Sustaining E-Commerce Profitability:

A Hybrid Quantitative Investigation Into Critical Success Factors (CSFs)

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ABSTRACT

In the contemporary digital landscape, e-commerce has rapidly evolved, reshaping consumer behaviour and the retail industry. This study explores the dynamic factors affecting customer satisfaction and profitability in e-commerce. Utilising a comprehensive methodological framework that includes fuzzy Delphi, fuzzy BWM, C-means clustering, and fuzzy COPRAS methods, the research identifies and prioritises critical success factors influencing online consumer behaviour. An analysis of 602 customer records classifies purchasing behaviours and demographic characteristics into distinct clusters. Key findings underscore the significance of customer reviews, recommendation systems, shopping satisfaction, and personalised shopping experiences in driving e-commerce success. Methodologically, the study demonstrates the effectiveness of advanced analytical techniques in managing uncertainty and complexity in e-commerce data. Despite its contributions, the research acknowledges limitations, including the cross-sectional nature of the data, sample size constraints, and the need for broader generalisability. Future research directions include integrating emerging technologies, conducting longitudinal studies, and developing cross-channel strategies to enhance customer engagement and profitability.

KEYWORDS

E-commerce, Profitability, Customer Behaviour, Critical Success Factors, Online Shopping, Fuzzy Delphi Method, Fuzzy BWM, C-means, Fuzzy COPRAS, Data Analysis.

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1 INTRODUCTION

1.1 FOCUS OF THE STUDY

Over the past few decades, there has been a remarkable shift in consumption patterns and behaviours (Liao et al., 2008). This transformation has been largely influenced by the advancement of the World Wide Web, the digitisation and digitalisation of various societal processes, and continuous enhancements in technology accessibility (Buldeo Rai, 2021; Ritter & Pedersen, 2020). These processes include the growing use of digital technologies to connect people, systems, companies, products, and services (Ritter & Pedersen, 2020). They also involve converting various interactions, communications, business functions, and models into digital formats, facilitating automation and expediting tasks (Guaita Martínez et al., 2022). This intricate concept presents complexity due to its associated facets, impacting organisations across different levels and contexts(Broekhuizen et al., 2021; Tiago et al., 2021). One significant facet of digitisation and digitalisation is the integration of e-commerce and online shopping into everyday life, permeating all societal strata and business realms, from email utilisation to smartphone applications. This integration has fundamentally reshaped the execution of daily activities for most individuals (Branca et al., 2020).

With the rapid evolution of online shopping , customer behaviour has become a challenging and dynamic field to navigate. (Jaller & Pahwa, 2020; Lissitsa & Kol, 2016). Since the historic occurrence of the first internet-based retail transaction in August 1994 (Lewis, 1994), the internet has been consistently transforming our shopping behaviours. E-commerce, a concept that was entirely unfamiliar just a few decades ago, is now steadily reshaping and redefining our everyday lives (Jaller & Pahwa, 2020). The rise of widespread online purchasing marks a pivotal moment in the history of the retail industry (Har et al., 2022).

E-commerce refers to the buying or selling of goods and services using computer networks. It involves using dedicated methods for placing orders without the necessity of conducting payment and delivery processes online (Publishing, 2011). Also, online shopping encompasses a wide range of activities, including exploring online stores and their offerings, seeking out product details, choosing payment methods, engaging with other customers and sellers, and ultimately making purchases of goods or services. (Cai & Cude, 2016). E-commerce is characterised by a highly competitive market (Park & Kim, 2003) with significant variability in customer behaviour, making it a complex sector to operate in (Hernández et al., 2010; Sismeiro & Bucklin, 2004).

Therefore, it is important to take customer behaviour into account when identifying the critical success factors (CSFs) for any e-commerce platform (Bilgihan et al., 2016; Buldeo Rai, 2021). Understanding and influencing customer behaviour can significantly impact an e-commerce (Park & Kim, 2003; Rita et al., 2019a).

In the context of e-commerce, customer behaviour accommodates several key dimensions, including purchase decision-making (Maity & Dass, 2014), satisfaction (Chang & Chen, 2009), trust (Hasan, 2016), loyalty (Gefen, 2002), online shopping experience (Jaller & Pahwa, 2020), cross-cultural differences (de Mooij & Hofstede, 2011), and customer switching behaviour (Keaveney & Parthasarathy, 2001).

The surge in e-commerce, influenced by the digital era and technological advancements, has reshaped consumer behaviour. The highly competitive and dynamic nature of online shopping underscores the need to understand and influence customer behaviour for success. Therefore, delving into this domain through rigorous academic methods and tapping into the wisdom of seasoned experts propel us toward a deeper understanding of customer behaviour, ultimately paving the way for enhanced.

1.2 Objectives and Motivation

Following years of development, the integration of the internet and mobile networks has become inseparable from both professional and personal spheres. E-commerce, identified as a key driver of growth in several countries (Yang et al., 2020), has transformed into a vital channel for meeting daily consumption needs, particularly in the realm of consumer goods. Online shopping is popular because it gives consumers easy access to products and prices, overcoming limitations of space, time, and variety (L. Yang et al., 2022).

The process of online purchase decision making is defined by its fluid essence and a high degree of flexibility (Karimi et al., 2015). Decision makers exhibit adaptability in their response to decision tasks (Klein & Yadav, 1989; Payne et al., 1988, 1993). As the decision-making process unfolds, individuals have the freedom to make choices and can take different paths. This flexibility is represented by the capacity to modify the sequence of steps in the process by adding, skipping, or reordering them based on individual preferences and needs (Dorn et al., 2010). The following section elucidate some of these dimensions to comprehend the importance of decision-makers' behavioural aspects in e-commerce.

Customer satisfaction is a significant objective in consumer marketing, representing an emotional reaction to a purchase (Chang & Chen, 2009). Ensuring customer satisfaction is important when

assessing the perceived value delivered by e-commerce. Key factors significantly influence customer satisfaction, customer needs, value, and costs (Lin, 2003).

In the same way, trust and loyalty are vital components of customer behaviour. According to Gefen's research on trust in e-commerce (Gefen, 2000), trust is described as the willingness to place oneself in a vulnerable position based on a sense of confidence or assurance in the trusted party. Trust becomes particularly essential in situations where it is practically impossible to fully regulate a business agreement, requiring reliance on the other party to refrain from unfair advantage and opportunistic behaviour (Deutsch, 1958; Fukuyama, 1995; Williamson & Mueller, 1986).

Additionally, customer loyalty has traditionally been conceptualised as an attitude construct. It refers to the positive attitude held by a customer towards e-commerce, which in turn influences their inclination to engage in repeat purchasing behaviour (Chang & Chen, 2009).

Furthermore, the online shopping experience is now regarded as an integral component of behavioural constructs in the realm of e-commerce (Kawaf & Tagg, 2017). Undoubtedly, with the Internet emerging as a significant platform for product and service delivery and the rise of a new generation commonly referred to as "digital natives" (Akçayır et al., 2016; Prensky, 2001), the significance of the online shopping experience has greatly increased. Experience is widely recognised as the primary battleground for competition in today's global market (Weinman, 2015).

It is noteworthy that the online shopping experience refers to the user experience of customers as they navigate through various stages, including website design, ease of navigation, product search capabilities, and overall convenience and satisfaction, which consist of dimensions and components (Michaud Trevinal & Stenger, 2014). For instance, “positive affect”, an integral component of the online shopping experience, signifies the perception of enjoyment and pleasure. Moreover, pleasure acts as a mediator between environmental stimuli and behavioural response, with particular emphasis on its relation to shopping experiences (Mosteller et al., 2014).

However, cross-cultural differences that encompass variations in cognitive abilities, cognitive styles, cultural patterns, and disparities in infrastructure and economic development (Liao et al., 2008) introduce substantial variance in online shopping behaviours. When examining the impact of cultural factors on customer behaviour in e-commerce, it is important to consider the differences in preferences, values, and levels of trust across diverse cultural contexts.

Maybe something that would say, essentially, customer switching behaviour is another part of customer behaviour in the realm of e-commerce. Customer switching behaviour (smallbusiness.chron.com, 2020) is recognised as the driving force behind customers' decisions to

transition from one e-commerce brand to another. Extensive research has examined switching costs from multiple angles. Burnham et al. (Burnham et al., 2003) deconstructed switching costs into procedural (related to time and effort), financial (measurable loss), and relational (causing psychological discomfort due to severed personal and brand connections) dimensions. This deconstruction demonstrates that switching costs extend beyond economic considerations to encompass psychological and emotional aspects. Consequently, switching costs can be defined as consumers' subjective perceptions of the time, money, and effort required when transitioning to alternative e-service providers (Chang & Chen, 2009).

On the other hand, as businesses navigate the age of big data, the significance of extracting valuable insights from vast datasets is underscored. In this context, customer segmentation, involving the categorisation of a large consumer base into smaller, more refined groups based on various social, behavioural, and consumption characteristics, has risen to prominence as a critical strategic approach. (Y. Li et al., 2021).

By grouping customers and ranking them with unique consumption habits, businesses can gain a more comprehensive understanding of consumer behaviours and preferences. Additionally, the results of customer segmentation enable enterprises to tailor products and services to suit the specific needs of different consumer groups (Calvo-Porral & Lévy-Mangin, 2018). Consequently, the selection of an appropriate method to segment customers and prioritise them holds both theoretical significance and practical relevance (Yoseph et al., 2020).

To encapsulate all points discussed, sustaining e-commerce profitability has become a critical challenge for businesses worldwide in today's fast-paced digital landscape. The continuous evolution of online shopping and consumer behaviour, coupled with intense market competition, demands a strategic approach that goes beyond short-term gains.

1.3 Statement of Purpose

The challenge at hand involves identifying the key aspects and dimensions of customer behaviour in e-commerce domain in order to ensure sustained success. This requires a strategic approach that focuses on creating value and achieving consistent profitability associated with e-commerce. By striking a balance between these factors, sustainable and responsible practices can be fostered, leading to long-term success in the e-commerce industry.

The motivation behind this research arises from the increasing significance of online shopping and maintaining profitability in the e-commerce industry (Chen et al., 2021; Fedirko et al., 2021; Ingaldi & Ulewicz, 2019; Oláh et al., 2019). This research aims to expand our understanding of this field and

make a valuable contribution to the existing body of knowledge. The following research questions have been formulated to guide my inquiry and achieve the objectives. Through comprehensive analysis and data collection, my goal is to provide precious insights and findings that can inform decision-making and deepen our understanding in this domain.

1.4 RESEARCH QUESTIONS

The Main Question

- What critical success factors (CSFs) are associated with profitability in e-commerce?

The Related Questions

- What are the antecedents of customer purchase decisions?
- What is the weight of each antecedent for the online customer decisions?
- What is the optimal grouping of customers with respect to their different recordings and attributes?
- What is the best approach to rank groups of customers?
- Based on customer evaluations, what recommendations can be proposed for improving profitability?

1.5 RESEARCH PHILOSOPHY

While research philosophy is a broad subject that cannot be covered comprehensively, it pertains to a study's assumptions, knowledge, and nature. This area of study concerns the particular method of acquiring knowledge, which is important to consider as researchers may hold diverse views about the nature of truth and knowledge. Philosophy aids in comprehending the underlying assumptions.

In my upcoming research, I have considered the "onion of the research process" (Saunders et al., 2007) concept to establish the philosophical position and research type (Figure 1). This onion comprises multiple layers that demonstrate a logical link between philosophies, approaches, strategies, objectives, and data collection methods. In my endeavour to adopt a quantitative approach, I applied a diverse array of fuzzy logic approaches to effectively analyse and process a sizable database. Considering the specific characteristics and attributes of my research, I have determined that the research philosophy of post-positivism aligns best with my research objectives.

As a result, I have identified the following layers in the onion of the research process that is be incorporated into my future research (Table 1).

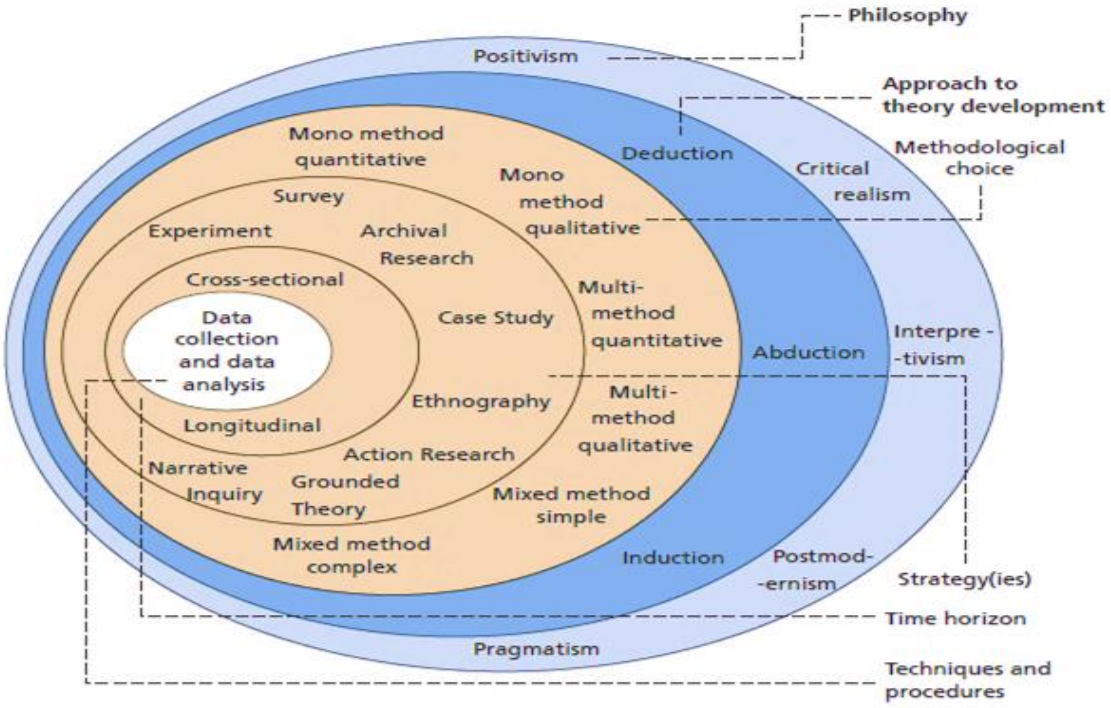

Figure 1: Onion of the research process

Table 1: Research Philosophy

Research Philosophy	Research Approach	Research strategy	Time Horizons	Data Collection	Sampling Strategy	Data Analysis
Post-positivism	*Induction*	*Survey*	*Cross-sectional*	*Secondary data*	*Non-probability*	*Quantitative*

Building on an understanding of the multifaceted landscape of e-commerce, this study aims to unravel the critical success factors (CSFs) tied to sustaining profitability in this dynamic industry. The transformative impact of online shopping, combined with the evolving dimensions of consumer behaviour, emphasizes the need for a strategic and forward-thinking approach to navigate the complexities of e-commerce. This study investigates the intricacies of customer behaviour, acknowledging its role in shaping the success of e-commerce platforms. The subsequent section will transition into a comprehensive review of the existing literature, providing a nuanced exploration of the various facets and theories surrounding e-commerce profitability and customer behaviour.

2 LITERATURE REVIEW

E-commerce is a lucrative industry, especially for consultants who provide valuable expertise in this field. It is nearly impossible to go through a newspaper or trade magazine without coming across an article discussing the triumphs or setbacks of various e-commerce ventures (Burt & Sparks, 2003; Gupta, 2014; Jain et al., 2021). E-commerce has been experiencing consistent growth in numerous developed countries (Escursell et al., 2021). Analysts project that market penetration in e-commerce in the US is expected to increase by as much as 25% by the year 2026 (Taylor, 2019).

Before proceeding further, it is important to establish a clear understanding of the term ”e-commerce” (Laudon & Traver, 2020; McKnight & Chervany, 2001). This term, also known as electronic commerce, encompasses a diverse range of online business activities related to the buying and selling of products and services. It refers to any business transaction in which the parties interact electronically, without physical exchanges or direct physical contact (Gupta, 2014). E-commerce surrounds a wide range of business transactions, including Business-to-Business (Shopify), Business-to-Consumer (Amazon), Consumer-to-Consumer (eBay), and Consumer-to-Business (SurveyMonkey).

One of the main aspects of e-commerce that makes the first impression on customers is its online platforms or applications. The e-commerce platform empowers customers with the ability to organise and categorise information, access online customer reviews and ratings, and enjoy an enhanced shopping experience with a wider range of options available (Bamfield, 2013b; Brynjolfsson et al., 2009).

On the other hand, sometimes certain factors can lead to a decrease in customer satisfaction during their online experiences, including inadequate security measures, privacy concerns, limited human contact and support, outdated technology, and poorly designed website pages (Bamfield, 2013b; Pauwels et al., 2011). The interactions, both online and offline, result in the generation of a massive amount of data and information. The systematic gathering, sorting, and analysis of this data are significant in gaining insights into the thoughts and preferences of online customers (Liu et al., 2020; Mergel et al., 2016; Moisander et al., 2020).

Numerous online shoppers often prefer waiting for feedback from early adopters before making a purchase decision to minimise the risk associated with buying a new product. E-commerce companies actively promote web-based social communities that enable consumers to exchange their personal experiences (Kim & Srivastava, 2007).

Covering these areas is necessary for understanding the relevance of the research because it establishes a foundational understanding of the broader context surrounding e-commerce and online purchasing decisions. By providing an overview of the definition of e-commerce and discussing decision-making aspects, you set the stage for exploring how e-commerce has evolved and the key factors influencing consumer behaviour online. Introducing the history of retailing and the evolution of e-commerce offers insights into the development and transformation of online shopping practices over time. Additionally, conducting a comprehensive literature review allows for a deeper exploration of the field's existing knowledge and research gaps, particularly concerning decision-making processes and success factors in online shopping and e-commerce.

Ultimately, I offered a summary of relevant research papers, with the aim of identifying key research challenges and understanding how decision-making influences the success of e-commerce. This review serve as the foundation for the subsequent phases of the research.

2.1 Retail Transformation: A Journey from Retail 1.0 to 4.0

Since the dawn of the first industrial revolution around 1760, humanity has witnessed a total of four industrial upheavals. Each of these revolutions has not only revolutionised manufacturing but has also significantly elevated the overall quality of human life (Reagan & Singh, 2020).

As the Industrial Revolution unfolded, it brought about great changes in the retail industry. First, during Retail 1.0, the introduction of steam engines enabled mass production and the rise of department stores. This led to Retail 2.0, where consumers benefited from more affordable products, resulting in the growth of shopping malls. Meanwhile, in Retail 3.0, the global adoption of online shopping via the internet transformed how we make purchases. This shift allowed us to buy virtually anything without leaving our homes, demonstrating how Retail 4.0 simplifies and enhances our lives. (Har et al., 2022).

Retail 4.0 includes a spectrum of omnichannel shopping possibilities and leverages a variety of Industry 4.0 technologies to enhance the overall shopping experience, service quality, and product offerings for customers (Jayaram, 2017; Sakrabani & Teoh, 2021)

While Industry 4.0 began to take shape around 2010, the term 'Retail 4.0' is relatively novel in the global retail landscape. Consequently, the adoption of Retail 4.0 technologies remains limited, particularly in developing nations, with the situation being even more challenging in the least developed countries (Har et al., 2022). Nevertheless, the adoption of modern technologies gained significant momentum due to the impact of the COVID-19 pandemic. Amid the coronavirus lockdown, individuals turned to online shopping, underscoring the seamless shopping experience offered by

new technologies that captivate customers. As a result, retailers found themselves compelled to adopt these technologies (Wright, 2020).

In response to the Industrial Revolution, the retail industry has experienced a fourfold transformation, divided into Retail 1.0, Retail 2.0, Retail 3.0, and Retail 4.0. The subsequent section will dig into the evolutionary journey of the retail sector.

2.1.1 Retail 1.0

The initial disruption in the retail landscape, known as Retail 1.0 or the era of mechanisation, commenced in the mid-eighteenth century and extended through the mid-nineteenth century. This period coincided with the introduction of electrification and the start of the second Industrial Revolution (Meyer, 2020). Throughout human history, craftsmanship has been central, with individuals crafting objects, including weapons, clothing, musical instruments, tools, and kitchenware, from raw materials sourced and cultivated on Earth (Reagan & Singh, 2020). However, a significant shift occurred in the late 1700s when factories emerged, employing steam-powered machinery for mass production, thereby attracting a new generation of urban workers (Har et al., 2022).

Before the late 1800s, local merchants dominated the retail landscape, offering a range of services to customers, including credit, repairs, and personalised product explanations. Transactions were conducted using physical cash, and merchants had to handle the physical depositing of cash and checks to keep the wheels of commerce turning (Ogilvie, 2011). Nevertheless, technological progress during the Industrial Revolution led to a substantial increase in the availability of affordable, high-quality goods (Learning, 2020). This transformation saw the emergence of department stores such as Bloomingdale's, Sears, and Macy's in cities like Chicago and New York City, catering to the expanding preferences of more prosperous Americans (Turow, 2017).

2.1.2 Retail 2.0

During the Second Industrial Revolution, often referred to as 'Industry 2.0' or the era of mass production, there was a significant ramp-up in the production of low-cost goods on a massive scale (Y. Wang et al., 2017). This surge in production facilitated the rapid growth of the automotive manufacturing sector (Har et al., 2022). The widespread availability of automobiles led to a migration of people from cities to suburban areas, resulting in the clustering of suburban shopping plazas and malls in distinct locales as suburban populations expanded (Reagan & Singh, 2020).

During this period, data marketing, which was in its nascent stages just a decade earlier, faced massive development as retailers began analysing transactions and conducting focus groups to gain insights into customer preferences and motivations (Yu, 2017). At the same time, loyalty cards

became popular, attracting shoppers with rewards and providing retailers with valuable visions into consumer behaviour. This era of electrification, known as Retail 2.0, was initiated in the early twentieth century and concluded with the emergence of automation in the late twentieth century (Har et al., 2022). The advent of credit cards further reshaped consumer behaviour, offering users convenience while proving beneficial to businesses, as individuals tended to spend more when using credit cards (Diaz, 2021).

2.1.3 Retail 3.0

The emergence of widespread online shopping marks a focal turning point in the history of the retail industry (Har et al., 2022). Retail 3.0 dawned with the arrival of the Internet, enabling global production, marketing, and consumption of products and services, as well as the extensive adoption of digital technologies (Reagan & Singh, 2020). During the 1990s, consumers gained virtually unlimited access to a vast array of products, and their shopping behaviour became less constrained by the physical location or operating hours of traditional brick-and-mortar stores. The Internet fundamentally altered how both retailers and customers perceived the integration of product, place, price, and time (Nöjd et al., 2020).

Digital disruptors, such as eBay, Taobao, Amazon, and Alibaba, emerged as formidable competitors, transforming traditional industries across the board, including brick-and-mortar stores, physical marketplaces, and supply chain logistics (Har et al., 2022). Thanks to online technological advancements and the evolution of online banking, consumers had access to a broad sample of products from international retailers, often at more competitive prices than those offered by local stores (Steel et al., 2013).

Furthermore, the expansion of interstate highways facilitated the rise of self-service convenience stores, big-box retailers, and large-scale outlets serving broader geographic areas (Reagan & Singh, 2020). Retail giants like Aeon, Tesco, Auchan, and Wal-Mart leveraged these trends to provide a wide range of deeply discounted items produced cost-effectively on a global scale during the era of computerisation and globalisation in Industry 3.0 (Har et al., 2022).

Retail 4.0 commenced in the early twenty-first century, succeeding Retail 3.0, which originated in the late twentieth century as automation gradually gave way to digitalisation.

2.1.4 Retail 4.0

The retail industry worldwide is currently experiencing a digital transformation, leading to the successful integration of multiple Industry 4.0 technologies (Shankar, 2018; Soutjis et al., 2017). At this stage, the swift ascent of omnichannel shopping solutions (Hüseyinoğlu et al., 2017), offering

significant convenience to consumers, is becoming increasingly prevalent. This marks the looming of the fourth evolution in the retail sector, commonly referred to as Retail 4.0 (Sakrabani & Teoh, 2021).

Retail 4.0 represents the fourth evolution in the retail industry, harnessing the power of Industry 4.0 technologies such as Artificial Intelligence (AI), Internet of Things (IoT), Cloud Computing, Big Data Analytics (BDA), and Augmented Reality (AR) to serve evolving customer demands (Har et al., 2022). It is the integration of technology, innovation, and human expertise, marked by brilliant advancements in production and data analytics technologies, with a particular focus on AI-driven techniques and digital manufacturing systems, transforming conventional systems into intelligent, responsive entities (Kamble et al., 2020). Remarkably, the COVID-19 pandemic, according to the United States Retail Index by IBM, accelerated the shift from physical retail to online shopping by approximately five years (Har et al., 2022). Retail giants like Walmart and Target have thrived by embracing omnichannel fulfilment strategies, offering grocery pickup and delivery services, thereby boosting their sales (Mason et al., 2020).

After discussing the evolution of retail from Retail 1.0 to 4.0 in this section, it appears that traditional retail models have undergone significant transformation in response to technological advancements and changing consumer preferences. Understanding this transformation is essential for contextualising the current retail landscape and highlighting the need for further research in adapting retail strategies to the digital age. Areas of potential further research could include exploring the specific challenges and opportunities faced by retailers in transitioning to digital platforms (Dannenberg et al., 2020; Reinartz et al., 2019), investigating consumer behaviour in omnichannel retail environments (Kazancoglu & Aydin, 2018; Mishra et al., 2021), and examining the impact of emerging technologies such as artificial intelligence and augmented reality on the future of retail (Le et al., 2018; Zhang et al., 2022).

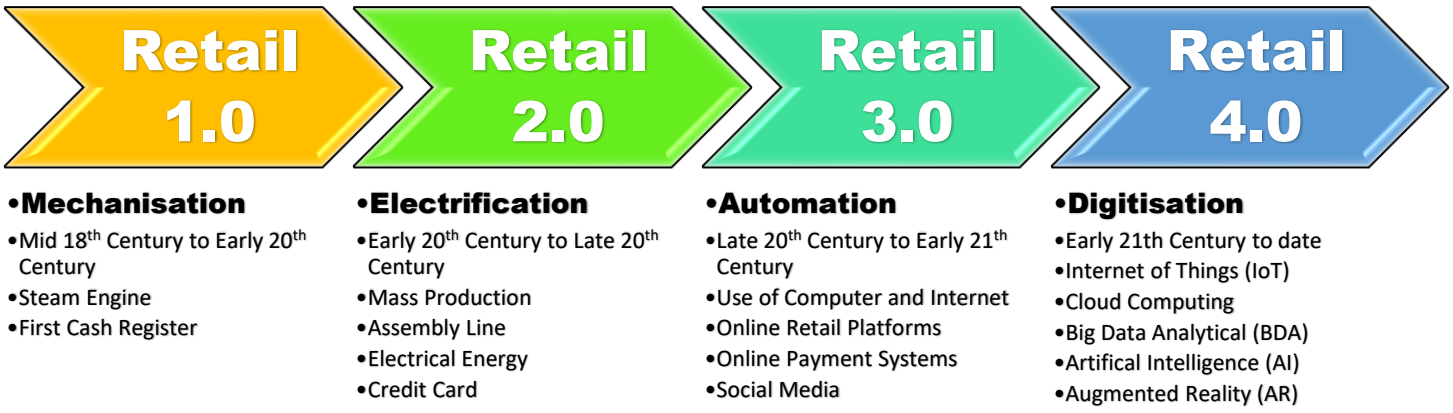

Figure 4: The Retail Industry Revolution (Har et al., 2022)

2.2 The Digital Shopping Revolution: E-Commerce Through the Ages

The history of e-commerce is a fascinating narrative of how technology has transformed the way people shop and conduct business online. I take a concise look at key milestones and brilliant developments in this evolutionary journey.

