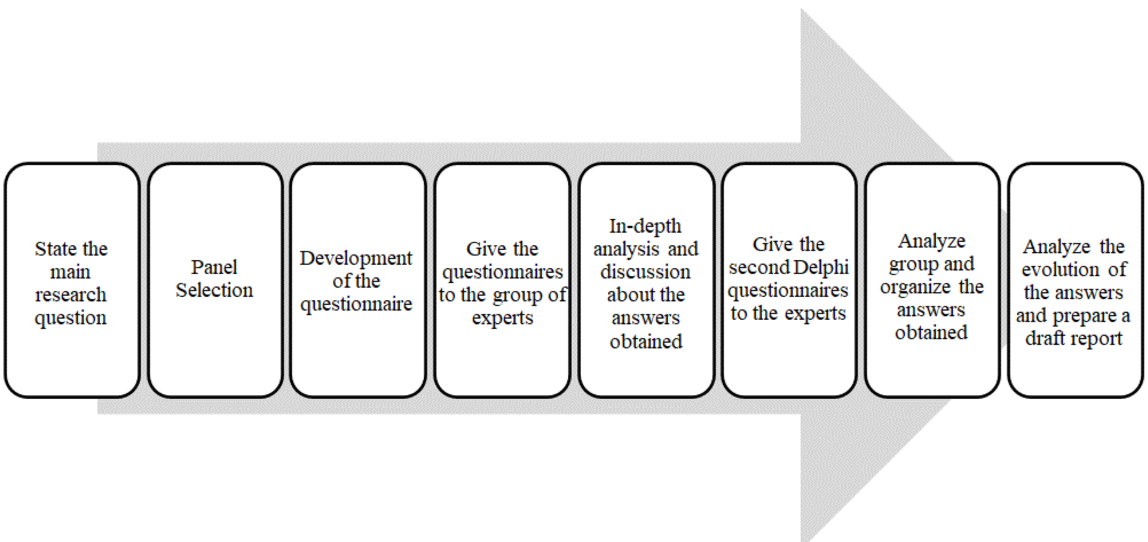

FIGURE 4.4 Stages of Delphi study. (Based on Hsu and Sandford, 2007; Torrecilla-Salinas, De Troyer, Escalona and Mejías, 2019).

The technique seeks a group of experts' opinions to assess agreement and resolve the disagreement on an issue (Jones and Hunter, 1995). The Delphi process comprised of two rounds. In round 1, the experts were asked to rank 18 statements independently across two domains, using a 5-point Likert scale ("strongly agree", "agree", "neutral", "disagree", "strongly disagree"). Participants have the opportunity to fill in a free-text within each segment of the survey for the chance to elaborate or explain responses. Experts demographics were collected, including gender, current job position, and industry.

Round 2 was also a survey to selected participants in round 1 to ask questions around additional statements and clarify some of their comments in round 1. Round 1 survey was distributed through an online form to the email addresses of the experts. A total of 9 statements were included in the first section. The second section also contains another 9 statements. The first domain is digital marketing, while the second domain is marketing analytics.

In Delphi exercises, up to 12 respondents are generally considered sufficient for consensus attainment. Larger sample size can skew the findings as consensus may be difficult to be reached (Crane, Henderson and Chadwick, 2017; Murphy, Black, Lamping, McKee, Sanderson and Askham, 1998). Also, group dynamics are more critical than the sample size (Slade, Dionne, Underwood and Buchbinder, 2014) regarding the quality of consensus. While our participants in both Round 1 and 2 were both 15 and 13, respectively, our experts cut across four key consumer industries with a large customer base, as shown in Table 4.3.

Table 4.3 Demographic Characteristics of Delphi Participants

Characteristic	Round 1 (n =14)	Round 2 (n = 13)
Gender		
Male	73.3%	69.2%
Female	26.7%	30.8%
Country of residence		
Nigeria	86.7%	86.7%
Cameroon	13.3%	13.3%
Industry		
Telecommunication	33.3%	30.8%
Financial (Banking)	20.0%	23.1%
Betting	20.0%	30.8%
FinTech	26.7%	14.4%

Notes: Participants cut across two countries in Africa and four industries characterized by a large customer base

Table 4.4 Industry and roles of Delphi participants

Industry	Roles
Telecoms	Senior Manager, Campaign Analytics
Banking	Manager, Digital Services
Betting	Manager, Digital and Value Proposition
Betting	Director, Consumer & Growth
FinTech	Senior Manager, Channels & Digital
Banking	Manager, Business Analytics & Modeling
Banking	Specialist, Value Proposition and Campaign Management
Telecoms	Manager, Youth and High-Value Segment
Telecoms	Manager, Customer Value - Commercial
FinTech	Specialist, Campaign and Analytics
Telecoms	Manager, Data Service and Digital Proposition
FinTech	Manager, Customer Value - Analytics
FinTech	Director, Value Proposition
Betting	Senior Manager, Marketing
Betting	Specialist, Campaign Management
Telecoms	Manager, Digital and Campaign
Telecoms	Manager, Analytics and Reporting

Table 4.5 Delphi study to build a consensus on the use of digital marketing and analytics for driving business performance

Digital Marketing	Round 1(n=14)			Round 2 (n=13)		
	Agree %	Disagree %	Neutral %	Agree %	Disagree %	Neutral %
1. We have a clear digital marketing strategy in our firm[b]	80.0%	6.7%	13.3%	76.9%	7.7%	15.4%
2. Digital marketing is perceived as important aspect of marketing in our firm[b]	86.7%	6.7%	6.7%	92.3%	0.0%	7.7%
3. We have a unit/department that is responsible for digital marketing activities in our firm[b]	86.7%	6.7%	6.7%	92.3%	0.0%	7.7%
4. Digital marketing in our firm has a budget of its own within the overall marketing budget[b]	80.0%	0.0%	20.0%	76.9%	0.0%	23.1%
5. Our firm measures the result of digital marketing against its objectives[b]	66.7%	20.0%	13.3%	69.2%	7.7%	23.1%
6. We use digital marketing to drive business revenue in our firm[b]	80.0%	13.3%	6.7%	84.6%	7.7%	7.7%
7. Currently, we use at least three digital channels to drive business revenue in our firm[b]	73.3%	20.0%	6.7%	76.9%	15,4%	7.7%
8. My firm has obtained measurable benefits from the use of digital marketing channels	60.0%	13.3%	26.7%	69.2%	0.0%	30.8%[a]
9. We have digital marketing solution that automates our digital engagement with our customers	66.7%	62.7%	6.7%	76.9%	23.1%	0.0%

Marketing analytics

10. We use analytics to make decisions that impact business performance in our firms[b]	93.3%	0.0%	6.3%	92.3%	0.0%	7.7%
11. Analytics is perceived as an important aspect of our marketing operations[b]	93.3%	0.0%	6.3%	92.3%	0.0%	7.7%
12. Our firm measures the result of marketing analytics against marketing initiatives and programs[b]	80.0%	6.7%	13.3%	84.6%	0.0%	15.4%
13. We have unit that is responsible for data mining and analytics in our firm[b]	100%	0.0%	0.0%	100.0%	0.0%	0.0%
14. We develop analytical models and operationalize their usage in our firm[b]	80.0%	6.7%	13.3%	84.6%	0.0%	15.4%
15. We have a customer engagement platform that is driven by analytical outputs in our firm[b]	73.3%	0.0%	26.7%	76.9%	0.0%	23.1%
16. Our firm use analytics to drive our business performance and revenue everyday[b]	93.3%	0.0%	6.3%	84.6%	0.0%	15.4%
17. In our firm, we invest in analytical tools, platforms and customer engagement solution regularly[b]	73.3%	0.0%	26.7%	76.9%	7.7%	15.4%
18. We leverage these tools, and solutions to drive marketing initiatives which impact business performance[b]	80.0%	0.0%	20.0%	76.9%	0.0%	23.1%

Note: Consensus was achieved when 70% of participants strongly agreed/agreed or strongly disagreed/disagreed with a statement

[a]Statements in this round of this domain include responses where 'neutral' exceeded 30% of total responses

[b]Stability of consensus (<10% variation) was achieved between Round 1 and Round 2

On the 19 experts invited across the four consumer industries with a large customer base in the Delphi study, 15 participants completed Round 1 (78.9%), and 13 of 19 completed Round 2 (68.4%). The experts' demographic characteristics in the study in each round are presented in Table 4.3. Across the two rounds, there was gender distribution consistency. Though more females slightly participated in Round 2 than Round 1 while over the quarters of the participants resided in Nigeria. Most of the respondents were senior professionals with many years of experience driving business performance for their organizations.

The expert's roles and industries are presented in Table 4.4 while group responses to each round of survey statements are presented in Table 4.5. By Round 1, a consensus was achieved for 15 of the 18 statements with 88.9%, while 16 statements achieved consensus by Round 2. Only one statement needed a second round before consensus was reached. Table 4.5 presents the experts' responses to the Delphi statements according to their appearance across the two domains.

The Delphi study aimed to identify how consumer firms with a large consumer base drive and optimize business performance through digital marketing and analytics. For the digital marketing domain, 6 (66.7%) of the 9 statements reached consensus in Round 1; by Round 2, a consensus has been reached on 7 of the statements (77.8%). A consensus was consistent in the marketing analytics domain as 100% consensus was achieved for all statements in Round 1 and Round 2. Participants could not reach a consensus on two statements in Round 2 within the digital marketing domain, as shown in the Delphi statements in Table 4.5. These are the result measurements of digital marketing against the set objectives and measurable benefits from the use of digital marketing channels – this aligns with the motivation for this dissertation. The existence of a digital marketing solution that automates digital engagement with customers reached consensus in Round 2.

The stability of consensus (<10% variation) was achieved for Round 1 and Round 2 across all the statements in the marketing analytics domain. One of the statements with consensus in Round 2 in the digital marketing domain did not attain the stability consensus (<10 variations) for both rounds. In round 2, within the digital marketing domain, more than 30% of participants reported not to be sure whether their firms obtain measurable benefits from the use of digital marketing channels. The proportion of the experts that reported not to be sure across the 18 statements in both streams are presented in Table 4.5.

In this dissertation, the Delphi survey achieved consensus across the 15 industry experts who completed two rounds on 100% of the 9 statements proposed on how analytics can help consumer firms with a large consumer base drive business performance. Furthermore, the survey reached a consensus on 77.8% of the statements that were put across to the expert to describe how digital marketing can drive and optimize business performance in the consumer firms with a large consumer base. The expert panel that constituted this study reached a consensus on most of the statements in this study.

It was clear that the measurement and evaluation of marketing investment in digital marketing activities are still challenging. While digital marketing is a component aspect of the marketing function in consumer firms, this study revealed that result measurement of digital marketing activities against performance objectives and business benefits is a challenge in consumer firms with a large customer base. This can help position future discussions and frameworks around the research on digital marketing and analytics in large consumer firms. The next chapter of this dissertation focuses on the summary of the case studies that are explored as a result of the identified gap from the literature review and the result of the Delphi study in this section.

CHAPTER FIVE: SUMMARY OF DISSERTATION ARTICLES

This chapter presents a clear description of the research process in every article of this dissertation and gives a concise summary of their main results. In summarizing the main results, each of the case studies' iterative process and how they evolve is highlighted along with the theory and data.

5.1 Case 1: A Diagnostic Customer Experience Measurement for Digital Marketing Channels

The Delphi survey result arose my curiosity as to why experts across three key firms with a large customer base have disagreed about the measurement of results across digital marketing channels. It is surprising why marketers within a large consumer firm will be putting the budget behind a channel without measuring such channels' performance against their objectives. I started to investigate the measurement and evaluation approach across digital channels. My curiosity made me realize that a case study approach would be best for me to unravel better some findings within the measurement approach of the digital channels.

This research case explores the measurement of customer experience in digital channels. Customer experience was measured through the traditional evaluative approach (non-real-time) against the diagnostic (real-time). By accessing real-time customer experience data, service providers can use this data to improve the customer experience and turn the real-time experience into real-time actions and programs that can enhance and drive business performance (Nickerson, 2015; Kumar, 2016).

In this case, the survey and experiment consider the mobile application channel of a mobile operator as a digital touch point. The case study shows that when the experience is measured at the *moment of truth*, that is, in the moment of the experience as against the tradition of scoring past interactions, insights can be generated, actionable, and operationalized in real-time.

This research case was motivated by the need to measure the customer experience across digital touch points diagnostically to resolve issues and improve customer experience in real-time. I investigate the effectiveness of customer experience measurement and the evaluative and diagnostic approach of a mobile network operator's mobile application channel in Nigeria. The experience was in real-time while customers are using the mobile application of the mobile operator. Also, customers' non-real-time experience that has used the mobile application before was also measured through a survey.

The executive marketing managers of this mobile network wanted to uncover two things (i) can the customer experience be measured in real-time within the digital channel? (ii) can they measure experience in real-time and leverage the result to improve customer experience to optimize the customer value? After an interview with the marketing executives on digital channel alternatives, it was agreed to measure customer experience using the mobile app channel. The customer experience of the mobile operator application while the customers are using the app and carrying out service transactions were measured. I also use evaluative means to measure the customer experience weeks after customers have performed revenue-generating activities on the mobile app. A pop-up application is developed that pops up when the application is in use. The design is so simple that customer experience can be captured immediately after a particular transaction on the mobile app is performed.

When customer experience is measured using the diagnostic approach in Month1, immediate actions are taken, and the improvements are seen along all tested parameters at Month2 and Month3. For evaluative measures done after three weeks that the customer used the mobile application, there is a consistent decline in customer satisfaction in Month2 and Month3 across all tested parameters. Real-time actions could not be taken to address customer complaints (see Table 5.1).

Table 5.1 Diagnostic and evaluative measure of customer experience of mobile application channel of the mobile operator – NPS

	Diagnostic and real-time			**Evaluative measure**		
	M1	M2	M3	M1	M2	M3
Likelihood to recommend	82.1	82.3	82.6	82.2	67.2	60.9
Network coverage	83.3	86.3	86.4	80.2	70.1	65.2
Network quality	86.8	89.5	89.8	85.3	72.3	70.4
Image	84.4	89.9	87.5	84.3	80.2	81.5
Pricing and tariffs	81.7	83.3	84.2	80.2	75.6	73.7
Schemes and promotions	83.7	83.9	84.7	82.1	80.2	80.2
Plans and Packages	84.5	86.6	88.7	84.5	78.3	78.5
VAS	82.2	85.0	86.0	82.0	79.3	78.5
Internet services	85.8	86.6	89.7	84.0	78.2	70.1

There are no visible differences in the NPS in the diagnostic measure, but M2 and M3 NPS for the evaluative decline. I believe this is because most of the customers had forgotten their experience, and the answers they gave were not a true reflection of their actual mobile application experience. For the network quality and internet parameters, operators were able to layer the customers' real-time responses with other network elements to fine-tune experience and improve the quality of service near real-time. The diagnostic measurement helps to resolve so many issues that would have led to customer attrition or dormancy. One of the complex revelations was that some of these issues were not coming from mobile operators. An example is an issue relating to the settings on the customer's phone, which is outside the mobile operator's control. Real-time experience measurement helped resolve these types of issues because such customers are quickly called and guided through the settings or related procedures, which immediately improved the overall customer experience and increased usage.

Table 5.2 Summary of main findings (Article 1)

Main Findings	
Voice of customer initiatives	1. Firms need to invest in the capabilities and systems to capture and measure customer experience in real-time and across channels 2. Investment and budget for the voice of customer initiatives cannot be easily justified if improved customer experience cannot be measured
Diagnostic customer experience measurement	3. Diagnostic customer experience requires the integration with various data sources across the enterprise to make the captured information through the diagnostic measurement approach useful for the marketers 4. The customer experience diagnostic measurement approach gives firms a real-time actionable insight that can be quickly leveraged to address customer dissatisfaction 5. The customer experience diagnostic measurement approach complements the established evaluative approach in tracking the overall success of voice of customer initiatives towards improving the experience and overall bottom line

5.2 Case 2: Towards Fuzzy Analytics (FA) for Digital Video Advertising Campaign Effectiveness and Customer Experience

The second case study focuses on the need for firms to have a good customer experience measurement grip. Having understood from Case study 1, I started exploring a more robust customer experience measurement methodology for consumer firms. The question is centered around how a digital consumer's customer experience can be measured through a cutting-edge analytical method. The case considered the video advertisement effectiveness along with the customer experience of digital video viewers. Using fuzzy analytics (FA), the customer experience was measured at the *moment of truth*.

In studying the customer experience and effectiveness of digital video advertisement, a fuzzy evaluation approach was used to model the customer experience of the digital video viewers. The study began by considering three segments of mobile users. Through the fuzzy set theory, linguistic terms are defined and expressed as Triangular Fuzzy Numbers (TFNs).

A cross-section of mobile users with different mobile devices was randomly selected along with the 2G, 3G, and 4G capabilities of the devices and mobile network. Videos and ads were tracked for these segments of users over two weeks, while a real-time online survey was enabled for these users at intervals. It is expected that customers will remember their video experience fully at this time, and their judgment can be leveraged for the improvement of the mobile operator's services.

This study captures the mobile video and viewer’s *(n=150)* perception over the evaluation criteria. These were transformed into pre-defined fuzzy numbers. The determination of the weight of customer experience evaluation from online questionnaires follows. This led to the derivation of fuzzy perceived experience scores. The final conversion of the fuzzy experience score into the linguistic terms reflects the video ad viewers' customer experience. The study provides a theoretical and empirical overview of digital video advertisement effectiveness and customer experience measurement.

The membership function of a fuzzy number $\tilde{A}$ is represented as:

$$f_A(x) = \begin{cases} \dfrac{x-b}{b-a}, a \le x \le b, a \ne b \\ \dfrac{x-c}{b-c}, b \le x \le c, b \ne c \\ 0, otherwise \end{cases} \qquad 5.2.1$$

Then, $\tilde{A}$ is referred to as TFN and denoted as $\tilde{A}$ = (a, b, c). A comparison between TFNs is very critical in decision making because of its flexibility nature and openness. In order to compare and later rank more than two fuzzy numbers simultaneous, Integral values for TFNs are proposed.

Equation (5.2.2) defines the integral values for TFN $\tilde{A}$ as follows:

$$I(A) = \left(1-\alpha\right)\int_0^1 g_A^L(\mu)du + \alpha\int_0^1 g_A^R(\mu)du,$$

where

$$0 \le \alpha \le 1,$$

and

$$\alpha = \frac{1-\alpha}{2}a + \frac{1}{2}b + \frac{\alpha}{2}c \qquad 5.2.2$$

The α, which is the index of optimism is representing the degree of optimism for a person. The higher the α, the higher the degree of optimism. This index represents the level of optimism of a decision maker. In this case, a mobile viewer of the advertisement. Suppose the mobile user experience is neutral or moderate, the value of α equals 0.5. When α = 0.5, the total integral value of the TFA $\tilde{A}$ equals:

$$I(A) = \left(1 - \frac{1}{2}\right)\int_0^1 g_A^L(\mu)du + \frac{1}{2}\int_0^1 g_A^R(\mu)du = \frac{a+2b+c}{4} \qquad 5.2.3$$

Equation 5.2.1-5.2.3 are directly used in the customer experience measurement computation.

In this computation, four procedural steps are followed.

1. ***Step 1: Definition of TFNs linguistic variables***

Customer experience measurement criteria and corresponding linguistic values are first defined. See Table 5.3.

Table 5.3. Linguistic variable scale

Number	Linguistic variable
1	Bad Experience
2	Fair Experience
3	Good Experience
4	Very Good Experience
5	Excellent Experience

Mobile users need to select on their screen for a given value from ‘bad experience’, ‘fair experience’, ‘good experience’. ‘very good experience’ and ‘excellent experience’. See the scale and its linguistics values in Table 5.4.

Table 5.4 TFN and linguistic variables

Linguistic Variable	Symbol	TFN
Bad Experience	BE	(0, 0, 1.5)
Fair Experience	FE	(0,1.5,2.5)
Good Experience	GE	(1, 2.5, 4)
Very Good Experience	VE	(2.5,3.5,5)
Excellent Experience	EE	(3.5, 5, 5)

2. Step 2: Defining weight of linguistics variables

Suppose *Ci* denote the evaluation criteria of user experience, and let *Wi* denote corresponding *Ci*, *i* =1, 2, …., *n*. The weights of *Ci* are defined as the peak, (a_p, 1) of central triangular fuzzy number (a_i, a_p, a_2) for each linguistic value. Each linguistic variable comes with different weight. See Table 5.5.