2.2.1 1970s and 1980s

The appearance of electronic commerce as a concept coincided with the rise of Electronic Data Interchange (EDI) systems. EDI involves the continuous exchange of information between different organisation, facilitated by Information Technology (IT) (Holland et al., 1992).

EDI has empowered businesses to electronically exchange standardised business documents like purchase orders and invoices. From a strategic perspective, EDI systems have played a key role in transforming the fundamental approaches adopted by numerous organisations in their business processes (Cash & Konsynski, 1985; Malone et al., 1987).

In numerous companies, EDI systems have evolved into Information Technology (IT) platforms where they initiate and implement business enhancement endeavours (Venkatraman & Zaheer, 1990).

EDI collaborations usually involve comprehensive IT agreements between two or more parties, enabling the seamless exchange of data and documents. (Kumar & Van Dissel, 1996). Trading partners utilise computer and telecommunications technology to exchange standardised business documents and data throughout an extensive value chain that links suppliers and companies. (Johnston & Vitale, 1988).

In 1979, Michael Aldrich, a pioneering English inventor and entrepreneur, achieved a significant breakthrough in the realm of commerce. He ingeniously fused a customised television set with a transaction-processing computer, pioneering the earliest secure electronic data transmission system.

This visionary accomplishment served as the cornerstone for the modern concept of online shopping. Aldrich's innovation restructured the landscape of business transactions, enabling smooth online engagements between businesses and customers, as well as facilitating smooth business-to-business interactions (Aldrich, 2011).

Table 2: Case sample and EDI application areas (Holland et al., 1992)

US Companies	**Instruments**	**Rail**	**Steel**	**Picture**	**Bank**	**Hospital**	**Petrol**	**Light**
Industry	Electronics	Transport	Heavy Engineering	Imaging Products	Banking	Health Care	Petrochemical	Manufacturer
EDI Application Areas	Purchasing, selling, Production and CAD	International transport, distribution, and electronic funds transfer	Production, distribution, selling, and product information	Purchasing, selling, and forward integration	Cash management	Selling, and EDI service operator	Selling, distribution, and cash management	Production, selling, and forward integration

Initially unveiled in 1980, this ground-breaking system was positioned as a solution for business-to-business interactions and quickly gained traction in the markets of the United Kingdom, Ireland, and Spain (Aldrich, 2023; Winterman & Kelly, 2013).

In 1982, the Boston Computer Exchange made history as the world's first e-commerce platform, specialising in helping people sell their used computers. Essentially, it served as an online marketplace for individuals looking to trade their old computer equipment (Simakov, 2020). While systems like Electronic Data Interchange (EDI) and Electronic Fund Transfer (EFT) had been in use since the early 1970s, the e-commerce explosion did not occur until the early 1990s (Baourakis et al., 2002).

2.2.2 1990s

E-commerce was enabled by the birth of the Internet and personal computers. Tim Berners-Lee's development of the World Wide Web at CERN in 1989, which became accessible to the public in 1991, has since become the predominant means for billions of individuals to access the Internet. The World Wide Web initiative was a pragmatic effort aimed at creating a global information network using the technology available at the time (Berners-Lee et al., 1992).

The Internet stands as a prime example of the positive outcomes resulting from continuous investment and focused research and development in information infrastructure. It began with early packet-switching research and grew through collaborative efforts involving government, industry, and academia (Leiner et al., 2009). This expansion paved the way for the development of the first online shopping systems, enabling customers to place orders with just a few keystrokes.

This decade witnessed remarkable growth in e-commerce,

- **1992:** In 1991, the National Science Foundation (NSF[1]) opened up commercial internet use by removing restrictions, allowing businesses and individuals to access it. Then, in 1992, Charles Stack leveraged his software design and programming skills to create the revolutionary online bookstore Book Stacks Unlimited, marking the birth of the world's first online book marketplace (Vidal & Mitchell, 2013).

- **1994:** Mosaic and Netscape were the first graphical web browsers to appear on the market, while Microsoft's Internet Explorer came later, bundled as a component of its Windows 95 operating system (Seefeldt & Thomas III, 2009). It is challenging to picture a time before web browsers, but in 1994, Netscape Navigator became the initial browser to gain popularity on the Windows operating system. Microsoft's decision to make its browser freely available essentially compelled other popular browsers of the era to follow suit, encouraging an even greater number of users to venture online.

- **1994:** Bezos left his employment as vice-president of D. E. Shaw & Co., a Wall Street firm, and moved to Seattle. He began to work on a business plan for what would eventually become “Amazon.com” (Bezos, 1998). Jeff Bezos founded “Amazon.com” as an online bookstore, marking the beginning of the modern e-commerce era. The company was founded in 1994, spurred by what Amazon founder Jeff Bezos called his "regret minimisation framework," which described his efforts to fend off any regrets for not participating sooner in the Internet business boom during that time.

- **1995:** eBay came into existence as a platform for online auctions (Gitlin, 2011). After a weekend of coding on his personal computer over Labour Day, eBay's founder, Pierre Omidyar, introduced “Auction Web”. This website was dedicated to creating an honest and open marketplace that would connect buyers and sellers, marking the birth of the Auction Web (ebayinc.com/company/our-history).

- **1995:** The introduction of Secure Sockets Layer (SSL) encryption technology marked a brilliant moment in enhancing the security of online transactions. SSL, or Secure Sockets Layer, is a cryptographic Internet security protocol. It was initially developed by Netscape in 1995 to ensure privacy, authentication, and data integrity in online communications. SSL serves as the

[1] NSF is a U.S. government agency that funds scientific research and education to advance knowledge and innovation.

precursor to the modern TLS (Transport Layer Security) encryption that is widely utilised today (Clark & Van Oorschot, 2013).

- **1998:** PayPal was established, offering a secure and user-friendly method for conducting online payments. It is an American e-commerce company renowned for its expertise in Internet money transfers. It gained substantial prominence through its close association with the online auction giant eBay, which was its owner from 2002 to 2015. The creation of PayPal resulted from the merger of "X.com" and "Confinity", enabling users to securely make payments for purchases or transfer funds between accounts through online transactions (Trautman, 2015).

2.2.3 2000s

E-commerce continued to grow and diversify,

- **2000:** The dot-com bubble burst led to the downfall of numerous e-commerce enterprises (Goodnight & Green, 2010). However, survivors such as Amazon and eBay not only weathered the storm but also flourished.

- **2005:** Amazon launched Amazon Prime, a subscription service that offered free two-day shipping and additional benefits, setting new benchmarks for customer loyalty programs (Alimahomed-Wilson & Reese, 2021).

- **2007:** Apple revolutionised mobile e-commerce by launching the iPhone, which made online shopping accessible through smartphones. Much like how the Internet fuelled the growth of e-commerce in the 1990s, the widespread use of smartphones is now reshaping global business products and services. This shift is evident in the record-breaking online retail spending, which reached $43.4 billion by 2010 (Na, 2011).

2.2.4 2010s

E-commerce became more ubiquitous and integrated with social media as well as mobile technology,

- **2010:** The rise of social commerce saw businesses leveraging social media platforms to sell products directly to consumers. Social commerce is a form of commerce mediated by social media involving convergence between the online and offline environments (Zhang & Wang, 2012).

- **2014:** Alibaba Group, the Chinese e-commerce powerhouse, made history with its fascinating Initial Public Offering (IPO) on the New York Stock Exchange. This historic moment came as Alibaba applied for its IPO on the NYSE, poised to set a new record as the largest IPO ever, turning a remarkable success story into reality. (Havinga et al., 2016).

- **2015:** Amazon unveiled the Amazon Echo, a voice-activated smart speaker, along with Alexa, its virtual assistant, ushering in a surge in voice commerce. Voice commerce, often referred to as voice shopping, involves using voice assistants to place online orders. This trend has garnered widespread attention in mainstream media (Chaudhuri & Terlep, 2018; Creswell, 2018).

- **2017:** Walmart's strategy to rival Amazon included the acquisition of an e-commerce retailer. As part of this adjustment, in 2016, Walmart made a significant move by purchasing the online retailer 'Jet.com' for $3.3 billion, strengthening its position in the e-commerce market (Walton).

2.2.5 2020s

The COVID-19 pandemic accelerated the growth of e-commerce as consumers turned to online shopping for safety,

- **2020:** E-commerce sales surged globally as lockdowns and social distancing measures were implemented, pushing many businesses to prioritise their online presence (Alcedo et al., 2022; Eriksson & Stenius, 2020; Guo et al., 2021; Sharma, 2020).
- **2021:** The adoption of online grocery shopping, contactless payments, and kerbside pickup continued to grow, reshaping the retail landscape (Heins, 2023; Rout et al., 2022).

E-commerce continues to evolve with emerging technologies like artificial intelligence (Soni, 2020), augmented reality (Chandra & Kumar, 2018), and blockchain, which play roles in enhancing customer experiences (Shin, 2019). The history of e-commerce demonstrates how technology and consumer behaviour have shaped the way we buy and sell goods and services in the digital age. In recent decades, the advancement of information technologies has driven the arrival of omnichannel retailing. In the era of Retail 4.0, omnichannel retailing requires the comprehensive integration of various channels, offering customers unparalleled flexibility and convenience (Lee, 2017).

Similarly, in section 2.2, I examined the digital shopping revolution and the evolution of e- commerce through the ages. This literature review underscores the profound impact of e-commerce on consumer behaviour, market dynamics, and business strategies. Identifying key trends and developments in e-commerce provides valuable insights for understanding the current landscape and anticipating future shifts in consumer preferences and market trends.

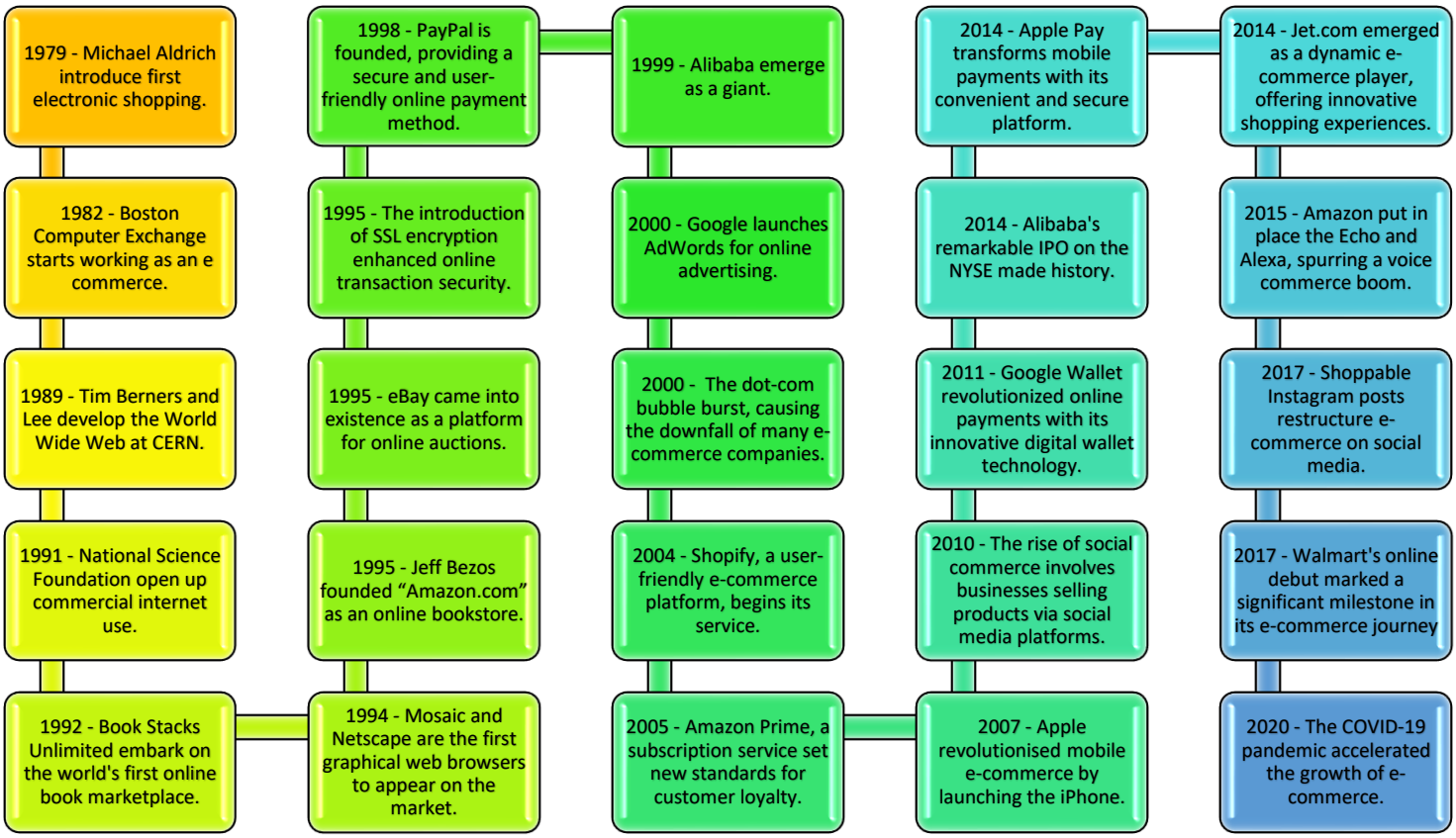

Figure 7: E-commerce Evolution - A Historical Timeline

Moving forward, potential areas for further research include investigating the role of emerging technologies such as blockchain and virtual reality in shaping the future of online shopping (Boukis, 2020; Shin, 2019), exploring strategies for enhancing the online shopping experience (Izogo & Jayawardhena, 2018; Susiang et al., 2023), and examining the sustainability implications of e-commerce practices (Ignat & Chankov, 2020; Kennedyd et al., 2022).

2.3 Decision Making Concept

As the evolution of retail and the digital shopping revolution has been traced, it is clear that comprehending consumer decision-making processes is essential in adapting to the digital era. This evolution prompts pondering how consumer behaviour has evolved and what influences decision-making in online shopping. This section explores the concept of decision-making, addressing pertinent questions that emerge from the discussed evolution.

2.3.1 Definition

People make decisions regularly, and decision-making can be quite complex and challenging (Zavadskas et al., 2014). Decision making is a process of making a choice from a number of alternatives to achieve a desired result (Eisenfuhr, 2011). “Rationality” as a crucial element of decision making is the reason for doing something, and to judge a behaviour as reasonable is to be able to say that the behaviour is understandable within a given frame of reference (Elbanna, 2006). It encompasses methodical, purposeful, sober, and consistent behaviours that are psychologically efficacious and logically intelligible, yet may present a challenging multiplicity of meanings in seemingly casual usage. "rationality" involves deliberate, systematic, and calculable actions or behaviours guided by specific purposes or goals (Brubaker, 2013). Like many other commonly used words, "rationality" has come to mean many things. In many of its uses, "rational" is approximately equivalent to "intelligent" or "successful" (March, 1994).

2.3.2 Decision Making Styles

Research indicates that managers who prefer "Thinking" utilise intuition to make cognitive leaps informed by objective data, resulting in a higher quantity of high-quality decisions than their counterparts. Conversely, "Sensing/Feeling" types tend to invest their time in seeking socially acceptable decisions, which translates to fewer decisions made and lower perceived effectiveness overall (Hough & Ogilvie, 2005).

Most often, decision-making is seen as a process of making rational choices. This idea has a long history in our understanding of human behaviour, and its lasting relevance comes from its practicality and its alignment with human aspirations. Theories of rational choice, while sometimes presented formally, often rely on the everyday language we use to understand and discuss our choices (March, 1994).The decision-making style, whether intuitive or rational, acts as a moderating factor in the relationship between the knowledge creation process and organisational performance (Abubakar et al., 2019).

Management style and decision-making create an organisation’s culture (Sulich et al., 2021). Managers are charged with the duty of guiding their organisation toward the accomplishment of objectives and stated goals. This demands not only versatility and expertise but also effective knowledge management and a high level of decision-making prowess (Abubakar et al., 2019).

Decision-making style refers to the habitual and learned patterns of response individuals exhibit when faced with problems or situations (Scott & Bruce, 1995). It is closely linked to cognitive style, as suggested by (Behling et al., 1980), who associate intuitive information gathering with “feeling as information evaluators” and systematic information gathering with “thinking as information

evaluators". Harren (Harren, 1979) proposed a classification scheme for decision-making style, encompassing two opposing categories: "Intuitive" and "Analytical".

As a result, individuals can be consistently classified as either intuitive or analytical in their approach to information gathering and evaluation.

I. Intuitive Decision-Making Style

Decision-makers may detect patterns, emotions, or connections among seemingly unrelated facts. Intuition is frequently experienced as a sudden awareness of information (Ritter & Dijksterhuis, 2014; Sauter, 1999). Intuition can be described as a vague sense or a feeling of patterns or relationships. It is also often referred to as "holistic thinking", "immediate insight", where you see the answer without necessarily knowing how you arrived at it, or as "a rapid retrieval technique of knowledge chunks and patterns shaped by past experiences"(Abubakar et al., 2019; Seal, 1990; Thorne, 1990).

There are several ways to trigger intuition. ***"Detection"*** involves uncovering verifiable truths that can help solve a problem. ***"Evaluation"***, on the other hand, can be muddled by the interplay of emotions and feelings (Hodgetts et al., 2017; Sauter, 1999).

The role of intuition in decision-making has been conceptualised as a two-step process:

- Explicit decision-making using emotions and
- Implicit decision-making by drawing on previous decisions (Bierman et al., 2005)

Similarly, Patton (Patton, 2003) identified three sources of intuition employed by decision-makers:

1) General experience, which accumulates over time through normal life experiences,
2) Innate responses, instinctual reactions to situations often inherent rather than learned, and
3) Focused learning, where deliberate efforts are made to cultivate habits and foster intuitive responses.

A recent study discovered that intuition enhances project success and overall corporate performance (Açıkgöz et al., 2014). However, some studies have consistently shown that people demonstrate persistent and often unnoticed overconfidence (Arkes et al., 1986; Brown & Jones, 1998; Sieck & Arkes, 2005) as well as a tendency towards conservatism (Lim & O'Connor, 1996) in their decision makings. These biases should be recognised as integral aspects of intuitive decision-making rather than mere random errors (Burton et al., 2020; Hodgkinson et al., 2009; Sadler-Smith, 2007).

II. Analytical Decision-Making Style

Decision-makers are often compelled to consider multiple alternative scenarios and probabilities for each option before reaching a decision (Busari & Spicer, 2015; Oliveira, 2007). According to Dean and

Sharfman (Dean Jr & Sharfman, 1993), rationality is defined as "the extent to which the decision-making process involves the collection of relevant information and relies on the analysis of this information to make a choice". Rationality plays a vital role in decision-making, defining a rational agent as one who consistently selects the action that maximises its expected performance (Johnson-Laird and Byrne 1991).

Analytical decision-making theory, alternatively known as choice theory (Arrow 1989), provides a framework for comprehending and often formally modelling social and economic behaviours. At its core, rational choice theory posits that individual choices shape societal behavioural patterns and individuals evaluate the costs and benefits of various courses of action before making decisions (Zavadskas & Turskis, 2011).

Analytical decision-making comprises a thorough examination of evidence and a structured process that demands time and conscious effort (Fitzgerald et al., 2017). These rational procedures assist decision-makers in establishing relevant decision criteria, identifying a comprehensive set of alternatives, and objectively evaluating each option (Kaufmann et al., 2012).

In contrast to an intuitive decision-making style, the analytical decision-making style involves a systematic consideration of all possible decision choices (Abubakar et al., 2019; Baird, 1991; Tetlock et al., 1993). Analysing available options through an analytical decision-making style requires decision-makers to consciously assess options and their potential consequences. Moreover, analytical decision-making is characterised by its conscious and thoughtful nature, largely devoid of irrationality and biases, resulting in improved decision quality (Pacini & Epstein, 1999) and enhanced work and organisational performance (Busari & Spicer, 2015; Singh, 2014; Smolka et al., 2018; Uzelac et al., 2016).

2.3.3 Decision Making Process

Decision making is a fundamental cognitive process in human behaviour, involving the selection of a preferred option or course of actions from a range of alternatives, guided by specific criteria (Wang & Ruhe, 2007). Decision makers make decisions by following a process composed of steps supported by tactics to do each step (Nutt, 2003). These steps serve as a systematic guide to uncover the "what" and "why" behind their decisions.

In the literature, diverse process types are delineated, ranging from the descriptive account of what decision-makers commonly practice to the prescriptive recommendations of researchers (Daft, 1995; Eisenhardt & Zbaracki, 1992; Nutt, 1989; Nutt, 2008).It is typically assumed that administrative decision-making follows a rational process (Lunenburg, 2010).

In accordance with the rational model, the decision-making process can be divided into six distinct steps (Schoenfeld, 2010):

- Identifying the problem
- Generating alternatives
- Evaluating alternatives
- Choosing an alternative
- Implementing the decision
- Evaluating decision effectiveness

Figure 10: The Process of Decision Making (Schoenfeld, 2010)

Once a problem is identified, the next step involves generating alternative solutions to address the problem. These alternatives are subjected to careful evaluation, and the most promising one is selected for implementation. The chosen alternative is then continuously assessed to ensure its immediate and sustained effectiveness. If any challenges or issues arise during this process, it may necessitate revisiting earlier stages, essentially recycling the decision-making process.

This highlights that decision-making follows a logical sequence of activities, where problem identification precedes alternative generation. Additionally, decision-making is an iterative process, as depicted in Figure 4. It represents a recurring event, allowing individuals to draw insights from past decisions and apply them to future ones.

2.3.4 Multi Criteria Decision Making (MCDM)

The practice of decision-making has a long history, although the exact origins of the field are not entirely clear. However, the beginnings of decision analysis/utility theory and multiple objective mathematical programming can be traced separately (Köksalan et al., 2011). One of the earliest references to Multiple Criteria Decision Making (MCDM) (although not termed as such) can be attributed to Benjamin Franklin (1706-1790), the American statesman.

Franklin reportedly used a simple paper system to make important decisions, which he explained in a letter to his friend Joseph Priestly. He would write the arguments in favour of a decision on one side of a sheet of paper and the arguments against it on the other side. He would then cross out arguments on each side that were relatively of equal importance. While Franklin mentioned the

concept of "weight" in his method, he did not describe actual weights. When all the arguments on one side were crossed out, he would support the side with the remaining arguments (Köksalan et al., 2016).

Multi Criteria decision-making (MCDM) involves making choices when there are many conflicting factors to consider. In an MCDM scenario, various options undergo evaluation against multiple criteria to identify the most suitable alternative(s) (Rezaei, 2015). Also, fuzzy decision-making is employed when data is unclear or incomplete (Kahraman et al., 2015).

Multiple Criteria Decision Making (MCDM) has witnessed rapid growth across various disciplines. Its central challenge revolves around evaluating a set of alternatives against multiple, often conflicting criteria (Triantaphyllou & Triantaphyllou, 2000). Numerous contemporary researchers have delved into MCDM-related issues, which consider decision-making in scenarios with multiple, potentially contradictory criteria.

In the realm of decision making, efforts have been made to develop methods and approaches throughout history. Some recent actions and improvements in the Decision-Making process are briefly summarised in Table 3.

Table 3: Actions and Improvements in the Decision-Making Process

No.	Researcher	Year	Description
1	**Benjamin Franklin**	1706-1790	Simple paper-based system
2	**John von Neumann and Oskar Morgenstern**	1944	Game Theory
3	**Ttucker & Kuhn**	1951	Formulation of Optimal Conditions in Nonlinear Planning
4	**Charnes, Cooper, and Ferguson**	1955	Goal Programming
5	**Bernard Roy**	1961	Electre
6	**Bruno Contini & Stan Zionts**	1968	A Model of Multiple Developed Criteria
7	**Mac Crimon**	1968	Simple Additive Weighting (SAW)
8	**Thomas Saaty**	1970	AHP- Analytic hierarchy process
9	**Howard Raiffa**	1970	IIASA- International Institute for Applied Systems Analysis
10	**Zeleny & J.L. Cochrane**	1972	International Conference Formation
11	**Zionts & Wallenius**	1973	Solving multi-index linear programming problems
12	**Srinivasan & Shocker**	1973	LINMAP- linear programming technique for multidimensional analysis of preference
13	**Ralph Keeney & Howard Raiffa**	1976	A book based on the theory of multi-index values
14	**Hwang & Yoon**	1981	TOPSIS- Technique for Order of Preference by Similarity to Ideal Solution
15	**Matarazzo**	1986	MAPPAC - Multicriteria Analysis of Preferences by means of Pairwise Alternatives and Criterion comparisons
16	**Pitz**	1987	DECAID
17	**Matarazzo**	1988	PRAGMA

No.	Researcher	Year	Description
18	**Opricovic**	1988	VIKOR- Vise Kriterijumska Optimizacija I Kompromisno Resenje
19	**Smith and Speise**	1991	Logical Decision
20	**Bana e Costa and Vansnick**	1994	MACBETH - Measuring Attractiveness by a Categorical Based Evaluation TecHnique.
21	**Thomas Saaty**	1996	ANP- Analytic Network Process
22	**Xiaozhan Xu**	2001	SIR- Superiority and Inferiority Ranking Method
23	**Zavadskas et al.**	2006	MOORA- Multi-Objective Optimization on the basis of Ratio Analysis
24	**Zavadskas et al.**	2010	ARAS- A new additive Ratio ASsessment
25	**Zavadskas et al.**	2010	COPRAS- Complex Proportional Assessment
26	**Zavadskas et al.**	2011	SWARA- Step-wise Weight Assessment Ratio Analysis
27	**Zavadskas et al.**	2012	Multi MOORA
28	**Zavadskas et al.**	2012	WASPAS- Weighted Aggregated Sum Product ASsessment
29	**Zavadskas et al.**	2014	KEMIRA- KEmeny Median Indicator Ranks Accordance
30	**Mehdi Keshavarz et al.**	2015	EDAS- Evaluation Based on Distance from Average Solution
31	**Jafar Rezaei**	2015	BWM – Best Worst Method

Over the past decades, there has been a significant surge of interest and development in the following key aspects of MCDM (Zavadskas et al., 2014):

- ***FORMAL MODELS:*** This includes algorithms, procedures, and selection paradigms designed to tackle MCDM challenges.
- ***EVALUATION THEORIES:*** These involve assumptions relating to values or preferences and the structured representations of these values or preferences.
- ***ASSESSMENT METHODOLOGIES:*** This encompasses the elicitation, estimation, and scaling of individuals' preferences, utilities, and subjective probabilities within the context of MCDM situations (Fishburn, 1978).