Table 5.5. Weight of linguistic variables

Linguistic Variable	Weight, W_i
Bad Experience	(1.5, 1.5, 4)
Fair Experience	(1.5, 4, 6.5)
Good Experience	(4, 6.5, 9)
Very Good Experience	(6.5, 9, 11.5)
Excellent Experience	(9, 11.5, 11.5)

3. Step 3: Weights and TFNs Grouping

Criteria that are measured in TFNs are combined with corresponding weights to obtain the overall customer experience. Let the set of linguistic terms be A_c = {BE, FE, GE, VE, EE}. In assessing the customer experience, c_i denotes the measurement result of each experience criterion C_i, and $c_i \in A_c$. The corresponding TFN of c_i is represented by $\hat{c}_i$. In order to simplify the customer experience approximation, the linguistic terms in assessing the customer experience level of the video ad viewer are presented by TFNs $\tilde{A}$.

Following the measured criteria and their associated weights in *step* 1 and *step* 2 respectively, the overall customer experience $\tilde{A}$ can be derived from the following equation:

$$A = \left(\frac{1}{\sum_{i=1}^{n} W_i} \right) \otimes \left(W_1 \otimes \tilde{c}_1 \oplus W_2 \otimes \tilde{c}_2 \oplus \ldots \oplus W_n \otimes \tilde{c}_n \right) \quad 5.2.4$$

4. *Step 4: Ã Transformation into Linguistic Terms*

For the advertisers to better understand the overall customer experience level and not relying on the score or scale, there is a need for the transformation of TFN of customer experience $\tilde{A}$ into linguistic terms, which is the original form. Few methods such as shortest distance have been proposed for the conversion of the fuzzy numbers to corresponding linguistic terms (Schmucker, 1985; Liou and Chen, 2006).

In this study, (Yoon and Choi, 2019) methodology is leveraged to incorporate ranking fuzzy numbers with integral value in order to convert fuzzy numbers to their associated linguistic term.

Suppose,

$u_1 = BE,\ u_2 = FE,\ u_3 = GE,\ u_4 = VE,\ u_5 = EE,$

Following equation 5.2.3 with $\alpha = 0.5$, the integral value of $\hat{u}_1 = 1, 2, \ldots 5$, can be obtained and later used as a preference comparison standard.

In finding j, we can have, $I\left(u_j\right) \le I\left(A\right) \le I\left(u_{j+1}\right)$

Let

$$P = \min\left\{ I(A) - I\left(u_j\right), \left| I(A) - \frac{I\left(u_j\right) + I\left(u_{j+1}\right)}{2} \right|, I\left(u_{j+1}\right) - I(A) \right\} \qquad 5.2.5$$

For the conversion, one of the following rules holds:

If

$$P = I(A) - I\left(u_j\right),$$

then, we represent the customer experience by ***û**_j_*.

If

$$P = I\left(u_{j+1}\right) - I(A),$$

then the customer experience level is given by ***û**_j+1_***.**

in case,

$$P = I(A) - \frac{I\left(u_j\right) + I\left(u_{j+1}\right)}{2},$$

then the customer experience level is between $\hat{u}_j$ and $\hat{u}_{j+1}$**.** Before the decision, the integral value of $\hat{u}_i$ = 1, 2, …5, are derived by equation 5.2.3 with α = 0.5.

Table 5.6 represents the integral values of each linguistic terms.

Table 5.6. Integral Values for $\hat{u}_i$.

Linguistic term	BE	FE	GE	VE	EE
Corresp. TFN	$\hat{u}_1$	$\hat{u}_2$	$\hat{u}_3$	$\hat{u}_4$	$\hat{u}_5$
I($\hat{u}_i$)	0.375	1.375	2.5	3.625	4.625

In making linguistic decision, the integral values have been used as a guidance. The result for this experiment follows these computational procedures.

Computational Outcome

From the online questionnaires that popped up after the termination of the video ad, which was viewed by the mobile users, responses for each criterion from the questionnaire were analyzed by taking the arithmetic mean from the scale. In order to have a smooth conversion to define TFN from linguistic variable, the scale is rounded off to nearest whole number. Following *step 2*, the weight of each criterion is determined.

An example of computation from a video advertisement viewer is presented. Summation of weight is calculated as:

$$\sum_{i=1}^{n} Wi = 65$$

We combined the TFNs of criteria and associated weights to arrive at the customer experience in equation 5.2.4.

Hence,

$$A = \left(\frac{235}{65}, \frac{412}{65}, \frac{535}{65} \right)$$

We used equation 5.2.3 for obtaining integral value $\tilde{A}$ which is 3.10204. This shows that linguistic terms that represents customer experience falls between *"Good Experience"* (***$\hat{u}_3$***) and *"Very Good Experience"* (***$\hat{u}_4$***). In a similar manner, all other viewers were calculated along their associated variables. The average integral value for all viewers with 3G capable device is 2.5177141. This shows that customer experience is between (***$\hat{u}_3$***) and (***$\hat{u}_4$***) which is between *"Good Experience"* and "*Very Good Experience"* in linguistic terms.

Table 5.7 Summary of main findings (Article 2)

Main Findings	
Subjective nature of customer experience	1. The subjective tendency of customer experience is fuzzy. Therefore, a linguistics approach can be leveraged for the measurement of digital customer experience
Fuzzy Analytics (FA) approach to customer experience measurement	1. A straightforward and easy to follow approach are highlighted in the study for customer experience measurement of digital video viewers 2. The study reveals the importance of the linguistic model and how it can enhance the customer experience measurement modeling 3. Captured perception of digital consumers can be transformed into pre-defined fuzzy numbers and fuzzy experience scores that reflect the customer experience of digital customers 4. Brands can leverage the experience of their digital customers in real-time to improve their services to their customers

5.3 Case 3: Analytical Approach to Digital Channel Performance Optimization of Mobile Money Transactions in Emerging Markets

The third case was driven by my curiosity to understand analytics' power in driving business performance in a consumer firm with a large customer base. This case study examined mobile money revenue performance optimization from the mobile operator perspective through an analytics-driven target selection across channels. This study focused on how service providers can maximize their customer base's potential across acquisition, growth, and retention through a comprehensive marketing strategy.

In achieving this, the study developed a target selection and campaign optimization framework for mobile money customers along two channels of transaction. This study's key analytical method is the combination of fuzzy c-means clustering and RFM (recency, frequency, monetary) algorithm for the target selection development through the customers' usage logs *(n= 300)* of a mobile service provider.

Two mobile channels of transactions along the behavior of customers that use these channels for mobile money transactions are evaluated through a fuzzy modeling method in this study. Fuzzy c-means (FCM) is used for the clustering in the product-space of RFM variables (Bezdec, 1981). The ability of the algorithm to search for spherically distributed clusters in the datasets makes it a choice for many applications in the literature. The definition of obtained clusters from the clustering is done on the product space variables. When Gustafson-Kessel (GK) (1979) algorithm is used, the fuzzy clustering becomes the product space of the RFM variables (Gustafson & Kessel, 1979). To adapt the shape of the clusters to the distribution across the data points, the algorithm leverages adaptive distance measure, which results in ellipsoidal clusters. While the focus of this study is not so much on the details of the FCM and GK algorithm, the study uses the FCM algorithm to analyze the importance of two different mobile channels to different customer groups. This generates strategic insights for mobile operators on how to target different customer segments for mobile money transactions across various channels.

The fuzzy c-means clustering techniques is used in this study for profiling mobile money users. This aims to determine the appropriate selection and targeting across USSD and mobile application transactional channels for effective revenue optimization programs and campaign implementation. Several revenue optimization methods and different campaign methods exist for generating incremental revenue across the customer base. However, these campaigns cannot be maximized if marketers cannot accurately profile and target different groups for different programs across different channels accurately. If selection and targeting are not correctly done through robust modeling and techniques, the implementation of the programs below the line can lead to revenue dilution and value erosion (Nayeri & Rostami, 2016).

Data collection

The model is developed with transaction data from a mobile service provider in an emerging market. The data set contains mobile money transactions and other mobile services usage and behavioral activities on the network. Each customer has a user ID and the usage history of mobile money transactions for the last 90 days. The entire data set contains customers with different mobile money transactional behavior. It includes customers who performed mobile money and other cellular activities on the network. Also, some customers only performed other mobile services without performing mobile money transactions. Other relevant fields within the data set are the channel of transactions. While some customers were consistent with a channel for their mobile money transactions, some leveraged multiple channels within a short period, according to the dataset.

From the pool of customers within the data set, the study analyses a random subset of customers (n=300). From the randomly selected sample of mobile customers, 145 of them have used at least one mobile money service in the last 60 days.

Model development

This section explains the selection model that consists of both the fuzzy clustering and the RFM algorithm in this study. The fuzzy c-means and the RFM model aim to identify the right mobile money customers and the right channels upon which a revenue optimization opportunity or campaigns can be deployed across the mobile operator customer base.

Figure 5.1 shows the architecture and the methodology of the model development and the campaign optimization structure.

Fuzzy clustering is a type of unsupervised algorithm technique that partitions into different groups. These groups are overlapping by leveraging both similarity and dissimilarity within and among the groups, respectively. The significant disparity between the general clustering technique and fuzzy clustering is the ability of fuzzy clustering to assign data points to more than a cluster. The converse is the case for classical clustering techniques. A decision must be made on the most suitable cluster for a data point in case data points belongs to more than a cluster in classical clustering. The number of clusters is also known in advance (Ansari & Riasi, 2016). The equation below represents the objective function of this algorithm.

$$J = \sum_{i=1}^{c}\sum_{k=1}^{n} u_{ik}^{m} d_{ik}^{2} = \sum_{i=1}^{c}\sum_{k=1}^{n} u_{ik}^{m} \left\| x_k - v_i \right\|^2 \qquad 5.3.1$$

Whenever the value m that is a real number is larger than 1, x_k is the k^{th} data point, v_i represents the centroid of the i^{th} cluster, u_{ik} represents the degree to which the data point k belongs to a cluster i, and $\left\| x_k - v_i \right\|$ is the Euclidean distance between k^{th} data point and i^{th} cluster center. A matrix U can be defined by using u_{ik} with c rows and n columns such that every individual element of the matrix can have value 0 and 1. The algorithm is similar to classical c-means if all the elements of a matrix U are either 0 or 1. The elements in each column must sum up to 1, while all elements of the matrix U can have any value between 0 and 1. In other words:

$$\sum_{i=1}^{c} u_{ik} = 1 \quad , \forall k = 1, ..., n \qquad 5.3.2$$

Equation 5.3.2 shows that the sum of the proportions of each data point belonging to each of the c different clusters should be equal to 1. By minimizing the objective function with the above condition together, we have:

$$V_i = \frac{\sum_{k=1}^{n} u_{ik}^{m} x_k}{\sum_{k=1}^{n} u_{ik}^{m}}, \quad u_{ik} = \frac{1}{\sum_{j=1}^{c} \left(\frac{d_{ik}}{d_{jk}} \right)^{\frac{2}{(m-1)}}} \qquad 5.3.3$$

Several clustering techniques can be used for solving U and V along with several iterations. However, the most popular among these techniques is the fuzzy c-means and Gustafson-Kessel clustering methods. When RFM variables in Table 5.8 are used for the mobile money customer clustering along two different channels, the clustering space consists of the product-space of RFM features due to the small dimensionality of the feature space of the RFM.

Table 5.8. The research approach for target selection model and revenue optimization opportunity

Optimization Areas	**Description**
Recency	When did the customer make his last mobile money transaction?
Frequency	How often does the customer make a mobile money transaction within a defined cycle?
Monetary	What is the value of the transaction the customer makes on his mobile wallet within a defined cycle?

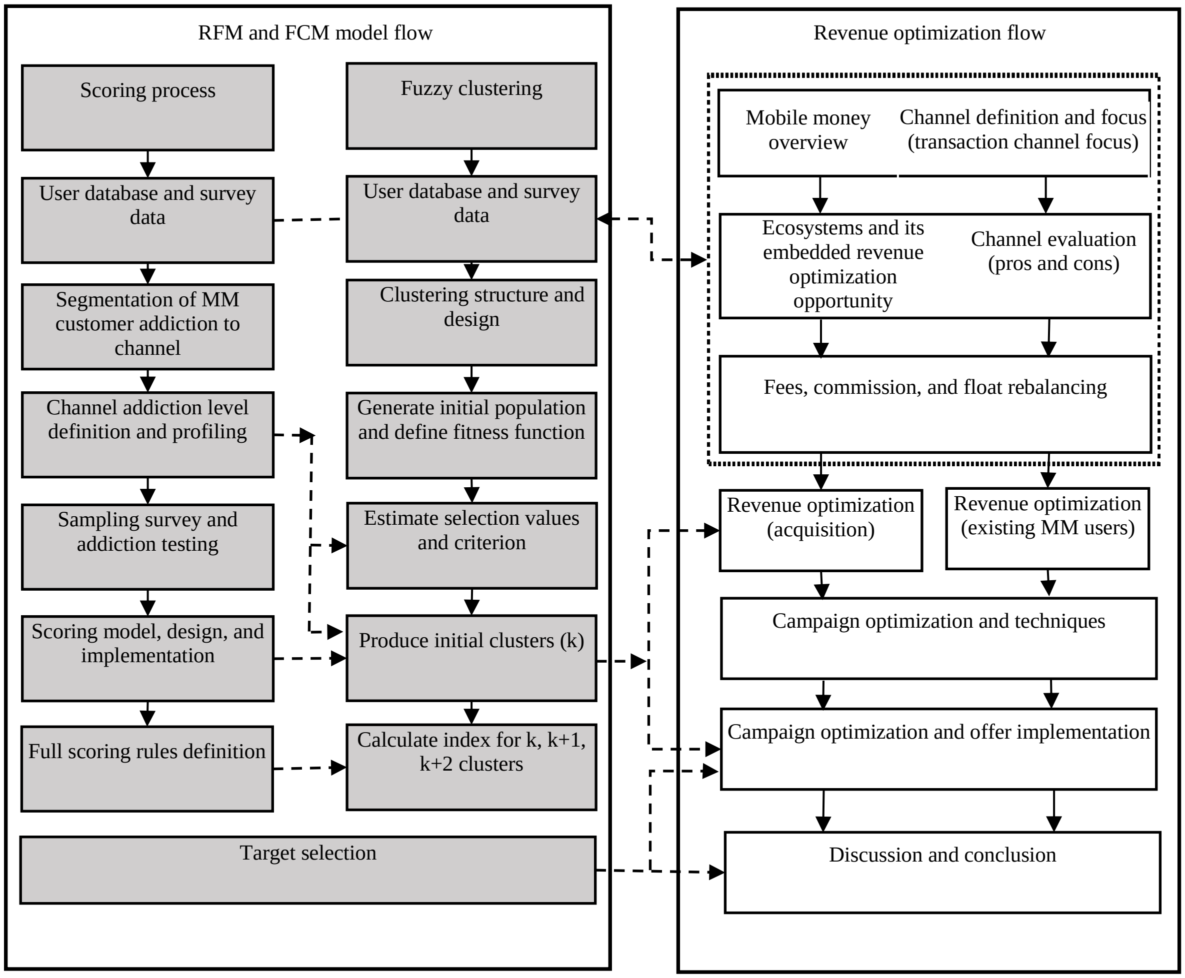

FIGURE 5.1 Target selection model – Fuzzy c-means and RFM

This study's originality resides in the selection model of how mobile operators can optimize their revenue from mobile money services. The model links both the analytics that will help target and profile the right customers to the offering and programs that can influence customer behavior to generate increment revenue through mobile money transactions. For the target selection, fuzzy c-means is combined with the RFM algorithm to model customer behavior for appropriate treatment. Details of offering and mapping and one-to-one marketing approach through the right transaction channel and selection output are also discussed.

The normalized data includes variables such as the tenure of the customer on the network, the time the customer became an active mobile money user and, the time of most recent transaction of mobile money service. The frequency of transactions and value of transactions are also covered. For the fuzzy clustering, the GA-Fuzzy clustering application was used. The customers are divided into five clusters, as shown in Table 5.8. The clusters are *“very good user,” “good user,” “medium user,” “low user,”* and *“very low user.”* Each of the clusters has characteristics that are defined through the RFM model in Table 5.9.

Table 5.9. Clusters definition and characteristics obtained from the combined algorithm

Clusters	**Description**
Very Good User	Very low recency (current users); high frequency and very high transaction value
Good User	Low recency (current users), high frequency and high transaction value
Medium User	Medium recency (starts showing dormancy trait), medium frequency and medium transaction value
Low User	High recency (showing high dormancy trait), low frequency and low transaction value
Very Low User	Very high recency (dormancy is very high), very low frequency with a very low transaction value

Table 5.10. Recency distribution

	Recency – RFM + FCM								
Clusters	P10	P20	P30	P40	P50	P60	P70	P80	P90
Very Good User	1	2	3	3	4	5	7	8	10
Good User	12	15	18	21	24	28	28	29	33
Medium User	32	33	35	37	37	38	38	39	40
Low User	42	43	43	45	45	46	47	47	48
Very Low User	50	52	52	53	54	55	55	56	57

Table 5.11. Frequency distribution

	Frequency – RFM + FCM								
Clusters	P10	P20	P30	P40	P50	P60	P70	P80	P90
Very Good User	2	4	7	11	20	22	34	40	50
Good User	1	1	2	3	7	9	13	19	21
Medium User	1	1	1	1	1	1	2	3	5
Low User	1	1	1	1	1	1	1	2	2
Very Low User	1	1	1	1	1	1	1	1	1

Table 5.12. Monetary value distribution

	Monetary – RFM + FCM								
Clusters	P10	P20	P30	P40	P50	P60	P70	P80	P90
Very Good User	1,250	3,455	5,456	7,546	9,998	13,678	18,540	35,006	48760
Good User	300	350	1,705	3,555	8,457	11,560	17,650	19,560	30,557
Medium User	300	350	350	350	350	350	385	5,465	10,500
Low User	300	300	300	300	300	300	300	750	5,500
Very Low User	350	350	350	350	350	350	350	350	3,568

The cluster center for each of the criteria was calculated. Percentile distribution of transaction activity delay was also calculated across clusters for the channel of the transaction, as shown in Tables 5.10, 5.10, and 5.12. Delay represents the number of days of inactivity between two consecutive days of transaction activity. About 70% of the medium users are trial users with only one day of activity. About 80% of low users are also trial users. These two clusters qualify for optimization campaigns that will give other mobile services as a bonus or incentive for any mobile money transaction the customer performs. The threshold of the value of the transaction can be a campaign reward condition for the customer to get the instant mobile service reward, which can be data volume or other value-added services with a defined validity.

Table 5.13 Summary of main findings (Article 3)

Main Findings	
Clustering, segmentation, and target selection	1. Fuzzy c-means clustering and RFM algorithm are efficient for marketing campaign target selection 2. Fuzzy c-means clusters the customer base in conjunction with the RFM algorithm – this normalizes the prepaid nature of the mobile market in the emerging markets 3. Clusters along their associated characteristics can be matched with appropriate campaigns and programs suitable for revenue optimization at every stage 4. The analytical model output enables appropriate cross-selling and up-selling ability that can optimize the revenue from the mobile money users
Mobile money revenue optimization	5. *Other mobile products and services:* Other existing services of mobile service providers serve as appropriate incentives for driving the adoption and usage across the mobile money customer lifecycle 6. *Dormancy and inactivity management*: There must be standard customer base management programs for dormant and inactive segments of the mobile money customers
Campaign tools and capabilities	*7.* An integrated customer base program that can optimize the base potential requires campaign tools and systems which must be invested upon by the service providers *8.* The integration among the mobile money systems and the billing systems must be perfect for enabling a seamless, rewarding process in real-time with other mobile services immediately after a campaign-induced mobile transaction is performed.