On the other hand, the term 'criterion' can pose challenges for decision-makers. A criterion essentially serves as a standard for judgment, enabling the assessment and differentiation of one choice or course of action as more desirable than another (Dictionary). In most problems, multiple objectives or criteria are present, often with different units of measurement. MCDM methods embrace a variety of approaches, broadly categorised into two main types (Zavadskas et al., 2014):

- **Multi-Attribute Decision Making (Discrete MCDM):** This category focuses on discrete decision scenarios. MADM art is closely tied to the "Rational Choice Theory", which assumes that individuals are motivated by monetary incentives and the profit potential. This allows the construction of formal models predicting human behaviour. People act rationally

within certain constraints and based on the information available to them. While rationality plays a significant role, human actions can also involve non-rational elements (Scott, 2000).

- **Multi-Objective Decision Making (Continuous MCDM):** These methods address continuous decision contexts. MODM methods deal with open-ended design problems, aiming to create the optimal solution within specific design constraints and quantifiable objectives. Designers face the challenge of selecting materials and constructions for complex design issues (Jahan & Edwards, 2013).

MCDM can be envisioned as a systematic process for evaluating real-world situations. It involves considering distinct qualitative/quantitative criteria in certain/uncertain/risky environments in order to find a suitable course of action/choice/strategy/policy among several available options (Raju, Kumar 2013). Moreover, MCDM methods can be classified based on the information type, as Larichev proposed (Larichev, 2000; Zavadskas & Turskis, 2011). This classification is illustrated in Figure 5:

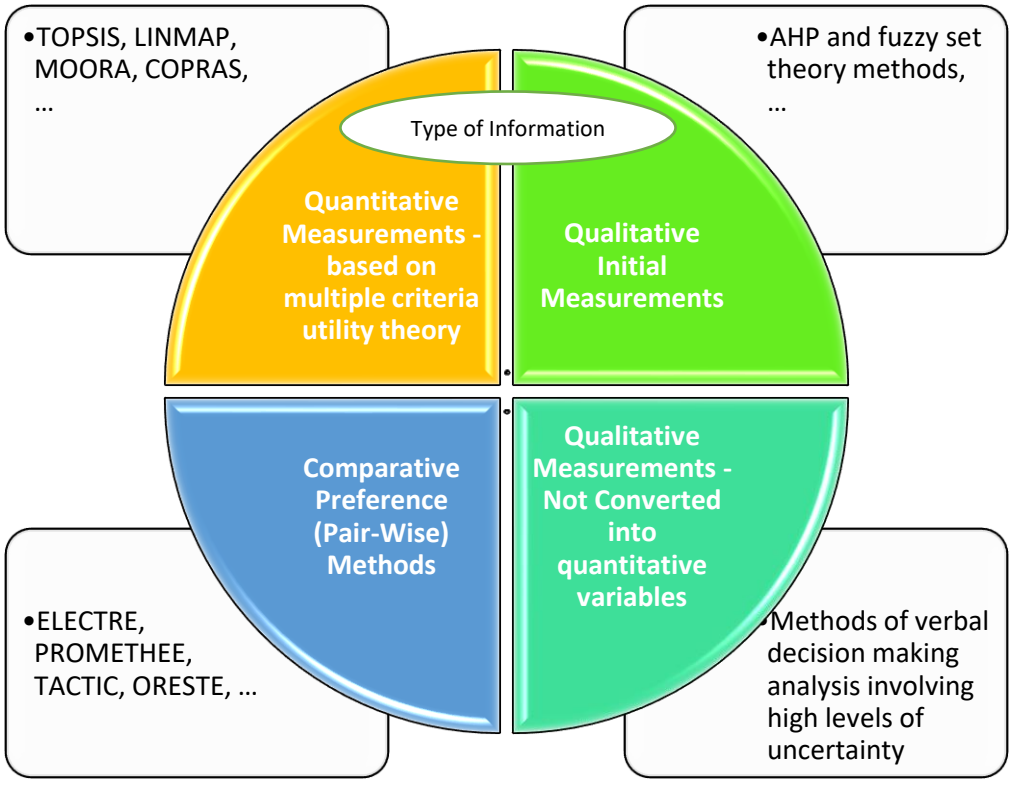

Figure 13: Classification of MCDM Methods Based on Information Type

Figure 14: Classification of MCDM Methods Based on Information Type

Multicriteria Decision Making (MCDM) represents an advanced domain within operations research, focusing on creating and applying decision support tools and methods to address complex decision challenges that include multiple conflicting criteria, goals, or objectives (Kahraman et al., 2015).

Moreover, Fuzzy Multicriteria Decision Making (FMCDM) models serve to evaluate alternatives based on predefined criteria, involving either a single decision-maker or a committee of decision-makers. These models use linguistic values represented by fuzzy numbers to assess the suitability of alternatives against criteria and determine the importance weights of criteria (Chen & Hwang, 1992). A linguistic variable refers to a variable with values expressed as words or sentences in a natural or artificial language (Zadeh, 1997). It is important to note that various methods are applied in the upcoming research, as suggested to address and solve fuzzy MCDM problems (Kahraman et al., 2015).

2.4 Success Factors in Online Shopping: Understanding Customer Behaviour

A company capable of anticipating customer purchasing behaviour stands to gain various advantages, such as an enhanced rate of customer acquisition, increased sales, and improved competitiveness (Qiu et al., 2015). Data analytics assists companies in painting a vivid picture of consumer behaviour, getting a deep understanding of their preferences, devising effective marketing strategies, pinpointing sales opportunities, and fostering enduring customer loyalty (Wassouf et al., 2020). This intricate process often results in complex decision-making scenarios, especially when numerous factors come into play and influence the company's decision-making processes (KH Lim, 2021).

Browsing, searching, and completing a purchase on e-commerce websites could often prove to be a time-consuming and occasionally frustrating experience for consumers (Kim & Srivastava, 2007). As outlined by Erevelles, Fukawa, and Swayne (Erevelles et al., 2016), data consumer analytics involve uncovering concealed visions about consumer behaviour from vast datasets and leveraging the knowledge through meaningful interpretation. This knowledge is useful for uncovering ambiguous patterns within customer behaviour and forecasting future buying patterns. Retailers are advised to allocate resources to comprehensively understand customer purchasing patterns and behaviours. (Lee, 2017).

Furthermore, retailers analyse transaction data by tracking customer activities both online and in physical stores, enabling them to acquire a more profound insight into consumer behaviour and preferences (Zamil et al., 2020). It is important to highlight that marketing intelligence in emerging retail concepts is achieved through the collection and analysis of user data. This process yields valuable perceptions of user behaviour and buying trends, which are then utilised for marketing purposes (Har et al., 2022).

Within the realm of e-commerce and online trading, competition has intensified significantly. With an abundance of product information now accessible online, it has become common for customers

to explore items in physical stores while concurrently seeking additional information online, sometimes even completing their purchases on competitors' websites. Hence, it becomes important to gain a deep understanding of customer purchasing habits and behaviours to proactively adapt to market dynamics (Lee, 2017).

The retail industry has witnessed a significant transformation in recent years, with the development of the digital era and the rise of e-commerce platforms. Meanwhile, the COVID-19 pandemic catalysed even more rapid changes in consumer behaviour and preferences. In the midst of the COVID-19 pandemic, contactless buying methods that eliminate the need for physical touch have gained widespread appreciation. Consumer behaviour patterns have subtly shifted, with many individuals expressing a preference to avoid visiting physical stores. Instead, they have turned to online shopping and various contactless purchasing options as a safer and more convenient alternative (Luanjun, 2020).

E-commerce companies are at the forefront of adopting big data analytics as they strive to maintain a competitive edge in their industry. These firms handle a vast amount of data, comprising both structured and unstructured formats. While structured data primarily consists of demographic information, such as names, ages, genders, dates of birth, addresses, and customer preferences, unstructured data encompasses various types of user interactions, including clicks, likes, links, tweets, and voice data (Akter & Wamba, 2016).

Numerous efforts have been made to understand and model online shopping behaviour with the goal of comprehensively analysing consumer preferences and enhancing online shopping satisfaction (Chen & Chang, 2003; Darley et al., 2010; Hsia et al., 2008; Lee, 2002; Rout et al., 2022; Smith & Rupp, 2003). Several studies have explored the variations in behaviour, considering individual traits. However, there are still gaps in our understanding of how individuals approach purchase decisions and how these processes occur. Consequently, it should be pivoted from studying the adoption of online shopping to examining genuine online consumer behaviour and pinpointing specific consumer groups based on their decision-making styles (Karimi et al., 2015).

As the e-commerce and online trading landscape continues to evolve, it will be significant to examine the critical success factors (CSFs) impacting customer purchase decisions, which are instrumental in driving profitability in this dynamic environment. This examination includes the complex interplay between customer behaviour, decision-making processes, and the nuanced nature of uncertain concepts, all of which influence e-commerce success substantially. Recognising the significance and interconnected nature of these ideas, the concept of Decision Making and Customer Behaviour in

the context of Online Shopping is explored, seeking a more comprehensive understanding of the factors driving online purchases.

To understand the success factors for interacting and trading with online individuals and purchase decision making process, the first step is to review relevant research in this field.

2.4.1 Navigating the E-Commerce Purchase Decision Process

In the world of e commerce, understanding consumer preferences and connecting them with their favourite products is essential (Zhu et al., 2019). In the field of marketing and data analytics, there has been extensive research focused on analysing and predicting online purchasing behaviour (Kooti et al., 2016; Pavlou & Fygenson, 2006; Van den Poel & Buckinx, 2005). These studies primarily rely on clickstream data, which forms the core of the data collected from e-commerce websites and offers a comprehensive understanding of customers' online behaviours (Sismeiro & Bucklin, 2004; Su & Chen, 2015; Van den Poel & Buckinx, 2005). In this context, a wide array of variables that may influence purchasing behaviours has been identified, assessed, and utilised as inputs for prediction models. These variables encompass customer demographics, detailed browsing patterns, repeat visits, historical online behaviour, and more (Zhu et al., 2019). Apart from clickstream data, some researchers (Kim & Srivastava, 2007; Kooti et al., 2016; Lu et al., 2010) have endeavoured to incorporate external factors, such as social connections, friends, or virtual communities, into the analysis of purchasing behaviour.

While factors like price and product quality predominantly influence purchasing decisions in offline settings, online purchase choices may be influenced by a range of additional factors (Mousavizadeh et al., 2016). Multiple studies in the context of information systems, economics, computer science, and marketing have explored this area. Many empirical investigations aim to uncover how a visitor's interactions during a website visit, and the content they are exposed to, influence their online purchasing decisions (Zhu et al., 2019). Several studies have investigated the numerous elements influencing online purchase decisions. These studies have highlighted some of various factors, including product type, prior website experience, gender, website quality, consumer satisfaction, consumer personality, visual product presentation, usability, delivery, convenience, pre-purchase and post-purchase services, transaction-related services, product satisfaction, trust, loyalty, security, privacy, and pricing strategy, all of which play roles in shaping consumers' decisions to make online purchases (Bai et al., 2008; Brown et al., 2003; Chen et al., 2010; Colla & Lapoule, 2012; Marceda Bach et al., 2020; Park & Kim, 2003; Park et al., 2005; Poddar et al., 2009; Qureshi et al., 2009; Rita et al., 2019b; Suh & Han, 2003).

Decision-making inside a physical store relies on face-to-face interactions and is enhanced by feedback and communication facilitated by in-store sales representatives. This personal interaction and the availability of diverse language support results in a high level of engagement within the in-store channel (Maity & Dass, 2014).

In contrast, when it comes to decision-making in e-commerce, the process revolves around accessing websites or applications through computer devices (Clarke III, 2008), including laptops, desktop computers, tablets, other internet-enabled devices. These websites or applications predominantly apply text and images to convey information to consumers (Maity & Dass, 2014), and as a result, studying the decision-making process of online consumers holds significant value (L. Yang et al., 2022).

Internet consumers are individuals who deploy the Internet as a means of engaging in e-commerce. Consumer decision-making behaviour embraces the entire process, from generating demand to making final purchase decisions. The model of the five-stage purchasing decision process is a commonly employed instrument for marketers seeking enhanced insights into their customers and their actions (P. Kotler & K.L. Keller, 2006). In e-commerce, the general process of online consumers' purchasing decisions aligns with the five-stage model of the *Consumer Buying Process (Engel et al., 1986)*, including need recognition, information search, evaluation of alternatives, purchase decisions, and post-purchase behaviour (Han, 2021; Karimi et al., 2015; Kim & Srivastava, 2007).

I. NEED RECOGNITION

In the e-commerce world, the consumer buying process begins with sparking interest. Unlike traditional markets, the Internet shoppers find their inspiration mainly on the Internet itself. Here is how:

- **Online Media:** Various online sources provide information that directly or indirectly influences consumer preferences.
- **Online Communities:** Internet users share their shopping experiences in virtual spaces like forums and discussion boards, even highlighting products in some communities.
- **Online Business Promotion:** Online companies use strategies such as online advertising, bidding, auctions, and public relations activities to ignite consumers' desire to make purchases.

Shopping online offers consumers additional information and convenience, allowing them to choose products and compare prices more easily (L. Yang et al., 2022). When internal and external factors stimulate consumers, they may notice a gap between what they want and what they have. If they have the means, this gap turns into a desire to buy. In e-commerce, consumers often discover new wants and needs (Han, 2021). The process of making online purchase decisions is dynamic and

remarkably flexible. Decision-makers exhibit adaptability in their responses to decision tasks (Karimi et al., 2015). The opening requirement is interest indicating the tendency of people to join online activities out of curiosity and the satisfaction of achieving success. The next is personality display, the desire for individuals to use the Internet to reveal their unique plans. The final one is gathering communication, where consumers seek opportunities to connect and engage with others who share similar experiences (Han, 2021). At the end of the day, the initial decision is whether or not to use a website or application (an e-commerce platform) for the purchase (Kim & Srivastava, 2007).

II. INFORMATION SEARCH

The Internet has significantly enhanced the efficiency of information search (Zeng & Reinartz, 2003). Product information significantly influences buying behaviour and has been demonstrated to impact both the information search and the information processing stages (Karimi et al., 2015). Knowledgeable consumers carefully search for and choose information and process it selectively (Chen & Chang, 2003), which results in a less complex decision-making process.

E-commerce main advantage is screened information, allowing consumers to lower the costs associated with information search and processing information (Park & Kim, 2003). Also, searching for information during the shopping process resembles window shopping, as it involves transferring details about a product from the vendor's website to a consumer (Chen et al., 2017). When consumers recognise a need and are motivated to buy a specific product or service, they initiate information search through various means. Online, they recruit search engines, shopping websites, forums, and other tools for efficient, convenient, and comprehensive information collection (Han, 2021).

During this decision step, the customer needs extra assistance because they aim to narrow down their list of products for comparison. They also want to minimise the risk associated with buying a new product and make a satisfying decision (Kim & Srivastava, 2007). While E-commerce has notably increased information search efficiency and affected consumer purchasing behaviour, the level of enthusiasm for information collection varies based on several factors.

Firstly, consumers' product knowledge is vital. Familiar products require less information search, relying more on experience, while new products prompt higher search intentions (Han, 2021).

Secondly, the value of the purchased product correlates positively with consumers' search intention; for low-risk, low-value items, decisions are experience-driven, while high-value products necessitate thorough information collection due to concerns about risks and information asymmetry. Thirdly, time constraints impact search intentions, with consumers less inclined to gather information when decisions must be made quickly.

Lastly, the degree of involvement reflects consumers' willingness to invest time and energy in the purchase process, especially for complex purchases where comprehensive information collection, multi-faceted selections, and comparisons are common (Han, 2021). Additionally, it is important to note that decision-making for online purchases is a dynamic and highly adaptable process, as highlighted by various studies (Karimi et al., 2015; Klein & Yadav, 1989; Payne et al., 1988, 1993).

III. EVALUATING OF ALTERNATIVE

Once customers receive related information from various sources, they analyse and compare different products to select the most appropriate ones. After deciding to explore an online store, the individual looks for a product on online networks. The exploration involves reading editorial reviews, reviewing customer feedback, and making comparisons based on preferences such as price, customer reviews, and ratings provided by other customers. At this stage, a decision is required regarding which product to purchase, along with the choice of rating helpful reviews that contributed to the purchase decision (Kim & Srivastava, 2007).

Consumers with extensive knowledge tend to begin with a limited set of alternatives, driven by a clear understanding of their preferences (Brucks, 1985; Cowley & Mitchell, 2003). They approach the evaluation process with predefined criteria, demonstrating confidence in their ability to search for information (Schmidt & Spreng, 1996). Their efficient information processing capabilities enable them to assess information effortlessly (Alba & Hutchinson, 1987; Cowley & Mitchell, 2003), resulting in reduced evaluation time and cycles (Karimi et al., 2015).

On the other hand, individuals with low knowledge face limitations in gathering and adapting pertinent information for assessing options (Malhotra, 1983). Consequently, they engage in more intensive processes, requiring additional cycles and time. Due to a lack of awareness regarding fitted options and decision criteria, they consider a broader range of alternatives and criteria (Karimi et al., 2015).

The decision-making process revolves around the alternatives' constructs (Diehl & Poynor, 2010; Shocker et al., 1991) and evaluation criteria (Moore & Lehmann, 1980). The number of alternatives or the consideration set, a term often used in marketing literature, refers to the count of options under consideration. The count of evaluation criteria represents the attributes employed to assess the available choice options against each other (Karimi et al., 2015).

Consumers choose products by judging functions, styles, reliability, prices, and after-sales services based on a specific evaluation standard. This evaluation relies on consumers' "*utility value*[2]*"(Pohekar & Ramachandran, 2004)*, and even within the same consumer, different value is assigned to various evaluation standards. Consequently, goods are ranked according to their "*utility value"*, helping consumers form their ideal product choices (Han, 2021; Karimi et al., 2015; Kim & Srivastava, 2007). For online consumers, the Internet streamlines information search, and comparison shopping websites offer detailed product information, aiding in quick decision-making (Han, 2021).

IV. PURCHASE DECISION

Consumers' purchasing decision-making process exhibits new features and rules due to the numerous distinctions between e-commerce and traditional marketing (Han, 2021). Understanding how consumers make purchase decisions is a matter of concern for both merchants and scholars, particularly given the context of consumers navigating online shopping platforms (L. Yang et al., 2022). To persuade consumers to choose a product on its website, a company emphasizes offering competitive prices, favourable shipping conditions, and superior after-sales services compared to other online shopping platforms. To achieve this, most companies leverage customer ratings of product suppliers. Also, consumers evaluate factors such as price, shipping date, service quality, rewards, recommendations, and more. Social network platforms enable customers to assess e-commerce websites, fostering trust through reviews written by previous customers. E-commerce sites consider several recommendations for a selected product, incorporating reasons like free shipping. They apply recommendation features based on general customer behaviour, suggesting items purchased by others with similar preferences. Additionally, e-commerce platforms can employ social influence by recommending products based on a customer's social community members' behaviour, enhancing personalised recommendations (Kim & Srivastava, 2007).

Some research suggests that factors like comment length, rating, and sentiment are pivotal in influencing purchase decisions (Chua & Banerjee, 2015; Liu & Park, 2015; Uhl, 2011). However, other certain factors, such as pre- and post-purchase consultation dialogues with customer service, are not visible on the shopping webpages (L. Yang et al., 2022).

Moreover, considering key insights from the recent study conducted by Luming Yang and colleagues (L. Yang et al., 2022) in purchase decision-making, several priceless aspects merit attention:

[2] Multi-Attribute Utility Theory (MAUT) entails considering the decision maker's preferences using a utility function defined over a set of attributes. Determining the "*utility value"* involves establishing single-attribute utility functions, verifying preferential and utility-independent conditions, and deriving multi-attribute utility functions. These utility functions can exhibit either additively separable or multiplicatively separable characteristics to single attribute utility.

- Sales volume and the number of high-quality negative comments are the most influential factors in consumers' online shopping decisions.
- Sales volume is crucial, transmitting trust and reducing perceived risk for consumers.
- High-quality negative comments significantly impact consumer trust and inhibit online purchase intentions, especially when multiple comments highlight the same issue.
- Immediate feedback and proper handling of high-quality negative comments are essential for online store operations and directly impact potential consumers' purchase decisions.
- The number of comments and comments with pictures are the second-most impactful factors, enhancing the authenticity and credibility of online reviews.
- A large number of comments signifies high sales, stimulating purchasing conformity among potential consumers.
- Store type and video presentation have the least impact, with video descriptions improving consumer cognition.
- The influence of the number of followers on consumers' online purchase decisions is almost negligible due to factors like low repurchase behaviour and the diverse product range of comprehensive stores.

Customers, in their purchasing process, engage in information gathering to facilitate their decision-making (Bai et al., 2015). In the domain of e-commerce, research indicates that factors related to the merchant (such as website design, reputation, and service quality), the product (including specifications and quality), or individual factors (like trust and self-efficacy) play a substantial role in influencing consumer purchase decisions (Bai et al., 2015; Chen et al., 2017; Li et al., 2013).

V. POST-PURCHASE BEHAVIOUR

After making a purchase, online consumers commonly assess the actual properties of the product in comparison to their expectations, influencing their satisfaction level. If the product exceeds expectations, consumers feel very satisfied; if it aligns with expectations, they feel basically satisfied; and if it falls short, dissatisfaction ensues. Post-purchase sentiments are often shared with friends and family, extending the impact. Consumer comments in various channels, such as forums and blogs, can influence the decisions of strangers. Key factors affecting post-purchase satisfaction include corporate image and commitment, consumption experience, after-sales service, and safety and reliability. Meeting promises, providing a positive overall buying experience, offering convenient after-sales service, and ensuring safety contribute to enhanced consumer satisfaction (Han, 2021).

An e-commerce company can promote customer engagement by suggesting relevant communities related to a product and updating customers on community activities. Participation tends to increase when individuals encounter diverse opinions and receive feedback. E-commerce platforms notify customers through email about feedback on their reviews or opinions from friends. Leveraging social influence data from E-commerce interactions and transaction information, E-commerce websites have significant potential to enhance sales by aiding customers throughout their decision-making process (Kim & Srivastava, 2007).

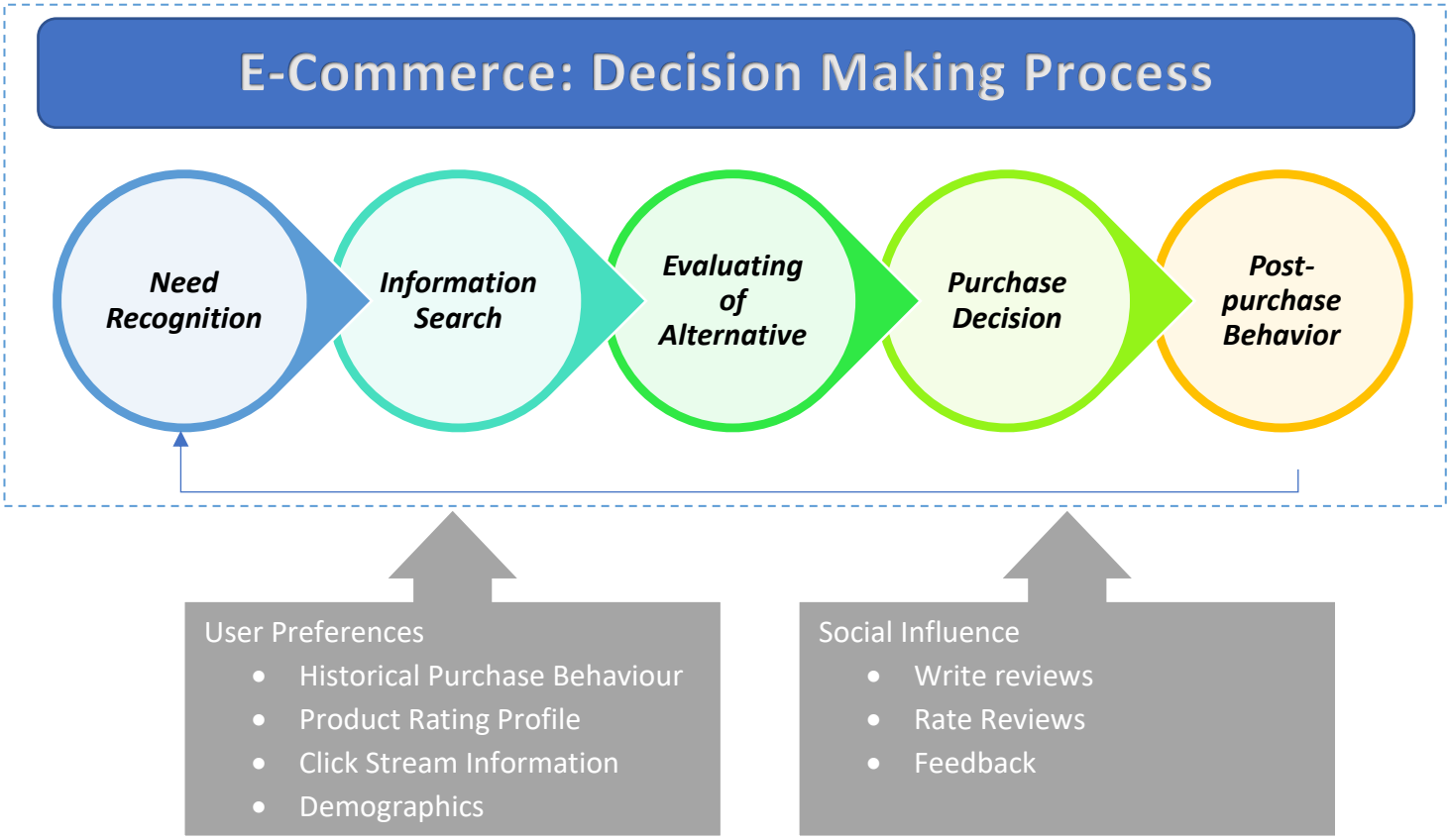

Figure 16: E-Commerce - decision making process

2.4.2 Critical Success Factors Review: Preceding Studies

To grasp e-commerce success, we need to look back and study what factors have made it work. This part of the paper looks at past studies and history to find out the key things that have made e-commerce successful. By learning from what others have found before, I hope to understand how these factors have changed over time and why they still matter today. This helps us see what counts for profitability in online business.

In the ever-evolving landscape of e-commerce, researchers have increasingly turned their attention to understanding customer behaviours during online purchases. As the foundations of e-commerce began to take root and shape the way we shop, a multitude of studies emerged, aiming to uncover

the critical factors driving consumer decisions. By investigating these research articles, it becomes apparent that certain key areas have garnered significant attention.

Among these it seems, *user online shopping experience* (Ameen et al., 2021; Hartson & Pyla, 2012; Khalifa & Liu, 2007; Luo et al., 2012; Mosteller et al., 2014; Trevinal & Stenger, 2014), *customer satisfaction* (Eid, 2011; Kassim & Asiah Abdullah, 2010; Liu et al., 2008), *product information* (Häubl & Trifts, 2000; Park & Kim, 2006; Park & Kim, 2003; Rowley, 2000; Xu et al., 2020), *trust privacy and security* (Lăzăroiu et al., 2020; McCole et al., 2010; P. Riquelme & Román, 2014; Qalati et al., 2021; Tran, 2020), *price & perceived value* (Hsin Chang & Wang, 2011; H.-W. Kim et al., 2012; Lim et al., 2016; Zhou et al., 2007), *customer reviews and feedback* (Elwalda et al., 2016; Mudambi & Schuff, 2010; Thakur, 2018; Wei & Lu, 2013), *shipping and return policies* (Bower & Maxham III, 2012; Hjort & Lantz, 2016; Janakiraman et al., 2016), *online customer service (e-service)* (Lee & Lin, 2005; Rita et al., 2019b), *loyalty* (Anderson & Srinivasan, 2003; Tsao et al., 2016; Wassouf et al., 2020), *switching behaviour* (Calvo-Porral & Lévy-Mangin, 2015; Chuang & Tai, 2016; Han et al., 2011), *cross-cultural differences* (Chen et al., 2015; Liao et al., 2008; Park & Jun, 2003), *cart interactions* (Huang et al., 2018; Khan et al., 2022; Rubin et al., 2020), and *future purchase intentions* (Ginting et al., 2023; Qureshi et al., 2009; Wu et al., 2014) emerge as significant factors influencing online consumer behaviour. This scrutiny reflects the growing recognition of the complex interplay between diverse strategies and numerous factors in shaping the online shopping experience.

The following table (Table 4) reviews some research conducted on online shopping behaviour, spanning diverse perspectives. This review offers insights into the critical success factors identified in prior studies.

Table 4: Exploring Critical Success Factors in Online Shopping Behaviour: A Review

Factor	Article	Summary / Key Findings	Authors	Methodology / Tool Used	Date
User Online Shopping Experience	Identifying key factors affecting consumer purchase behaviour in an online shopping context	• How online shopping differs from in-person interactions, • Information quality and security perceptions influence customer satisfaction and purchasing behaviour,	Chung-Hoon Park, Young-Gul Kim,	Applying a five-point Likert scale	2003
	Toward a conceptualization of the online shopping experience	• Consumers' experiences in online shopping, proposing a conceptual framework through a literature review, • Identifying four core dimensions (physical, ideological, pragmatic, and social),	Aurélia Michaud-Trévinal, Thomas Stenger,	Qualitative research through focus group interviews	2014
	The Impact of the Multi-channel Retail Mix on Online Store Choice: Does Online Experience Matter?	• How consumers' online store preferences change with more online shopping experience, • By gaining experience, factors like product variety and loyalty programs become more important,	Kristina Melis, Katia Campo, Els Breugelmans, Lien Lamey,	A multinomial logit model	2015
	The construction of online shopping experience: A repertory grid approach	• Understanding of online customer experience in e-shopping by investigating consumers' own perceptions through Kelly's personal construct theory (PCT), • The diverse nature of experience and emphasizing the need for a user-centric approach in theoretical and methodological frameworks,	Fatema Kawaf, Stephen Tagg,	The repertory grid technique for data collection	2017

Factor	Article	Summary / Key Findings	Authors	Methodology / Tool Used	Date
	User experience in personalized online shopping: a fuzzy-set analysis	• A complexity theory framework to investigate how trust, privacy, emotions, and experience collectively influence consumers' purchase intentions in personalized online shopping environment,	Ilias O. Pappas	Fuzzy-set Qualitative Comparative Analysis (QCA)	2018
Customer Satisfaction	The Impact of Website Quality Dimensions on Customer Satisfaction in the B2C E-commerce Context	• The impact of website quality dimensions on customer satisfaction in business-to-consumer e-commerce, • Identifying critical variables such as website design, interactivity, informativeness, security, responsiveness, and trust	Hsiu-Fen Lin	Structural Equation Modelling (SEM)	2007
	The effect of perceived service quality dimensions on customer satisfaction, trust, and loyalty in e-commerce settings: A cross cultural analysis	• The interplay among perceived service quality, satisfaction, trust, and loyalty in e-commerce, • Perceived service quality notably shapes customer satisfaction, subsequently influencing trust. Both satisfaction and trust contribute to loyalty through word of mouth,	Norizan Kassim, Nor Asiah Abdullah,	Structural Equation Modelling (SEM)	2010
	How convenient is it? Delivering online shopping convenience to enhance customer satisfaction and encourage e-WOM	• The dimensions of online convenience affecting consumer intention in online shopping, • Identifying possession, transaction, and evaluation as key factors and offering insights for e-commerce retailers to improve satisfaction and e-WOM,	Paulo Duarte, Susana Costa e Silva, Margarida Bernardo Ferreira,	Confirmatory Factor Analysis (CFA) and Covariance-Based Structural Equation Modelling (CB-SEM)	2018
	The Influence of Online Shopping Determinants on Customer Satisfaction in the Serbian Market	• The relationship between online shopping determinants and consumer satisfaction, proposing a research model comprising seven variables: security, information availability, shipping, quality, pricing, time, and customer satisfaction,	Nebojša Vasić, Milorad Kilibarda, Tanja Kaurin,	Confirmatory Factor Analysis (CFA) with Partial Least Squares (PLS)	2019
	Predicting overall customer satisfaction: big data evidence from hotel online textual reviews	• The impact of linguistic attributes and customer involvement on overall satisfaction, • Active involvement in review communities positively affects satisfaction,	Yabing Zhao, Xun Xu, Mingshu Wang,	A Multivariate Linear Regression Analysis	2019
Product Information	The fluent online shopping experience	• The impact of perceived fluency of online verbal information on consumers' cognitive effort and positive affect during online shopping, • Perceptual fluency affects both cognitive effort and positive affect,	Jill Mosteller, Naveen Donthu, Sevgin Eroglu,	Structural Equation Modelling- (SEM) based Partial Least Squares (PLS)	2014
	Understanding online purchase decision making: The effects of unconscious thought, information quality, and information quantity	• What a rich information in online shopping impacts decision satisfaction, focusing on the role of unconscious thought, • How information quantity, quality, and thought mode influence consumer satisfaction when purchasing experience products online,	Jie Gao, Cheng Zhang, Ke Wang, Sulin Ba,	Analysis of Variance (ANOVA)	2012
	Complexity or simplicity? Designing product pictures for advertising in online marketplaces	• The impact of visual complexity and complexity contrast on buyers' perceptions of pleasantness in online shopping, • Buyers prioritize the conspicuousness of product pictures over the information conveyed when facing visually overwhelming images,	Kewen Wu, Julita Vassileva, Yuxiang Zhao, Zeinab Noorian, Wesley Waldner, Ifeoma Adaji,	The Stimulus Organism Response (SOR) framework	2016
	Consumer Pre-purchase Search in Online Shopping: Role of Offline and Online Information Sources	• Consumer information search behaviour in online shopping, • Consumers utilize both traditional offline and online sources, with preferences varying based on the product type and individual factors like Internet experience, need for cognition, and age,	Krishna Akalamkam, Joy Kumar Mitra,	Analysis of Variance (ANOVA), and Manipulation Check using T-tests	2017
	Conceptualization of omnichannel customer experience and its impact on shopping intention: A mixed-method approach	• Omnichannel customer experience in the retail industry, • Developing a survey instrument and a nomological model that considers perceived compatibility and perceived risk as key factors linking omnichannel experience to shopping intention,	Si Shi, Yi Wang, Xuanzhu Chen, Qian Zhang,	Smart Partial Least Squares (PLS)	2020
Trust Privacy and Security	Building Customer Trust in Mobile Commerce	• The crucial role of trust in online customer relationships, • Emphasizing how customer scepticism about e-commerce, exacerbated by a lack of personal interaction and perceived risks, inhibits trust,	Keng Siau, Zixing Shen,	Analysis of Variance (ANOVA)	2003

Factor	Article	Summary / Key Findings	Authors	Methodology / Tool Used	Date
	The Impact of Customer Trust and Perception of Security Control on the Acceptance of Electronic Commerce	• The influence of customer perceptions of security control on e-commerce acceptance, with trust as a mediating factor, • Focusing on Internet banking as the research domain,	Bomil Suh, Ingoo Han,	Technology Acceptance Model (TAM)	2014
	Consumer perception of interface quality, security, and loyalty in electronic commerce	• The connections between customer interface quality, perceived security, switching costs, and customer loyalty in e-commerce, • Customer interface quality and perceived security positively influenced customer satisfaction and switching costs,	Hsin Chang, Su Wen Chen,	Structural Equation Modelling (SEM)	2009
	Trust and e-commerce: a study of consumer perceptions	• Trust in online B2C relationships • A framework based on key factors like perceived market orientation, site quality, and technical trustworthiness,	Brian J. Corbitt, Theerasak Thanasankit, Han Yi,	Correlation Tests & Linear Regression	2003
	Modelling and testing consumer trust dimensions in e-commerce	• Empirically tests a path model to examine how Internet vendors can enhance trust, • Focusing on three trust dimensions: competence, integrity, and benevolence, and their influence on overall trust,	Tiago Oliveira, Matilde Alhinho, Paulo Rita, Gurpreet Dhillon,	Partial Least Squares (PLS)	2017
Price & Perceived Value	Perceived value, transaction cost, and repurchase-intention in online shopping: A relational exchange perspective	• A framework to analyse the impact of both value-related and transaction cost-related factors on the intention of online shoppers to repurchase, • It defines cost as consisting of three components: information searching cost, moral hazard cost, and specific asset investment,	Lei-Yu Wu, Kuan-Yang Chen, Po-Yuan Chen, Shu-Ling Cheng,	Analysis of Variance (ANOVA)	2014
	The moderating effect of customer perceived value on online shopping behaviour	• The influence of e-service quality, customer perceived value, and customer satisfaction on customer loyalty in online shopping. • E-service quality and customer perceived value impact customer satisfaction, which in turn affects customer loyalty,	Hsin Chang, Hsin-Wei Wang	Structural Equation Modelling (SEM) and Linear Hierarchical Regression	2011
	Price dispersion in the small and the large: Evidence from an internet price comparison site	• Analysing over four million daily price observations for over 1,000 consumer electronics products, • The internet prices converge towards a uniform "law of one price",	Michael R. Baye, John Morgan, Patrick Scholten	Clearinghouse Models	2004
	Consumer choice behaviour in online and traditional supermarkets: The effects of brand name, price, and other search attributes	• The value of brand names and consumer price sensitivity in online versus traditional supermarkets, • The brand names are more important online when less product information is available. Online choices prioritize factual information over sensory cues, leading to higher price sensitivity,	Alexandru M. Degeratu, Arvind Rangaswamy, Jianan Wu	The Store Choice Model & The Brand Choice Model	2000
	Online shopping acceptance model, a critical survey of consumer factors in online shopping	• The growing importance of understanding consumer acceptance of online shopping, • The lack of a comprehensive view on this subject,	Lina Zhou, Liwei Dai, Dongsong Zhang,	Online Shopping Acceptance Model (OSAM)	2007
Customer Reviews & Feedback	Research Note: What Makes a Helpful Online Review? A Study of Customer Reviews on Amazon.com	• The factors influencing the perceived helpfulness of customer reviews in the online purchase decision-making process, • Utilizing the concepts of search and experience goods from information economics,	Susan M. Mudambi, David Schuff	Tobit Regression	2010
	Predicting the “helpfulness” of online consumer reviews	• The challenge posed by the vast volume of online reviews for consumers and businesses, • The importance of online reviews in the decision-making process and proposes machine learning models to predict the helpfulness of these reviews,	Jyoti Prakash Singh, Seda Irani, Nripendra Rana, Yogesh Dwived, Sunil Saumya, Pradeep Kumar Roy,	Ensemble Learning Technique (Gradient Boosting Algorithm)	2017
	Online Reviews: Do Consumers Use Them?	• How negative online reviews influence consumers' evaluations and intentions towards retailers and post-product decisions,	Patrali Chatterjee,	Retailer Reviews from Comparison Shopping Engines	2001
	Consumer’s rule: How consumer reviews influence perceived trustworthiness of online stores	• Two studies demonstrate that consumer reviews are more influential than overall store reputation or assurance seals in determining consumer trust in online stores,	Sonja Utz, Peter Kerkhof, Joost van den Bos,	Analysis of Variance (ANOVA)	2012

Factor	Article	Summary / Key Findings	Authors	Methodology / Tool Used	Date
	Effectiveness of online consumer reviews: The influence of valence, reviewer ethnicity, social distance and source trustworthiness	• The impact of reviewer ethnicity, review valence, and social distance on perceived reviewer trustworthiness, brand attitude, and purchase intention. • Findings reveal that review valence, reviewer ethnicity, and social distance significantly affect perceived reviewer trustworthiness,	Carolyn A. Lin, Xiaowen Xu,	Analysis of Variance (ANOVA)	2017
Shipping and Return Policies	The impact of returns policies on profitability: A fashion e-commerce case	• The effects of returns policies on consumer behaviour and profitability using transactional data,	Klas Hjort, Björn Lantz,	Multiple Regression Analysis	2016
	Consumer Return Policies in Omnichannel Operations	• Pricing and return policy decisions of omnichannel retailers, considering customer behaviours and uncertainties regarding product valuation realization, ultimately providing insights into why some firms opt for full refunds while others charge fees for online returns,	Leela Nageswaran, Soo-Haeng Cho, Alan Scheller-Wolf,	Full Refund & Partial Refund Policies	2020
	Consumer return policies in presence of a P2P market	• How the presence of peer-to-peer (P2P) second-hand goods markets impacts retailers' optimal return policies,	Tingting Li, Jinxing Xie, Xin Liu,	Analysis of Variance (ANOVA)	2020
	Return shipping policies of online retailers: Normative assumptions and the long-term consequences of fee and free returns	• Equity-based return policies where customers pay for return shipping if deemed at fault, • Contrary to retailer assumptions, customer perceptions of fairness do not reverse the consequences of free or fee-based returns,	Amanda B. Bower, James G. Maxham,	A Longitudinal Event Field Study (over four years with online customers)	2012
	The customer consequences of returns in online retailing: An empirical analysis	• The impact of product returns on subsequent shopping behaviour in the online marketplace, • Despite being seen as a cost centre, the returns management process can significantly influence repurchase behaviour,	Stanley E. Griffis, Shashank Rao, Thomas J. Goldsby, Tarikere T. Niranjan,	Transaction Cost, Consumer Risk, and Procedural Justice Theories	2012
E- Service	The impact of e-service quality and customer satisfaction on customer behaviour in online shopping	• Understanding how e-service quality dimensions impact customer satisfaction, trust, and behaviour in online shopping,	Paulo Rita, Tiago Oliveira, Almira Farisa,	Partial Least Squares (PLS)	2019
	E-service quality: a model of virtual service quality dimensions	• The importance of service quality in e-commerce and introducing a conceptual model for determining e-service quality,	Jessica Santos,	Focus Groups and Qualitative Analysis,	2003
	E-service quality: A meta-analytic review	• Developing a conceptual framework through means-ends-chain theory for E-service quality,	Markus Blut, Nivriti Chowdhry, Vikas Mittal, Christian Brock,	Pearson Correlation Coefficient,	2015
	Integrating service quality with system and information quality: An empirical test in the e-service context	• The 3Q model, integrating service quality (SQ) with system quality (SysQ) and information quality (IQ) to understand website adoption, • It tests relationships among these quality constructs,	J Xu, I Benbasat, RT Cenfetelli,	The 3Q model in the "information getting" stage of e-service,	2013
	An assessment of customers' e-service quality perception, satisfaction and intention	• Web service quality dimensions and their impact on customer satisfaction and Behavioural intentions in e-business, • It identifies perceived risk, web content and service, and convenience as key dimensions,	Godwin J. Udo, Kallol K. Bagchi, Peeter J. Kirs,	A conceptual model to investigate the influence of web service quality,	2010
Loyalty	Customer Loyalty in E-Commerce	• How service quality and trust influence customer loyalty for online vendors, • Finding that perceived better service quality boosts loyalty directly and through increased trust,	David Gefen,	SERVQUAL,	2002
	Consumer perception of interface quality, security, and loyalty in electronic commerce	• How customer interface quality and perceived security influence customer satisfaction, switching costs, and ultimately customer loyalty in e-commerce,	Hsin Chang, Su Wen Chen,	Structural Equation Modelling (SEM)	2009
	A strategic approach to building online customer loyalty: Integrating customer profitability tiers	• A strategic framework for managing online loyalty, blending theoretical insights from consumer loyalty literature with contemporary internet practices,	Dennis A. Pitta, Frank Franzak,	Integrating theoretical concepts from consumer loyalty literature	2006
	Intensifying online loyalty! The power of website quality and the perceived value of consumer/seller relationship	• How website quality affects customer value and loyalty, • System quality and e-service quality positively impact the perceived value of the consumer/seller relationship,	Wen-Chin Tsao, Ming-Tsang Hsieh, Tom M.Y. Lin,	Partial Least Squares (PLS)	2016

Factor	Article	Summary / Key Findings	Authors	Methodology / Tool Used	Date
	Customer loyalty in e-commerce: an exploration of its antecedents and consequences	• Factors influencing customer loyalty in online B2C contexts, • Identifying eight factors that affect e-loyalty, except convenience, and developing measurement scales for them,	Srini S. Srinivasan, Rolph Anderson, Kishore Ponnavolu,	A multi-item scale instrument	2002
Switching Behaviour	An integrative framework for customer switching behaviour	• Examining factors affecting customer switching intention in banking, including satisfaction, loyalty, trust, and perceived value,	Seyed Mohammad Mosavi, Mohamad Sadegh Sangari, Abbas Keramati,	Homogeneity Tests and Non-response Bias Tests	2018
	Research on customer switching behaviour in the service industry	• Reviewing past research on switching behaviour to understand its characteristics and findings and identifies advancements in the field, • Key predictors like satisfaction, switching costs, and alternative attractiveness are commonly used,	Yi-Fei Chuang, Yang-Fei Tai,	Meta-analysis	2015
	Customer Switching Behaviour in Online Services: An Exploratory Study of the Role of Selected Attitudinal, Behavioral, and Demographic Factors	• Identifying differences between online service switchers and continuers, • Switchers rely more on word-of-mouth, use services less, and exhibit lower satisfaction and involvement,	Susan M. Keaveney, Madhavan Parthasarathy,	Selecting a representative sample of online service subscribers,	2001
	Investigating switching intention of e-commerce live streaming users	• Why users switch between e-commerce live streaming (ELS) platforms using the Push-Pull-Mooring (PPM) model, • Analysing survey responses, finding factors like dissatisfaction, privacy concerns, and perceived negativity influence switching intentions,	Dingyu Ye, Fufan Liu, Dongmin Cho, Zhengzhi Jia,	Using the Push-Pull-Mooring (PPM) model	2022
	Vendor Consideration and Switching Behaviour for Buyers in High-Technology Markets	• How organizational buyers in high-tech markets consider and switch to new vendors, • Analysing computer workstation equipment purchases,	Jan B. Heide, Allen M. Weiss,	A sequential logit model	1995
Cross-Cultural Differences	Content preparation for cross-cultural ecommerce: a review and a model	• The importance of tailoring content in e-commerce websites to suit the preferences of users from different cultural backgrounds, • It proposes a conceptual model that explores how cultural factors influence consumers' information processing in cross-cultural e-commerce,	H. Liao, R. W. Proctor, G. Salvendy,	A comprehensive approach to investigating the influence of culture on information processing in cross-cultural e-commerce	2008
	E-Loyalty formation: A cross-cultural comparison of Spain and Colombia	• Investigating online shopping behaviour and loyalty among Colombian and Spanish consumers, • Finding nationality influences loyalty, with affective elements vital for Colombians and enjoyment in the shopping process crucial for Spaniards,	Nathalie Peña García, Irene Gil Saura, Augusto Rodríguez-Orejuela,	A transversal cross-cultural quantitative study,	2018
	E-commerce web site loyalty: A cross cultural comparison	• Investigates e-loyalty in e-commerce sites using DeLone and McLean's IS Success Model, • Proposing a model including information, system, service quality, trust, and customer satisfaction	Jengchung Victor Chen, David C. Yen, Wannasri Pornpriphet, Andree E. Widjaja,	DeLone and McLean's IS Success Model	2015
	A cross-cultural comparison of Internet buying behaviour	• Comparing the Internet usage, perceived risks, and buying behaviour between Korean and American consumers,	Cheol Park, Jong-Kun Jun,	The Regression Analysis	2003
	Cultural dimensions in online purchase behaviour: Evidence from a cross-cultural study	• How cultural differences influence consumers' online buying behaviour, • Using a model based on Hofstede's theory and the theory of planned behaviour, • It investigates the impact of national culture on various factors such as website usability, trust, perceived risk, and intention to use,	Francesca Pratesi, Lala Hu, Riccardo Rialti, Lamberto Zollo, Monica Faraoni,	Confirmatory Factor Analysis (CFA), Structural Equation Modelling (SEM),	2021
Cart Interaction	Online shopping cart abandonment: a consumer mindset perspective	• How consumers' mindsets affect online shopping cart abandonment, • It finds those with an abstract mindset are more likely to complete purchases, reducing cart abandonment, as they assign greater importance to products in their carts compared to those with a concrete mindset,	Daniel Rubin, Chrissy Martins, Veronika Ilyuk, Diogo Hildebrand,	Examining the effect of consumer mindsets on purchase intentions, (Abstract vs Concrete)	2020

Factor	Article	Summary / Key Findings	Authors	Methodology / Tool Used	Date
	Online shopping cart abandonment: A review and research agenda	• The study systematically reviews articles on online shopping cart abandonment (OSCA) from 2003 to 2022, • It reveals that research often relies on the S-O-R model and buyer behaviour theory, focusing on the US and China using quantitative methods,	Siqi Wang, Jun-Hwa Cheah, Xin-Jean Lim,	Focusing on the utilization of the Stimulus-Organism-Response (S-O-R) model and buyer behaviour theory	2022
	To purchase or to remove? Online shopping cart warning pop-up messages can polarize liking and purchase intention	• Examining warning messages' impact on consumer attitudes and purchase intentions in online shopping carts, • Five studies show that reminding consumers to clean their carts affects liking and purchase intention,	Haichuan Zhao, Xuehua Wang, Lan Jiang,	Using statistical analyses	2021
	Mobile shopping cart abandonment: The roles of conflicts, ambivalence, and hesitation	• Investigating high shopping cart abandonment rates in the mobile channel, using the cognition-affect-behaviour (CAB) paradigm, • It finds emotional ambivalence increases hesitancy during checkout, leading to abandonment,	Guei-Hua Huang, Nikolaos Korfiatis, Chun-Tuan Chang,	Using statistical analyses based on the cognition-affect-behaviour (CAB) paradigm	2018
	Social commerce advertising avoidance and shopping cart abandonment: A fs/QCA analysis of German consumers	• Investigating shopping cart abandonment resulting from ad avoidance on social media, • It considers cognitive, affective, and behavioural ad avoidance, along with factors like perceived goal impediment and prior negative experiences,	Asad Khan, Sajad Rezaei, Naser Valaei,	Applying Fuzzy Sets/Qualitative Comparative Analysis (fs/QCA)	2022
Future purchase intentions	What Effects Repurchase Intention of Online Shopping	• Investigating factors influencing repurchase intention in online shopping, including e-service quality, price perception, and experiential marketing, mediated by customer satisfaction,	Lily Suhaily, Yasintha Soelasih,	Structural Equation Modeling (SEM)	2017
	The Role of Online Experience in the Relationship Between Service Convenience and Future Purchase Intentions	• Investigating how online convenience and shopping experience affect consumer satisfaction and future purchase decisions, • The study finds customer satisfaction and shopping experiences positively influence purchase intention, with satisfaction mediating these relationships,	Swapan Kumar Saha, Paulo Duarte, Susana C. Silva, Guijun Zhuang,	Partial Least Squares Structural Path Modelling	2022
	Moderating effects of online shopping experience on customer satisfaction and repurchase intentions	• Customer experience moderates the relationships between performance expectancy and satisfaction, as well as between satisfaction and intention to repurchase,	Ilias O. Pappas, Adamantia G. Pateli, Michail N. Giannakos, Vassilios Chrissikopoulos,	Structural Equation Modelling (SEM)	2013
	Customer repurchase intention: A general structural equation model	• Presenting a service sector model of repurchase intention, examining factors like service quality, equity, value, satisfaction, loyalty, switching cost, and brand preference, • It finds perceived quality indirectly affects satisfaction through equity and value perceptions,	Phillip K. Hellier, Gus M. Geursen, Rodney A. Carr, John A. Rickard,	Structural Equation Modelling (SEM)	2003
	Trust, Satisfaction, and Online Repurchase Intention: The Moderating Role of Perceived Effectiveness of E-Commerce Institutional Mechanisms	This study explores how e-commerce institutional mechanisms impact trust and repurchase behaviour in online shopping. It introduces the concept of the perceived effectiveness of these mechanisms (PEEIM) and finds that PEEIM negatively moderates the relationship between trust and repurchase intention, diminishing trust's role in driving repeat purchases.	Yulin Fang, Israr Qureshi, Heshan Sun, Patrick McCole, Elaine Ramsey, Kai H. Lim,	the theory of organizational trust as a framework and used statistical analysis	2014

Having reviewed the research on online shopping behaviour in the table above, it is clear that various perspectives have contributed valuable insights into critical success factors. Moving forward, through synthesising diverse research perspectives, this paper aims to provide a comprehensive analysis of online shopping behaviour and its implications.

2.4.3 Unlocking Success: E-Commerce Critical Success Factors

With the express evolution of technology, many experiences, including the shopping process, have transitioned, either partially or entirely, to the digital area (Kawaf & Tagg, 2017). After years of progress, the internet and mobile networks have seamlessly integrated into both work and personal

life. E-commerce has emerged as a main driver of growth in numerous countries (Yang et al., 2020), with online shopping evolving into a crucial avenue for meeting daily consumption needs, particularly in the realm of consumer goods (L. Yang et al., 2022).

Thanks to technological progress, companies are now connecting with their customers through diverse channels, including e-commerce, mobile commerce, and physical stores (Maity & Dass, 2014). Consumers are fascinated by e-commerce platforms for the convenience they provide in shopping, which is unbound by constraints of space, time, and product diversity. The convenience and wealth of information offered by online shopping empower consumers to make informed choices, comparing products and prices with ease (L. Yang et al., 2022).

A company that can foresee customer buying patterns will experience several advantages, such as a better rate of acquiring customers, increased sales, and elevated competitiveness (Qiu et al., 2015). Prior studies have conducted numerous investigations to examine the factors that influence purchase intention in the context of online shopping (L. Yang et al., 2022).

Transitioning from the broader context of e-commerce's evolution and significance, I now focus on a detailed examination of critical success factors. I explore these factors in detail, providing insights into their significance and implications for e-commerce businesses. Through this analysis, I aim to provide a comprehensive understanding of the factors driving success in e-commerce and informing strategic decision-making.

- **User Online Shopping Experience**

As e-commerce continues to expand, updated information about customer behaviour and its importance in maximising profitability has found widespread application across various research domains in e-commerce.

Notably, the field of online shopping, closely tied to consumer behaviour, has garnered considerable attention (Hsieh & Tsao, 2014). The key element for success in e-commerce lies in the development of a website as well as applications characterised by excellent system quality, information quality, and electronic service quality (e-service quality) (Tsao et al., 2016). Creating high-quality websites is instrumental in fostering user willingness to engage with e-commerce systems, amplifying satisfaction levels, expanding market reach, and augmenting sales volumes (DeLone & McLean, 2003, 2004).