5.4 Case 4: Fuzzy Expert Pricing Systems and Optimization Techniques in Marketing Science

There is a gap between general model predictions and market reality, which Fuzzy logic has the capability of bridging for the marketers. Fuzzy logic achieves this by providing marketers with the opportunity of combining robust human experts in the form of linguistic rules to formulate a knowledge-base. These rules are systematically developed into a marketing tool that provides intelligent pricing decision support for marketers in a dynamic and competitive environment.

This case study reviews three expert pricing systems modeled to help consumer firms in the pricing decision-making process. These are Price-Strat, FuzzyPrice, and exPrice expert pricing tools. The development and effectiveness of these pricing systems were examined, and their attributes in pricing products and services. Pricing has always been one of the primary issues of every business. Setting the right price has an immediate effect on the company's revenue and profitability. For pricing decision-making, numerous parameters must be taken into consideration. First, the company must decide the strategic aims of its pricing moves. These can be due to the need for survival under intense competition or scarce resources. Also, the need to maximize profit and sales growth can account for a price change. Having the right pricing tools and models helps marketers to respond to the needs of the customers, competition and enhance consumer customer experience toward an acceptable level of profitability.

This study reveals that these pricing expert systems (Price-Strat, FuzzyPrice, and exPrice) leverage both descriptive and inference statistics in building the fundamentals of their fuzzy model with details of relevant components of the pricing tools. Price-Strat stands out as one of the unique pricing expert systems. It is a hybrid expert system that leverages historical market data and commercial managers' experiences to arrive at the most appropriate pricing solution for different industries, such as banking, aviation, and telecommunication. FuzzyPrice pricing expert system combines fuzzy logic and fuzzy reasoning methods to arrive at the appropriate price combination across the product portfolio. The exPrice expert system, on the other hand, is a product and pricing expert system in which four variables were used during the development. The variables are the elasticity of demand in relation to price, market structure, level of business activities, and business goals.

Table 5.14 Summary of main findings (Article 4)

Main Findings			
Attributes	**Price-Strat**	**Fuzzy Price**	**exPrice**
System Type	Hybrid Expert System	Hybrid Expert System	Expert System
Operations	“If-then” rules and price scenarios responses	“What-If” scenarios.”	“If-then” production rules
Pricing Application	Multiple industries	Multiple industries	Multiple industries
Unique feature	Easy adaption of variants to different consumer industries	Scenario-oriented along with sensitivity and profit margin analysis	Flexibility and modularity
System Improvements	Large scope for improving profitability for all Price-Strat family of tools	The weighting of each competitor’s actions and extending variable to include variable such as advertisement	Presented as a system open for new production rules extension without modifying the existing ones

5.5 Case 5: A Fuzzy Logic Expert System for Pricing Digital Services: Case of Price Adjustment for Mobile Service Provider

The insights that were revealed during the study of Fuzzy expert system pricing systems in Case study 4 and how it can help consumer firms solve challenging pricing issues motivated the study for this case study. In driving a large consumer firm's business performance and revenue optimization, commercial managers must get their pricing right.

The increase in awareness on the part of the consumers and the emergence of smart shoppers have made the pricing of products and services more complex and critical within the marketing functions. Also, in a competitive consumer market, strategic pricing can play an essential role in the business performance trajectory if appropriate tools are available for ensuring the right price points.

In a competitive market where a pricing decision, if it goes wrong, can be catastrophic for a brand due to lack of evidence on how the market would react to the price change, experts can leverage fuzzy linguistic terms to navigate the problem. The ability of fuzzy logic for obtaining the associated ambiguity that characterized pricing decisions with the application of imprecise data motivates fuzzy logic in this study of price adjustment.

This study solves a pricing adjustment problem in a mobile telecommunication industry that is characterized by many challenges. First, the price war among the competitions in the mobile market drives traffic growth without a commensurable increase in revenue. As a result, there is enormous pressure on network capital expenditure (CAPEX) investment, quality of experience, and customer experience.

In this case study, a Fuzzy expert knowledge-based pricing system is developed to solve network traffic, price war, and business revenue challenges in the competitive mobile market. The core of this Fuzzy logic model lies in its ability to recommend digital and data services related price points within a competitive and price war mobile environment. The proposed pricing system is experimentally evaluated through a pilot on a few segments of a mobile service provider's customer base in an emerging market and later scaled-up to a broader base. Upon implementation, data service revenue increased, and overall gross margin increased with a reduction in data traffic, resulting in better throughput and network quality. This resulted in better customer experience with improved net promoter score (NPS).

The objective is to solve a mobile service provider's problem in an emerging market, which is predominantly a prepaid market with an upward price adjustment of the firm’s data services portfolio. The market was characterized by a fierce price war of data services. The situation got worse for all the players when the market leader joined the bandwagon and reduced data price significantly, leading to tremendous value erosion across the market. As a result, the mobile service provider in question became the most expensive operator in the market. At the start of the price war, the firm retained its pricing by leveraging its network quality and perception of customers on the firm's better network quality compared to competitions. Shortly after the market leader joined the price war by reducing prices of data-related services, the firm needed to protect its customer base as it was clear that in no time, value and volume share would shift to the market leader due to the nature of the market which is predominantly a prepaid market where customers are carrying multiple SIM cards. Therefore, the firm responded by also reducing its prices of the data services portfolio. As a result of the response of the firm to the price war, the following happened:

a) The firm network capacity became congested, especially in vital geographical locations, critical to the business revenue. The traffic grew significantly within a very short time.
b) Customer experience was impacted due to degraded network quality.
c) Gross margin was negatively impacted.

This study proposes and implements a new Fuzzy knowledge-based pricing expert system for mobile telecommunication services named Fuzzy Digital Price System (FDPS). Fuzzy Digital Price System provides a solution to the four major problems associated with strategic pricing in the mobile market. These are demand estimation, cost estimation, competitive analysis, and final price point recommendation. FDPS leverages a model that depends on three phases of construction, as shown in (Figure. 5.2, 5.3, and 5.4). In phase 1, the pricing and commercial experts give input into the system about their knowledge of the market, competitions, and their historical expertise about price changes outcomes.

They do this through a combination of "what-if scenarios." They combine this with the rich customer data that are readily available about customer behavior within the service provider enterprise and market research data to make a rich market knowledge base.

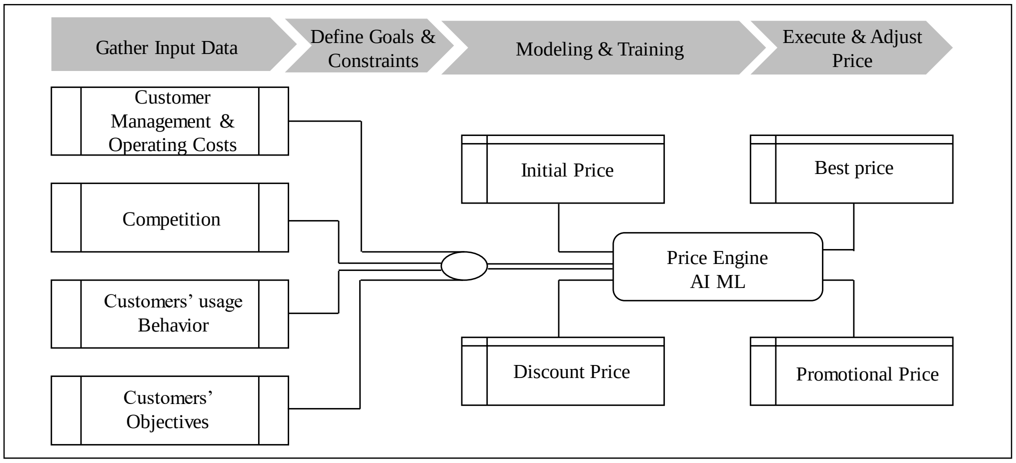

FIGURE 5.2 Price engine framework

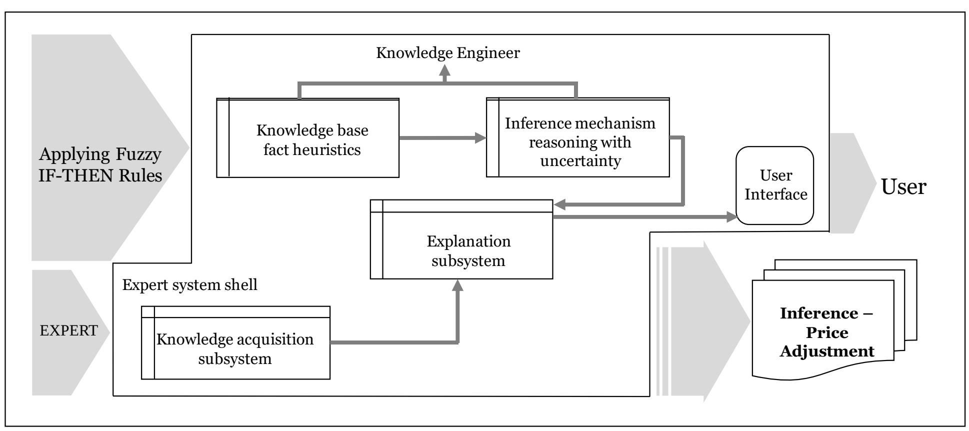

FIGURE 5.3 Expert system tools and associated components for price adjustment

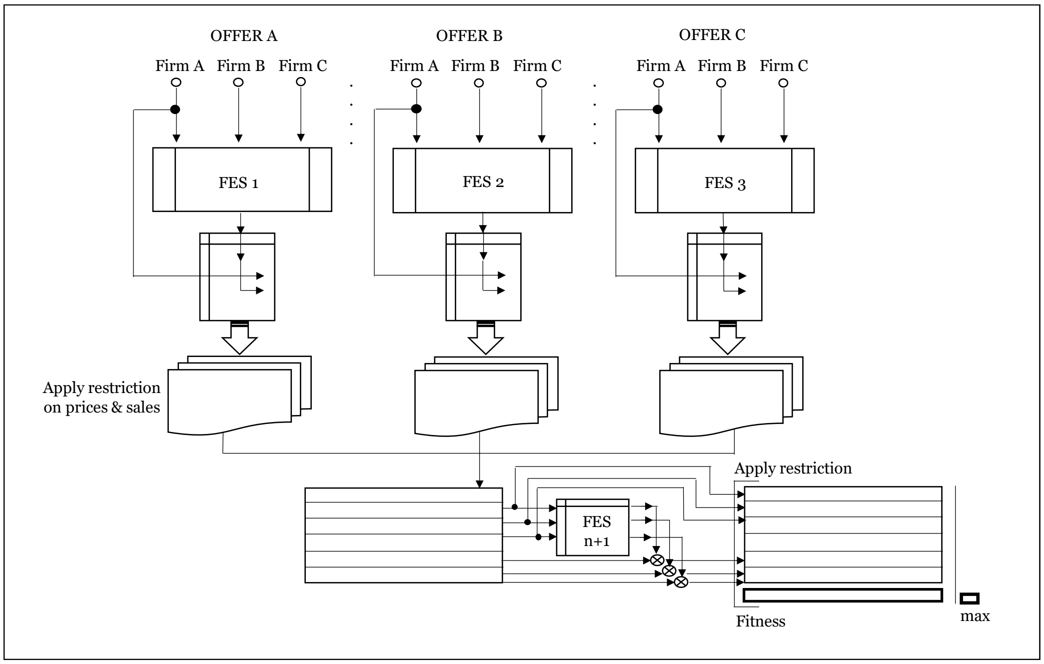

FIGURE 5.4 System architecture

Price adjustment case - problem statement

The objective is to solve the problem confronting a mobile service provider in an emerging market, which is predominantly a prepaid market with an upward price adjustment of the firm's data services portfolio. The market was characterized by a severe price war of data services. The situation got worse for all the players when the market leader joined the bandwagon and reduced data price significantly, leading to tremendous value erosion across the market. As a result, the mobile service provider in question became the most expensive operator in the market. At the start of the price war, the firm retained its pricing by leveraging on its network quality and perception of customers on the firm's better network quality as compared to competitions.

Shortly after the market leader joined the price war by reducing prices of data-related services, the firm needed to protect its customer base as it was clear that in no time, value and volume share would shift to the market leader due to the nature of the market which is predominantly a prepaid market where customers are carrying multiple SIM cards. Therefore, the firm responded by also reducing its prices of the data services portfolio. As a result of the response of the firm to the price war, the following happened:

1) The firm network capacity became congested, especially in vital geographical locations that are critical to the business revenue. The traffic grew significantly within a very short time.
2) Customer experience was impacted due to degraded network quality.
3) Gross margin was negatively impacted.

Due to the above changes in the business metrics, the firm was left with only two options. The first option was to invest in the network expansion to improve the quality of services. The second option was to adjust the price upward to allow traffic growth to align with the business revenue. The later was a preferred option for the firm as the first option will involve so much capital expenditure which the firm was not ready to invest in the network at that time.

Price adjustment model objectives

The objectives are to set the price of all data service offerings within the portfolio with the aim to:

1) Protect the revenue of the existing data customers on the customer base.
2) Reduce data traffic to address the customer experience due to the data network congestion experience.
3) Increase the overall revenue of the data portfolio.

Fuzzy pricing model development

This study proposes and implements a new Fuzzy knowledge-based pricing expert system for mobile telecommunication services named Fuzzy Digital Price System (FDPS). Fuzzy Digital Price System provides a solution to the four major problems that are associated with strategic pricing in the mobile market. These are demand estimation, cost estimation, competitive analysis, and final price point recommendation (Tzafesta, 1994; Tzafestas, Raptis and Moschos, 1994).

The available data across the enterprise of a mobile service provider, coupled with the data from the market research and the years of experience of different functions in the commercial roles of the mobile operators, would serve as input to the system. The Fuzzy Digital Price System (FDPS) organizes all this information accordingly to create and form the "knowledge-based."

In a competitive environment, the price point that maximizes profitability and aligns with strategic objectives are generated from the knowledge base through the underlying mathematical tools. This system uses fuzzy logic and fuzzy reasoning methodology in the computation of appropriate combinations of the price points for telecommunication digital services and products. The pricing output is expected to align with the overall business strategy and the marketing strategy of the firm while considering all the associated strategic constraints. While the system is somewhat restricted to short or midterm pricing as a result of the pricing volatility in the telecommunication industry, the inference is leveraging on the price changes in the market with projected competition reaction to an adjustment in price (Hesami, Nosratabadi and Fazlollahtabar, 2013).

FDPS constructs

FDPS leverages on a model that depends on three phases of construction, as shown in FIGEURE. 5.2, 5.3 and 5.4 (Tzafestas, Raptis and Moschos, 1994; Ruiz-Mezcua, Garcia-Crespo, Lopez-Cuadrado, and Gonzalez-Carrascoa, 2011). In phase 1, the pricing and commercial experts give input into the system about their knowledge of the market, competitions, and their historical expertise about outcomes of price changes. They do this through a combination of *"what-if scenarios"*. They combine this with the rich customer data that are readily available about customer behavior within the service provider enterprise, along with market research data to make the rich market knowledge base.

A rigorous interrogation of the knowledge base by the inference mechanism takes place in the second phase for the determination of profit margin maximization discussion around different sensitivity parameters. As an output at this stage, projected sales and profit margin on the products are provided. In the last and the third phase, the extracts which are new data as a result of the system profit maximization decisions are used as back-check, and the model trains itself to learn about the environment to enrich its knowledge base to improve future decision making.

What-if scenarios

A key feature of FDPS is that all its workings follow *"what-if"* scenarios. The scenarios are the brain of the entire inference procedure of FDPS. Different scenarios also compute price adjustment by competition, adoption, and revenue from various products and services. The fuzzy what-if scenarios along the fuzzy rules are used in the FDPS system (Flores, Mombello, Jardini, Rattá and Corvo, 2011).

FDPS considers the mobile operator in this case (*Firm A*) with two competitions offering the same digital products. The product offerings, in this case, are data services that are provided to customers as data bundles of different volumes in megabytes and gigabytes (MB/GB) with divergent validity or expiry date at various price points as shown in Table 5.15.

Table 5.15. Competitive landscape of data services in the market.

Validity	Data Price	Volume (Megabytes)			
Days	Naira (N)	FIRM A	FIRM B [a]	FIRM C	Comments
24 Hours	100	50	30	30	
7 days	200	200 [b]	200	200 [c]	
30 Days	500	500	750	750	
30 Days	1,000	1,000	1,500	1,500	
30 Days	1,200	1,500	-	-	Only Firm A has this price point
30 Days	2,000	2,000	3,500	3,500	
30 Days	2,500	3,500	-	5,000	Firm B does not compete on this price point
30 Days	3,500	5,000	-	7,000	Firm B does not compete on this price point
30 Days	5,000	-	10,000	10,000	Firm A does not have this price point
30 Days	8,000	11,500	-	16,000	Firm B does not compete on this price point
30 Days	10,000	15,000	22,000	22,000	

a Introduces a 500% deal on selected price plans.
b At this price point, Firm A has a night plan of 1GB (11 pm – 5 am) with 7-day validity.
c Firm C has an acquisition offer at this price point. One-off offer for the weekend

Firm A is our case firm, and Firm B and Firm C are the other competitions within the market. Suppose a price adjustment is carried out by Firm B and C on their data portfolio. A fuzzy "what if scenario" for the problem that is also a fuzzy rule may be represented as follows:

IF dPrice A is *PNegativeHigh*

AND *dPriceB* is *PNegativeLow*

AND *dAPrice* is *PZero*

THEN *dASales* is *SNegativeMedium*

Where *dPriceA* and *dPriceB* are fuzzy linguistic variables representing adjustment in the prices of the data services of competitor *A* and competitor *B*, respectively. The *dAprice* and *dASales* are fuzzy linguistic variables representing the adjustment in price and products sales of the *firm A*. *PNegativeHigh*, *PNegativeLow*, *PZero* and *SNegativeMedium* are fuzzy sets representing a high decrease in price point, a low decrease in price point and almost no change in price and high decrease in sales respectively (Tzafestas, Raptis and Moschos, 1994).

Human experts formulate the "what-if scenarios," and following the business managers expert's intuition, appropriate fuzzy sets are defined for the antecedents and the descendent rule. The systems take several scenarios of this form and store. In the case of data services that are bundled products for telecommunication operators, the "intra-portfolio side effects are simple to manage. When a typical network provider makes a price move in the data services portfolio, the move cuts across all products within the data services portfolio. The daily, weekly, monthly bundles will be adjusted accordingly. This is because of the nature of the products. For some, *"intra-portfolio side effects"* may need to be accommodated and accounted for. This effect is the impact that the adjustment of the price of some offerings within the company portfolio has on the sales of other offerings and products within the portfolio (Hesami, Nosratabadi and Fazlollahtabar, 2013).

However, due to the complexity and sensitivity of price adjustment, human decision making as a role will remain essential. Experienced commercial managers still need to make the final decision among several alternatives. In this FDPS, this point is taken into consideration as several price points are obtained with final decisions in the hands of human experts.

FDPS architecture

Illustration of FDPS architecture is given in FIGURE 5.4. FDPS is a combination of several fuzzy experts working in parallel with simple blocks with underlying computations (Li, Liu and Li, 2011). Price adjustment by competitions serves as input into the system along with every product of the firms. The impact of the price adjustment is predicted by all the products (N) in the portfolio, along with a layer of n fuzzy expert systems that are independent. Along the "what-if scenarios" that have been built, the effect of the price adjustment on the revenue of the individual product is captured. The market characteristics are obtained by the rules contained in each of the expert systems. Reactions are fed into the fuzzy expert system following any price move by competition. At this stage, several outputs are considered based on acceptance or rejection following their alignment with the overall strategic objective of the organization. In the case of the mobile telecommunication industry, the network capacity, regulatory, and other factors would be considered at this stage.

A final selection is made from the final table following the possible level of price adjustments with the view of aligning with the company's overall strategic aims such as profit, sales, and other network metrics such as capacity.

System and Structure

The system inputs are the various changes in data pricing across all players in the market at each product level. These contain all product price points, validity, and data volume at every level. The expected output that is desired from the system is a set of values for all data offerings that will address the three objectives above.