As web-related software and hardware technologies mature, shopping website managers must extend their focus to other critical factors influencing enterprise success (Corritore et al., 2003). One such factor is the enhancement of online service quality, which proves beneficial in building website

brand equity (Tsao & Tseng, 2011). Furthermore, the online shopping experience emerges as another influential factor impacting consumers' product judgments and serving as a pivotal reference variable for marketers engaged in market segmentation (Park et al., 2012). Collectively, these factors are indispensable elements for the success of shopping websites and applications that are considered as user experience through online shopping. Therefore, it is important to tailor smartphone applications, social networking pages, websites, and mobile-friendly web pages based on users' expectations and preferences. This ensures that these platforms effectively engage customers and encourage ongoing virtual interactions with the company (Bilgihan et al., 2016).

On the other hand, the evaluation of customer interface quality in the context of online shopping involves four essential components. Firstly, convenience is gauged by the ease of navigation and user-friendliness, addressing the common issue of incomplete e-commerce transactions due to shoppers struggling to quickly access necessary information. Secondly, interactivity measures the degree of two-way communication with customers, highlighting its role in substituting for the interpersonal dynamics of physical stores and positively influencing consumer response. Thirdly, customisation focuses on the website's ability to tailor offerings to individual customers, increasing the likelihood of finding desired products and creating a perception of expanded choices. Lastly, character relates to the overall image projected by the online store through design elements, impacting the visual appeal and instilling confidence in users, thereby enhancing the overall shopping experience (Chang & Chen, 2009).

This means an extensive online shopping experience enables customers to better assess the benefits and risks associated with products or services, fostering a sense of comfort with online retailers (Melis et al., 2015; Soopramanien, 2011). Also, the repurchase behaviour in online retail is significantly influenced by the shopping experience, as noted in various studies (Ling et al., 2010; Melis et al., 2015). In contrast, inexperienced online shoppers often express concerns about issues like personal information leaks and unauthorized credit card use, contributing to hesitancy in online shopping (Saha et al., 2023).

Research suggests that experienced online shoppers exhibit greater self-confidence, leading them to engage in online activities more frequently compared to their inexperienced counterparts (Tsao et al., 2016). Highly experienced customers, being more confident in their judgments, differ from their less experienced counterparts (Flacandji & Krey, 2020; Saha et al., 2023). Overall, positive experiences with online platforms foster favourable attitudes, enhance customer satisfaction, and influence the intention to repurchase (O. Pappas et al., 2014).

Moreover, A poor experience undermines the link between customer satisfaction and the intention to repurchase (O. Pappas et al., 2014). On the other hand, Roy Dholakia and Zhao (Roy Dholakia & Zhao, 2010) argued that satisfying experienced customers is more challenging, given their wealth of information, making their decision-making process more intricate than that of inexperienced customers.

Also, research endeavours in user experience design are a widely pursued area, focusing on crafting web atmospherics and meticulously designing the online shopping environment to evoke specific user experiences (Kawaf & Tagg, 2017).

When strategizing the launch of a product or service, online retailers must consider their marketing approaches based on the experience level of their target audience. For those well-versed in online shopping, companies should concentrate on implementing mechanisms that enhance the performance of the online shopping platform. High-experience customers tend to make more rational decisions compared to their low-experience counterparts (Cheema & Papatla, 2010). In addressing low-experience customers, it is crucial for firms to recognise that factors such as effort expectancy and self-efficacy play a more influential role. Therefore, investments should be directed towards improving the online shopping platform's user-friendliness and ease of use (O. Pappas et al., 2014).

- **Customer satisfaction**

Customer satisfaction is commonly described as the assessment made by customers after a purchase, comparing their pre-purchase expectations with the actual performance of the product or service (Duarte et al., 2018). There exists a significantly positive correlation between the overall perception of service quality, specifically online convenience, and satisfaction (Jun et al., 2004). Consequently, an enhancement in the convenience offered by the online retailer positively influences customer satisfaction (Koo et al., 2008). This implies that a higher level of convenient service contributes to an increased perceived value, leading to elevated satisfaction (Duarte et al., 2018). Customers are more likely to be satisfied and engage in repeat transactions when they can conveniently and effortlessly experience the benefits of the services (C. L. Hsu et al., 2010). Therefore, an improvement in convenience by online service providers correlates with an increase in customer satisfaction.

The quality of a purchasing decision is primarily reflected in customer satisfaction, making it a reliable indicator of decision quality (Gao et al., 2012). In the literature on decision-making, there is a common assumption that superior purchasing decisions result in higher levels of customer satisfaction (Chan et al., 2009). This assumption suggests that individuals who make sound decisions

tend to experience greater satisfaction during and after the process compared to those who make poor decisions. Research has indicated that satisfaction can be segmented into two dimensions based on different moments in the decision-making process: pre-consumption satisfaction, also known as decision satisfaction, reflects consumers' overall feelings regarding the information provided and the processes employed to make a decision (Gao et al., 2012). The second dimension is post-consumption satisfaction, which arises after using the product or service. Post-consumption satisfaction is measured by evaluating whether subjects are willing to recommend the products to others (Kohli et al., 2004).

In general, studies have consistently shown that customer satisfaction acts as a mediator in the relationship between service convenience[3] and behavioural intention (Chang & Polonsky, 2012; Connolly & Bannister, 2008; Kumar et al., 2020; Le-Hoang, 2020; Saha et al., 2021; Yin et al., 2019). Empirical evidence supports the idea that the convenience offered by online stores positively impacts customer satisfaction (Koo et al., 2008; Ngoc Thuy, 2011) and that service convenience, in turn, has a positive effect on customer satisfaction, leading to behavioural intentions (Duarte & Silva, 2020; Elizabeth Lloyd et al., 2014; Roy et al., 2018).

Enhanced service convenience instils confidence and satisfaction in customers, increasing the likelihood of repeat experiences (C. L. Hsu et al., 2010). Therefore, a convenient service contributes to perceived value (Ngoc Thuy, 2011), and customer satisfaction acts as a mediator between service convenience and future purchase intention (Saha et al., 2023).

While existing studies have linked behavioural intentions to loyalty, word-of-mouth, price sensitivity, and repurchase intentions (Jones et al., 2006; Smink et al., 2019; Y. Zhao et al., 2020), the specific interplay between service convenience, customer satisfaction, and repurchase intention requires further examination.

There are empirical evidence supporting the positive influence of customer satisfaction on future purchase intention, emphasising the complex nature of convenience sub-dimensions in shaping customer behavioural intentions (Cao et al., 2018; Chang & Polonsky, 2012). In summary, customer satisfaction acts as a vital mediator, channelling the positive impact of service convenience towards future purchase intentions (Saha et al., 2023).

[3] Service convenience refers to a customer's perception of the time and effort needed to access a (Berry, L. L., Seiders, K., & Grewal, D. (2002). Understanding service convenience) has become a critical element for online businesses aiming to maintain competitiveness. Given consumers' limited time and energy, their inclination towards online shopping is primarily driven by the quest for efficiency (Roy, Lassar, and Shekhar, 2016). So, since service convenience stands out as a primary motivator for consumers embracing online shopping (Roy et al., 2017), it is unsurprising that online retailers are making substantial investments in elevating the convenience aspects of their service offerings.

Product Information

The Internet has become a highly influential information source, significantly influencing the process of acquiring information (Zeng & Reinartz, 2003). The increasing focus of research is on the characteristics of online information and its influence on shopping behaviours, drawing more attention (Mosteller et al., 2014). Portable devices are now an integral part of the daily routine for constantly connected individuals. This presents distinct possibilities for service industries to leverage various platforms for engaging and maintaining online relationships with an expanding pool of connected customers (Bilgihan et al., 2016).

From the standpoint of customers, they accumulate information during the product purchase process to assist in their decision-making (Bai et al., 2015). Within the scope of e-commerce, research indicates that elements related to the merchant (such as website design, reputation, service quality), the product itself (including specifications and quality), or individual factors (like trust and self-efficacy) significantly impact consumer purchase decisions (Chen et al., 2017).

Through online shopping, consumers benefit from increased information and convenience in product selection and price comparison. The extent to which customers can employ information to enhance their ability to make judgments and improve decision quality plays a crucial role in determining the efficiency of the electronic marketplace (Wu & Lin, 2006). Customers favour e-commerce platforms as they offer a shopping experience unrestricted by time, space, and product categories (L. Yang et al., 2022). An illustration of this is evident when searching for a book on offshore sailing on Amazon, where a comprehensive overview of existing literature is available. This stands in contrast to the comparatively limited selection on the same subject at a local bookshop. Consequently, consumers find themselves in a situation where they have broad access to a significantly larger information repository (Wind & Mahajan, 2002). Also, web designers should be mindful of providing accessible information and user-friendly design interfaces that streamline the process of conducting information searches on the website (Wolfinbarger & Gilly, 2001).

Advancements in communication networks, protocols, computers, and user interface design have played an important part in the development of the Web, online publishing, and e-commerce. Today, consumers can access extensive information repositories from any location and at any time (Bilgihan et al., 2016). Facilitating consumers' access to more comprehensive information about product attributes, comparative pricing, availability, and the overall value proposition enhances the process of acquiring products (Brown et al., 2003). In the process of making purchasing decisions, customers actively seek out information to guide their choices. (Bai et al., 2015). The inclusion of online

personalisation features enables customers to perceive information in a more seamless and user-friendly manner, contributing to an enhanced shopping experience (Mosteller et al., 2014).

In e-commerce, research indicates that various factors related to the merchant, including website design, reputation, and service quality, as well as factors associated with the product information, such as specifications and quality, and individual factors like trust and self-efficacy, play a significant role in influencing consumer purchase decisions (Bai et al., 2015; Li et al., 2013; Luo et al., 2012).

One of the aspects of the Internet is its ability to streamline information searches for consumers, significantly improving the process of acquiring products. This improvement is achieved by granting consumers access to extensive details about product attributes, comparative pricing, availability, and the overall value proposition. This is particularly beneficial when the Internet is utilised alongside traditional retail channels. It is evident that this influential method of retail patronage demands a thorough understanding, given its pervasive use across various aspects of the shopping process (Brown et al., 2003).

Search involves accessing information sources to explore product alternatives. In the pre-Web era, consumers faced a fundamental challenge due to incomplete and biased information access. Dealing with confusion, obscure language, and obfuscation was common (Zeng & Reinartz, 2003). The Web has emerged as a powerful information source, profoundly influencing the process of acquiring information. Currently, consumers enjoy broad access to a substantially expanded information base (Fung & Fung, 2001).

Given that search is information-based and the Web excels in information storage and processing, the Internet has substantially improved the efficiency and effectiveness of the consumer decision-making process- (Smith & Brynjolfsson, 2001).

- **Trust, Privacy and Security**

As digital platforms continue to progress, online shopping landscapes are also developing, presenting consumers with an expanding array of choices throughout the purchasing journey and enhancing the quality of services and products available to them (Pappas, 2018).

Building trust stands as the paramount factor in attracting e-commerce buyers (Chang et al., 2013). Trust is a considerable factor in customers' decision-making process when it comes to whether to make purchases from online stores (Fortes et al., 2017). Trust is a belief, confidence, sentiment, or expectation regarding buyer intention or likely behaviour (Wu et al., 2018) . A lack of trust serves as a significant obstacle to the widespread adoption of e-commerce (Chang et al., 2013). Customer trust is assessed in three dimensions, including *competence*, *integrity*, and *benevolence*, and it was

discovered that customers with high overall trust exhibited a greater inclination toward engaging in e-commerce (Chang et al., 2013).

Earlier studies indicate that e-service quality has a positive impact on trust (Chiou & Droge, 2006; Cho & Hu, 2009; Rasheed & Abadi, 2014; Wu et al., 2010; Wu et al., 2018). It is noted that service quality directly fosters customer trust and indirectly influences trust through the mediation of customer satisfaction (Alrubaiee & Alkaa'ida, 2011).

Trust is a key aspect of online shopping, not only between the Internet merchant and the customer but also between the customer and the computer system executing the transaction (Lee & Turban, 2001). Trust serves to diminish uncertainty, especially when the degree of familiarity between the customer and the transaction security mechanism is insufficient (Wu et al., 2018).

Trust emerges as a consistent determinant, as highlighted by various studies (Reichheld et al., 2000b; Schlosser et al., 2006; Smith, 2002). The foundational elements of trust, often referred to as "trust generating activities," include transaction security, trustworthiness, on-time delivery, reasonable prices, product and service performance, and follow-up service and support.

Building upon trust, perceived value assumes significance, representing a customer's overall evaluation of benefits versus costs in a marketing context. This broad construct considers prices, incurred costs, and benefits relative to competitors (Pitta et al., 2006).

When customers possess a considerable level of trust in online shopping, their tendency to make a purchase is heightened (Gao, 2011). Additionally, if customers have previously made purchases on a website and had a positive buying experience, they are more likely to make repeat purchases from the same website (Rita et al., 2019b). Findings support a positive correlation between customer service, trust, and the intention to make a purchase (Chek & Ho, 2016).

When customers trust online retailers, they are likely to recommend the online retailer to their friends, indicating a transfer of customer trust to the online retailer (Wu et al., 2018). It is also emphasised that online trust is important for customers to endorse a brand or website (Kim & Stoel, 2004). Before recommending a website to others, customers typically require satisfaction with their experience and trust in the information provided by the website (Loureiro et al., 2018). The provision of high-quality service enhances both customer trust and satisfaction (Rita et al., 2019b). Customer trust, in turn, positively influences repurchase intentions and word-of-mouth recommendations (Rita et al., 2019b) and has a positive impact on making recommendations as well (Gremler et al., 2001). Given that both customer trust and satisfaction significantly shape customer behaviour, managers must integrate these factors into their marketing strategy (Rita et al., 2019b).

In e-commerce, boosting consumers' e-trust is major due to the heightened risk compared to traditional environments (Chou et al., 2015). Numerous studies underscore the significant role of e-trust in online purchase decisions, especially when consumers lack sufficient information about the seller (Wang & Emurian, 2005). The success of a virtual store hinges on consumers perceiving its website as reliable and worthy of e-trust (Bilgihan, 2016).

E-trust is defined as the confidence a consumer has in an e-merchant's reliability and integrity to successfully conduct online transactions (Peštek et al., 2011). In the context of e-commerce, e-trust includes consumer beliefs and expectations about the online vendor's characteristics. Consumers seek an online vendor willing and able to act in their interest, maintain transactional honesty, safeguard personal information, and fulfil promised merchandise delivery (Peña-García et al., 2018). The importance of e-trust in e-commerce is highlighted, emphasising its impact on consumer perceptions and their willingness to engage with and establish relationships with online vendors (Mohd-Any et al., 2015).

It should be noted that the combination of security features aimed at increasing customers' trust in the online vendor can complicate the website's usability, thereby impacting customer satisfaction (Shen & Chiou, 2010). Trust and privacy (Lee & Rha, 2016), along with the factor of experience (O. Pappas et al., 2014), can influence consumers' attitudes and assessments during online shopping. As marketers employ interactive technologies to shape consumer behaviour (Kaptein & Eckles, 2012), they formulate strategies based on logical reasoning, emotional appeals, and solicitation of input or feedback from and for consumers (Pappas et al., 2017).

Recent investigations into personalisation have underscored the pivotal role of trust in the online vendor, privacy, and emotions (Bleier & Eisenbeiss, 2015; Pappas et al., 2016). The results reveal various unique and equally impactful mixtures of trust, privacy, emotions, and experience that illustrate the intention to make a purchase in personalised online shopping. None of these factors independently are enough or indispensable in elucidating purchase intentions; rather, the combination of these factors can generate a strong intention to purchase, effectively avoiding instances of low or medium purchase intentions (Pappas, 2018).

Consideration must be given to various risks encompassing online payment, privacy, and security when engaging in online shopping. The typical process involves membership registration, online payment, and the completion of various forms for purchasing goods. Therefore, the crucial factor is trust, which starts with the reliability of promises made by enterprises in terms of privacy and security and will extend to trust in product information available online (Han, 2021). Online consumer

attitudes are shaped by trust, privacy, and security factors, ultimately impacting their consumption behaviour.

Moreover, security and privacy pertain to safeguarding credit card payments and privacy of shared information (Blut, 2016). The credibility and service quality of a website are enhanced by emphasizing security and assurance (L. Wang et al., 2015). Schmidt et al. (Schmidt et al., 2008) emphasised the importance of website privacy and security, crucial factors when customers share private information during online transactions.

▪ Price & Perceived Value

The literature underlines that when retailers simplify customers' product searches, it expedites and streamlines the entire online shopping journey for the buyer (Kollmann et al., 2012). With a heightened level of search convenience, online shoppers can effortlessly locate desired products and compare prices without the need to physically visit multiple locations (Dekimpe et al., 2020; Jiang et al., 2013; L. Yang et al., 2022), all while minimising the risk of abandoning the purchasing process midway (Saha et al., 2023).

Price serves as a crucial determinant influencing customer satisfaction, directly impacting perceived usefulness, and consequently shaping overall customer satisfaction (H.-W. Kim et al., 2012). Numerous studies investigate the strong correlation between price and customer satisfaction, with findings suggesting that the pricing factor significantly influences the satisfaction levels of online customers (Jiradilok et al., 2014). Online shoppers, unable to physically inspect products, exhibit high price sensitivity (Liu & Arnett, 2000). Furthermore, the ease of visiting various online stores and comparing prices contributes to customers seeking the best deal, enhancing their satisfaction (Lim & Dubinsky, 2004). However, contrary opinions exist, as some empirical studies in the United States and EU suggest that online consumers may have less price sensitivity than their offline counterparts, and online prices may even be higher (Richards et al., 2017). Another hypothesis proposed that online commerce's search efficiency surpasses that of offline commerce, resulting in friction-free commerce (Bakos, 1997). While many scholars support the first hypothesis (Xie & Kwok, 2017; Zhao et al., 2015), opposing views also exist (Grewal & Lindsey-Mullikin, 2006), creating a diversity of perspectives in the e-commerce market.

The notion of value is extensively explored in marketing. Throughout the transaction process, buyers assess the benefits derived from the efforts invested by sellers in upholding their mutual relationship (Tsao et al., 2016). Consumers evaluate the cost-performance of goods when considering product value, while service value is associated with the effectiveness of the service (L. Yang et al., 2022).

Customers compare their gains with their sacrifices to gauge the value of the relationship. When the gains surpass the sacrifices, positive relationship values are formed, requiring collaborative effort from both the seller and the buyer (Walter et al., 2001). If consumers perceive they have gained more value from the consumer/seller relationship (such as reduced costs, product innovation, high quality, or a positive image), they will appreciate and value their collaborative association with the sellers, aspiring for a long-term relationship. For sellers, the escalating value of the consumer/seller relationship establishes a higher threshold before customers consider switching to another supplier. Once a robust long-term relationship is established, buyer loyalty directly impacts the seller's profits (Geiger et al., 2012). Therefore, creating substantial relationship value is pivotal for sustaining prolonged cooperation between both parties.

- **Customer Reviews & Feedback**

Online reviews, also known as online feedback, include both positive and negative comments, product quality assessments, and service information (Kwark et al., 2014). Functioning as a platform for information exchange (Siering et al., 2018), online reviews illustrate helping consumers mitigate risks and significantly influence their decisions when making online purchases (Ren & Hong, 2019).

Ratings and reviews work as a distinctive social commerce toolkit, enabling individuals to share product feedback and guide each other's decisions through unbiased perspectives and personal experiences (Shadkam & O'Hara, 2013). From a business standpoint, platforms for ratings and reviews assist retailers in seamlessly incorporating customer feedback and community features directly into their websites (Chen et al., 2017). Given that both customer satisfaction and trust notably influence customer behaviour, managers must integrate these aspects into their marketing strategies. Commonly, online stores include feedback features on their websites to capture customer sentiments. Post-receiving the ordered goods, customers can share their feedback on the online store's website, engaging in actions by extending their experiences to friends. Offering small incentives like exclusive discounts for future purchases serves as a motivating factor for customers to share their buying experiences, potentially attracting more visitors to the company's online store (Rita et al., 2019b).

Empirical studies in various domains, including cinema, games, books, and catering, have revealed a positive correlation between the number of comments and sales volume (Lu et al., 2013). Customers can be encouraged to contribute reviews or rate products by suggesting relevant product communities and updating them on community activities. Participation in discussions tends to rise when individuals encounter diverse opinions, including those that may be different or even incorrect, and receive feedback on their viewpoints from others. Consequently, e-commerce platforms notify

customers through email regarding feedback on their reviews or opinions shared by friends (Kim & Srivastava, 2007).

Additionally, some research indicates that negative comments have a more pronounced impact on reducing purchase intentions compared to positive comments (Chong et al., 2016; Oh et al., 2016). Various factors related to reviews have been extensively examined (Hong et al., 2017; Karimi & Wang, 2017), such as review length, rating, and sentiment. Review length, also referred to as review depth (Mudambi & Schuff, 2010), generally shows more comprehensive information and detailed descriptions in longer reviews, reducing uncertainty and increasing diagnosticity (Chua & Banerjee, 2015). Consequently, review length positively influences customer satisfaction (Guo & Zhou, 2017; Shen et al., 2018).

E-commerce websites have significant potential to boost sales by assisting customers throughout their decision-making process, leveraging social influence data obtained from e-commerce interactions alongside transaction information (Kim & Srivastava, 2007). On many e-commerce platforms, consumers can assign star ratings to online stores, reflecting their satisfaction with the product (Benlahbib, 2020). Studies on these types of reviews indicate that review ratings can positively impact the helpfulness of online reviews (Huang et al., 2015; Liu & Park, 2015).

The term "sentiment" refers to an attitude, and researchers emphasise that reviews with strongly positive or negative sentiments are more helpful for customers (Yang et al., 2019). Furthermore, the inclusion of pictures in reviews provides information that evokes emotions and leaves a lasting impression on customers (Mou et al., 2020). Scholars have affirmed that pictures in comments can enhance the effectiveness of reviews (Min et al., 2017; Chen et al., 2019), thereby reinforcing positive or negative purchase intentions.

Measuring social influence among consumers on an e-commerce website and the customers' feedback offers several advantages. Firstly, it provides online shoppers with a variety of high-quality and personalised product reviews from trusted sources, influencing their purchasing decisions. Secondly, product-producing companies can receive direct and detailed feedback from customers, enabling them to better predict market trends. Thirdly, e-commerce platforms can identify highly influential opinion leaders, optimizing marketing strategies based on the social network surrounding these leaders (Kim & Srivastava, 2007).

In essence, feedback empowers individuals to tailor and gradually refine the subsequent stages in the diffusion and communication process, aligning with the preferences of the target customer (Wigand, 1997).

Shipping and Return Policies

There is a limited body of research on return policies (Hjort & Lantz, 2016). It's worth noting that despite the considerable interest in online purchase behaviour, scholars have surprisingly not extensively explored the realm of product returns (Bonifield et al., 2010).

Product returns are a common and costly challenge (Bower & Maxham III, 2012). Several retailers have implemented return shipping policies with the aim of controlling their expenses (Kandra, 2000; Meyer, 1999). After the purchase, convenience becomes more significant, particularly in relation to the consumer's perceived time and effort spent when contacting the company again after buying the product (Berry et al., 2002). The straightforward and often cost-free return process significantly diminishes customers' perceived risks associated with returning unwanted items (Kawaf & Tagg, 2017).

Retailers employ returns policies in diverse ways; before purchase, as a signal of the retailer or product quality level (Bonifield et al., 2010; Mukhopadhyay & Setaputra, 2007), and after purchase, to influence product evaluations (Kim & Wansink, 2012). These returns policies can exhibit varying degrees of leniency, identifying five dimensions: time, money, effort, scope, and exchange (Janakiraman et al., 2016). As exemplified by Amazon.com, distant retailers often adopt an equity-based return shipping policy (Bower & Maxham III, 2012).

The importance of post-purchase relief has been underscored in recent years due to the challenges faced by consumers in returning products bought online (Duarte et al., 2018) and shipping policies (Bower & Maxham III, 2012). The factors influencing this typically involve the consumer's need for product repair, maintenance, or exchange (Berry et al., 2002). Furthermore, if websites prioritise offering information on a diverse range of products, ensuring swift product delivery, and providing convenient return processes, consumers will derive more enjoyment and excitement from their shopping experiences (C. Kim et al., 2012; Tsao et al., 2016).

Customers' perceptions of their purchases are significantly influenced by the convenience, speed, and thoughtfulness of the return process (Han, 2021). Retailers with efficient checkouts and user-friendly return policies are rated highly in terms of transaction convenience (Seiders et al., 2000). Retailers should closely monitor their delivery procedures and post-possession convenience, including return policies and processes (Saha et al., 2023). A key advantage of online shopping is the elimination of the commerce settings (Bower & Maxham III, 2012; Janakiraman et al., 2016).

Lenient return conditions are often implemented as a marketing incentive to attract and retain loyal customers, thereby increasing sales (Hjort & Lantz, 2016). However, the direct correlation between

increasing sales and maximising profitability is not guaranteed, with profit being the primary consideration for firms (Yan, 2009). While free returns may lead to increased order frequency, they can also decrease the average value of orders (Lantz & Hjort, 2013). Despite this, a free return policy remains valuable for e-commerce (Yan, 2009). The research on return policies is evolving, addressing profitability and loyalty aspects in B2C e- need for customers to wait in lines (Wolfinbarger & Gilly, 2001). Positive experiences with post-possession services, such as timely delivery, money-back guarantees, and hassle-free returns and exchanges, can enhance customer satisfaction and encourage repeat online shopping. This contributes to creating enjoyable experiences and mitigating any reservations customers may have (Saha et al., 2023).

Free return policies positively impact the online consumer experience and contribute to increased sales (Lantz & Hjort, 2013; Mukhopadhyay & Setaputra, 2007). While Griffis et al. (Griffis et al., 2012) suggest that enhanced consumer loyalty may offset the costs associated with a lenient return policy, research by Hjort et al. (Hjort & Lantz, 2016) indicates that the total contribution of repeat customers per year is higher when they are also returners.

Sometimes, return policies can also reduce profitability. Hjort and Lantz (Hjort & Lantz, 2012) found increased sales, but they concluded that offering the same delivery and return conditions to all customer types is generally not optimal for profitability. They argue against providing free delivery and return policies unless required legislatively or competitively. Janakiraman et al. (Janakiraman et al., 2016) challenge the assumption that all forms of return policies affect product purchases and returns similarly. They suggest that returns policies benefit retailers, at least in terms of increased product purchase. Existing research indicates that customer behaviour evolves over time as past purchases influence subsequent behaviour (Hernández et al., 2010).

▪ E-Service (Online Customer Service)

In the rapidly expanding realm of global e-commerce, businesses are striving to secure a competitive advantage by leveraging e-commerce for customer interactions (Lee & Lin, 2005). Prior studies have explored how the customer service offered by online retailers impacts customers' perceptions of service quality and satisfaction (Wolfinbarger & Gilly, 2003). Notably, seasoned and successful enterprises acknowledge that the fundamental factors determining success or failure extend beyond website visibility and competitive pricing, placing significant importance on the quality of online customer service (e-service) (Yang, 2001; Zeithaml, 2002).

The rise of digital devices has enabled businesses to emphasise a service-dominant logic, delivering not just high-quality goods and services but also tailored services aligned with customer preferences

(Bordoloi et al., 2019; Lee, 2018; Vargo & Lusch, 2004, 2008, 2016; Xie et al., 2016). With a significant shift in customer preferences from traditional retailing to online shopping, the nature of service interactions between firms and customers has substantially transformed (Bordoloi et al., 2019). For instance, traditional retail sales, which surpassed $3 trillion in the USA in 1999, have since experienced a significant decline, leading to the closure of many established retailers (e.g., K-Mart, Circuit City, Toy R Us, Blockbuster), while others face financial hardships (e.g., Sears, JCPenney, Neiman Marcus) (Lee & Lee, 2020).

Numerous scholars have explored the notion of e-service quality (Rita et al., 2019b), revealing that the attributes of e-service quality are closely linked to overall e-service quality, customer satisfaction, and subsequent repurchase intentions (Blut et al., 2015), ultimately contributing to enhanced profitability.

E-service quality includes customers' comprehensive evaluations of the excellence and quality of e-service delivery within the virtual marketplace (Santos, 2003). Over the last two decades, research has underscored the influence of service quality on consumption decisions, and recent applications have extended these insights to the realm of e-commerce (Wolfinbarger & Gilly, 2003; Yang & Jun, 2002). Additionally, previous studies have underscored the positive impact of perceived service quality on both customer satisfaction and purchase intentions (Martensen et al., 2000; Rust & Zahorik, 1993)

Numerous scholars have proposed various attributes and dimensions for assessing e-service quality. Dabholkar (Dabholkar, 1996) conducted an early study on technology-based self-service quality, identifying five key attributes: speed of delivery, ease of use, reliability, enjoyment, and control. Results indicated that control and enjoyment significantly influenced service quality, ease of use was a crucial determinant, particularly for high waiting time and control groups, while speed of delivery and reliability had no impact on service quality.

Instances of applying service quality metrics include evaluating virtual community websites (Kuo, 2003), measuring satisfaction with e-commerce channels (Devaraj et al., 2002), and identifying factors influencing website success (Liu & Arnett, 2000). Online shopping involves various sub-processes, such as navigation, information search, transactions, and customer interactions, collectively perceived by customers as an overall process and outcome. During a single visit to an online store, customers may not delve into each sub-process in detail (Van Riel et al., 2001).

For online customers, realising the potential benefits of the internet relies on high-standard e-service quality (Yang, 2001). With the ease of comparing product technical features and prices online, e-

service quality emerges as a pivotal factor for customers, who anticipate service levels equal to or exceeding those in traditional channels (Santos, 2003).

Parasuraman et al. (Parasuraman et al., 1988) define service quality as the perceptual gap between customer expectations and evaluations of service experiences. They introduce the SERVQUAL model, a multi-item scale, to measure service quality. The SERVQUAL model comprises five dimensions:

- Tangibles (related to physical facilities and personnel appearance),
- Reliability (ability to consistently and accurately deliver promised services),
- Responsiveness (willingness to assist customers promptly),
- Assurance (employee knowledge instilling trust and confidence in customers), and
- Empathy (provision of caring and individualized attention by the service provider).

The SERVQUAL scale has become a widely employed tool for assessing information system service quality, as evidenced by its application in various studies (Adil et al., 2013; Babakus & Boller, 1992; Coulthard, 2004; Ladhari, 2009; Lee & Lin, 2005; Teshnizi et al., 2018). Its versatility extends to the evaluation of e-commerce system service quality, with notable references in literature (Devaraj et al., 2002; Kim & Lee, 2002). Researchers investigating e-service quality have extended the use of the SERVQUAL scale to measure services in diverse contexts, such as web-based service (Kuo, 2003; Negash et al., 2003), internet retail (Barnes & Vidgen, 2001; Kaynama & Black, 2000), and electronic banking (Zhu et al., 2002)

Moreover, scholars have suggested the necessity of reformulating SERVQUAL scale items for meaningful application in the online shopping context, considering the distinct characteristics of this setting (Santos, 2003; Van Riel et al., 2001). Therefore, a partial reformulation of the SERVQUAL model, incorporating the nuances of online shopping, needs to be considered.

The widely adopted approach for measuring service quality is the SERVQUAL model (Parasuraman et al., 1988), which remains popular in many research (Alrubaiee & Alkaa'ida, 2011; Kansra & Jha, 2016; Kitapci et al., 2014). In the realm of online business, researchers have adapted SERVQUAL into several models, including WebQual (Barnes & Vidgen, 2002; Loiacono et al., 2002), eTailQ (Wolfinbarger & Gilly, 2003), E-S-Qual (Parasuraman et al., 2005), and the hierarchical model of e-service quality proposed (Blut et al., 2015).

On the other hand, customer service in the context of e-service quality consists of service level and returns handling/return policies during and after the sale (Blut, 2016). Unlike offline businesses, online customers may navigate the purchasing process independently, with some businesses offering web-based synchronous media such as live chat facilities and online help desks for customer

assistance (Turel & Connelly, 2013). Blut (Blut, 2016) suggests that customer service contributes to e-service quality and fulfilment.

Fulfilment involves activities ensuring customers receive their orders accurately and on time (Blut, 2016). Post-payment dissonance is more likely in online shopping due to the inability to directly inspect products before purchase (Liao & Keng, 2013). Ensuring timely delivery, order accuracy, and delivery conditions is crucial for superior e-service quality and customer satisfaction. Customer satisfaction is a significant determinant of online customer behaviour, influencing future actions such as repurchase and loyalty (Philip Kotler & Kevin Lane Keller, 2006; Udo et al., 2010).

- **Loyalty**

In recent years, the attention of both practitioners and academics was drawn to the transformative potential of e-commerce in reshaping the interaction between stores and consumers (Peña-García et al., 2018). Loyalty has become a focal point for both scholars and practitioners, as it signifies a key objective in competitive strategies aimed at achieving long-term business success (Zheng et al., 2017). This assertion holds true for commerce as a whole, emphasising the significance of examining the factors influencing consumer loyalty in the context of e-commerce within the study of online consumer behaviour (Peña-García et al., 2018).

The conventional literature on relationship marketing underscores perceived value and satisfaction as precursors to consumer loyalty (Ravald & Grönroos, 1996). Relationship marketing aims to establish connections between firms and various entities in their microenvironments, particularly consumers. Consequently, companies capable of delivering greater value are anticipated to foster consumer relationships and engender loyalty. The intersection of loyalty and perceived value is also examined within the framework of brand equity theory in the customer-brand relationship (Kuo & Hou, 2017). The theory posits additional influential factors preceding loyalty, including satisfaction and enjoyment (Cai & Xu, 2006).

Satisfaction emerges as a pivotal determinant of consumer loyalty (Heskett et al., 1994) and is seen as an outcome of perceived value (Howard & Sheth, 1969). According to Ravald & Grönross (Ravald & Grönroos, 1996), consumers must also have confidence that a company can meet their needs, fulfil commitments, and establish e-trust, a concept highlighted by Pavlou (Pavlou, 2003) as a potential determinant of loyalty.

In some studies, perceived risk is explored as a counterpoint to e-trust, while enjoyment serves as a hedonic element contributing to perceived value and influencing consumer satisfaction and loyalty.

Additionally, the examination of consumer loyalty encompasses attitudinal, behavioural, and word-of-mouth (WOM) aspects (Peña-García et al., 2018).

Loyalty has evolved into a main concept for establishing sustainability and gaining competitive advantages in businesses (Tseng et al., 2017), prompting numerous studies on the subject. In the traditional shopping literature, loyalty is often conceptualised as a four-stage construct: cognitive (pertaining to consumer knowledge of the store), affective (relating to the attitudinal perspective), conative (leading to intentions), and behavioural (Oliver, 1999). Researchers typically explore loyalty within this framework either as an attitude based on preferences and affection, as purchase behaviour involving actual purchase, purchase intention, and repeat purchase, or as a multidimensional construct combining both perspectives (Watson et al., 2015).

Attitudinal loyalty in this context is expressed through repurchase intention and positive word of mouth (WOM) (Srinivasan et al., 2002). In the e-commerce context, attitudinal loyalty refers to the consumer's positive attitude toward an online store, leading to repurchase behaviour (Anderson & Swaminathan, 2011). Casaló et al. (Casalo et al., 2007) define attitudinal loyalty as a consumer's willingness to revisit the same retailer, driven by the belief that the value received from that firm exceeds the value available from other alternatives (Hallowell, 1996).

For instance, some customers who did not care much about “Amazon.com s”’ features, like customer reviews, remained loyal. They were ready to pay a bit more because of the site's excellent customer service (Wolfinbarger & Gilly, 2001).

In the 1980s, marketers prioritised customer loyalty, investing significantly in customer relationship management programs. Ironically, consumers often do not consciously recognise customer loyalty, which, in behavioural terms, typically translates to repeat purchasing. Many company efforts focus on increasing the percentage of repeat purchases among current customers. Predictive models by marketing strategists emphasise the considerable profitability impact of boosting the rate of repeat purchases among existing customers (Pitta et al., 2006).

Maintaining loyal customers in the online shopping realm is typically seen as challenging (Gommans et al., 2001). Customer loyalty is vital for the success of e-commerce (Bamfield, 2013a; Cao & Li, 2015). Customer loyalty is defined as a positive attitude towards e-retailing, leading to repeated purchases (Luo & Bhattacharya, 2006). Loyalty is closely tied to these repeat transactions, signifying a customer's allegiance to a specific e-commerce retailer. The relationship between satisfaction and loyalty is nuanced and influenced by factors like commitment, trust, and consumer involvement, varying across industries (Olsen, 2007).

Consumer loyalty appears to hinge on several elements. Firstly, trust plays a crucial role, necessitating consumers to have confidence in the vendor or product. Secondly, the transaction or relationship must offer a perceived value that surpasses that provided by competitors. Thirdly, by leveraging the initial two factors, marketers have the potential to foster a positive emotional attachment in customers. This emotional response may manifest as a steadfast commitment to their brands, proving resistant to change (Pitta et al., 2006).

Online loyalty is characterised by a lasting commitment to make repeat purchases, maintaining positive attitudes toward the seller, and expressing the intention to recommend (Holloway et al., 2005; Zeithaml et al., 1996). Researchers have determined that enhancing the perceived value in the consumer-seller relationship is important in reinforcing consumer loyalty towards a website. Online shopping includes a holistic journey from browsing to post-sales service. A well-organised layout and categorised product system facilitate easy order placement for consumers, contributing to the delight of discovering new products (Tsao et al., 2016). The positive experience encountered during the shopping process, even when time seems to escape notice, catalyses heightened online loyalty (Luo et al., 2012).

Establishing a robust and enduring relationship between parties is paramount, as buyers' loyalty significantly impacts the seller's profits (Geiger et al., 2012). Therefore, fostering a high relationship value is essential for sustaining long-term collaboration between both parties (Tsao et al., 2016). Scholars argue that online loyalty refers to both active word-of-mouth (WOM) recommendations and sustained customer patronage (Holloway et al., 2005; Zeithaml et al., 1996).

In the context of e-loyalty, online customers can effortlessly access websites with just a click (Brynjolfsson et al., 2009). Strengthening the relationship between overall loyalty and satisfaction leads to a reciprocal connection where satisfaction enhances loyalty, subsequently reinforcing satisfaction. To sum up, factors such as e-service quality, product quality, perceived value, customer expectations, perceived quality, and e-loyalty significantly contribute to customer satisfaction in the online shopping environment, ultimately boosting consumer spending online (Nisar & Prabhakar, 2017) and leading to loyal online customers.

- **Switching Behaviour**

In the dynamic landscape of online commerce, understanding and influencing customer switching behaviour is significant (Clemes et al., 2010). Exploring the intricacies of switching behaviour reveals the key factors that can either retain or redirect online consumers (Liao et al., 2008). Switching behaviour, a critical aspect of customer decision-making, profoundly impacts the success of an online

businesses. Scholars are motivated to study the area due to the advantages of retaining customers and the negative impacts of switching behaviour (Chuang & Tai, 2016).

Some companies eager to incorporate engaging experiential features into their website to keep visitors engaged and returning may overlook the importance of serving transaction-oriented customers well. These customers, focused on efficiency and convenience, are less likely to switch to competitors if they can easily find what they need, complete transactions smoothly, and receive timely deliveries. Providing prompt responses to inquiries and meeting their needs promptly fosters loyalty, even if they are not interested in browsing or interacting with others on the site (Wolfinbarger & Gilly, 2001).

Research on switching behaviour often explores the relationships between switching intentions and various influencing factors (Antón et al., 2007; Han & Hyun, 2013; Han et al., 2011). In numerous articles investigating customer switching behaviour and intentions, researchers have identified many predictor variables. Factors driving switching intentions include service failures, attractiveness of alternatives, price, dissatisfaction, lack of trust, and negative experiences. Conversely, factors discouraging switching intentions include switching costs, subjective norms, and interpersonal relationships. Satisfaction often serves as a mediator between determinant factors and switching intentions, while switching costs moderate the relationship between intention and factors such as attitude and satisfaction (Chuang & Tai, 2016). Additionally, the attractiveness of alternatives may moderate the relationship between intention and service performance, satisfaction, and perceived price (Chuang & Tai, 2016). Moreover, studies within specific industries, such as hospitality and online services, highlight industry-specific variables influencing switching intentions, providing valuable insights for service providers aiming to retain customers and mitigate switching behaviour (Hou et al., 2011; Hsieh et al., 2012; Sánchez-García & Currás-Pérez, 2011; Zhang et al., 2012).

Perceived service quality plays an elegant role in shaping visitors' satisfaction and subsequent behavioural intentions, such as revisiting a website (Leung et al., 2011). When customers have a positive experience on a site, they are more likely to return (Gounaris et al., 2010). The decision to revisit a website mirrors the switching behaviour between service providers, where customers continue using the online service category but switch providers (Keaveney, 1995). Some researchers explored factors influencing intentions to revisit a website (Taylor & Strutton, 2010), while others affirmed a significant positive relationship between customer satisfaction and site revisits (Gounaris et al., 2010). Overall, customers often rely on their past retail service experiences to inform decisions and formulate strategies for repeat behaviour (Rita et al., 2019b).

Understanding customer switching intention and exploring the interconnection of various influential factors can significantly impact efforts to reduce switching behaviour (Mosavi et al., 2018). Customer switching intention refers to the chance of a customer ending a current service relationship (Wirtz et al., 2014). Studies across different service contexts have revealed key determinants of switching intention (Mosavi et al., 2018).

For instance, in the mobile phone industry, switching intention is negatively influenced by customer satisfaction, switching costs, and habits, while it is positively affected by the attractiveness of alternatives (Hsin Chang & Wang, 2011). Both customer satisfaction and loyalty negatively influence switching behaviour in traditional mobile services (Calvo-Porral & Lévy-Mangin, 2015).

In the hospitality sector, customer satisfaction mediates the relationship between service performance and switching intention, with switching costs, relational investment, and alternatives' attractiveness moderating this relationship (Han et al., 2011). In online banking, factors like perceived usefulness, ease of use, and offline trust positively influence switching, while offline loyalty and switching costs have a negative impact (Lee et al., 2011).

The findings establish a theoretical framework for understanding consumer switching intentions and offer practical guidance for service providers and online retailers to maintain customer loyalty and mitigate switching behaviour.

- **Cross-Cultural Differences**

In recent years, academics have been captivated by the potential of e-commerce to transform numerous aspects of the interaction between stores and consumers (Peña-García et al., 2018). E-commerce has been recognised as a swiftly expanding and modern distribution avenue, especially in developing nations (Elbeltagi & Agag, 2016). Companies perceive e-commerce to enhance efficiency, competitiveness, and overall economic and social welfare, contributing significantly to global trade, job creation, and national development (Rodriguez, 2022). Moreover, the influence of national identity-related cultural differences on consumer perceptions regarding the effective application of information technology has been a consistent focus within this domain (Chen et al., 2015).

Cultural factors are expected to significantly influence the acceptance and use of the Internet in global marketing endeavours. For instance, the impersonal and systematic nature of online shopping may not align well with cultures focusing on personal interactions, such as those influenced by Confucian principles. Additionally, cultures characterised by high uncertainty avoidance are less inclined to embrace early Internet marketing initiatives, even if other cultural considerations are addressed (Peña-García et al., 2018). Nonetheless, certain commentators perceive online

transactions as inherently devoid of cultural influence and highly personalised, believing that they facilitate closer connections between parties (Peterson et al., 1997).

The worldwide accessibility of the Internet, along with its versatile communication capabilities, renders it an ideal tool for international interactive marketing endeavours. Conducting international consumer research within a cross-cultural framework is essential for gaining deeper insights into global online consumer behaviour (Jarvenpaa et al., 1999; Park & Jun, 2003).

On the other hand, an online presence enables retailers to connect with consumers globally (Quelch & Klein, 1996). Within this context, cross-validation of the Internet consumer trust model aims to deepen the understanding of fostering enhanced trust among online merchants (Jarvenpaa et al., 1999). Valuable insights into effective research methodologies for investigating cultural variations in trust are provided in a few studies (Doney et al., 1998). Additionally, cross-cultural disparities, trust considerations, and underlying factors could be noted for future investigations (Jarvenpaa et al., 1999).

Cross-cultural studies have demonstrated that consumers from various cultural backgrounds hold different perceptions regarding the trustworthiness of e-retailers (Ashraf et al., 2014; Jarvenpaa et al., 1999). Moreover, due to the unique characteristics of online shopping, such as the inability to physically interact with products, it is often perceived as risky (Pavlou, 2003). This uncertainty underscores the significance of trust in the adoption of e-commerce. Consequently, perceived behavioural control and cross cultural differences assume a crucial role in the context of online shopping (Ashraf et al., 2014).

- **Cart Interaction**

An online shopping cart is a digital platform where customers can browse, select, and temporarily store items from retail websites before deciding whether to proceed with a purchase (Kukar-Kinney et al., 2022). In simpler terms, a standard shopping cart should include basic features like adding items to the cart and completing the checkout process using various available payment methods (Gupta, 2013). Also, cart Interaction usually denotes how users interact with the shopping cart feature on an e-commerce platform. This interaction entails tasks like adding or removing items, adjusting quantities, and moving through the checkout process (X. Zhao et al., 2020). It includes the design and functionality geared towards enhancing user experience and making shopping intuitive, smooth, and effective. Enhancing cart interaction can result in improved conversion rates, greater customer satisfaction, and ultimately, more successful transactions for online retailers.

The history of e-commerce shopping carts started with the emergence of the World Wide Web as a major information platform. E-commerce shopping cart applications enable consumers to make direct purchases over the Internet using web browser models (Bigne et al., 2005).

In today's competitive market, designing a successful shopping cart application includes considering factors such as information load, complexity, and novelty. Complexity relates to the number of features and marketing levels, and novelty, which encompasses unexpected or unfamiliar site elements, are critical aspects (Falk et al., 2005). Designers must also address diverse consumer needs and expectations, as online shoppers represent varied demographics and cultural backgrounds (Elliot & Fowell, 2000).

A user-friendly design is important for the success of any shopping cart application, given its broad user base (Elliot & Fowell, 2000). Additionally, developing a profitable online shopping platform necessitates significant investment in design, development, testing, and maintenance, along with a focus on providing exceptional customer service (Gupta, 2013).

On the other hand, it is essential to recognise that cart interaction, with its multitude of details impacting consumer decision-making, should be viewed as an integral aspect of online shopping behaviours. Marketers and retailers face a significant managerial challenge related to the widespread occurrence of online shopping cart abandonment (Kukar-Kinney et al., 2022). This phenomenon refers to customers adding items to their online shopping cart but failing to complete the purchase during the same session (Kukar-Kinney & Close, 2010). Research indicates that globally, over 80% of online shopping carts are abandoned, resulting in substantial unrealised sales revenue (Statista, 2020). This high rate of abandonment prompts two important questions for marketers; “What motivates consumers to add items to their cart beyond intending to make a purchase?”, and “Why does cart abandonment occur (Kukar-Kinney et al., 2022)?”

The other aspect of cart interaction could be e-commerce cart retargeting, which involves strategically using targeted advertisements to re-engage potential customers who have abandoned their online shopping carts (J. Li et al., 2021).

Several studies have investigated online shopping cart abandonment, shedding light on its underlying factors and implication (Khan et al., 2022). Cognitive factors, such as perceived entertainment value and price anticipation, have been identified as significant contributors to cart abandonment among US online shoppers (Kukar-Kinney & Close, 2010). In the realm of mobile shopping, studies highlight hesitation at checkout and emotional ambivalence as key factors, particularly notable during the COVID-19 pandemic (Huang et al., 2018; Wang et al., 2022). Research on construal-level theory

suggests that abstract mindsets lead to product consideration, while concrete mindsets prompt immediate purchases (Rubin et al., 2020). Studies involving Chinese consumers indicate that cart abandonment is influenced by comparisons with other retail websites and added products (Xu & Huang, 2015). Also, applying uncertainty reduction theory among Chinese customers identifies performance, description, and seller uncertainties as predictors (Tang & Lin, 2019). Moreover, online shoppers with an abstract mindset (as opposed to a concrete one) tend to assign greater importance to the products in their carts. Consequently, they are more inclined to complete their purchases, leading to a decrease in shopping cart abandonment (Rubin et al., 2020).

- **Future purchase intentions**

The internet's rapid growth has propelled online shopping, offering e-vendors ample opportunities to engage with customers. Prioritising high-spending and frequent buyers is essential for businesses, making customer retention a key concern for gaining a competitive advantage (O. Pappas et al., 2014). Hence, it is important to perceive key factors that influence customers' intentions to make future purchases.

Customer loyalty towards either an online or offline vendor is significantly influenced by their overall satisfaction. Satisfaction, in turn, accounts for a considerable amount of the variance in the intention to repurchase (Giannakos et al., 2011). Also, increased customer retention and repurchase intentions may stem from higher levels of customer satisfaction (Ittner & Larcker, 1998). Furthermore, It illustrates that as customer satisfaction decreases, it becomes increasingly challenging for a company to retain them and cultivate a strong relationship (Anderson & Srinivasan, 2003).

The marketing literature indicates that service convenience is a key motivator for consumers to engage in online purchasing (Duarte et al., 2018; Jiang et al., 2013). Improved online convenience enhances consumers' satisfaction and ultimately encourages repeat purchases. Therefore, understanding how to enhance service convenience is crucial for success in online business (Saha et al., 2023). Service convenience is a significant part in shaping customers' perceptions and expectations of online retailers, influencing their future purchasing decisions (O. Pappas et al., 2014).

Favourable experiences during the online shopping process heighten purchase intentions and reduce uncertainty (Holloway et al., 2005). The online shopping experience notably influences customer motivation, particularly through convenience (Yeo et al., 2017). The online shopping experience positively impacts customers' intentions to repurchase (Kim et al., 2007). Consequently, customers are more willing to make future purchases when they derive pleasure from shopping online (Saha et

al., 2023). Specifically, research shows a significantly positive correlation between the online shopping experience, customer satisfaction, and intentions to repurchase (O. Pappas et al., 2014).

Online consumers' likelihood to repurchase is shaped by satisfaction, perceived usefulness, ease of use, enjoyment, and self-efficacy in Internet shopping. These factors are intertwined, with satisfaction influenced by perceived usefulness, ease of use, confirmation, and positive shopping experiences online. Perceived usefulness is in turn affected by behaviour modelling, positive online experiences, self-efficacy, and confirmation. Confirmation, influenced by positive experiences and behaviour modelling, also impacts ease of use significantly. Additionally, positive online experiences contribute to higher self-efficacy. The empirical findings offer valuable insights and suggestions for future research (Chen, 2012; Chiu et al., 2009; Fared et al., 2021).

3 METHOD

In this part, I transition from the theoretical underpinnings explored in the literature review to the practical implementation of the research. The methodology serves as the roadmap guiding the investigative journey, providing the framework through which I aim to uncover insights and contribute to the body of knowledge in the field of e-commerce. Building upon the foundation laid by previous research and theoretical frameworks, I embark on a systematic exploration of critical success factors and customer clusters within the e-commerce landscape. Through a rigorous and comprehensive methodological approach, I seek to illuminate the intricacies of decision-making processes and their impact on the success of e-commerce ventures.

3.1 RESEARCH ARCHITECTURE

The research is structured around three essential phases, as depicted in Figure 7. Over the course of these delineated phases, four methods, namely fuzzy Delphi, C-Means, FBWM, and FCOPRAS, is utilised to analyse critical success factors (CSFs) and customer clusters, with the aim of weighing the determinant CSFs and ranking customers in an e-commerce context.

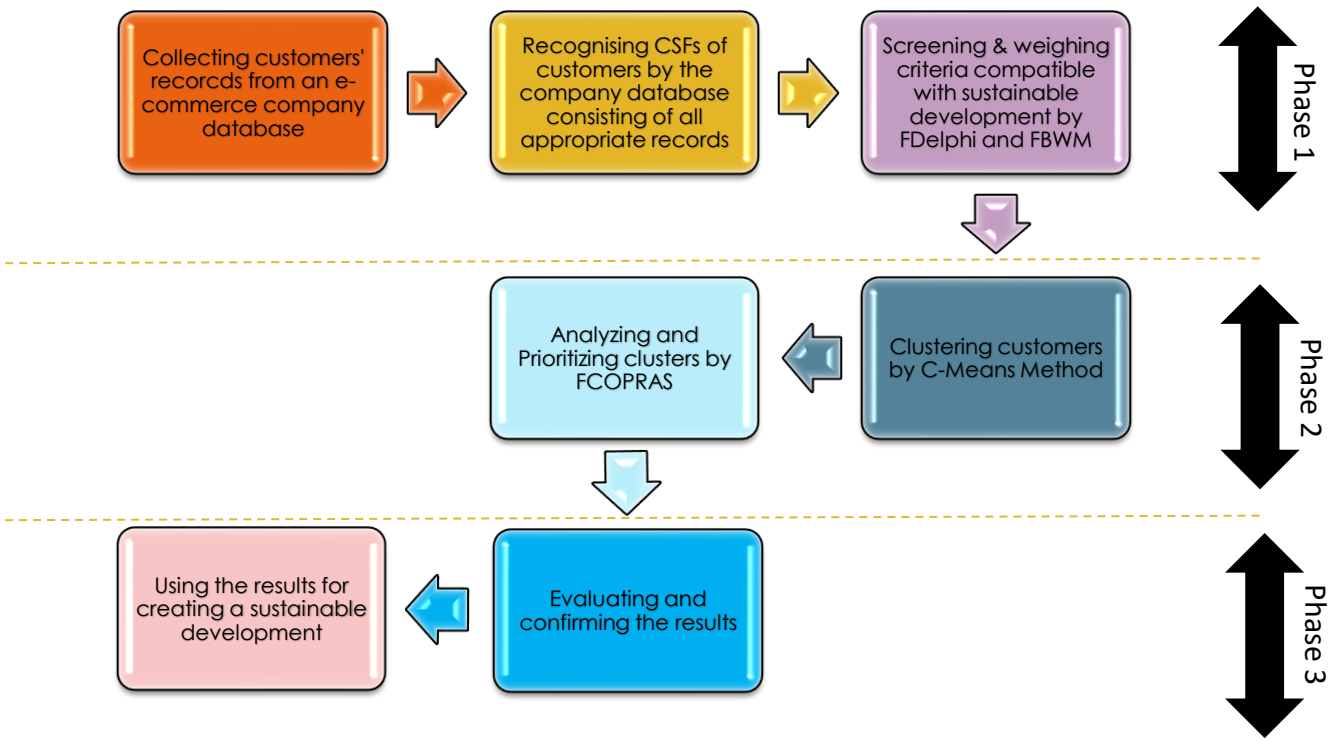

Figure 18: Research Structure

Decision-making involves the process of choosing the most suitable alternative from a given set (Janis & Mann, 1977; Plous, 1993). Effective decision-making plays a pivotal role in achieving success across various disciplines, particularly in fields that involve handling vast amounts of information and knowledge. When multiple criteria are taken into account, it is referred to as Multi-Criteria Decision-

Making (MCDM) (Triantaphyllou & Triantaphyllou, 2000; Zeleny, 2012). To address the challenges associated with decision-making in such contexts, multi-criteria decision analysis (MCDA) emerged as a branch of operations research. Its purpose is to facilitate the resolution of these complex issues.