Similar problems were treated by (Singh and Bennavail, 1993; Tzafestas, Raptis and Moschos, 1994; Bijakšić, Markić and Bevanda, 2019), in their systems, which they refer to as PRICESTRAT, FUZZYPRICE, and exPrice, respectively. While the industries they considered were different from the mobile telecommunication industry, the modeling processes are similar. Also, the strategic aim of price adjustment alters the approach and could not enable a side by side comparison. Moreover, the market portfolio was segmented by the validity of data offers into daily, weekly and monthly bundles under each product segment; every competition has a list of offerings – refer to Table 5.15.

The price increase is a very sensitive exercise, especially in a fiercely competitive market that is prepaid predominant, where the cost of switching is meager. About the sales of competition, no assumption was made. The strategic constraints are the objectives of the price adjustment, as mentioned in the above section.

On the fuzzy expert systems, three systems were developed and designed with 70 rules each. Price changes in the competition products are the inputs of these systems. Outputs are the changes in product uptake and revenue of firm A. A fourth expert system was designed. Since the price adjustment will shift the uptake of daily, weekly, and monthly takers, the forth fuzzy expert system is used to compensate for this intra–portfolio effects of the price adjustment of the different models. The forth fuzzy expert system contains 92 rules. All rules are from the subject expert following their experience and reasoning.

Several scenarios are created following the competition price changes along with the data product segments, which are daily, weekly, and monthly. A market research was conducted to understand customer preference for the price adjustment direction. Considering the situation of the firm *A* at this time, there are three clear approaches to go about increasing the price of the data services. All these approaches must address the strategic constraints of revenue increase and protection, network congestion management, and customer experience. These approaches are:

1) Reduction of volume in Megabyte (MB) and reverting to the old price.
2) Retaining the data volume but increasing the price per Megabyte (MB).
3) Retaining the data price and volume but offloading portion of the data volume to the off-peak period when the network is relatively underutilized.

These three scenarios are loaded into the three fuzzy expert systems that highlight revenue projection for each product along with the fourth system that compensates for the cannibalization of the products within the three other segments – the intra-portfolio effects. The system is insensitive to the absolute figure as a result of inputs and outputs that are percentages of changes. A single array is mapped out with the input-output pairs of the results. Strategic constraints are considered, and the restrictions are also applied while the exclusion of the combination is provided. The linear programming procedure is used for the evaluation of the final combination, and those with maximum fitness are selected following the desired criterion.

Results

In managing the constraints and the management objectives, the customer base is segmented into existing data bundle customers. These are customers that are currently buying data services, and we represent them by existing customers *(EC)*. The second segment is the prospective data bundle or new customers (*NC*). These are customers that are not buying data services or the newly acquired customers. From these two broad segments, we have other segments, which are the price-sensitive customers *(PS)* and the non-price sensitive *(NPS)* customers. Price and non-price sensitive customers are known due to their past responses to promotional campaigns on the network. The off-loading of the recent incremental data flux on all certain data products to off-peak is one of the outputs of the simulation. This is positioned to reduce over-utilization during the off-peak period and potentially increase data revenue. However, this was well managed such that the customer experience of an existing customer is not affected. All these segments are fed into different models. The different price adjustment approach that fits different segments are selected by the business managers and are implemented along with the various marketing mix strategy, as shown in FIGURE 5.5 below.

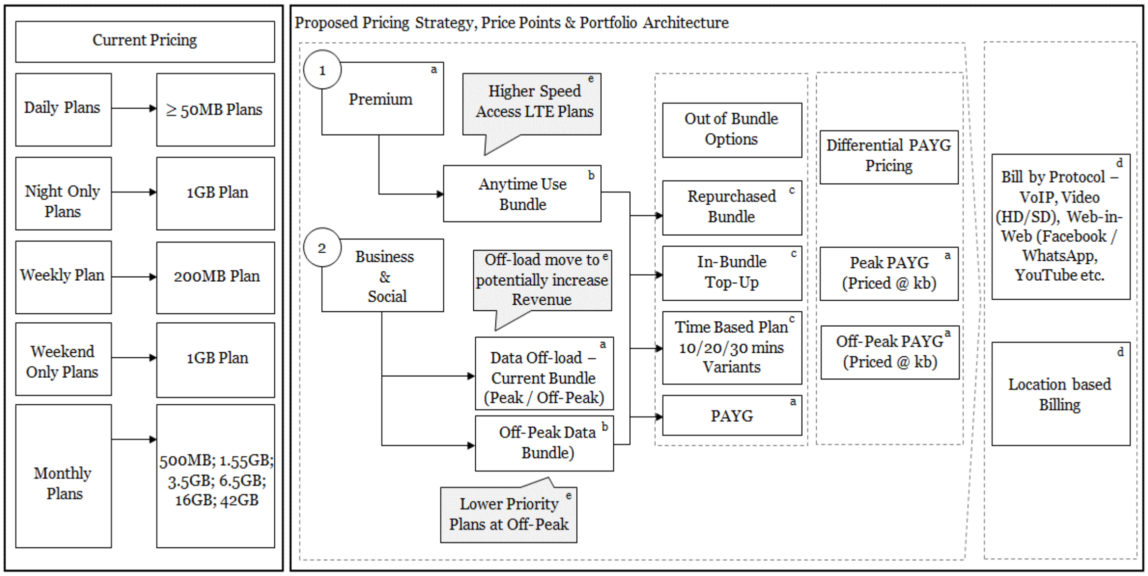

FIGURE. 5.5 The architectural representation of product portfolio – current and FDPS output

a Potential revenue increase
b Existing price plans
c New billing opportunity
d Innovation
e Proposed strategy

For the customers that are new to data services or non-data customers (*NC*), appropriate price adjustment, and price points for each product segment are suggested. Also, for existing data services, customers, price adjustment approach, and price points at the product level are presented to decision-makers.

With a well-thought-through approach using the proposed Fuzzy Data Price System (FDPS), different price points and strategies were suggested for all products and services. The business manager selection achieved the desired business objectives of the firm *A*. Data services revenue increased instantly by 5% month on month with a 1.3%-point increase in gross margin. The network witnessed a 14% reduction in data traffic, resulting in better throughput and network quality. This resulted in a better customer experience, which impacted the net promoter score (NPS) of the firm in the next quarter.

Other marketing mix, such as channels of engagement, are well managed during the period of the implementation. Existing codes for purchases are maintained for existing customers. New codes with different price points were created for new customers. There was no above the line (ATL) such as TV and Radio or social media campaign for the data price adjustment – this was to manage customer perception of not being expensive. All communication was below the line in a one-to-one marketing approach. All online, retail, and billboards were updated accordingly with commercially available revamped data plans. The firm used an aggressive BTL campaign to drive uptake and performance.

Table 5.16 Summary of main findings (Article 5)

Main Findings	
Fuzzy Expert Systems	1. Fuzzy knowledge-based pricing expert system can provide multiple solutions to strategic pricing associated problems in a large consumer industry setting which are: a) Demand estimation problem; b) Cost estimation problem; c) Competitive analysis d) Final price point recommendation 2. A fuzzy expert system takes and organizes data across the enterprise – data such as market research information, years of experience of domain experts, and competition data as input to create and form the knowledge-base 3. Scenarios are the brain of the expert system's entire inference procedure – (Fuzzy Digital Pricing System (FDPS)). 4. Different scenarios can compute price adjustment by competition, adoption, and revenue from various products and services through the “what-if” and fuzzy rules.
Price Adjustment of Digital Services	5. In a competitive environment, the price point that maximizes profitability and aligns with strategic objectives can be generated from the knowledge-base of the fuzzy expert system

	6. Clear objectives and constraints must be clear for the successful implementation of an expert system for price adjustment in a consumer market with fierce competition 7. Further improvements in the expert system that will lead to more accurate recommended price points can be achieved as long as the input data quality improves.

5.6 Case 6: Battle for Digital Customer Ownership Between the Telco and Over-the-top (OTT) Players: Emerging Markets Perspective

This case study is a shift from fuzzy Analytics and application into the exploration of advanced analytics to proffer solutions to some imminent challenges that are confronting the digital consumers, the mobile telecommunication industry (Telco), the government, and all Telco industry stakeholders due to the digital evolution and explosion in this era. In many domains, the global Over-the-Top (OTT) players have established scales across their business models, thereby putting enormous pressure on the Telcos (Stone, 2015).

OTT players cut across messaging, voice, digital media, and cloud services. WhatsApp and WeChat are examples of key players in the instant messaging segment. In the voice segment, Skype, WhatsApp, and Viber are known brands. However, within the digital media space, Facebook and YouTube are key players, while Google and OneDrive are examples of OTT in the cloud segment. Also, the live streaming segment is becoming very significant with rapid potential within OTT services.

This case study assesses the potential risk that OTT players pose to the telecommunication industry's survival by exploring the OTT activities within the Telco ecosystem. In exploring this battle between the Telcos and OTT players within the telecommunication space, this study also examines digital mobile customers' activities on their connected mobile devices. In doing so, the entire digital protocol services of a cellular provider in an emerging mobile market are explored to quantify and analyze mobile customers' digital behavior to OTT applications.

In this study, the battle for digital customer ownership between the Telcos and OTT players highlights important emerging issues in the digital world. The case provides an OTT management framework overview. It proceeds to discuss a strategic framework and way forward for Telcos and industry on how to manage the threats and excesses of the OTT players' activities within a telecommunication network. The study uses an experiment through a deep packet inspection (DPI) analytics and the service control gateway (SCG) of an emerging mobile operator in Nigeria. The study quantifies the significance of the threat and the penetration of the OTT providers within the Telco landscape. The results show the OTT services on the mobile network service provider's network and reveal the OTT services' consumption pattern. It also revealed the contribution of the OTT to key network metrics of the Telcos.

In addressing the OTT threats while protecting the Telco's stakeholder value, the study proposes the OTT threat management framework. The strategic framework is in two parts – offensive and defensive - see FIGURE 5.5. Offensive strategy for the management of OTT activities call for Telco to put on their innovative caps. For Telcos to monetize OTT activities and address the OTT value erosion tendencies, innovation is required on the part of the telecommunication service providers. Telco must explore innovation in the delivery of their products and services to either leverage OTT services or compete with OTT providers.

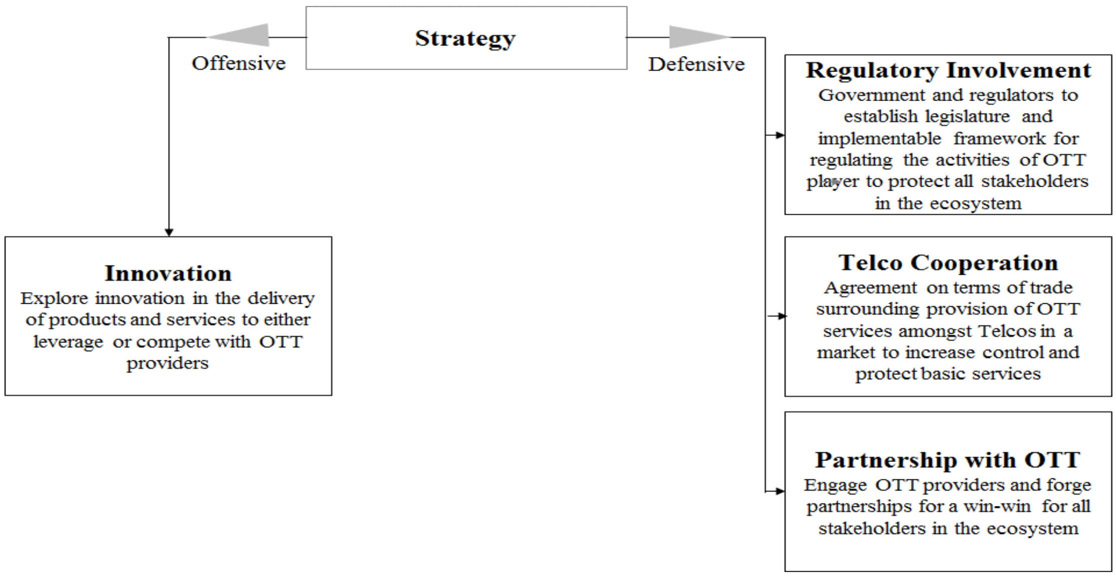

FIGURE 5.6 OTT threat management framework overview

To demonstrate the significance of the OTT players within the Telco and digital landscape, and how vital the OTT content and services are to the mobile consumers, this study explores the database of a mobile service provider in Nigeria. This service control gateway (SCG) experiment through a deep packet inspection (DPI) analytics determine the following:

1) Quantify the OTT providers that exist on a typical telecommunication network and their activities by using a mobile network with millions of customer base as a case.
2) Access the top OTT players' activities across the Telco's primary services – data and voice services.
3) Understand the consumer - OTT behavior and major protocols such as streaming, web browsing, social networks, and others.

As digital traffic continues to grow, Telco will continue to be under immense pressure to increase capacity to meet the customer data appetite, demand, and growth in customer experience expectation. How Telco managers can monetize the threats posed by the global OTT players and deliver an acceptable level of services to their digital customers is one of the questions this study tries to answer. OTT services are here to stay, and Telco should expect to see more of them latching and gaining traffic share on the network as digital technology and innovation continue to rise. However, the growth of these OTT services presents significant opportunities to the Telco.

While some of the recommendations in this study would require the Telcos' regulatory buy-in, there are quick-win scenarios for the Telcos. The main findings of this study are summarized in (Table 5.7) below.

Table 5.17 Summary of main findings (Article 6)

Main Findings	
OTT threats management framework	8. **Defensive strategy** a) **Regulatory involvement:** Government and regulators to establish a legislature and implementable framework for regulating the activities of OTT players to protect all stakeholders in the ecosystem. b) **Telco cooperation:** Agreement on terms of trade surrounding the provision of OTT services amongst Telcos in a market to increase control and protect basic services c) **Partnership with OTT:** Engage OTT providers and forge partnerships for a win-win for all stakeholders in the ecosystem 9. **Offensive strategy** **a)** **Innovation:** Explore innovation in the delivery of products and services to either leverage or compete with OTT providers
Digital mobile customers & OTT relationship	10. Activities of the OTT services on a typical mobile network are enormous. The mobile operator cannot ignore them – they must be monetized for Telcos not to be turned into a connectivity pipe of commoditized infrastructure. 11. Voice over IP (VoIP) contributes 7% of a typical mobile operator's total voice traffic in Nigeria. Over 121 unique OTT players were seen driving traffic within 14 days of deep packet inspection analytics. WhatsApp accounted for 62.8% to the VoIP traffic, while Skype and True Caller application followed by 13.8% and 6.9% of the total VoIP traffic.

Telco Industry stakeholders	12. Regulators need to study the digital ecosystem and develop a robust and implementable framework that will enable OTT players to remit the necessary taxes and levies on a digital advertisement within their regulatory, geographical boundaries. 13. Public policy needs to respond to the OTT threats to protect the stakeholders' investments.

The Telco pressure for infrastructure expansion because of increased traffic should be monetized and not allow only global OTT players to benefit from this capital expenditure on network expansion. As digital technology and innovation continue to evolve, new services will be emerging, which will continue to disrupt the Telco business models. To survive this challenge, Telcos cannot be stagnant from the point of innovation and structure.

5.7 Case 7: Fuzzy Analytics Application in Digital and Consumer Marketing: A Literature Review

This study is an extract of the summary of the literature review of this dissertation. By drawing on a literature review, this paper explores Fuzzy Analytics (FA) within the marketing field. This study presents a clear and definitional framework with distinctive characteristics of FA's useful methods in the marketing field. Through a systematic review of the literature, a final portfolio of 376 scholarly articles. FIGURE 5.7 shows the study selection process. Also, Table 5.17 show categorization along with five identified application areas in marketing science: (1) fuzzy modeling, (2) web analytics, (3) performance analysis, (4) fuzzy clustering and segmentation, and (5) fuzzy market analysis. This exploration provides more in-depth insights into the cross-cutting FA approach and applications in digital and consumer marketing, which generates a forward-looking future research challenges and opportunities in theory and practice.

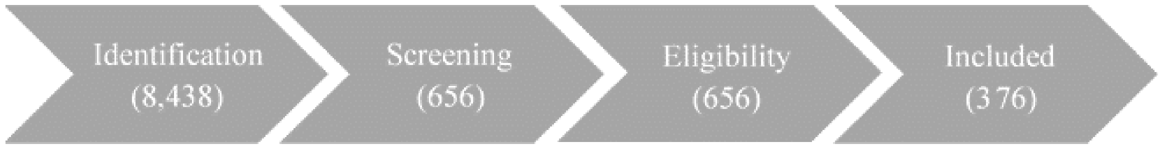

FIGURE 5.7 Flow diagram of the study selection process

Table 5.18 Categorization and classification of the main topic into streams of fuzzy application (FA) in marketing

Categorization	Article Classification	Categorization (%)
Fuzzy Modeling	1. Fuzzy Application in Social Networks 3. Fuzzy Application in Expert Systems 4. Fuzzy Application in Recommendation Engine 5. Fuzzy Optimization and Multi-Criteria Decision Making (MCDM)	42%
Web Analytics	1. Fuzzy Application in Web Analytics 2. Fuzzy Application in Online Marketing	17%
Performance Analysis	1. Fuzzy Application in Performance Measurement 2. Fuzzy Application in Marketing Programs	2%
Fuzzy Clustering	1. Fuzzy Application in Customer Data Mining 2. Fuzzy Segmentation and Clustering	35%
Fuzzy Market Analysis	1. Fuzzy application in Scoring Methods 2. Fuzzy Application in Portfolio Marketing Techniques	4%

The main findings of this study are summarized in Table 5.18. The result reveals an output of an extensive systematic literature review detailed in Chapter 2 of this dissertation.

Table 5.19 Summary of main findings (Article 7) - refer to Table 2.1

Main Findings	
Fuzzy Analytics (FA) classification	1. Extensive systematic literature reveals of Fuzzy Analytics application in digital consumer space reveals five identified application areas (1) fuzzy modeling, (2) web analytics, (3) performance analysis, (4) fuzzy clustering, and segmentation, and (5) fuzzy market analysis.
Fuzzy Analytics (FA) in marketing science	2. The use of fuzzy analytics (FA) in data mining and clustering within the marketing field aligns with the growing consumer data and the big data evolution. 3. Issues associated with digital marketing include qualitative criteria that can be evaluated by using linguistic terms and some quantitative imprecise and vague data. 4. The usage and application of fuzzy analytics (FA) in marketing is old but evolved substantially over the last few years. 5. In the digital marketing space, FA has been widely applied around Web Analytics (WA). 6. The use of FA in marketing science started to evolve from 2003 7. Many research applications in marketing have emerged using FA as the modeling techniques. The application around fuzzy modeling, which consists of expert marketing systems and recommender systems, will continue to grow along with artificial intelligence (AI) techniques

Finally, this study provides relevant implications for both practitioners and academics. From the theoretical point of view, linking and identifying the aspects and fields in which FA has been applied to marketing science reveals the opportunities that are embedded in fuzzy theory and methods.

CHAPTER SIX: DISCUSSION

6.1 THEORETICAL CONTRIBUTIONS AND CONCLUSION

This dissertation's theoretical contributions are in four major areas related to the questions posed by this research. In this section, I discuss the findings and the research questions in conjunction with the existing body of knowledge.

RQ1: To what extent can consumer firms with a large customer base drive and optimize business revenue through digital marketing and analytics.

This dissertation represents the first to attempt to assess the level of opportunity and the extent to which large consumer firms can leverage digital marketing and analytics to drive business performance by (1) linking consumer marketing activities and business performance with digital marketing channels, and (2) linking consumer marketing activities and business performance to firms' analytic capabilities.

Linking consumer marketing activities and performance with digital marketing channel: The creation and enhancement of marketing channels for customer engagement in driving business revenue have always been one of the critical challenges of marketing functions (Chen et al., 2014; Keeling et al., 2019; Hollebeek et al., 2019; Letheren, 2019; Dessart et al., 2019). As consumer firms with a large customer base continue to grow their marketing channels, the engagement opportunity for their businesses to grow and optimize their revenue is also on the increase (Hollebeek et al., 2019).