MCDM involves ranking all the alternatives and selecting the optimal one by applying specific approaches and existing decision information while considering various criteria. MCDM plays the main role in decision science, systems engineering, and management science. It has found extensive applications in diverse fields including engineering, economics, and management (Hester et al., 2013; Stewart, 1992; Wallenius et al., 2008; Zavadskas & Turskis, 2011). Over time, a wide range of multi-criteria decision-making methods (MCDM) have been developed to address the challenges across different circumstances and fields of application (Lahdelma et al., 2000; Løken, 2007; Słowiński, 1986; Tonietto & Carbonneau, 2004a, 2004b).

In addition to multi-criteria methods, certain complementary approaches are particularly well-suited for decision-making problems. Tools such as fuzzy sets or numerical simulations, despite lacking the fundamental structure required for performing a multi-criteria analysis, have proven highly valuable for the exploration of complex and uncertain decision landscapes. They excel in dealing with aspects such as uncertainty or risk, which are commonly encountered in decision-making environments but can be difficult to handle using traditional MCDM methods (Jato-Espino et al., 2014). In the research, I have employed a wide range of MCDM methods combined with fuzzy numbers to deal with uncertainties.The specific reasons for employing each method, along with their advantages and disadvantages, are outlined in Table 5.

Combining multiple methods is necessary to tackle the complexity of the research problem. Each method serves a specific purpose, contributing to a comprehensive analysis of critical success factors (CSFs) and customer clusters in e-commerce.

I started with the Fuzzy Delphi method to establish expert consensus on CSFs. Its ease of use and ability to handle uncertainty make it suitable for gathering insights. Next, the Fuzzy BWM method was employed to evaluate and weigh CSFs. Its ability to determine optimal weights is valuable for assessing the importance of criteria.

Then, the C-Means method was used to cluster customers based on attributes. Its capacity to handle multiple criteria make it effective for segmentation. Lastly, I utilised the Fuzzy COPRAS method to evaluate and rank clusters. Its use of cost and benefit indicators and fuzzy approach ensure robust analysis.

This sequential approach leverages each method's strengths, resulting in a thorough examination of CSFs and customer clusters in e-commerce.

Table 5: Advantages & Disadvantages of Applied Methods

Method	Reason to use	Advantages	Disadvantages
Fuzzy Delphi	**To get a consensus among the experts for identifying customers' CSFs**	(1) Easy to understand and complete the questionnaire	(1) Complex for modelling in software
		(2) Takes into account uncertainty by using TFN[4] and transfer linguistic terms into quantitative values	(2) A time-consuming process to utilize
		(3) One of the most popular methods for moderating factors	
Fuzzy BWM	**Evaluating and weighing customers' CSFs**	(1) A novel NLP[5] model that can be implemented using Lingo software	(1) Requires a high degree of expertise
		(2) Determines optimal weight for each factor by finding the optimal solution in a global search space	(2) A time-consuming process to utilize
		(3) A simple approach for evaluating the consistency of each expert	(3) Relies on subjective input from experts
		(4) Few comparisons, thus less confusing for experts	(4) Not be applicable in all situations
		(5) More appropriate for a large number of criteria	
		(6) Can handle the uncertainty in data (opinions) using the fuzzy approach	
C-Means	**Clustering customers as per attributes**	(1) Easy to apply with MATLAB[6] & MathWorks	(1) Sensitivity to initial conditions
		(2) Capable to employ multiple criteria in clustering	(2) Difficulty in determining the optimal number of clusters
Fuzzy COPRAS	**Evaluating and ranking clusters**	(1) Uses cost and benefits indicators as a compromising approach	(1) Complex for modelling in software
		(2) Easy to apply and fill the questionnaire by experts	(2) A time-consuming process to utilize
		(3) Employing a fuzzy approach for uncertainty	(3) Relies on subjective judgments from experts

3.2 FUZZY NUMBERS

In 1965, L.A.Zadeh (Zadeh, 1965) introduced the notion of fuzzy subsets, which opened the door for the study of uncertainty and imprecision in set theory. Later on, in 1986, K.Atanassov (Atanassov & Atanassov, 1999) generalised this phenomenon by introducing intuitionistic fuzzy subsets, which further expanded the applicability of fuzzy logic in various domains. These advancements in fuzzy set theory allowed researchers to address many real-life problems more accurately, as seen in several studies cited in references (Kacprzyk & Zadrożny, 2001; Szmidt & Kacprzyk, 2001, 2002).

[4] Triangular Fuzzy Number
[5] Non-Linear Programming
[6] MATrix LABoratory

In order to measure the degree of fuzziness in a fuzzy set or system, many researchers have focused on developing measures of fuzziness (Szmidt & Kacprzyk, 2001). References are examples of studies that explore and analyse different measures of fuzziness (Zeng & Li, 2006).

Fuzzy numbers, which are a generalisation of classical numbers, have become an important tool for decision-making in various fields. Fuzzy numbers play a important role in modelling real-life problems, especially in tasks such as ranking, prioritising, and optimising. By using fuzzy numbers, decision-makers can take into account uncertainty and imprecision in their decision-making processes, making them more robust and reliable. The proposed methodologies consider the uncertain nature of the available data (Chen, 2000).

In fuzzy set theory, the membership function assigns a grade of membership to each object, typically ranging from zero to one. Various membership functions are considered by researchers, with the most common ones being triangle, trapezoid, and Gauss membership functions (Chen & Wang, 2010). During the study, Triangle Membership Functions or the Triangular Fuzzy Numbers (TFN) is applied. A TFN such "f" can be defined by (f1, f2, f3) (Amoozad Mahdiraji et al., 2018a; Hsieh et al., 2004).

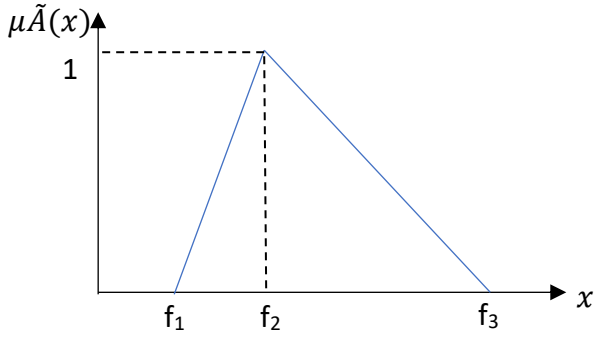

Figure 20: TFN Membership Function

The membership function μ_f of f is defined as follows:

$$\mu\tilde{A}(x) = \begin{cases} 0 & x < f_1 \\ \dfrac{x - f_1}{f_2 - f_1} & f_1 \leq x \leq f_2 \\ \dfrac{x - f_3}{f_2 - f_3} & f_2 \leq x \leq f_3 \\ 0 & x > f_3 \end{cases}$$

Also, the operations involving fuzzy triangular numbers applied in this study are defined as follows (Triantaphyllou & Lin, 1996; Yoon & Hwang, 1995):

$$\tilde{f} + \tilde{f} = (f_1 + f_1, f_2 + f_2, f_3 + f_3)$$
$$\tilde{f} \times \tilde{f} = (f_1 \times f_1, f_2 \times f_2, f_3 \times f_3)$$
$$\tilde{f} \div \tilde{f} = (f_1 \div f_3, f_2 \div f_2, f_3 \div f_1)$$

3.3 DEFUZZIFICATION

Defuzzification is the process of converting fuzzy output, which is represented by fuzzy numbers, into crisp values that can be used in decision-making. In fuzzy logic-based decision-making systems, the output generated is typically represented as a fuzzy set or a fuzzy number, which captures the degree of uncertainty or imprecision in the decision.

In practical decision-making, the need for precise and actionable values arises. To support this, the fuzzy aggregated consensus is converted into a crisp aggregated value through defuzzification. This crisp value serves as the basis for the final decision-making process, enabling decision-makers to take concrete actions (Yu et al., 2009).

To address this issue, a defuzzification process is necessary. Defuzzification involves identifying the Best Non-fuzzy Performance (BNP) value (Triantaphyllou & Lin, 1996). Several methods of defuzzification are available, such as mean-of-maximum, centre-of-area, a-cut methods, Minkowski method, and graded mean integration representation (GMIR) (Duckstein, 1995; Guo & Zhao, 2017; Van Leekwijck & Kerre, 1999). In the proposed research, the Graded Mean Integration Representation (GMIR) (Guo & Zhao, 2017) and Minkowski method (Torkayesh et al., 2023) was used.

These methods are selected based on their robustness and effectiveness in handling complex decision-making problems in the context of e-commerce. The GMIR method offers a systematic approach for integrating heterogeneous data sources and synthesising diverse perspectives, making it well-suited for analysing critical success factors and customer clusters (Guo & Zhao, 2017). Similarly, the Minkowski method provides a versatile framework for measuring distances and similarities between data points, enabling accurate clustering and classification of customers based on their attributes and preferences (Zavadskas et al., 2017). The selection of these methods reflects their widespread use and proven efficacy in addressing the study's research objectives.

Overall, defuzzification is a crucial step in fuzzy logic-based decision-making systems, as it enables decision-makers to take concrete actions based on the output generated by the system.

3.4 DELPHI METHOD

The first Delphi experiment took place many years ago, and it has been over 60 years since the publication of the initial article outlining its procedure and application (Dalkey & Helmer, 1963). Throughout this extensive period, the Delphi Method has gained widespread recognition and has been used as a valuable tool for prediction and decision-making. It has experienced various stages of development, moving from a secretive military-oriented approach to subsequent phases characterised by novelty, popularity, criticism, and re-examination (Rieger, 1986).

The Delphi method is a survey technique used to gather expert opinions, characterised by anonymous responses, iterative feedback, and statistical group responses (Hwang & Lin, 2012; Ishikawa et al., 1993). In the initial version, however, due to differences in interpretation, ambiguity could arise in experts' opinions. To address this, Murray, Pipino, and Gigch (1985) proposed combining fuzzy set theory with the Delphi method, giving rise to the Fuzzy Delphi Method. Originating from traditional Delphi techniques and fuzzy set theory, the Fuzzy Delphi Method resolves the inherent ambiguity in expert opinions in group decision-making contexts. Previous studies primarily utilized triangular, trapezoidal, or Gaussian fuzzy numbers for fuzzy membership functions. This study employed triangular membership functions and fuzzy theory to facilitate group decision-making, enhancing flexibility and objectivity in evaluation.

The Fuzzy Delphi Method implementation involves several key steps (Y.-L. Hsu et al., 2010):

1- **Opinion Collection:** Experts provide evaluation scores for each factor's significance using linguistic variables in questionnaires.
2- **Fuzzy Numbers Setup:** Fuzzy numbers are calculated for each factor's evaluation values given by experts, determining the significance of each factor.
3- **Defuzzification:** The fuzzy weights of alternate elements are converted into definite values using a simple centre of gravity method.
4- **Screening Evaluation Indexes:** Factors meeting the threshold criteria are identified as evaluation indexes, aiding in the selection of pertinent factors from a pool of options.

Through these steps, the Fuzzy Delphi Method enhances the efficiency and quality of questionnaires, enabling a more objective screening of evaluation factors based on statistical results.

Over time, the Delphi Method has expanded its range of applications and has been subjected to rigorous scrutiny and numerous evaluations, which have shed light on both its strengths and weaknesses. It is widely regarded as the most prominent forecasting technique, bearing its own distinctive name and relying on expert opinions (Landeta, 2006).

The Delphi method originated in the late 1940s at the RAND Corporation (Kaplan et al., 1949), where researchers began exploring the scientific use of expert opinion. Initially employed in a military defence project, the method was later declassified and widely adopted for various purposes. The Delphi method involves obtaining a reliable consensus or group opinion through intensive questionnaires with expert feedback (Dalkey & Helmer, 1963). Over time, the technique expanded beyond the need for consensus and became a valuable social research tool for resolving complex problems by engaging a group of experts (Linstone & Turoff, 1975).

In 1963, Helmer and Dalkey from the Research and Development (RAND) Corporation introduced the concept of Delphi method. The traditional Delphi method combined with fuzzy theory, as proposed by Zade in 1965, to effectively model uncertainty in real-world environments (Lee & Hsieh, 2016). It is a technique that facilitates effective communication among a group of individuals who possess valuable insights, with the aim of collectively addressing and resolving complex problems (Linstone & Turoff, 1975).

3.4.1 Fuzzy Delphi Steps

Fuzzy Delphi Method was proposed by Ishikawa (Ishikawa et al., 1993), and it was derived from the traditional Delphi technique and fuzzy set theory (Hsu & Sandford, 2019). The Fuzzy Delphi Method offers several advantages including (Bui et al., 2020; Habibi et al., 2015; Y.-L. Hsu et al., 2010; Ishikawa et al., 1993):

- ***HANDLING AMBIGUITY:*** Fuzzy Delphi Method effectively handles ambiguity and uncertainty in expert opinions by integrating fuzzy set theory, allowing for imprecise judgments.
- ***FACILITATING GROUP CONSENSUS:*** Fuzzy Delphi Method promotes group consensus through iterative, anonymous feedback, facilitating convergence of viewpoints.
- ***FLEXIBILITY IN EVALUATION:*** Employing triangular fuzzy numbers, Fuzzy Delphi Method offers flexibility in evaluation, accommodating a range of opinions and uncertainty.
- ***ENHANCING OBJECTIVITY:*** By systematically weighing and aggregating opinions, Fuzzy Delphi Method reduces bias and enhances objectivity in decision-making.
- ***APPLICABILITY ACROSS DOMAINS:*** Applicable across various domains, Fuzzy Delphi Method can address complex problems in different industries.
- ***IMPROVED EFFICIENCY:*** Despite its iterative nature, Fuzzy Delphi Method offers a structured framework, leading to quicker decision outcomes compared to traditional methods.

Based on the approach, the Fuzzy Delphi Method analysis comprises five stages, as depicted in Figure 9 (Alaloul et al., 2016). Currently, the Fuzzy Delphi Method is mainly used for screening with fuzzy

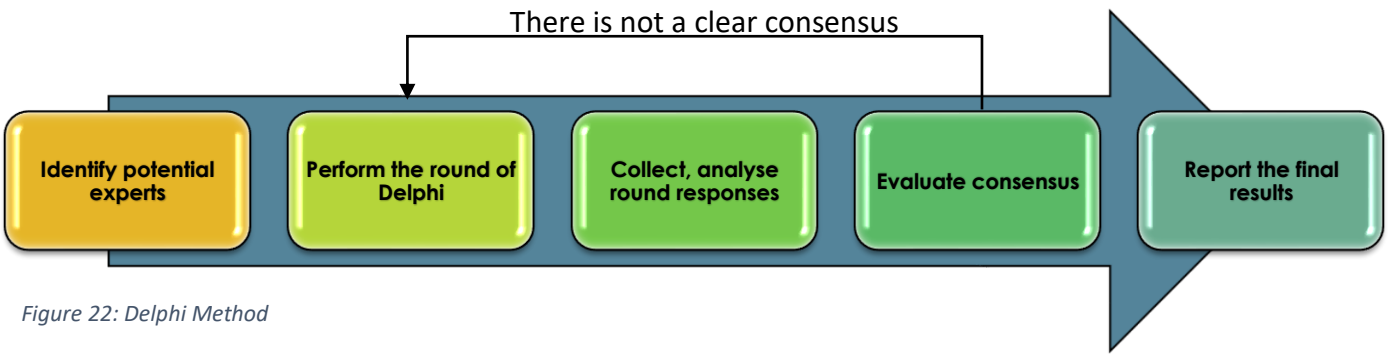

Figure 22: Delphi Method

sets in various fields like humanities, management, business, physical sciences, and engineering (Saffie & Rasmani, 2016).

This study employed the Fuzzy Delphi Method to identify essential factors in the initial stage. Recruiting fuzzy theory helps address variations in experts' interpretations, allowing for more flexible assessments and enhancing questionnaire efficiency and quality. This approach leads to the identification of more objective evaluation criteria based on statistical results (Hsu & Sandford, 2019). The steps for implementing the Fuzzy Delphi Method in this research are outlined below (Amoozad Mahdiraji et al., 2022; Mahdiraji et al., 2019):

Expert opinions are based on a linguistic spectrum, and these terms are then converted into one of the Triangular Fuzzy Numbers (TFNs) listed in Table 6.

Table 6: Linguistic Terms - Triangular Fuzzy Numbers

Linguistic Terms	**Fully insignificant**	**Moderately insignificant**	**Medium**	**Moderately significant**	**Fully significant**
Triangular Fuzzy Numbers (TFNs)	(0, 0, 0.25)	(0, 0.25, 0.5)	(0.25, 0.5, 0.75)	(0.5, 0.75, 1)	(0.75, 1, 1)

I. Fuzzy values are employed in the following equation (1), where A_{ave} represents the average value of a factor based on expert opinions.

$$A_{ave} = \left(\frac{1}{n}\sum_{i=1}^{n} a_1^i, \frac{1}{n}\sum_{i=1}^{n} a_2^i, \frac{1}{n}\sum_{i=1}^{n} a_3^i\right) \qquad (1)$$

In the equation (1), the TFNs (Triangular Fuzzy Numbers) assigned by experts, denoted as (a_1^i, a_2^i, a_3^i) are used, with i indicating the expert number.

II. The values obtained in the previous step are converted to a single value through the process of defuzzification, as shown in equation (2) which is known as “Minkowski method”. Here, γ represents the resulting defuzzified value of the specific factor under consideration.

$$\gamma = a_1 + \frac{a_3 - a_2}{4} \qquad (2)$$

III. The process described above is repeated. If the disparity between the two phases is below a predefined threshold, set at 0.2 in this study based on previous literature (Abdulkareem et al., 2021; Cheng & Lin, 2002), then the process concludes. However, if the difference exceeds this threshold, the process will be repeated.

IV. The criteria are accepted if their defuzzified average value γ surpasses the threshold S. In the paper, S is considered to be 0.5 representing the ratio of expert consensus based on expert opinions and previous literature (Amoozad Mahdiraji et al., 2022; Cheng & Lin, 2002).

3.4.2 Panel Size for Experts

Constructing the panel of experts is a critical aspect of the research process, and it directly influences the reliability and validity of the results (Adler & Ziglio, 1996; Kittell-Limerick, 2005; Rowe & Wright, 1999). Therefore, it is essential to ensure that the selected experts meet four key requirements (Adler & Ziglio, 1996; Giannarou & Zervas, 2014; Skulmoski et al., 2007):

- **Expertise and Knowledge:** Experts should possess knowledge and experience acquired through thorough investigation and professional endeavours.
- **Willingness to Participate:** They should demonstrate a willingness to actively engage and contribute to the research process.
- **Availability of Time:** Experts need to have sufficient time available to participate effectively in the research.
- **Effective Communication Skills:** Effective communication skills are crucial to facilitate constructive discussions and feedback exchanges.

Identifying knowledgeable individuals for the expert panel can be accomplished through various methods, such as literature reviews or recommendations from reputable institutions and experts. This often involves purposive and snowball sampling techniques (Bryman & Bell, 2011; Saunders et al., 2009).

Two other crucial considerations when conducting the Delphi technique are the panel size and the response rate. While there are no strict rules governing these factors, several principles apply:

- ***PANEL SIZE:*** The size of the expert panel should align with the research's objectives (Giannarou & Zervas, 2014). Larger panels may be suitable for certain investigations, while smaller, more homogeneous panels can yield valuable results (Cantrill et al., 1996; Mullen, 2003). It is worth noting that larger panels tend to have reduced group errors and improved decision quality (Skulmoski et al., 2007). A sample size of around 20 experts is often considered sufficient (Mullen, 2003).
- ***RESPONSE RATE:*** The response rate can vary across disciplines and research interests (Mason & Alamdari, 2007). While there is no universal standard, a higher response rate is generally desirable. However, it's important to recognise that larger groups may experience higher

dropout rates (Ellis, 1988). Nevertheless, a sample size of approximately 20 experts, with efforts to retain participants, is commonly recommended (Mullen, 2003).

Ultimately, the choice of expert panel size is influenced by the research's specific requirements and the need for homogeneity, as smaller panels of 10 to 15 individuals can provide valid and valuable results (Skulmoski et al., 2007); (Turoff & Linstone, 2002).

3.5 BEST WORST METHOD (BWM)

Rezaei introduced the Best-Worst Multi-Criteria Decision-Making Method (BWM) as a modern approach to resolving problems related to decision-making involving multiple criteria (Rezaei, 2015, 2016). The BWM method begins by selecting the best and worst criteria, typically the most desirable and least desirable, respectively. Next, the decision-maker performs pairwise comparisons between each of these two criteria and the remaining criteria using a BWM questionnaire. A Consistency Index is then formulated to establish the weights of the decision-making criteria. Additionally, a Consistency Ratio is proposed to assess the reliability of the comparisons made using the BWM (Rezaei, 2015, 2016). The definitions of the Consistency Index and Consistency Ratio will follow.

The suggested method utilised a technique to evaluate decision-making criteria, taking into account their benefits when compared to other MCDM methods. This method was preferred due to its ability to require fewer comparison data while producing more consistent and dependable results.

Expanding the traditional BWM to encompass fuzzy environments is of both theoretical and practical significance, as the conventional BWM is constrained by its reliance solely on crisp values for comparisons (Wu et al., 2019). Introducing fuzziness into the BWM framework allows for more comprehensive and nuanced assessments, enhancing its applicability and effectiveness in complex decision-making scenarios (Guo & Zhao, 2017).

The best-worst method (BWM), developed by Rezaei (Rezaei, 2015), is a technique used to determine the weights of criteria. Various approaches to the BWM have been introduced, including linear (Rezaei, 2016), FBWM (Guo & Zhao, 2017), Euclidean BWM (EBWM) (Kocak et al., 2018), Z number version BWM (ZBWM) (Aboutorab et al., 2018), and multiplicative BWM (MBWM) (Brunelli & Rezaei, 2019).

All the procedure is explained below (Amoozad Mahdiraji et al., 2022):

- Determining Best and Worst criteria (for the study, it comes from fuzzy Delphi ranking),
- Designing BWM questionnaires and sending them to experts' groups,
- Assigning the weights to criteria,
- Calculating the Consistency Ratio (CR),
- Determining the final weights of selected criteria,

3.5.1 Fuzzy BWM Procedure

The Fuzzy Best-Worst Method (FBWM) was selected for this study over other methods, such as the Analytic Hierarchy Process (AHP) and traditional Best-Worst Method (BWM) for several compelling reasons. First, FBWM incorporates fuzzy logic, which allows for a more nuanced and realistic expression of expert judgments under uncertainty, unlike AHP and traditional BWM. This enhanced capability makes FBWM adaptable to various contexts, effectively accommodating the natural imprecision in human judgments better than conventional methods. Additionally, FBWM requires less comparison data, making it more efficient and practical for complex decision-making scenarios. These advantages collectively make FBWM a superior choice for this study (Amoozad Mahdiraji et al., 2018a; Rezaei, 2015, 2016).

In this context, the FBWM, as described by Guo and Zhao (2017), is applied. The entire course of actions is detailed below:

I. A set of decision factors (criteria) labelled as $\{F_1, F_2, \dots, F_n\}$ must be identified to guide the decision-making process.

II. Experts or focus groups initially have to select the Best and Worst criteria, with no direct comparison involved. In this study, however, the author adapted this step by using the ranking results obtained from the Fuzzy Delphi method to determine the Best and Worst criteria.

III. Experts or focus groups express their preference for the best factor (criteria) in linguistic terms. These linguistic preferences are then translated into Triangular Fuzzy Numbers (TFNs), represented as $\{\tilde{A}_{b1}, \tilde{A}_{b2}, \dots, \tilde{A}_{bn}\}$, following table (Table 7). Each $\tilde{A}_{bj}$ corresponds to the fuzzy preference degree of the best criteria compared to the j_{th} criterion.

IV. Experts or focus groups express their preference for factor (criteria) other than the worst one using linguistic terms. These linguistic preferences are then converted into Triangular Fuzzy Numbers (TFNs), as outlined in the same table, denoted as $\{\tilde{A}_{1w}, \tilde{A}_{2w}, \dots, \tilde{A}_{nw}\}$. Each $\tilde{A}_{jw}$ represents the fuzzy preference degree of the j_{th} criterion compared to the worst criterion.

Table 7: The Best Worst Method Linguistic Terms Triangular Fuzzy Numbers (TFNs)

Linguistic Terms	TFNs
Equal	(1, 1, 1)
Fairly quite better	(1, 2, 3)
Quite better	(2, 3, 4)
Extremely quite better	(3, 4, 5)
Better	(4, 5, 6)
Fairly much better	(5, 6, 7)
Much better	(6, 7, 8)
Extremely much better	(7, 8, 9)
Fully better	(8, 9, 9)

V. The model presented in equation (3) below is solved to determine optimal weights using the General Algebraic Modelling System (GAMS) or Lingo software, resulting in $\{W_1, W_2, \dots, W_n\}$; where W_j^l shows the lower limit of a Triangular Fuzzy Number (TFN), and W_j^m and W_j^u represent the moderate and upper limits of the TFN weights.

$$Min\ \varepsilon, \quad s.t. \begin{cases} \left| \frac{(w_B^l \ \ w_B^m \ \ w_B^u)}{(w_j^l \ \ w_j^m \ \ w_j^u)} - (A_{Bj}^l \ \ A_{Bj}^m \ \ A_{Bj}^u) \right| < \varepsilon \\ \left| \frac{(w_j^l \ \ w_j^m \ \ w_j^u)}{(w_w^l \ \ w_w^m \ \ w_w^u)} - (A_{jw}^l \ \ A_{jw}^m \ \ A_{jw}^u) \right| < \varepsilon \\ \sum_1^j S(W_j) = 1 \\ S(W_j) = \frac{1}{6}(W_j^l + 4W_j^m + W_j^u) \\ W_j^l \le W_j^m \le W_j^u, \quad W_j^l \ge 0 \end{cases} \qquad (3)$$

VI. The Consistency Ratio (CR) for the comparisons is determined using equation (4). In this study, CRs below 0.6 are deemed acceptable.

$$CR = \frac{\varepsilon^*}{CI} \qquad (4)$$

CI represents the "Consistency Index", which is calculated based on the preference of the best criteria over the worst criteria (A_{BW}). The CI values are provided in Table 8.