The evolution of digital channels has provided marketers with this rare opportunity. However, in an environment with a large consumer base having a large amount of customer data, optimal leveraging of these channels becomes a challenge if techniques and analytics that can drive insights in real-time for one-to-one marketing of the customer base are not available or not implemented (Martin and Murphy 2017). Therefore, these dissertation findings show that Fuzzy Analytics (FA) avail marketers the opportunity to leverage the rich customer data across the enterprise in real-time to generate incremental revenue for the consumer within a large customer base across digital channels support Mende et al., (2019) suggestions.

Moreover, this dissertation's findings emphasize the need for firms with a large consumer base to implement a recommendation engine driven by underlying analytics, such as machine learning techniques in driving business revenue across digital marketing channels.

Through robust case studies, this dissertation has shown that when analytics techniques are layered on both digital and non-digital channels of consumer firms, digital channels are more promising (Case 3). It was found that digital marketing channels are not optimized because the analytics driving the engagement and marketing activities and customer presentations are not robust enough. These finding also supports Verhoef et al. (2016), Columbus (2019) and Rahwan et al. (2019) submissions.

Linking consumer marketing activities and performance to firms' analytic capabilities:

In this modern age, it is difficult for consumer businesses to survive without leveraging their customers' information and behavior in their possession through analytics. The traditional way of leveraging an expanded marketing analytics team in an environment with a large customer base is proving to be problematic, expensive, and time-consuming (Verhoef et al., 2016). Moreover, it has no sustainable advantage anymore. It is low and prone to error with a high switching cost and slow to insights and decisions (Rizkallah, 2017). Firms are now trying to make technology the center of their solution rather than people. Marketers are using technology for processes standardization, high agility without high investments, and trying to use artificial intelligence (AI) for medium to high complex tasks to drive business performance, which this dissertation (Case3; Case 5) demonstrated in its findings with Fuzzy Analytics (Leung et al., 2018; Mende et al., 2019).

Marketers have the responsibility to drive business performance within an organization. As a matter of fact, in a consumer business with a large customer base, marketing drives the whole organization. Every other functional department in a service-based or utility firms with hundreds and millions of consumers depend on marketing initiatives to plan their strategic direction. IT and technology rely on marketing initiatives to determine the scaling up of their systems and capabilities. Sales need marketing initiatives to push products into the market. Invariably, a sizeable consumer-based firm thrives under a robust and active marketing department. As a result of this enormous responsibility, the entire organization looks up to marketing to bring out robust initiatives to solve performance problems.

However, marketers are often limited due to the systems, analytical capabilities, and other limiting challenges in leveraging the insights from the rich customer data. They are often faced with data silos challenges, old data types, legacy tools, systems and technology, incomplete view of customer behavior, and backward-looking (Homburg et al., 2017; Mende et al., 2019).

In line with many authors, this dissertation's findings support the claim that a firm that has developed its analytical capability and leverages the rich customer data across the enterprise through automation will compete favorably and optimally drives its customer base performance (Case 1; Case 2; Case 3; Case 4 and Case 5).

Research gap context

This dissertation identifies four areas of gap where literature has been silent as to how Fuzzy Analytics (FA) has been leveraged by firms with large consumer base to drive business performance through digital marketing and channels: (1) customer experience; (2) pricing, (3) targeting and profiling and, (4) innovation.

The findings in this dissertation show that firms can be in a better position to measure digital customer experience (CX) in real-time through robust analytics (Case 1). This will help firms better serve the customers, which will improve customer revenue, stickiness, and loyalty (Jarvinen and Karjaluoto, 2015; Welling and While, 2016). This dissertation's findings have also shown that through robust pricing tools that are pivoted through analytics, price points can be determined while revenue is optimized across digital services (Case 5). Through its findings, this dissertation emphasized the need for right profiling and targeting of the customer base for marketing activities (Case 3). The impact of wrong profiling for marketing activities is enormous for firms with a large customer base. Apart from the value that is being eroded, the cost of targeting and impacting customer experience is also huge (Verhoef et al., 2016).

When a firm understands its customer base through data mining and analytics of behavior across the base, innovative products and services will be developed and launched by the marketers (Case 6). One of the reasons why products are not innovative is that marketers often fail to understand their customer base (García, Lizcano, Ramos and Matos, 2019; Ryan, Jones, 2009; Sturiale and Scuderi, 2016). The findings of this dissertation align with this position.

Conclusion: The knowledge of consumer firms with a large customer base is advanced in this dissertation by the need for the firms to continue to grow revenue from their existing base through marketing analytics. For firms, this will mitigate the impact of some customer behaviors. They need robust and advanced analytical techniques to understand the customer base and provide tailored services to their customer base. This dissertation explores how Fuzzy Analytics, a cutting-edge subset of AI, can drive consumer revenue in consumer firms with a large customer base.

Therefore, there is a need for consumer firms with a large customer base to drive and optimize business revenue though digital marketing and analytics. The analytics need advanced techniques, and fuzzy approach is one of them.

RQ2: Why do some consumer firms drive and optimize business revenue from digital and marketing analytics while others do not?

Marketing automation and integrated systems: Consumer firms with a large customer base that have not invested in a well-integrated CRM and customer marketing solution cannot leverage the rich data across her enterprise towards business optimization (Ambler & Robert, 2008; Lengiz, Ibrahim, and Ali; 2016; Kotler, Kartajaya, Setiawan, 2016). This submission aligns with the findings of this dissertation (Case 3). Marketing automation facilitates the orchestration and integration of tools, people, and processes through automated workflows (Huang and Rust, 2018). It is software or platforms that follow a pre-programmed rule such as fuzzy expert systems that is well discussed and implemented in this dissertation across customer experience (Case 1 and Case 2), pricing (Case 4 and Case 5), and targeting and selection of customers (Case 3).

However, AI, in which Fuzzy Analytics is a subset, is the theory and development of computer systems to perform tasks that typically require human intelligence, such as visual perception, product preference, decision-making between two offers acceptance (Ghahramani 2015; Mnih et al., 2015; Davenport 2020).

Marketing automation driven by analytics has a single purpose: to let machines perform repetitive, monotonous tasks (Longoni et al., 2019). Findings in this dissertation reveal that consumer firms that invest in such analytics-driven automation tend to drive their business performance effectively (Case 3). In marketing operations, automated systems such as campaign management solutions and analytical models get input from data across the enterprise. Generally, the result is a more efficient, cost-effective approach and workforce that is more productive for a business. This approach frees up time for marketing professionals to focus on more important tasks that require the personal touch and ability to reach out to millions of customers (Baum et al., 2011; Reese 2018; Kaplan and Haenlein 2019). The findings in this dissertation show that this is one reason why some firms leverage digital marketing channels and analytics to drive and optimize performance while others do not.

Customer Value Management: Recent developments and advancement in technology have enabled firms with a large customer base to link all digital touch points to enterprise databases. This data availability across the enterprise has accelerated Customer Value Management (CVM) practice in large consumer firms. Customer Value Management (CVM) is the art and science by which brands optimize customer lifetime value and elongate customer lifecycle using advanced data analytics and robust channel management towards a one-to-one marketing approach (Bohling et al., 2006; Kim & Muhopadhyay, 2011; Rigby & Ledingham, 2004; Rigby, Reichheld & Schefter, 2002; Verhoef & Lemon, 2015).

In the management and marketing practice in the last decade, CVM practice's growth has been regarded as one of the critical developments (Santonino, 2020; Verhoef & Lemon 2013). CVM can be re-phrased as a marriage of data analytics and marketing to improve customer life cycle and value. Brands' engagement channels are rapidly converging towards digital as a result of digital transformation and innovations (Case 6). Hence, it has become vital for brands to understand how to optimize the opportunities in the digital space to drive effective and profitable one-to-one marketing (Gallino & Moreno 2014). However, many consumer firms are still struggling to leverage CVM in maximizing business revenue. According to the findings in this study, consumer firms with a large customer and weak CVM practice will struggle to optimize business performance, especially in a very competitive market (Case 3).

Customer Value Management (CVM), as described in this study, is the overall and end to end customer base management of firms along with the new customer attraction, retention of existing customers, development of current customers, and value optimization of services to different segments across the customer base to drive the business performance.

This function is achieved by developing people, processes, analytics, systems, and technology capabilities (Kordupleski, 2003; Verhoef & Lemon, 2015).

People, processes, analytics, systems, and technology capabilities: From the findings of this dissertation, large consumer firms that will drive and optimize business revenue from digital and marketing analytics will, in general, invest in people, develop processes, advanced in analytics with a considerable focus on systems capabilities. CVM comprises three major core branches. All functions and activities embedded in these functions are critical for effective customer base management of large consumer firms – these are commercial, analytics, and operations. A firm that will drive performance through digital marketing and analytics must have people and personnel that can effectively manage the large consumer base across these lines.

The commercial function is responsible for the end to end campaign and program design process with the appropriate definition of key KPIs success for every campaign across digital channels. This branch is also saddled with the strategy's responsibility, along with the planning and content creation. This function is responsible for tracking how the campaigns are doing and align the performance with all the stakeholders within and outside the marketing function. Stakeholders can include advertisers, content creators, campaign vendors, and the finance department.

The analytics core function deals with the preparation of data and the generation of insights from the available data sources across the enterprise to leverage the data for campaign purposes to correct a trend and address an issue to improve customer behavior towards products and services. It is also responsible for analytical models' development and their daily operationalization on the customer base. For firms to maximize the opportunity of digital channels, such a firm's analytics function should be majorly responsible for developing models, mining data, and generating embedded insights from data. The data management should be left for the technology or information technology department of the firm. With this, CVM Analytics will leverage the enterprise's information to facilitate the effective management of the customer base and digital touch points for business performance optimization and customer experience enhancement. With this approach in mind, technology specifications focus will center on the best approach that will support customer management rather than the technology (Branda, Lala & Gopalakrishna, 2018; Verhoef & Lemon 2013). The reporting of campaigns across systems and campaign lifecycle are also part of the activities of this function.

Operations functions are responsible for the execution of the campaigns. It is a function that works directly with the campaign solutions, which comprise of systems within the enterprise and third-party systems. They are responsible for the campaign and offer configuration, testing across digital channels, and assuring quality before the launch of the campaign (Anderson and Simester, 2011; Liu, Laguna, Wright and He, 2014). The responsibility of the smooth running of CVM projects such as integration with other third-party systems and measurement of the campaign success lies within this function (Kietzman, 2018). According to the findings, these are the factors that differentiate consumer firms with large customer base apart from each other when leveraging the embedded opportunities in the digital and marketing analytics.

Conclusion: Determining the appropriate marketing channel for a campaign proposition and aligning the channel with the customer base's right target segment is one of the significant challenges within the marketing functions. Once a firm cannot effectively achieve this, neither channel nor performance can be optimized. Therefore, consumer firms with a large customer base must invest in marketing people on specific skills that cut across commercial, analytics, and operations for successful customer base management. Robust investments must be made on systems and integration across all enterprise systems for full automation of marketing activities for effective customer base management and innovative products and services.

Therefore, some consumer firms do well than others in driving their business performance through digital and marketing analytics. This is due to their understanding of their customer base through advanced analytics and innovation, investment in their people, systems, tools, automation and integrated campaign management solutions.

RQ3: How can consumer firms deploy digital marketing and analytics in driving and optimization of business revenue?

Innovations that the digital ecosystems have witnessed in recent years have brought about a massive transformation into the digital space (Friedrich, Hall and El-Darwiche, 2015). This transformation due to innovative digital services and platforms has brought with them many changes that cut across many industries and the way consumer firms go to market with their products and services (Case 6). For large consumer firms in the service or utility industry to compete, they must have the capability to engage their customer base below the line (BTL) in a one-to-one marketing approach (Case 3).

Integrated customer base management framework: Findings in this dissertation reveal that such BTL and segmented engagement require the availability of robust capability and tools that are integrated with all data sources across the enterprise for seamless delivery of such targeted campaigns. For such consumer firms to optimize revenue potential from the large customer base, campaign management tools must be in place. Following this dissertation's findings, a clear and holistic customer base management framework is required to help brands optimize embedded opportunities in these digital channels. While these tools, integrations, and systems may be expensive, their payback time is almost immediate compared to the incremental revenue they will generate.

Understanding the customer base: A successful deployment of integrated digital marketing and analytics platforms and processes for driving a firm's business performance starts from fully understanding the customer base (Gallino and Moreno, 2014). According to this dissertation's findings, firms can achieve this by leveraging existing customer relationships and transactional data and ends with strategic deployment of marketing intervention activities to grow customer satisfaction and, ultimately, customer revenue through digital channels. (Verhoef, Reinartz, and Krafft, 2010).

The concept of customer base management through CVM with a blend of innovations across the digital space is still relatively new, and only a few brands have been able to successfully implement this rich customer base management approach to drive their proposition development and revenue optimization strategy (Eggert, Ulaga, Frow and Payne, 2018). The mobile telecommunication industry is one sector that understands this concept extremely well and has used it to increase revenue and, at the same time, improve customer satisfaction (Dadzie, Dadzie and Winston, 2019).

This dissertation findings have established that as digital channel expansion continues to change the way the brands engage with their customers, brands need to continue to identify customer segments based on their behavior, the needs and preferences of each segment along different channels to drive a profitable business (Branda, Lala and Gopalakrishna, 2018).

Conclusion: Findings reveal that firms' deployment of digital marketing and analytics to drive business performance involves specific steps on the part of the firms**.** Firms need to uncover the anonymity associated with the customer across digital channels to serve the customer well. A robust integrated platform of identity management in the digital marketing space is also essential for brands. As soon as a brand has developed the capability to uncover a customer's identity across all digital touch points and links with internal data, it can then leverage customer emotion, motivation, behavioral and environmental context to drive value and service to the customer (Case5).

Moreover, brands need to move a step forward in predicting propensity for behavior to address customer issues proactively. Firms also need to transform the personalization capability of brands to manage their customer expectation. Capabilities like text analytics and the use of AI and ML will contextually help in real-time targeting and improve customer engagement and customer response to call to action (Case 3). While doing these, measurement methodologies must be incorporated into the entire campaign and engagement process for proper tracking performance and incremental revenue – this is one of the critical findings of the Delphi survey of this dissertation. All these will help a large consumer firms to drive business performance through the deployment of digital marketing and analytics.

6.2 MANAGERIAL IMPLICATIONS

The submission of Johnston et al. (1999) regarding one of the merits of case studies is true for this dissertation – it generates robust insights for the practice and managers. These managerial implications across the case studies in this dissertation are highlighted so that marketers will be able to use digital marketing and analytics to drive and optimize business performance across any large consumer base.

Analytics and its associated techniques can be operationalized within the day to day marketing functions of firms with a large customer base. Findings in this dissertation show that marketing analytics approach and techniques could be simplified and adopted while leveraging the rich and robust data that the consumer firms have within their enterprise. For marketers tasked with driving the business revenue performance through analytics, fully integrated campaign management would be required before analytics output can be optimally leveraged.

Also, marketing automation of the analytical models' extracts into the integrated campaign management solution with the ability to configure offerings and deliver timely communication is the secret of the success across the digital channels. No matter how accurate an analytical model can be, if marketers do not automate the end-to-end process delivery of the campaign, the marketing programs' results cannot be encouraging.

Marketers must take cognizance of the importance of channels in the course of driving business revenue and performance. Digital channels have come with a robust opportunity for marketers. However, the traditional channels still have their place in the way marketers take their products to the market (Opreana and Vinerean, 2015). For firms to fully leverage the power of analytics in driving business performance, marketers must be equipped with an integrated and robust campaign management solution. The solution must be integrated to enable automation across base management operational activities and eliminate manual iterations as much as possible.

For marketers, using data analytics to improve customer experience and target the right set of customers is very important for optimizing digital marketing campaigns. As large consumer firms continue to increase their digital marketing budget yearly, demand for more customer experience trackable events will also rise. Hence, a need for more innovative ways on the part of marketers to measure campaign effectiveness along the customer experience journey to justify digital marketing's growing budget (case 1 and Case 3).

As marketing practitioners continue to find the appropriate balance for the allocated digital budget and the effectiveness of these channels, findings in this dissertation narrow the effectiveness and customer experience measurement gap in the digital space (Case 1 and case 2).

Pricing is an integral part of the marketing function and critical to a firm's overall survival. It is an aspect of the marketing mix that a firm cannot afford to get wrong. Whenever commercial managers consider the right price point for products or services, factors such as marketing strategy, competition, and the associated value that consumers perceive to be suitable for the products must top the list for consideration (Case 4 and Case 5).

Price adjustments are tools used by firms to remain competitive amidst a turbulent and fiercely competitive market (Case 5). In practice, managers are confronted with pricing-related decision-making with enormous business performance consequences if the products are not well priced. In such a situation, when managers lack enough evidence, or when experts lack all the relevant data to make an informed judgment, experts leverage fuzzy linguistic terms. Fuzzy logic draws its strength from its ability to absorb ambiguity and apply vagueness and imprecise data to make a sound judgment, such as pricing decisions.

Another important implication for managers among the findings of this dissertation is that poor techniques and capabilities for channel optimization of the consumer base across available channels often undermine these channels' performance. Results indicated that clustering is efficient for target selection (Case 3). The mapping of clusters with the appropriate digital channel of transactions revealed that business performance could be optimized along the digital channel. Moreover, the analytic model's output enables suitable cross-selling and up-selling campaigns to optimize the customer base.

I would like to encourage marketers to pay more attention to the measurement and evaluation of marketing investment in digital marketing activities – the panel study in this dissertation reveals that this is still a challenge. The marketers must be able to account for the incremental revenue that is derived from all channels – both digital and non-digital.

6.3 LIMITATION AND AVENUES FOR FUTURE RESEARCH

The findings in this dissertation serve as eye-openers for promising research areas outside the focus of this study. While this dissertation focuses on business performance revenue optimization through digital marketing and analytics, it somewhat ignores the discussion on the measurement of the digital channel's performance. While this dissertation findings establish that performance can be optimized through the digital channel by analytics, the measurement of different digital channel performance is also a robust area for future research (Bell, Gallino, & Moreno, 2014; Verhoef, Kannan, & Inman, 2015).

This dissertation leverages Fuzzy analytics as the analytical approach to establish analytics' power in driving business performance across the digital channel. Fuzzy Analytics (FA), as demonstrated in this dissertation, is a subset of cutting-edge artificial intelligent (AI) techniques. Other AI techniques such as machine learning (ML) also allow researchers to explore the capability that digital channels have provided the marketers in a large consumer base.

Findings in this study reveal the impact of digital innovations on mobile operators' business model and performance. More research is needed to investigate how to quantify digital innovation's impact across other industries with a large customer base.

While I was trying to see how Fuzzy Analytics (FA) has been used in driving the business performance in consumer firms at the beginning of this dissertation, four areas have been silent in the literature. Application of Fuzzy analytics in leveraging customer experience improvement; applying Fuzzy Analytics in optimizing business performance through pricing; Fuzzy Application in target and selection; and leveraging analytics for base management innovation are all areas that have not seen so much of attention. The case studies in this dissertation, along with the findings, address all the identified gaps. However, there is still more research opportunity in this domain, especially when applying other analytics methods in the optimization process.

Generally, for future works, only a little discussion exists in which researchers have used FA in the context of driving marketing and business performance. This opens research opportunities in the digital marketing space for the application of FA across digital channels. There is a considerable research opportunity in applying FA to current problems and realities daily confronting consumer businesses and marketers in this digital age.

One limitation widely shared by literature reviewers is that many articles would have been involuntarily omitted during the final portfolio preparation in a systematic review of the literature. While it may not be exhaustive, this dissertation draws conclusions from a comprehensive and extensive list of published articles. Thus, it opens the door for potential overlaps between areas in which FA has been applied in the field of marketing science.

Detail explanation regarding the evolution of the research question along the dissertation development has been explained. The need for the case study method for the research questions and its appropriateness for this dissertation has also been clearly explained. Furthermore, why the mobile telecommunication industry has been chosen as an industry with a large consumer base, upon which these dissertation case studies are grounded, has also been detailed.

Three research areas exist where transparency cannot be compromised – they are data collection, analysis, and reporting stages. This is vital for other researchers to perform the same research and make quality interpretation in their own way. (Dubois and Gibbert, 2010). However, according to Järvensivu and Törnroos (2010), in abductive studies, analytical results' validity is not guaranteed by transparency. Easton (2010) argues that the most critical aspect of validity comes from critical realism and its associated philosophical assumptions of which interpretation is a vital component of the findings. Therefore, I am aware that despite the rich customer data at my disposal, which I leveraged in all the cases in this dissertation, the data source is still limited to only one industry among several industries with large consumer firms. Though my data collection method, which consists of actual customer data, has been argued to be the best data collection method in the literature (Piekkari et al., 2010; Woodside and Wilson, 2003), it is safe to assume that consumer behavior across different industries will be slightly different.

REFERENCES

1. Abbasimehr, H. M. Setak, S. (2013). A framework for identification of high-value customers by including social network-based variables for churn prediction using neuro-fuzzy techniques, *International Journal of Production Research*, 51(4), 1279-1294.

2. Adlassnig, K. P. (1986). Fuzzy set theory in medical diagnosis, *IEEE transactions on Systems*, Man and Cybernetics SMS bf 16, 260–265.

3. Aghaei, C. A., Salehi, H.; Md Yunus, M.M., Farhadi, H., Fooladi, M., Farhadi, M. and

4. Ajayi, A., Aderounmu, G., Soriyan, H. (2010). An adaptive fuzzy information retrieval model to improve response time perceived by e-commerce clients, *Expert Systems with Applications*, 37(1), 82-91.

5. Al-Najjar, D. and Al-Najjar, B. (2014). Developing a multistage predicting system for corporate credit rating in emerging markets: Jordanian case. *Journal of Entrepreneur. Inf. Manag*. 27, 475–487.

6. Ale, N. A. (2013) Comparison between two main academic literature collections: Web of science and Scopus databases. *Asian Soc. Sci.* 2013, 9, 18–26.

7. Akay, M., Cohen, D. and Hudson. (1997). Fuzzy sets in life sciences, *Fuzzy Sets and Systems.* 90, 219–224.

8. Alavijeh, Z. (2015). The Application of Link Mining in Social Network Analysis, Advances in Computer Science: *An International Journal,* 4 (3).

9. Ambler, T., and Roberts, J. H. (2008). Assessing marketing performance: Don't settle for a silver metric. *Journal of Marketing Management*, 24(7-8), 733–750.

10. American Marketing Association. (2016) American Marketing Association Dictionary. Available at: https://www.ama.org/resources/Pages/Dictionary.aspx [Last accessed September 14th, 2020].

11. Anderson, E. T. and Simester, D. (2011). A Step-by-Step Guide to Smart Business Experiments, *Harvard Business School.*

12. André, Q., Carmon, Z., Wertenbroch, K., Crum, A., Frank, D., Goldstein, W., Huber, J., van Boven, L., Weber, B., and Yang, H. (2018). Consumer choice and autonomy in the age of artificial intelligence and big data," *Consumer Needs and Solutions*, Vol. 5. No. 1-2, pp. 28-37.

13. Andrew, M., Goehring, J., Hui, S., Pancras, J. and Thornswood, L. (2016). Mobile promotions: a framework and research priorities. Journal of Interactive Marketing, 34, 15-24.

14. Antonio, V. (2018). How AI is changing sales. Harvard Business Review, July 30. Retrieved February 11, 2019, from https://hbr.org/2018/07/ how-ai-is-changing-sales.

15. Anthony, Susan & Jack, Susan (2009). Qualitative case study methodology in nursing research: An integrative review. *Journal of advanced nursing*, 65(6), 1171-1181.

16. Arruda, L., França, S. and Quelhas, O. Mobile Computing: Opportunities for Improving Civil Constructions Productivity. *Int. Rev. Manag. Bus. Res*. 2014, 3, 648–655.

17. Bag. T. and Samanta. S. (2008). A comparative study of fuzzy norms on a linear space, *Fuzzy Sets and Systems*, 159(6), 670-684.

18. Baum, S., Goertzel, B., and Goertzel, T. (2011). How long until human-level AI? Results from an expert assessment, *Technological Forecasting and Social Change,* 78(1), 185–195.

19. Baum, S., Goertzel, B., and Goertzel, T. (2011). How long until human-level AI? Results from an expert assessment. Technological Forecasting and Social Change, Vol. 78 No 1, pp. 185–195.

20. Baye, M., Santos, B. and Wildenbeest, M. (2016). Search Engine Optimization: What Drives Organic Traffic to Retail Sites? *Journal of Economic and Strategic Management,* 25(1), 6-31.

21. Behrens, A. Use of intervals and possibility distributions in economic analysis. *J. Oper. Res. Soc.* 1992, 43, 907–918.

22. Bell, David R., Santiago Gallino, and Antonio Moreno. (2014). How to Win in an Omnichannel World. MIT *Sloan Management Review*, 56, 45–53.

23. Bijakšić, S. Markić, B., and Bevanda, A. (2017). Expert pricing system as part of marketing mix". *Informatol*. Vol. 50, pp. 3-4.

24. Bhaskar, R. (1988). A realist theory of science*, Hemel Hempstead,* Harvester Press

25. Blattberg, R., Kim, B., and Neslin, S. (2008). Database marketing: analyzing and managing customers. New York, *Springer*.

26. Boateng, S. L. and Boateng R. (2014). Philosophical debates in Marketing and the application of critical realism to online relationship market in *Boatent, S L (in Print) Essays from my PhD, first Edition*, Pearl Richard Foundation.

27. Bohling, T., Bowman, D., LaValle, S., Mittal, V., Narayandas, D., Ramani, G. and Varadarajan, R. 2006. CRM implementation: effectiveness issues and insights. *Journal of Service Research,* 34(4): 184–194.

28. Bojadziev, G., and Bojadziev, M. (1997). Fuzzy logic for business, finance, and management. Advances in fuzzy systems – application and theory, *World Scientific,* 12.

29. Bolton, R., Lemon, K., and Verhoef, P. (2004). The theoretical underpinnings of customer asset management: a framework and propositions for future research. *Journal of the Academy of Marketing Science*, 32(3), 271-292.

30. Bourne, M., Kennerley, M. and Franco-Santos, M. (2005). Managing through measures: A study of impact on performance, *Journal of Manufacturing Technology Management* 16 (4), 373–395.

31. Branda, A., Lala, V., and Gopalakrishna, P. (2018). The marketing analytics orientation (MAO) of firms: identifying factors that create highly analytical marketing practices, *Journal of marketing Analytics,* 6, 84-94.

32. Brinberg, D. and McGrath, J. E. (1985) Validity and the Research Process, Sage Publications, Beverly Hills, CA Patton, M. Q. (2002) *Qualitative Research & Evaluation Methods*, Sage, Thousand Oaks, CA.

33. Buckley JJ (2003). Fuzzy Probabilities. Physica-Verlag, Heidelberg, Germany.

34. Charrié J. and Janin L. (2015) Le numérique : comment réguler une économie sans frontière?, La note d'analyse 35, Paris, France Stratégie.

35. Busca, L., and Bertrandias, L. (2020). A Framework for Digital Marketing Research: Investigating the Four Cultural Eras of Digital Marketing, *Journal of Interactive Marketing*, 49, 1 – 19.

36. Carrasco, R., Blasco, M., García-Madariaga, J. and Herrera-Viedma, E. (2018). A fuzzy linguistic RFM model applied to campaign management, *International Journal of Interactive Multimedia and Artificial Intelligence*.

37. Carrasco, R., Blasio, M., García-Madariaga, J., and Herrera-Viedma, E. (2018). A fuzzy linguistic RFM model applied to campaign management, *International Journal of Interactive Multimedia and Artificial Intelligence.*

38. Casillas, J. and Francisco, M. 2009. Mining uncertain data with multi-objective genetic fuzzy systems to be applied in consumer behavior modeling. *Expert Systems with Applications,* 36, 1646-1659.

39. Chaudhuri, A., and De, K. (2011). Fuzzy support vector machine for bankruptcy prediction, *Applied Soft Computing,* 11 (2), 2472–2486.

40. Chauhan, R. and Kaur, H. (2014). “Predictive Analytics and Data Mining: A framework for optimizing decisions with R tool”, Advances in *Secure Computing, Internet Services, and Applications,* 3-88, IGI Publishers, USA.

41. Chen, J., and Stallaert, J. (2014). An economic analysis of online advertising using behavioral targeting. *MIS Quarterly,* 38(2), 429–449.

42. Chen, Y. S. and Cheng, C. H. (2013). Hybrid models based on rough set classifiers for setting credit rating decision rules in the global banking industry. *Knowl. Based Syst,* 39, 224–239.

43. Chen, L., and Chiou, T. (1999). A fuzzy credit-rating approach for commercial loans: a Taiwan case, *Omega,* 27(4), 407–419.

44. Chiang, W. (2017). Discovering customer value for marketing systems: an empirical case study, *International Journal of Production Research,* 55 (17), 5157-5167.

45. Columbus, L. (2019). 10 charts that will change your perspective of AI in marketing. Forbes, July 07. Retrieved on July 09, 2020 from https://www.forbes.com/sites/louiscolumbus/2019/07/07/10-charts-that-will-change-your-perspective-of-ai-in-marketing/amp/

46. Corchado, E., Abraham, A., Ponce, A.C., Ferreira de Carvalho, L.: Hybrid intelligent algorithms and applications. *Information Science.* 180(14), 2633--2634 (2010)

47. Cotter, A., Shamir, O., Srebro, N., and Sridharan, K. (2011). Better mini-batch algorithms via accelerated gradient methods. *Advances in Neural Information Processing Systems 24 eds J. Shawe- Taylor, R. Zemel, P. Bartlett, F. Pereira, and K. Weinberger* (Cambridge, MA: MIT Press), pp. 1647–1655. Available online at http://books.nips.cc/papers/files/nips24/NIPS2011_0942.pdf

48. Court, D., Elzinga, D., Mulder, S., and Vetvik, O. J. (2009). The consumer decision journey. *McKinsey Quarterly,* (3), 96–107.

49. Crane, D., Henderson, E. (2016). Chadwick DR. Exploring the acceptability of a ‘limited patient consent procedure’ for a proposed blood-borne virus screening programme: a Delphi consensus building technique. *BMJ Open.*

50. Dadzie, K., Dadzie, C., and Winston, E. (2019). The transitioning of marketing practices from segment to customer-centric marketing in the African business context: Toward a theoretical research framework, *Journal of African Business,* 20(2), 206-223.

51. Da Silva, I. (2020) “Gábor Rekettye (2019). Value Creation 4.0- Marketing Products in the 21st Century”, *Transnational Marketing Journal. London*, UK, 8(1), pp.

52. Davenport, T., Guha, A., Grewal, D. and Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, Vol. 48, pp. 24-42 https://doi.org/10.1007/s11747-019-00696-0

53. Demicco, P., Klir, C. J. (2004), Fuzzy Logic in Geology, Eds, *Elsevier Publication.*

54. Denecker, O., Gulati, S., Niederkorn, M. (2014). The Digital Battle that Banks Must Win. *McKinsey & Company,* Washington, DC. http://www.mckinsey.com/insights/financial_services/the_digital_battle_that_banks_

55. Dessart, L., Aldás-Manzano, J. and Veloutsou, C. (2019). Unveiling heterogeneous engagement-based loyalty in brand communities, *European Journal of Marketing*, available at https://doi.org/10.1108/EJM-11-2017-0818.

56. Dobson, P. J. (2002). Critical realism and information systems research: Why bother with philosophy, *Information Research*, 7(2), 1-13.

57. Donze, L., and Meier, A. (2012). Applying fuzzy logic and fuzzy methods in marketing. *In: Meier, A. and Donze, L (eds). Fuzzy methods for customer relationship management and marketing*, 1-14. *Business Science Reference, Hershey.*

58. Downward, P. and Mearman, A. (2007). Retrodiction as mixed-methods triangulation in Economic Research: Reorienting Economics into Social Science, *Cambridge Journal of Economics*, 31(1), 77-99.

59. Dubois, A. and Gibbert, M. (2010). Case Study Research in Industrial Marketing, Industrial Marketing Management, 39(1), 1-178.

60. Dubois, A., and Gadde, L. E. (2002). Systematic combining: An abductive approach to case research. *Journal of Business Research*, 55(7), 553–560.

61. Dubois, D. and Prade, H. (1980). Fuzzy Sets and Systems: Theory and Applications, *Academic Press*, New York.

62. Dubois, D. and Prade, H. (1987). Editorial, *Fuzzy Sets and Systems*, 24, 259–262.

63. Easton, G. (2002). Marketing: A critical realism approach, *Journal of Business Research*, 55(2), 103-109.

64. D'Urso, P. and Giordani, P. (2006). "A weighted fuzzy c-means clustering model for fuzzy data, Computational Statistics and Data Analysis, 50(6), 1496-1523, *Elsevier Science Pub.*

65. Easton, G. (2002). Marketing: A critical realism approach, *Journal of Business Research*, 55(2), 103-109.

66. Easton, G. (2010). Critical realism in case study research, *Industrial marketing management*, 39(1), 118-128.

67. Efe, B. (2016). An integrated fuzzy multi-criteria group decision-making approach for ERP system selection, *Applied Soft Computing*, 38, 106-117.

68. Eggert, A., Ulaga, W., Frow, P., and Payne, A. (2018). Conceptualizing and communicating value in business markets: From value in exchange to value in use. *Industrial Marketing Management*, 69, 80–90.

69. Elim M. Noam. (2019). Media and Digital Management, Palgrave Macmillan

70. Enache, Ioan-Constantin and Gruia, Romulus. (2015). Understanding the restaurants customers. Food choices and business implications.

71. Enache, Ioan-Constantin. (2012). Modelarea în marketingul educaţional. Aplicaţie pentru învăţământul superior românesc." Phd Dissertation.

72. Engelking, R. (1977). General Topology, *PWN,* Warszawa.

73. Ensslin, L.; Ensslin, S.R.; Lacerda, R.T.; Tasca, J.E. (2010), ProKnow-C, Knowledge Development Process—Constructivist. Available online: http://www.ucdoer.ie/index.php/Education_Theory (accessed on 20 December 2020).

74. Ertay, Tijen and Cengiz, Kahraman. (2007). Evaluation of Design Requirements Using Fuzzy Outranking Methods. *International Journal of Intelligent Systems,* 22, 1229-1250.

75. Felt, L. and Robb, M. (2016). Technology Addiction: Concern, Controversy, and Finding Balance, *Methodological Innovations in Social Change.*

76. Flores, W., Mombello, E., Jardini, J., Rattá, G., and Corvo, A. (2011). Expert system for the assessment of power transformer insulation condition based on type-2 fuzzy logic systems". *Expert Systems with Applications, vol.* 38, pp. 8119–8127.

77. Flyvbjerg, B. (2011). Case study. In Norman K. Denzin & Yvonna S. Lincoln (Eds.), *The Sage handbook of qualitative research* (4th ed., pp.301-316). Thousand Oaks, CA: Sage.

78. Francisco, M. and Casillas, J. (2009). Marketing intelligent systems for consumer behavior modeling by a descriptive induction approach based on Genetic Fuzzy Systems. *Industrial Marketing Management,* 38, 714-731.

79. Franco-Santos, M., Kennerly, M., Micheli, P., Martinez, V., Mason, S., Marr, B., ... Neely, A. (2007). Towards a Definition of a Business Performance Measurement

System. *International Journal of Operations and Production Management*, 27(8), 784–801.

80. Freksa C. (1994) Fuzzy Systems in AI: An Overview. In: Kruse R., Gebhardt J., Palm R. (eds) Fuzzy-Systems in Computer Science. Artificial Intelligence / Künstliche Intelligenz. Vieweg+Teubner Verlag. https://doi.org/10.1007/978-3-322-86825-1_12

81. French, K. (2018), "Your new best friend: AI chatbot." Retrieved February 13, 2020, from https://futurism.com/ai-chatbot-meaningful- conversation.

82. Friedrich, R., Hall, S. and El-Darwiche, B. (2015). Industry Perspectives: Telecommunications Trends and Strategy, (accessed February 1, 2020).

83. Fullam, J. (2017). Becoming a youth activist in the internet age: a case study on social media activism and identity development, *International Journal of Qualitative Studies in Education*, 30 (4), 406-422.

84. Gallino, S. and Moreno A. (2014). Integration of online and offline channels in retail: the impact of sharing reliable inventory availability information, *Management Science*, 60(6), 1434–1451.

85. Gans, J., Agrawal, A., & Goldfarb, A. (2017). How AI will change strat- egy: A thought experiment. Harvard business review online. Retrieved February 11, 2019 from https://hbr.org/product/how-ai- will-change-strategy-a-thought-experiment/H03XDI-PDF-ENG.

86. García, J. J., Lizcano, D., Ramos, C., and Mat, N. (2019). Digital Marketing Actions That Achieve a Better Attraction and Loyalty of Users: An Analytical Study, *Futures Internet*,

87. Garg, H. (2016). A Novel Accuracy Function Under Interval-Valued Pythagorean Fuzzy Environment for Solving Multicriteria Decision Making Problem. *International Journal of Intelligent Systems*, 31(1), 529-540.

88. Gary, L., Kotler, P. and Moorthy, S. (1992). Marketing models. New Jersey: Prentice-Hall.

89. George, A. L. and Bennett, A. (2005). Case Studies and Theory Development in the Social Sciences, *MIT Press,* Cambridge, MA.

90. Ghahramani, Z. (2015). Probabilistic machine learning and artificial intelligence. *Nature,* 521, 7553, 452–459.

91. Ghnemat, R., and Jaser, E. (2014). Toward Mobile Telecommunication Recommendation System through Intelligent Customers Categorization. International Journal of Computers and Technology, Vol 12 No. 7.

92. Ghnemat, R., and Jaser, E. (2014). Toward Mobile Telecommunication Recommendation System through Intelligent Customers Categorization. *International Journal of Computers and Technology,* Vol 12 No. 7.

93. Glaser, B. G. and Strauss, A. L. (1967). The discovery of grounded theory: Strategies for qualitative research. New York: Aldine Pub. Co

94. Goodwin, T. (2013). Inbound Marketing vs. Outbound Marketing: Understanding the Differences. retrieved from http://boldthinkcreative.com/inbound-marketing- vs-outbound-marketing-whats-the-difference/

95. Gray, J., and Rumpe, B. (2015). Models for digitalization. Software & Systems Modeling, 14(4), 1319-1320. doi: 10.1007/s10270-015-0494-9

96. Gök, O., Peker, S., and Hacioglu, G. (2015). The marketing department's reputation in the firm. *European Management Journal*, 33(5), 366–380

97. Goldberg, D. Nichols, D., Oki, B. and Terry, D. (1992). Using collaborative filtering to weave an information tapestry, *Communications of the ACM*, 35,61-70.

98. Gulsecen, S. and Kubat, A. (2006). Teaching ICT to teacher candidates using PBL: A

99. qualitative and quantitative evaluation. Educational Technology & Society, 9(2), 96-106.

100. Gupta, S., Leszkiewicz, A., Kumar, V., Bijmolt, T. and Potapov, D. (2020). Digital Analytics: Modeling for Insights and New Methods. *Journal of Interactive Marketing*, 51, 2-43.

101. Hanafizadeh, P., and Mirzazadeh, M. (2011). Visualizing market segmentation using self-organizing maps and Fuzzy Delphi method – ADSL market of a telecommunication company. *Expert Systems with Applications*, 38, 198–205.

102. Halligan, B., and Shah, D. (2014). *Inbound marketing - Attract, Engage, and delight customers online.* New Jersey, USA, Wiley.

103. Handley, A. and Chapman, C. (2010). *Content Rules*, NY, USA: Wiley.

104. Harrison, H., Birks, M., Franklin, R. and Mills, J. (2017). Case Study Research: Foundations and Methodological Orientations [34 paragraphs]. Forum Qualitative Sozialforschung / Forum: *Qualitative Social Research*, *18*(1), Art. 19,

105. Hazée, S., Van Vaerenbergh, Y., Delcourt, C. and Kabadayi, S. (2020). Service delivery system design for risk management in sharing-based product service systems: a customer-oriented approach. International Journal of Operations & Production Management, Vol. 40 No. 4, pp. 459-479.

106. Hellendoorn, H. and Thomas, C. (1993). Defuzzification in fuzzy controllers. *Journal of Intelligent Fuzzy Systems*, 1, 109 – 123.

107. Helmer, O. Looking Forward: A Guide to Futures Research; *SAGE Publications*, Beverly Hills, CA, USA, 1998.

108. Helmer, O.; Rescher, N. (1959). On the Epistemology of the Inexact Sciences. *Management Science*, 6, 25–52.

109. Helzlsouer K, Meerzaman D, Taplin S and Dunn BK (2020) Humanizing Big Data: Recognizing the Human Aspect of Big Data. *Frontier in Oncology*. 10(186).

110. Hesami, M., Nosratabadi, H.E. and Fazlollahtabar, H. (2013). Design of a fuzzy expert system for determining adjusted price of products and services, *Int. J. Industrial and Systems Engineering*, 13(1), pp.1–26.

111. Hills, C. A. Patton, M. Q. (2002) Qualitative Research & Evaluation Methods, *Sage*, Thousand Oaks, CA

112. Hitzler, P. and van Harmelen, F. (2010). A Reasonable Semantic Web, 39 – 44.

113. Holliman, G., and Rowley, J. (2014). Business to business digital content marketing: marketers' perceptions of best practice. *Journal of Research in Interactive Marketing*, Vol. 8 No. 4, 269-293. doi: 10.1108/jrim-02-2014-0013

114. Hofacker, C., Golgeci, I., Pillai, K.G. and Gligor, D.M. (2020). Digital marketing and business-to-business relationships: a close look at the interface and a roadmap for the future", *European Journal of Marketing*, 54(6), 1161-1179.

115. Hollebeek, L., Srivastava, R. and Chen, T. (2019). S-D logic-informed customer engagement: Integrative framework, revised fundamental propositions, and application to CRM, *Journal of the Academy of Marketing Science,* 47(1), 161-185.

116. Hollebeek, L., Sprott, D., Andreassen, T., Costley, C., Klaus, P., Kuppelwieser, V., Karahasanovic, A., Taguchi, T., Ul Islam, J. and Rather, R. (2019). Customer engagement in evolving technological environments: synopsis and guiding propositions, *European Journal of Marketing*, 53(9), 2018-2023.

117. Homburg, C., Jozic, D., and Kuehnl, C. (2017). Customer experience management: Towards implementing an evolving marketing concept, *Journal of the Academy of Marketing Science*, 45(3), 377-401.

118. Homburg, C., Vomberg, A., Enke, M., & Grimm, P. H. (2015). The loss of the marketing department's influence: Is it really happening? And why worry?

119. Homburg, C., Vomberg, A., Enke, M., and Grimm, P. H. (2015). The loss of the marketing department's influence: Is it really happening? And why worry*? Journal of the Academy of Marketing Science*, 43(1), 1–13.

120. Huang, M., and Rust, R. (2018). Artificial intelligence in service. Journal of Service Research, Vol. 21 No. 2, pp. 155–172.

121. Huang, M., and Rust, R. (2018). Artificial intelligence in service. *Journal of Service Research,* Vol. 21 No. 2, pp. 155–172.

122. Hsu, C.C. and Sandford, B.A. (2007). The Delphi technique: Making sense of consensus. *Pr. Assess. Res. Evaluation,* 12, 1–8.

123. Huang, C., Chen, M., Wang, C. (2007). Credit scoring with a data mining approach based on support vector machines, *Expert Systems with Applications*, 33(4), 847–856.

124. Huang, M., and Rust, R. (2018). Artificial intelligence in service, *Journal of Service Research*, 21(2), 155–172.

125. Järvensivu, T., and Törnroos, J. Å. (2010). Case study research with moderate constructionism: Conceptualization and practical illustration. *Industrial Marketing Management*, 39, 100–108

126. Jantzen, J. (2007). Foundations of fuzzy control. John Wiley & Sons, Ltd.

127. Jarvinen, J., and Karjaluoto, H. (2015). The use of web analytics for digital marketing performance measurement, *Industrial Marketing Management*, 50, 117–127.

128. Jerath, K., Fader, P. S., & Hardie, B. G. (2016). Customer-Base Analysis using Repeated Cross-Sectional Summary (RCSS) Data. European Journal of Operational Research, 249 (1), 340-350.

129. Johnson, D.S., Muzellec, L., Sihi, D. and Zahay, D. (2019). The marketing organization's journey to become data-driven, *Journal of Research in Interactive Marketing*, 13(2), 162-178.

130. Johansson, Rolf. (2003). Keynote speech at the international conference "Methodologies in Housing Research," Royal Institute of Technology in cooperation with the International Association of People–Environment Studies, Stockholm, September 22-24, 2003, http://www.psyking.net/htmlobj-3839/case_study_methodology-_rolf_johansson_ver_2.pdf [Accessed: September19, 2020].

131. Johnson, M.P. (2006). Decision models for the location of community corrections centers.

132. Johnston, W. J., Leach, M. P., & Liu, A. H. (1999). Theory testing using case studies in business-to-business research. Industrial Marketing Management, 28(3), 201-213.

133. Johnston, A. (2014), "Rigour in research: theory in the research approach," European Business Review, 26(3), 206-217.

134. Jones, J. and Hunter D. (1995). Consensus methods for medical and health services research. *BMJ*, 311:376–80.

135. Kabir, G., Hasin, A. (2011). Evaluation of customer-oriented success factors in mobile commerce using fuzzy AHP, *Journal of Industrial Engineering and Management*, 4(2), 361-386.

136. Kahraman, C. Yazici, I., and Karaşan, A. (2018). A literature survey on the usage of fuzzy MCDM methods for digital marketing, *Intelligent Systems: Concepts, Methodologies, Tools, and Applications.*

137. Kaltenrieder, P., Portmann, E., Binggeli, N., Myrach, T. (2015). A conceptual model to combine creativity techniques with fuzzy cognitive maps for enhanced knowledge management, In: *Fathi M. (eds) Integrated Systems: Innovations and Applications. Springer, Cham.*

138. Kaplan, A., and Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence, *Business Horizons,* 62(1), 15–25.

139. Kaushik, A. (2009). Web Analytics 2.0: The Art of Online Accountability and Science of Customer Centricity, *John Wiley & Sons,* Hoboken, NJ, USA, 2009.

140. Kaymak, U. (2001). Fuzzy Target Selection Using RFM Variables. In: *Proc. Of Joint 9th IFSA World Congress and 20th NAFIS Int. Conference,* Vancouver, Canada, 1038–1043.

141. Kaymak, U. and Setnes, M. (2001). Extended Fuzzy Clustering Algorithms, *Erim Report Series Research in Management.*

142. Kecman V (2001). Learning and Soft Computing: Support Vector Machines, Neural Networks, and Fuzzy Logic Systems (Complex Adaptive Systems). MIT Press, Cambridge, Massachusetts.

143. Keeling, D., de Ruyter, K., Mousavi, S. and Laing, A. (2019), "Technology push without a patient pull: examining digital unengagement (DU) with online health services," European Journal of Marketing, available at https://doi.org/10.1108/EJM-10-2017-0692

144. Khatwani, G., Srivastava, P. (2015). Identifying organization preferences of internet marketing channels using hybrid fuzzy MCDM theories, *Journal of Electronic Commerce in Organization*.

145. Kietzman, J., Paschen, J., and Treen, E. (2018). Artificial intelligence in advertising: How marketers can leverage artificial intelligence along the customer journey, *Journal of Advertising Research,* 58(3), 263-267.Kim, T., & Duhachek, A. (2018). The impact of artificial agents on per- suasion: A construal level account. ACR Asia-Pacific Advances.

146. Kim, S. and Mukhopadhyay, T. (2011). Determining optimal CRM implementation strategies', *Information Systems Research*, 22(3): 624–639.

147. Klir, G. and Folger, T. (1988) Fuzzy Sets, Uncertainty, and Information, *Prentice Hall*, Englewood Cliffs, NJ.

148. Kietzman, J., Paschen, J., and Treen, E. (2018). Artificial intelligence in advertising: How marketers can leverage artificial intelligence along the customer journey," *Journal of Advertising Research, Vol.* 58 No. 3, pp. 263-267.

149. Kocadağlı, O., and Keskin, R. (2015). A novel portfolio selection model based on fuzzy goal programming with different importance and priorities, *Expert Systems with Applications,* 42 (20), 6898–6912.

150. Kolomvatsos, K., Anagnostopoulos, C., Hadjiefthymiades, S. (2012). A Fuzzy Logic System for Bargaining in Information Markets, *ACM Transactions on Intelligent Systems and Technology,* 3(2), 32

151. Kong, E., and. Dietterich, T. (1995). Error-correcting output coding corrects bias and variance. In *Proceedings of the Twelfth International Conference on Machine Learning,* pp. 313–321.

152. Kordupleski, Ray. (2003). Mastering Customer Value Management: The Art and Science of Creating Competitive Advantage, *Customer Value Management Inc,* 2003

153. Kosko, B. (1994). Fuzzy systems as universal approximators, *IEEE Transactions on Computers,* 43 (11).

154. Kotler, P. (2009). Marketing management, *Pearson Education,* India.

155. Kotler, P., Gregor, W. T., and Rodgers, W. H. (1977). The marketing audit comes of age. *Sloan Management Review,* 18(2), 25–43.

156. Kotler, P., Kartajaya, H., and Setiawan, I. (2013). Marketing 3.0: From Products to Customers to the Human Spirit, *Wiley: Hoboken, NJ, USA.*

157. Kotler, P.; Kartajaya, H.; Setiawan, I. (2016). Marketing 4.0: Moving from Traditional to Digital; *John Wiley & Sons*: Hoboken, NJ, USA, 2016.

158. Kovács Balázs (2012). Automatic Analysis of in-depth Interviews: Detection of Brand Names and Respondents' Gender, *SEFBIS JOURNAL* 7, 31-37.

159. Kruzslicz Ferenc, Bagó Péter, Balogh L Dániel. (2009). Content analysis of Hungarian blogs on economics. *Culture of Business - Capital of Culture International Conference, Pécs*, 15 - 17 October 2009. Tudományos.

160. Kumar, A., Mangla, S., Luthra, S., Rana, S., and Yogesh, K. (2018). Predicting changing pattern: building model for consumer decision making in digital market, *Journal of Enterprise Information Management*, 31 (5), 674-703.

161. Kumar Rakesh Ranjan (2016). Value co-creation: Concept and measurement. Journal of the Academy of Marketing Science Vol 44(3), pp 290-315

162. Kumar, V., and Shah, D. (2009). Expanding the role of marketing: From customer equity to market capitalization. *Journal of Marketing*, 73(November), 119– 136.

163. Laha, A. (2006). Developing credit scoring models with SOM and fuzzy rule-based k- NN classifiers. *In IEEE International Conference on Fuzzy Systems (FUZZY),* Vancouver, BC.

164. Larry D. Kelley, Donald W. Jugenheimer and Kim Bartel Sheeham (2015). Advertising Media Planning – A Brand Management Approach, Fourth Edition, Routledge.

165. Lashinsky, A. (2019). Artificial intelligence: Separating the hype from the reality. Retrieved Feburary 11, 2019 from http://fortune.com/2019/ 01/22/artificial-intelligence-ai-reality/.

166. Lavalle, S., Lesser, E., Shockley, R., Hopkins, M. S., & Kruschwitz, N. (2011). Big data, analytics and the path from insights to value. *MIT Sloan Management Review*, 52(2), 21–31.

167. Lee, D., Hosanagar, K., and Nair, H. (2018). Advertising content and consumer engagement on social media: evidence from Facebook, *Management Science.*

168. Lee, D., Hosanagar, K., and Nair, H. (2018). Advertising content and consumer engagement on social media: evidence from Facebook, *Management Science*.

169. Lee, M. and Takagi, H. (1993) Integrating design stages of fuzzy systems using genetic algorithms. *IEEE Trans,* Paper 0-7803-0614-7/93.

170. Lee, S. Ahn, H. (2009). Fuzzy cognitive map based on structural equation modeling for the design of controls in business-to-consumer e-commerce web-based systems, *Expert Systems with Applications,* 36(7), 10447-10460.

171. Leeflang, P. S. H., Verhoef, P. C., Dahlström, P., and Freundt, T. (2014). Challenges and solutions for marketing in a digital era. *European Management Journal,* 32(1), 1–12.

172. Lehtinen, J., Aaltonen, K. and Rajala, R. (2019). Stakeholder management in complex product systems: Practices and rationales for engagement and disengagement, *Industrial Marketing Management,* 79(5), 58-70.

173. Leung, E., Paolacci, G., and Puntoni, S. (2018). Man versus machine: Resisting automation in identity-based consumer behavior. *Journal of Marketing Research,* 55(6), 818–831.

174. Li, M., Liu, L., and Li, C. (2011). An approach to expert recommendation based on fuzzy linguistic method and fuzzy text classification in knowledge management systems. *Expert Systems with Applications*, vol. 38, no. 7, pp.

8586–8596.

175. Liou, T and Chen, C. (2006). Subjective appraisal of service quality using fuzzy linguistic evaluation," *International Journal of Quality and Reliability Management*, vol. 23, no. 8, pp. 928-943.

176. Liu, C., Chen, S. (2009). Prioritization of digital capital measures in recruiting website for the national armed forces, *Expert Systems with Applications*, 36(5), 9415-9421.

177. Li, S, Barry, D., John, E., Russell, K and Yanging, D. (2002). Integrating group Delphi, fuzzy logic and expert systems for marketing strategy development: the hybridization and its effectiveness. *Marketing Intelligence and Planning*, 20(5), 273-284.

178. Li, S., Li, J. and Li, S. (2013). A web-based hybrid system for evaluating marketing and e-commerce web site performance, *Proceedings - 4th International Conference on Digital Manufacturing and Automation*, ICDMA.

179. Li, S., Li, J., He, H., Ward, P. and Davies, B. (2011). WebDigital: A Web-based hybrid intelligent knowledge automation system for developing digital marketing strategies, *Expert Systems with Applications*, 38 (8), 10606-10613.

180. Lilien, G. L. (2016). The B2B knowledge gap. *International Journal of Research in Marketing*, (In press).

181. Lingqvist, O., Plotkin, C. L., and Stanley, J. (2015). Do you really understand how your business customers buy? *McKinsey Quarterly*, (1), 74–85.

182. Linsone, H. and Turoff, M. (1975). The Delphi Method Techniques and Applications

183. Liu, Y., Kiang, M. and Brusco, M. (2012). A unified framework for market segmentation and its applications, *Expert systems with applications, 39* (11), 10292-10302.

184. Liu, Y., Laguna, J., Wright, M., and He, H. (2014). Media mix modeling – A Monte Carlo simulation study. *Journal of Marketing Analytics,* 2(3), 173–186.

185. Løkke, A and Sørensen, D. (2014). Theory Testing Using Case Studies. Electronic *Journal of Business Research Methods*, 12(1), 2014.

186. Longoni, C., Bonezzi, A., and Morewedge, C. (2019). Resistance to Medical Artificial Intelligence. *Journal of Consumer Research* (forthcoming).

187. Luo, X., Tong, S., Fang, Z., and Zhe, Q. (2019). Machines vs. humans: The impact of chatbot disclosure on consumer purchases. Unpublished working paper.

188. Luo, Y., Pang, S., and Qiu, S. (2003). Fuzzy cluster in credit scoring, in: Paper presented at *Title of the International Conference on Machine Learning and Cybernetics.*

189. Malhotra, R., and Malhotra, D. (2002). Differentiating between good credits and bad credits using neuro-fuzzy systems, *European Journal of Operations Research,* 136, 190–211.

190. Mamdani, Ebrahim. (1977). Application of fuzzy logic to approximate reasoning using linguistic synthesis. *Computers IEEE Transactions,* C-26(12), 1182-1191.

191. Martin, K. D. and Murphy, P. E. (2017). The role of data privacy in marketing. *Journal of the Academy of Marketing Science,* 45(2), 135–155.

192. Martinez-Lopez, Francisco and Jorge, Casillas. (2009). Marketing intelligent systems for consumer behavior modeling by a descriptive induction approach based on Genetic Fuzzy Systems. *Industrial Marketing Management,* 38, 714-731.

193. Mathur, Y. and Nand, A. (2014). Soft computing techniques and its impact in data mining, *International Journal of Emerging Technology and Advanced Engineering.*

194. Mavlanova, T., Benbunan, R., and Lang, G. (2016). The Role of External and Internal Signals in E-Commerce. *Decision Support Systems*, 87, 59–68.

195. McDonald, M. (2010). A brief review of marketing accountability, and a research agenda. *Journal of Business & Industrial Marketing,* 25(5), 383–394.

196. Megargel, A., Shankararaman, V and Reddy, S. (2018). Real-time inbound marketing: A use case for digital banking. *Handbook of blockchain, digital finance, and inclusion: Cryptocurrency, FinTech, InsurTech, and regulation*. 311-328.

197. Mende, M., Scott, M., Doorn, J., Grewal, D. and Shanks, I. (2019). Service Robots Rising: How Humanoid Robots Influence Service Experiences and Elicit Compensatory Consumer Responses, *Journal of Marketing Research*, 56(4), 535-556.

198. Mercanti-Guerin, M., and Bezes, C. (2017). Similarity in marketing: Scope, measurement, and fields of application, *Recherche et Applications en Marketing,* 32 (1), 83-105.

199. Merriam, Sharan B. (1998). Qualitative research and case study applications in education (2nded.). San Francisco, CA: *Jossey-Bass Publishers*.

200. Mikulich, L. eds., Machine Intelligence, *Halstead Press,* New York, 9, 149-194

201. Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A., Veness, J. and Bellemare, M. (2015). Human-level control through deep reinforcement learning, *Nature,* 518, 7540, 529–533.

202. Moher, D., Liberati, A., Tetzlaff, J. and Altman, D. G. (2009). Preferred reporting items for systematic reviews and meta-analyses: *The PRISMA statement. J. Clin. Epidemiol. 2009*, 6.

203. Mohanty, B., Passi, K. (2010). Agent based e-commerce systems that react to buyers' feedbacks–A fuzzy approach, *International Journal of Approximate Reasoning,* 51(8), 948-963.

204. Moon, T., and Sohn, S. (2010). Survival analysis for technology credit scoring adjusting total perception, *Journal of Operations Research Society,* 62 (6), 1159–1168.

205. Morgan, J. T. Parish, and G. Deitz (Eds.), Handbook of Research in Relationship Marketing (pp. 75). Northampton, UK: Edward Elgar Publishing.

206. Muriana, C., Piazza, T., and Vizzini, G. (2016). An expert system for financial performance assessment of health care structures based on fuzzy sets and KPI, *Knowledge-Based Systems*, 97, 1-10.

207. Murphy, M. K., Black, N. A., Lamping, D. L., McKee, C, M., Sanderson, C. F. and Askham, J. (1998). Consensus development methods, and their use in clinical guideline development. *Health Technol Assess.* 2, 1–88.

208. Murugananthan, A., Gandhi, G. (2020). Framework for Social Media Analytics based on Multi-Criteria Decision Making (MCDM) model. *Multimedia Tools and Applications,* 79, 3913–3927.

209. Nagy, Á., Szűcs, K., Kemény, I., Simon, J., and Németh, P. (2019). Opinion leadership, web shop effectiveness - an integrated model to predict recommendation and Interdisciplinary Management Research, 15, 652-664.

210. Naili, M., Boubetra, A., Tari, A. (2015). Fuzzy Multi-Criteria Decision-Making Methods for E-Commerce Issues. *Fuzzy Optimization and Multi-Criteria Decision Making in Digital Marketing,* 20.

211. Neely, A., Gregory, M., and Platts, K. (1995). Performance Measurement System Design: A Literature Review and Research Agenda. *International Journal of Operations and Production Management,* 15(4), 80–116.

212. Nickerson (2015) Customer experience diagnostics. OpinionLab, 2015. Retrieved from: http://www.opinionlab.com/wpcontent/uploads/2015/12/WP_Customer_Experience_Diagnostics.pdf (Last accessed, September 2017).

213. O'Sullivan, D., & Butler, P. (2010). Marketing accountability and marketing's stature: An examination of senior executive perspectives. *Australasian Marketing Journal*, 18(3), 113–119.

214. O'Sullivan, D., Abela, A. V., & Hutchinson, M. (2009). Marketing performance measurement and firm performance: Evidence from the European high- technology sector. *European Journal of Marketing,* 43(5/6), 843–862.

215. Okoli, C. and Schabram, K. A. (2010). Guide to Conducting a Systematic Literature Review of Information Systems Research, *Sprouts:* Phoenix, AZ, USA, Volume 10.

216. Onwuegbuzie, A.J., Collins, K.M., Leech, N.L., Dellinger, A.B., Jiao, Q.G. (2010). A meta-framework for conducting mixed research syntheses for stress and coping researchers and beyond. In Toward a Broader Understanding of Stress and Coping:

Mixed Methods Approaches, *Information Age Publishing:* Charlotte, NC, USA, 169–211.

217. Onwuegbuzie, A.J., Leech, N.L., Collins, K.M.T. (2012). Qualitative analysis techniques for the review of the literature. *Qual. Rep*, 17, 1–28.

218. Opreana, A., and Vinerean, S. (2015). A new development in online marketing: introducing digital inbound marketing. *Expert Journal of Marketing,* 3(1), 29-34.

219. Ou, Chin-Wen., Shuo-Yan, Chou. and Yao-Hui, Chang. (2009). Using a strategy-aligned fuzzy competitive analysis approach for market segment evaluation and selection. *Expert Systems with Applications,* 36, 527-541.

220. Parekh, J. (2018). Why Programmatic provides a better digital marketing landscape. Retrieved February 20, 2020, from https://www.adweek. com/programmatic/why-programmatic-provides-a-better-digital- marketing-landscape/

221. Patrutiu-Baltes, L. (2016). Inbound Marketing -the most important digital marketing strategy. *Economic Sciences,* Vol. 9, No. 2, pp. 61-68.

222. Payne, E., Peltier, J., and Barger, V. (2017). Omni-channel marketing, integrated marketing communications, and consumer engagement: A research agenda. Journal of Research in Interactive Marketing, Vol 11 No. 2, pp. 185-197.

223. Pedersen, I., Reid, S., & Aspevig, K. (2018). Developing social robots for aging populations: A literature review of recent academic sources. Sociology Compass, 12(6).

224. Pedrycz, W. (1996). Fuzzy modelling: Paradigms and Practices, *Kluwer Academic. Publications.*

225. Peker, S., Kocyigit, A. and Eren, P.E. (2017). A hybrid approach for predicting customers' individual purchase behavior", Kybernetes, Vol. 46 No. 10, pp. 1614-1631.

226. Piekkari, R., Plakoyiannaki, E., and Welch, C. (2010). Good case research in industrial marketing: Insights from research practice. *Industrial Marketing Management*, 39(1), 109–117.

227. Powell, A., Noble, C., Noble, S. and Han, S. (2018). Man vs. machine: Relational and performance outcomes of technology utilization in small business CRM support capabilities. *European Journal of Marketing,* Vol. 52 No. 3/4, pp. 725-757. https://doi.org/10.1108/EJM-10-2015-0750

228. Power, B. (2017). How AI is streamlining marketing and sales." Harvard Business Review, June 12. Retrieved Jan 11, 2020, from https://hbr.org/2017/06/how-ai-is-streamlining-marketing-and- sales.

229. Prónay, Szabolcs., and Hetesi, Erzsébet (2016). Symbolic consumption in the case of brand communities. *Society and Economy*, 38 (1), 87-102.

230. PwC (2017). Sizing the Prize: What is the Real Value of AI for Your Business and How Can You Capitalize? London: *PwC*.

231. Raman, K., Mantrala, M., Sridhar, S. and Tang, Y. (2012). Optimal Resource Allocation with Time-varying Marketing Effectiveness, Margins and Costs, *Journal of Interactive Marketing*, 26(1), 43-52.

232. Rahman, M.S., Hossain, M.A., Abdel Fattah, F.A.M. and Akter, S. (2020). Optimizing competitive performance of service firms in data-rich environment, *Journal of Service Theory and Practice*, 49, 1-19.

233. Rahwan, I., Cebrian, M., Obradovich, N., Bongard, J., Bonnefon, J. F., Breazeal, C., et al. (2019). Machine behavior. *Nature*, 568(7753), 477–486.

234. Ramkumar, V., Rajasekar, S., and Swamynathan, S. (2010). Scoring products from reviews through application of fuzzy techniques, *Expert Systems with Applications*, 37(10), 6862-6867.

235. Reese, B. (2018). The fourth age: Smart robots, conscious computers and the future of humanity, New York, NY, *Atria Books.*

236. Rekettye, Gábor and Rekettye, Jr., Gábor (2019). The Effects of Digitalization on Customer Experience (September 12, 2019). 2019 ENTRENOVA Conference Proceedings, Available at SSRN: https://ssrn.com/abstract=3491767 or http://dx.doi.org/10.2139/ssrn.3491767

237. Rigby, D. and Ledingham, D. (2004). CRM done right. *Harvard Business Review*, 84(11), 118–129.

238. Rigby, D. K., Reichheld, F. and Schefter, P. (2002). Avoid the four perils of CRM. *Harvard Business Review*, 80(2), 5–11.

239. Rizkallah, J. (2017). The Big (Unstructured) Data Problem." Forbes, June 5, 2017. Retrieved from https://www.forbes.com/sites/forbestechcoun-cil/2017/06/05/the-big-unstructured-data- problem/#57541ca2493a

240. Rohm, A., Hanna, R. and Crittenden, V. (2011). We are all connected: The power of the social media ecosystem, *Business Horizons,* 54(3):265-273.

241. Ross Timothy, J. (2010). Fuzzy Logic with Applications. *Third Edition, John Wiley & Sons.*

242. Royle, J., and Laing, A. (2014). The digital marketing skills gap: Developing a digital marketer model for the communication industries. *International Journal of Information Management*, 34(2), 65–73.

243. Ruiz-Mezcua, B. Garcia-Crespo, A., Lopez-Cuadrado, J., and Gonzalez-Carrascoa, I. (2011). An expert system development tool for non-AI experts. Expert Systems with Applications, 38, 597–609.

244. Ryan, D., and Jones, C. (2009). Understanding Digital Marketing: Marketing Strategies for Engaging the Digital Generation. *Kogan Publisher*.

245. Sanchez-Roger, M., Oliver-Alfonso, M., and Sanchiz-Pedregosa, C. (2019). Fuzzy logic and its uses in finance: a systematic review exploring its potential to deal with banking crises, *Mathematics, MDPI*, 7 (2019).

246. Sanchez-Roger, M., Oliver-Alfonso, M., and Sanchiz-Pedregosa, C. (2019). Fuzzy logic and its uses in finance: a systematic review exploring its potential to deal with banking crises, *Mathematics, MDPI*, 7.

247. Santonino, M.D. (2020). Review on Weinstein's superior customer value: finding and keeping customers in the now economy, *Journal of Marketing Analytics*, 8, 39–41.

248. Sayer, A. (1992). Method in social science: A realist approach, 2nd ed, London, *Routledge.*

249. Sayer, A. (2000). Realism and social science, London: *Sage*

250. Şengül, U. and Eren, M. (2015). Selection of digital marketing tools using fuzzy AHP fuzzy TOPSIS, *Fuzzy Optimization and Multi-Criteria Decision Making in Digital Marketing*, 97.

251. Schmucker, K. (1985). Fuzzy Sets, Natural Language Computations, and Risk Analysis," New York: Computer Science Press, Inc.

252. Şengül, U., Eren, M. (2015). Selection of digital marketing tools using fuzzy AHP fuzzy TOPSIS, *Fuzzy Optimization and Multi-Criteria Decision Making in Digital Marketing*, 97.

253. Shankar, V. (2018), "How artificial intelligence (AI) is reshaping retailing," *Journal of Retailing*, Vol. 94 No. 4, pp. Vi–xi.

254. Shaun Downey, Darryl Charles, "Distribution of Artificial Intelligence in Digital Games", International Journal of Intelligent Information Technologies, vol. 11, pp. 1, 2015

255. Sifiyabadi, J., Kolahi, B. and Valmohammadi, C. (2015). Key performance indicators measurement in service business: a fuzzy VIKOR approach, *Total Quality Management and Business Excellence*, (2015).

256. Simons, H. (2009). Case study research in practice. Los Angeles, CA, *Sage.*

257. Singh, M. G., Bennavail, J. C. (1993). PRICE-STRAT: A Knowledge Support System for Profitable Decision-Making During Price Wars". *Information and Decision Technologies,* 19, 227-296.

258. Slade, S. C., Dionne, C. E., Underwood, M. and Buchbinder, R. (2014). Standardized method for reporting exercise programmes: protocol for a modified Delphi study. *BMJ Open.*

259. Smith, M. (2006). Overcoming theory practice inconsistencies: Critical realism and information systems research, *Information and Organization,* 16(3), 191-211.

260. Smith, W. (1956). Product differentiation and market segmentation as alternative marketing strategies, *The Journal of Marketing,* 2 (1), 3-8.

261. Soegoto, E., and Simbolon, T. (2018). Inbound Marketing as a Strategy in Digital Advertising. *IOP Conference Series: Materials Science and Engineering*, 407, 012183.

262. Solon, O. and Laughland., O. (2018). Cambridge Analytica closing after Facebook data harvesting scandal. *The Guardian, May 2, 2018*. Retrieved from https://www.theguardian.com/ uk-news/2018/may/02/cambridge-analytica- closing-down-after-facebook-row-reports-say

263. Sohn, S., Kim, S., and Yoon, J. (2016). Technology credit scoring model with fuzzy logistic regression, *Applied Soft Computing,* 43,150–158.

264. Sostak, A. (2010) Mathematics in the context of fuzzy sets: basic ideas, concepts, and some remarks on the history and recent trends of development, *Mathematical Modelling and Analysis,* Volume X Issue x, 20xx, 1–20.

265. Stake, R. E. (2006) Multiple Case Study Analysis, *The Guilford Press*, New York, NY

266. Stake, Robert E. (2006). Multiple case study analysis. New York, NY: Guilford

267. Stewart, Alison (2014). Case study. In Jane Mills & Melanie Birks (Eds.), *Qualitative methodology:* A practical guide (pp.145-159). Thousand Oaks, CA: *Sage*.

268. Stewart, Alison. (2014). Case study. In Jane Mills & Melanie Birks (Eds.), Qualitative methodology, *A practical guide* (pp.145-159). Thousand Oaks, CA: Sage.

269. Stewart, D. W. (2009). Marketing accountability: Linking marketing actions to financial results. *Journal of Business Research*, 62(6), 636–643.

270. Stone, M (2015). The evolution of the telecommunications industry — What can we learn from it? *J Direct Data Digital Marketing Practice,* 16, 157–165.

271. Strauss, A., and Corbin, J. (1990). Basics of Qualitative Research: Grounded Theory Procedures and Techniques. Newbury, *Sage*.

272. Sturiale, A., and Scuderi, L. (2016). The Relationship between Product and Consumer Preference for Agri-Food Product: “Red orange of Sicily” Case. *IERI Procedia*, 8, 52–59

273. Sugeno, M. (1974). Theory of fuzzy integrals and its application, PhD Dissertation, *Tokyo Institute of Technology*, Tokyo, Japan.

274. Sugeno, M. (1985) An introductory survey of fuzzy control. *Inf. Sci.,*36, 59 – 83.

275. Susanto, S., Vasant, P., Bhattacharya, A. and Fransiscus, R. (2006). Fuzzy LP with a Non-Linear MF for Product-Mix Solution: A Case-Based Re-modelling and Solution. *Proceedings of the 9th Joint Conference on Information Science.*

276. Swanborn, P. (2010). Case Study Research: What, Why and How? *Sage*, London

277. Swani, K., Brown, B. P., and Milne, G. R. (2014). Should tweets differ for B2B and B2C? An analysis of Fortune 500 companies’ Twitter communications. *Industrial Marketing Management*, 43(5), 873–881.

278. Syam, N., and Sharma, A. (2018). Waiting for a sales renaissance in the fourth industrial revolution: Machine learning and artificial intelligence in sales research and practice. *Industrial Marketing Management,* Vol. 69, pp. 135–146.

279. Syau, Y. R., Hsieh, H. T. and Lee, E.S. (2001). Fuzzy numbers in the credit rating of enterprise financial condition. *Rev. Quant. Financ. Account,* 17, 351–360.

280. Szmigin, I. and Foxxall, G. (2000). Interpretive consumer research: How have we come? Quantitative Market Research: *An International Journal,* 3(4), 187-197.

281. Tavana, M. Khalili-Damghani, K., and Sadi-Nezhad, S. (2013). A fuzzy group data envelopment analysis model for high-technology project selection: a case study at NASA, *Computer and Industrial Engineering,* 66 (1), 10–23.

282. Tawfik, G., Mohamed, M., Dila, K, and Tam, D. (2019). A step by step guide for conducting a systematic review and meta-analysis with simulation data. *Tropical Medicine and Health,* 47 (1) (2019), 46.

283. Taylor, S., and Berridge, V. (2006). Medicinal plants and malaria: an historical case study of research at the London School of Hygiene and Tropical Medicine in the twentieth

284. century. Transactions of the Royal Society of Tropical Medicine and Hygiene, 100(8),

285. 707-714.

286. Temponi, Cecilia., John Yen. and Amos, Tiao. (1999). House of quality: a fuzzy logic-based requirements analysis, *European Journal of Operational Research,* 117, 340-354.

287. Thaker, S., and Nagori, V. (2018). Analysis of fuzzification process in fuzzy expert system, *Procedua Computer Science,* 132, 1308 -1316.

288. Torrecilla-Salinas, C. J., De Troyer, O., Escalona, M.J. and Mejías, M. A. (2019). Delphi-based expert judgment method applied to the validation of a mature Agile framework for Web development projects. *Information Technology. Management*, 20, 9–40.

289. Tsai, C. and Chen, M. (2010). Credit rating by hybrid machine learning techniques, *Applied Soft Computing*, 10 (2), 374–380.

290. Tzafestas, S. G. (1994). Fuzzy Systems and Fuzzy Expert Control: An Overview." *The Knowledge Engineering Review*, 9, 229-268.

291. Tzafestas, S., Raptis, S. and Moschos, N. (1994). A Hybrid Pricing Expert System Based on Fuzzy Reasoning.

292. Valenduc, G and Vendramin, Patricia (2016). Work in the digital economy: sorting the old from the new European Trade Union Institute

293. Verhoef PC, Reinartz WJ., and Krafft M. (2010). Customer Engagement as a New Perspective in Customer Management. *Journal of Service Research,*13(3):247-252.

294. Verhoef, P. and Lemon, K. (2015). Advances in customer value management. In R. M. Vernuccio, M., and Ceccotti, F. (2015). Strategic and organizational challenges in the integrated marketing communication paradigm shift: A holistic vision. European Management Journal, Vol. 33 No. 6, pp. 438–449.

295. Verhoef, P. and Lemon, K. (2013). Successful customer value management: key lessons and emerging trends, European Management Journal. 31, 1– 15.

296. Verhoef, P. C., and Leeflang, P. S. H. (2009). Understanding the marketing department's influence within the firm. *Journal of Marketing*, 73(March), 14– 37.

297. Verhoef, P., and Lemon, P. (2015). *Journal of Marketing:* AMA/MSI Special Issue, 80, 69–96.

298. Verhoef, P., Kannan, P., and Inman, J. (2015). From Multi-Channel Retailing to Omni-Channel Retailing: Introduction to the Special Issue on Multi-Channel Retailing, *Journal of Retailing*, 91(2), 174-181.

299. Verhoef, P., Kooge, E. and Walk, N. (2016). Creating Value with Big Data Analytics - Making smarter marketing decisions, *Routledge*, Taylor & Francis Group

300. Vipul Guptal K. and Celtek, Serkan. (2001). A fuzzy expert system for small business loan processing, *Journal of International Information Management*, 10(2), Article 2.

301. Wang, W., Malthouse, E., Calder, B., and Uzunoglu, E. (2017). B2B content marketing for professional services: In-person versus digital contacts. *Industrial Marketing Management*. doi: 10.1016/j.indmarman.2017.11.006

302. Wang, Y., & Kosinski, M. (2018). Deep neural networks are more accu- rate than humans at detecting sexual orientation from facial images. Journal of Personality and Social Psychology, 114(2), 246–257.

303. Wang, Y., and Feng, H. (2012). Customer relationship management capabilities. *Management Decision*, 50(1), 115-129.

304. Wasan, S.K., Bhatnagar, V. and Kaur, H. (2007). An Efficient Interestingness based Algorithm for Mining Association Rules in Medical Databases, *Advances in Systems, Computing Sciences and Software Engineering*, Springer, 167-172.

305. Webster, J. G., and Ksiazek, T. B. (2012). The dynamics of audience fragmentation: Public attention in an age of digital media. *Journal of Communication*, 62(1), 39–56.

306. Welling, R., & White, L. (2006). Web site performance measurement: Promise and reality. Managing Service Quality, 16(6), 654–670.

307. Wellmann, N. (2019). Are OTT messaging and mobile telecommunication an interrelated market? An empirical analysis, *Telecommunications Policy,* 43 (9).

308. Werro, N. Stormer, H., Meier, A. (2005). Personalized discount – A fuzzy logic approach. In Proceedings of the 5th IFIP *International Conference on eBusiness, eCommerce and eGovernment,* 375-387. Poznan, Poland.

309. Wilson J., Daugherty P., and Shukla P. (2016). How one clothing company blends AI and

310. Wilson J., Daugherty P., and Shukla P. (2016). How one clothing company blends AI and human expertise. Harvard Business Review, November 21. Retrieved February 11 from https://hbr.org/2016/11/

311. Woodside, A. and Wilson, E. (2003). Case study research for theory-building, Journal of Business and Industrial Marketing 18(6/7):493-508.

312. Li, X., Wong, H. and Wu, S. (2012). A fuzzy minimax clustering model and its applications, *Information Sciences: An International Journal,* 186 (1), 114-125, Elsevier Science Inc.

313. Yang, C. C., Ou, S.L. and Hsu, L. C. (2019). A Hybrid Multi-Criteria Decision-Making Model for Evaluating Companies' Green Credit Rating. *Sustainability,* 11, 1506.

314. Yankelovich, D., and Meer, D. (2006). Rediscovering Market Segmentation, *Harvard business Review* (2006).

315. Yazdi, H.S. Pourreza, R. and Sadoghi Yazdi, M. (2010). Constraint learning using adaptive neural-fuzzy inference system. *Int. J. Intell. Comput. Cybern,* 3, 257–278.

316. Yin, R. K. (1984). Case Study Research: Design and Methods. Beverly Hills, Calif: *Sage*

317. Yin, Robert K. (2014). Case study research: Design and methods. Los Angeles, CA, *Sage.*

318. Yoon, H. S, and Choi, H. S. (2019). The impact of life satisfaction of nursing students using the fuzzy regression model," International Journal of Fuzzy Logic and Intelligent System, Vol. 19, no. 2, pp, 59-66. http://doi.org/10.5391/IJFIS.2019.19.2.59

319. Yu, X., Guo, S., Guo, J. and Huang, X. (2011). Rank B2C e-commerce websites in e-alliance based on AHP and fuzzy TOPSIS. *Expert Systems with Applications,* 38(4), 3550-3557.

320. Zadeh, L. A. (1965). Fuzzy sets, *Information and Control*, 8 (1965), 338–353.

321. Zadeh, L. A. (1979). A theory of approximate reasoning. In: Hayes, J., Michie, D., &

322. Zandi, F. and Tavana, M. (2011). A fuzzy group quality function deployment model for e- CRM framework assessment in agile manufacturing, Computers and Industrial Engineering, 61(1), 1-19.

323. Zimmermann, H. (1991) Fuzzy Set Theory and its Applications, 2nd edn, *Kluwer Academic*, Dordrecht.

324. Zimmermann, H. (2001). Fuzzy Set Theory—and Its Applications, *Mathematics,* Springer.

325. Zumstein, D. (2010). Web analytics - analyzing, classifying and describing web metrics with fuzzy logic. *In Proceedings of the 6th International Conference on Web Information Systems and Technology,* (WEBIST)