Table 8: Consistency Index Values

Consistency Index Values (Rezaei, 2015)	A_{BW}	1	2	3	4	5	6	7	8	9
	CI	0.00	0.44	1.00	1.63	2.30	3.00	3.73	4.47	5.23

VII. The fuzzy extracted weights $(W_l \ \ W_m \ \ W_u)$ are defuzzified using equation (5), which W_j represents the weight of the j_{th} criterion.

$$W_j = \frac{1}{6}(W_l + 4W_m + W_u) \qquad (5)$$

3.5.2 Number of Experts

There are various Multi-Criteria Decision-Making (MCDM) techniques available by using pairwise questionnaires or other related methods, including Analytical Hierarchical Processing (AHP), Analytical Network Processing (ANP), Multi-Attribute Utility Theory (MAUT), Simple Multiple Attribute Rating Technique (SMART) among others, for ranking criteria or comparison (Bhattacharya et al., 2014; Mir et al., 2016; Scholz et al., 2017; Subramoniam et al., 2013; M. Wang et al., 2017; Wang et al., 2016).

However, the Best-Worst Method (BWM) holds advantages over these techniques. BWM requires fewer pairwise comparisons compared to other MCDM techniques like AHP (Rezaei, 2015). In BWM,

alternatives are compared with the best and worst alternatives only, thus requiring relatively less data than AHP, which necessitates pairwise comparisons among all alternatives.

Rezaei et al. (Rezaei et al., 2018) noted in their study "*Quality assessment of airline baggage handling systems using SERVQUAL and BWM"* that BWM can be applied with 4–10 experts. This method offers the additional advantage of requiring fewer experts for analysis, in addition to needing fewer data points (Gupta, 2018).

3.6 C-MEANS

The fuzzy C-Means algorithm is a widely used and reliable clustering algorithm that determines data membership degrees by iteratively minimising the cost function while ensuring that the sum of cluster membership degrees for each data point remains constant (Alsmadi, 2018). Fuzzy C-Means (FCM), proposed by Dunn (Dunn, 1973) and later improved by Bezdek (Bezdek, 2013), is an extension of C-Means where each data point can be a member of multiple clusters with membership values (fuzzy partitions).

The classical C-Means method is designed to divide n observations into c groups, with each observation being assigned to the cluster with the nearest means, which serves as a prototype for the respective cluster (Zhou et al., 2015). It results in u_{ij} is either 0 or 1 depending on whether object i is grouped into cluster j, and thus each data point is assigned to a single cluster (hard partitions).

Given, the partition-based K-Means algorithm (Petitjean et al., 2011) and the Fuzzy C-Means (FCM) algorithm (Guo et al., 2020; W. Wang et al., 2015) are commonly employed clustering techniques. While the K-Means algorithm assigns objects to clusters in a binary manner (either belonging or not), the FCM algorithm introduces the concept of partial memberships, allowing objects to have fractional memberships to multiple clusters (Z. Yang et al., 2022).

3.6.1 Fuzzy C-Means Clustering Process

The C-Means clustering pattern follows a specific process to assign data points to clusters. Here is a step-by-step overview of the C-Means method (Bezdek et al., 1984; Chen et al., 2006; Nayak et al., 2015):

- **Initialisation:** Select the number of clusters and randomly initialise the cluster centroids. Each centroid represents the centre of a cluster.
- **Membership Assignment:** Calculate the membership values for each data point, indicating their degree of belongingness to each cluster. This is done by measuring the distance between each data point and the cluster centroids. A common distance metric used is the Euclidean distance.

- **Centroid Update:** Update the cluster centroids based on the current membership values. The centroids are recalculated as the weighted average of the data points, with the membership values serving as weights.
- **Iteration:** Repeat steps 2 and 3 until convergence. Convergence is achieved when there is minimal change in the cluster centroids or when a predetermined number of iterations is reached.
- **Final Cluster Assignment:** Once the algorithm converges, assign each data point to the cluster with the highest membership value. This determines the final clustering solution.
- **Result Evaluation:** Evaluate the quality of the clustering solution using appropriate metrics such as the objective function, silhouette coefficient, or external validation measures if ground truth labels are available.

3.6.2 Fuzzy C-Means Clustering Algorithm

Fuzzy C-Means (FCM) is a highly researched area that attracts researchers from diverse fields, including computer science, mathematics, engineering, and optimisation. Fuzzy C-Means and its various versions have successfully addressed a wide range of problems spanning different domains (Nayak et al., 2015).

In different domains, the challenges approached by Fuzzy C-Means and its various versions typically share common characteristics: the need to cluster or categorise data where there is uncertainty or overlap between categories. This characteristic is crucial because many real-world scenarios involve data points that do not fit neatly into a single category but instead belong to multiple clusters to varying degrees. Fuzzy C-Means's ability to handle such ambiguity makes it particularly useful in fields like image processing, medical diagnosis, pattern recognition, and market segmentation. By providing degrees of membership for each data point across various clusters, Fuzzy C-Means offers a nuanced view of the data, enhancing decision-making and making it a versatile and powerful tool for addressing complex problems across diverse domains (Peters et al., 2013; Wu & Yang, 2002; Zangana & Abdulazeez, 2023).

Clustering methods are commonly categorised into four groups: *hierarchical*, *graph-theoretic*, *density function decomposition*, and *objective function minimisation* (Łęski, 2003). This paper concentrates on clustering methods that "*minimise objective functions"*.

For an unlabelled dataset $X = \{x_1, x_2, \dots, x_N\}$, where N represents the number of data points, the constrained fuzzy C-partition can be summarised as follows (Bezdek et al., 1984):

- Each vector's membership in one of C clusters $\{j = 1, 2, \ldots, C\}$ is expressed by the membership function u_{ij} for the ith data point $\{i = 1, 2, \ldots, N\}$. These membership values are subject to certain constraints, typically defined as,

$$\begin{cases} \forall i, \sum_{i=1}^{N} u_{ij} > 0 \\ \forall j, \sum_{j=1}^{C} u_{ij} = 1 \\ \forall i, j, u_{ij} \in [0,1] \end{cases}$$

- The clustering criterion employed here is the weighted within-group sum of squared errors, which is defined as follows:

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^{m} \|x_i - v_j\|^2$$

- Here, $V = \{v_1, v_2, \ldots, v_C\}$ represents the vector of cluster centers, and m is the weighting exponent.

3.7 COPRAS METHOD

The COmplex PRoportional ASsessment (COPRAS) method was introduced by Zavadskas et al. in 1994 (Zavadskas et al., 1994). Numerous scholars have acknowledged the COPRAS method's reliability and accuracy, and it is now widely utilised to tackle diverse multi-attribute problems in both engineering and management (Akhavan et al., 2015; Čereška, Podvezko, et al., 2016; Čereška, Zavadskas, et al., 2016; Ecer, 2014; Rasiulis et al., 2016).

Additionally, in the COPRAS method, the precision of performance measures is based on the direct and proportional relationship between the importance and usefulness of evaluated alternatives and a set of criteria (Tamošaitienė & Gaudutis, 2013). COPRAS with fuzzy sets information is a developed method for solving decision-making problems under uncertain situations, introduced by Zavadskas and Antucheviciene (Zavadskas & Antucheviciene, 2007).

COPRAS is a multi-criteria decision-making (MCDM) technique created to rank alternatives according to decision criteria (Zavadskas et al., 1994). The method consists of the following stages that is illustrated in Figure 10. (Amoozad Mahdiraji et al., 2018b)

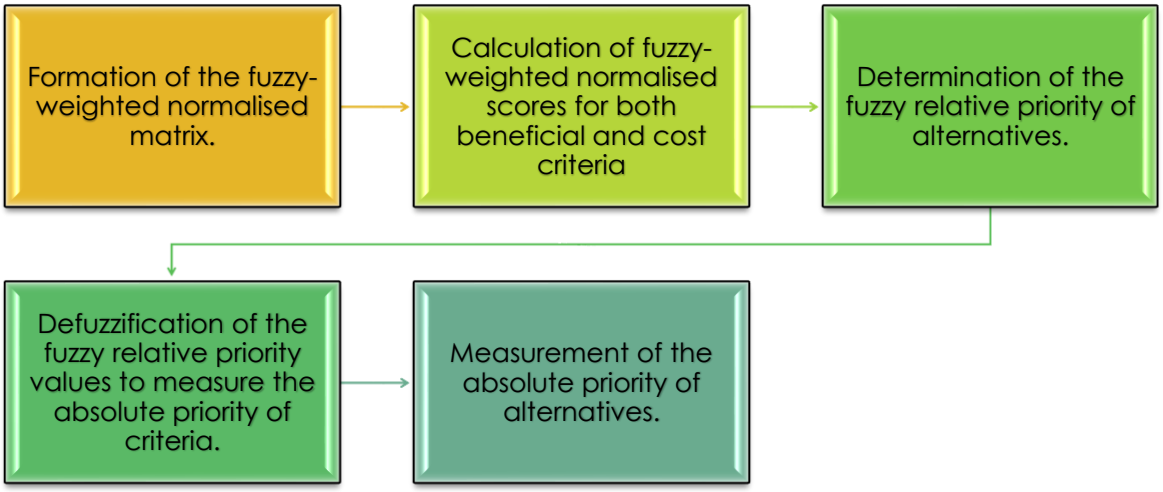

Figure 24: FCOPRAS Method Steps

To apply the FCOPRAS method, the following steps are presented (Amoozad Mahdiraji et al., 2022):

1. By applying linguistic terms provided in Table 9 and considering equation (6), the fuzzy-weighted normalised matrix will be constructed.

$$\tilde{v}_{ij} = \frac{\tilde{r}_{ij}\tilde{w}_j}{\sum_{i=1}^{m}\tilde{r}_{ij}} \; ; \; i = 1,2,3,\dots,m \; ; \; j = 1,2,3,\dots,n \qquad (6)$$

In this context, $\tilde{r}_{ij}$ represents the value of the i_{th} alternative based on the j_{th} criterion, with $\tilde{w}_j$ representing the weight of the j_{th} criterion obtained from the FBWM section. The variables m and n correspond to the number of alternatives and criteria, respectively.

Table 9: Triangular fuzzy numbers for linguistic terms of FCOPRAS

Linguistic Terms	TFNs
Extremely low	(0, 1, 2)
Low	(1, 2, 3)
Moderately low	(2, 3.5, 5)
Medium	(4, 5, 6)
Moderately high	(5, 6.5, 8)
High	(7, 8, 9)
Extremely high	(8, 9, 10)

2. To get fuzzy-weighted normalised scores, equation (7) is used to both beneficial (positive) and cost (negative) criteria.

$$\tilde{S}_{+i} = \sum_{j\in B}\tilde{v}_{ij} \; ; \; i = 1,2,3,\dots,m \qquad (7)$$

$$\tilde{S}_{-i} = \sum_{j\in C}\tilde{v}_{ij} \; ; \; i = 1,2,3,\dots,m$$

In equation (7), $\tilde{S}_{+i}$ represents the fuzzy beneficial score, while $\tilde{S}_{-i}$ represents the fuzzy cost score.

3. $\tilde{Q}_i$ refers to the fuzzy relative priority of alternatives. To calculate $\tilde{Q}_i$, equation (8) must be taken into account.

$$\tilde{Q}_i = \tilde{S}_{+i} + \frac{\tilde{S}_{-min} \times \sum_{i=1}^{m} \tilde{S}_{-i}}{\tilde{S}_{-i} \times \sum_{i=1}^{m} \frac{\tilde{S}_{-min}}{\tilde{S}_{-i}}} \qquad (8)$$

4. To determine the absolute priority of criteria, the fuzzy relative priority values are defuzzified using equation (9).

$$Q_i = f_1 + \frac{(f_3 - f_1) + (f_2 - f_1)}{3} \qquad (9)$$

5. By considering equation (10), the absolute priority of alternatives N_i will be measured.

$$N_i = \frac{Q_i}{Q_{max}} \times 100 \qquad (10)$$

Tackling optimal decision-making within an ever-evolving and data-rich environment, often referred to as large-scale decision-making (LSDM), presents significant challenges for organisations. While methodologies such as the Analytical Hierarchical Process (AHP) and Simple Additive Weighting (SAW), as well as non-decision-making approaches like Pareto analysis, are well-suited for similar scenarios, they may falter in delivering practical results when faced with uncertainty, extensive data, and the integration of both qualitative and quantitative criteria simultaneously (Amoozad Mahdiraji et al., 2018a; Mahdiraji et al., 2019).

In this research, the proposed manner is a hybrid approach that integrates four data mining and decision-making methods to assist with LSDM problems. For the first step, essential factors are identified and assessed under uncertain conditions using fuzzy Delphi and the Fuzzy Best-Worst Method (FBWM). Subsequently, the process continues by clustering large datasets using the C-Means method. At the final stage, the FCOPRAS method integrates qualitative and quantitative factors to rank the clusters, enabling decision-makers to establish clear priorities in any given situation.

3.8 DATA COLLECTION

The research focuses on a diverse study population, encompassing customers across different levels of engagement within the e-commerce sphere. Specifically, this includes individuals who regularly interact with the "Amazon" website and application.

Furthermore, the research expands its outreach to include experts and scholars who possess specialised knowledge in the realm of decision-making. These experts play a vital role in contributing their valuable insights and opinions to the research in all steps.

To facilitate data collection, the research employed questionnaires designed to extract related information from experts and consider customers' activities that come from a public database. These questionnaires and features from the database aimed to investigate various aspects, such as demographics, purchasing behaviours, individual priorities, online shopping experiences, and other relevant details.

The customer data and records were sourced from an open-source dataset, confirmed during the project's initial phase. To identify suitable experts, 96 professors, lecturers, and e-commerce specialists were contacted regarding their participation in the project. Based on their responses, a fuzzy Delphi questionnaire was sent to 15 of these experts over two rounds, and all questionnaires were completed.

The experts needed to be familiar with the procedure for the next step, which involved the fuzzy BWM (Best-Worst Method). Based on the correspondence, 12 experts agreed to participate in this phase.

Finally, for fuzzy COPRAS step, three top-quality professors were recruited to rank the clusters based on specific factors for the highly technical last part, which required specialised expertise. All correspondence and emails are available, but the names and related characteristics of the experts are withheld for ethical reasons.

3.9 Validity Across All Methods

Traditional methods often fall short of capturing the nuances of expert opinions in complex decision-making processes, especially those involving subjective and uncertain information. To address this, fuzzy methodologies such as the Fuzzy Delphi method, Fuzzy Best-Worst Method (BWM), and Fuzzy Complex Proportional Assessment (COPRAS) have been developed. These methods combine the systematic approach of traditional decision-making techniques with the flexibility of fuzzy logic, allowing for more accurate and reliable results. This section examines the validity of these methods, focusing on their key aspects and general principles that ensure their robustness and reliability.

- **Fuzzy Delphi Method**

1. ***EXPERT SELECTION***

❖ *Diverse Experts:* Ensures comprehensive and representative insights from a knowledgeable panel (Chu & Hwang, 2008).

- *Sufficient Number:* Typically involves 10-20 experts to capture a wide range of opinions (Mullen, 2003; Skulmoski et al., 2007).

2. QUESTIONNAIRE DESIGN

- *Clear and Relevant Questions:* Ensures that the responses are pertinent to the research objectives (Y.-L. Hsu et al., 2010).
- *Iterative Rounds:* Multiple rounds of feedback help refine expert opinions and reach a consensus (Saffie & Rasmani, 2016).

3. DATA ANALYSIS

- *Fuzzy Logic Application:* Manages uncertainty and subjectivity in expert opinions, enhancing the robustness of the analysis (Y.-L. Hsu et al., 2010).
- *Consensus Measurement:* Techniques to measure and improve consensus among experts increase the validity of the results (Giannarou & Zervas, 2014; Saffie & Rasmani, 2016).

4. RELIABILITY AND CONSISTENCY

- *Repeated Measures:* Ensures that responses are consistent across different rounds (Ishikawa et al., 1993; Tsai et al., 2020).
- *Statistical Validation:* Confirms the reliability and consistency of the collected data (Chan, 2022; Morales et al., 2018).

5. TRANSPARENCY

- *Detailed Documentation:* Comprehensive records of the process enhance transparency and replicability (Skulmoski et al., 2007).
- *Anonymity:* Maintaining the anonymity of experts prevents biases and promotes honest responses (Crisp et al., 1997; Giannarou & Zervas, 2014).

- **Fuzzy BWM (Best-Worst Method)**

1. PAIRWISE COMPARISONS

- *Structured Comparisons:* Experts compare the best and worst criteria, capturing precise preferences (Rezaei, 2015).
- *Consistency Check:* Validates the reliability of the pairwise comparison matrices (Rezaei, 2015, 2016).

2. FUZZY LOGIC APPLICATION

- *Handling Ambiguity:* Expresses uncertainty and vagueness in expert judgments (Guo & Zhao, 2017).
- *Aggregation of Opinions:* Accurately represents collective insights through the aggregation of fuzzy preferences (Guo & Zhao, 2017).

3. ***RELIABILITY***

- *Consistency Indices:* Checks and improves the reliability of comparisons (Rezaei, 2015, 2016).
- *Sensitivity Analysis:* Ensures that the results are robust to changes in input data (Amiri et al., 2021; Javad et al., 2020).

- **Fuzzy COPRAS (Complex Proportional Assessment)**

1. ***CRITERIA EVALUATION***

- *Comprehensive Analysis:* Evaluates alternatives against multiple criteria, ensuring a holistic assessment (Turanoglu Bekar et al., 2016; Zavadskas & Turskis, 2011).
- *Fuzzy Logic:* Incorporates fuzzy numbers to handle uncertainty in evaluating criteria and alternatives (Amoozad Mahdiraji et al., 2018a).

2. ***NORMALISATION AND WEIGHTING***

- *Normalised Scores:* Ensures that criteria scores are comparable across different scales (Yazdani et al., 2011; Zarbakhshnia et al., 2018).
- *Accurate Weighting:* Reflects the importance of each criterion accurately (Amoozad Mahdiraji et al., 2018a; Zarbakhshnia et al., 2018).

3. ***RANKING AND DECISION MAKING***

- *Proportional Assessment:* Ranks alternatives based on their performance relative to each criterion, providing a clear decision-making framework (Narang et al., 2021).
- *Consistency and Reliability:* Validation through consistency checks and sensitivity analysis ensures reliability (Amoozad Mahdiraji et al., 2018a; Dhiman & Deb, 2020).

The fuzzy Delphi method, fuzzy BWM, and COPRAS could provide valid, reliable, and consensus-driven insights for complex decision-making processes by adhering to these principles.

3.10 ETHICS

Ethical considerations in research are of paramount importance. To ensure the highest standards of ethics are maintained throughout the research process, several key steps have been implemented:

I. **Data Sourcing from Publicly Accessible Databases:** The research responsibly accesses publicly available online databases to retrieve the required customer information. This approach aligns with ethical guidelines as it utilises data that is already in the public domain, respecting individuals' privacy and data protection rights.

II. **Stringent Ethical Procedures for Questionnaires:** When administering questionnaires to experts and scholars, rigorous ethical procedures is adhered to. This includes obtaining informed consent from all participants, ensuring anonymity and

confidentiality of responses, and clearly outlining the purpose and objectives of the research. Additionally, participants have the option to withdraw their participation at any time without penalty.

III. **Protection of Personal Data:** All personal data collected from both customers and participants is handled with the extreme care and compliance with data protection regulations. Data is anonymised and securely stored to safeguard individuals' privacy.

IV. **Transparency and Informed Consent:** The research maintains complete transparency in its processes, ensuring that all participants are well-informed about the research objectives, their role in the study, and how their data is used. Informed consent is sought from each participant as a fundamental ethical practice.

V. **Research Approval:** If required, the research seeks approval from relevant ethics committees or institutional review boards to ensure that the research design and procedures adhere to ethical standards.

By upholding these rigorous ethical practices, the research aims to maintain the highest level of integrity, respect for privacy, and ethical conduct throughout its course. This commitment to ethics reinforces the credibility and reliability of the research findings.

To underscore these values and ensure adherence to ethical standards, the study places paramount importance on maintaining integrity, respecting privacy, and upholding ethical conduct at every stage. This dedication to ethical principles not only bolsters the credibility and reliability of the research findings but also underpins the process of obtaining approval from the university's ethics committee, as detailed in the appendix.

4 RESEARCH OUTPUT & FINDINGS

In this chapter, I undertaked an in-depth examination of events sourced from Amazon. Initially, following the research methodology, I thoroughly gathered essential data to pinpoint the critical success factors of e-commerce and decision-making criteria. This involved library research and database referencing. Subsequently, from the database, I identified 20 distinct primary factors, all of which exhibited conceptual proximity.

To further refine the analysis, I employed the fuzzy Delphi questionnaire, tapping into the insights of experts in the field. Through this process, I narrowed down the factors to a final count of 7.

Moving forward, I conducted a weighting procedure for these 7 main factors, using the fuzzy Best-Worst Method. Simultaneously, employing the C-MEANS method, I categorised the data into 5 distinct clusters. With clusters (alternatives) labelled as A1, A2,..., A5, and factors(criteria) denoted as F1, F2,..., and F7, along with their respective weights, I proceeded to rank and establish priorities using the fuzzy COPRAS method. In the subsequent sections, each step will be elaborated upon in comprehensive detail.

4.1 INITIAL STEPS AND DATA COLLECTION

Based on the research literature, the initial phase involved convening numerous meetings with experts and university lecturers to discuss matters concerning critical success factors (CSFs) for e-commerce platforms and their relevance to profitability. Subsequently, leveraging a publicly available database, data about e-commerce customers (Amazon company), including 23 distinct records for 602 customers, was procured for this study. The data collection was conducted in June 2023.

The dataset comprised 602 entries, encompassing a broad spectrum of 23 distinct variables (factors), including demographic information and other related questions in the field of customer behaviour during online shopping. After thorough discussions, I carefully selected 20 factors for the next phase. These were chosen based on perceptions from the literature review, with a focus on critical success factors, particularly customer needs. Moving forward, the research involves obtaining alternatives (clusters) using the C-Means clustering method and defining factors (criteria) through the fuzzy Delphi method. Then, I determined the weights of selected factors using FBWM. Finally, the FCOPRAS Method was employed to prioritise clusters, completing our methodology framework.

4.2 DETERMINING CRITERIA AND FACTORS APLLYING THE FUZZY DELPHI METHOD

4.2.1 Classification of Factors

Before commencing the analysis of factors via the fuzzy Delphi method, a table (Table 10) has been carefully crafted to provide a structured overview of these factors and their associated categories.

This table serves as a comprehensive reference point, facilitating the systematic exploration of the factors influencing customer behaviour in online shopping. Each question is listed in the first column, representing the distinct factors under scrutiny. These questions were carefully curated based on insights gleaned from an exhaustive literature review, which delved into the complex nuances of online consumer behaviour. The second column of the table serves a complementary role by categorising these factors into relevant subjects identified during the literature review process. This categorisation strategy enhances the clarity and organisation of the factors, enabling a more intuitive understanding of their interrelationships and implications.

Table 10: Classification of Factors Influencing Online Consumer Behaviour

No.	Questions	Categories
1	How often do you make purchases on Amazon?	User online shopping experience, Customer satisfaction, Trust privacy and security, E-service, Loyalty, Switching behaviour, Cross-cultural differences,
2	What product categories do you typically purchase on Amazon?	Product information, Price & perceived value, Switching behaviour, Cross-cultural differences,
3	Have you ever made a purchase based on personalised product recommendations from Amazon?	Trust privacy and security, Price & perceived value, Loyalty, Cross-cultural differences,
4	How often do you browse Amazon's website or app?	User online shopping experience, Customer satisfaction, Customer reviews and feedback, Loyalty,
5	How do you search for products on Amazon?	User Experience, Price & perceived value,
6	Do you tend to explore multiple search results pages or focus on the first page?	User online shopping experience, Cross-cultural differences,
7	How important are customer reviews in your decision-making process?	Product information, Customer reviews and feedback, Switching behaviour, Cross-cultural differences, Future purchase intentions,
8	Do you add products to your cart while browsing on Amazon?	Price & perceived value, Cart interactions, Customer reviews and feedback, Cross-cultural differences,
9	How often do you complete the purchase after adding products to your cart?	Price & perceived value, Cart interactions, Shipping and return policies, Switching behaviour, Cross-cultural differences
10	What factors influence your decision to abandon a purchase in your cart?	Customer satisfaction, Price & perceived value, Cart interactions, Trust privacy and security, Customer reviews and feedback, Shipping and return policies, Loyalty, Switching behaviour, Cross-cultural differences,
11	Do you use Amazon's "Save for Later" feature, and if so, how often?	Customer satisfaction, Cart interactions, Customer reviews and feedback, Shipping and return policies, E-service, Customer reviews and feedback, Switching behaviour, Cross-cultural differences, Future purchase intentions,
12	Have you ever left a product review on Amazon?	Product information, Customer reviews and feedback, Cross-cultural differences, Future purchase intentions,
13	How much do you rely on product reviews when making a purchase?	Product information, Customer reviews and feedback, Cross-cultural differences,
14	Do you find helpful information from other customers' reviews?	Product information, Customer reviews and feedback, Cross-cultural differences,
15	How often do you receive personalised product recommendations from Amazon?	Product information, E-Service, Cross-cultural differences
16	Do you find the recommendations helpful?	Shipping and return policies, Cross-cultural differences,
17	How would you rate the relevance and accuracy of the recommendations you receive?	E-Service, Cross-cultural differences, Customer satisfaction,
18	How satisfied are you with your overall shopping experience on Amazon?	Customer satisfaction, Price & perceived value, Shipping and return policies, E-Service, Cross-cultural differences,
19	What aspects of Amazon's services do you appreciate the most?	Cross-cultural differences, E-Service, User online shopping experience,
20	Are there any areas where you think Amazon can improve?	Customer satisfaction, Price & perceived value, User online shopping experience, Loyalty, Cross-cultural differences

4.2.2 Analysing Factors via Fuzzy Delphi Questionnaire

The primary factors for examination were identified by a panel of specialists and experts. To conduct this investigation, a fuzzy questionnaire was distributed among 15 experts, comprising university professors, academic researchers, and online sales specialists. These experts were carefully selected from various universities, with 10 individuals possessing degrees ranging from master's to doctorate and having a minimum of 5 years of experience in the field. Notably, the remaining 5 participants were chosen from companies that met the specified criteria and actively engaged in online sales.

Table 11: Characteristics of Expert Panel

Expert Type	***Number of Experts***	***Education Level***	***Experience (Years)***	***Ratio***
University Professors & Academic Researchers	10	Master's to Doctorate	5 to 12	67%
Online Sales Specialists	5	Bachelor's to Master's	5 to 10	33%

The answers given in the questionnaire were fuzzy, meaning they were not precise but rather vague or uncertain. To make sense of these responses, I needed to link words describing them with specific numbers in a particular way. Table 12 illustrates the relationship between verbal variables and fuzzy numbers.

Table 12: Linguistic Terms - Triangular Fuzzy Numbers

Linguistic Terms	*Not Important*	*Slightly Important*	*Important*	*Fairly Important*	*Very Important*
Fuzzy Number	(0, 0, 0.25)	(0, 0.25, 0.5)	(0.25, 0.5, 0.75)	(0.5, 0.75, 1)	(0.75, 1, 1)

During the first stage of the survey, participants from the expert group were provided with a questionnaire comprising 20 factors. They were tasked with providing their opinions on each factor using verbal variables listed in the questionnaire. Subsequently, based on the responses gathered from the initial questionnaire and applying equations (10) and (11), the fuzzy average for each component was calculated.

$$A_i = \left(a_1^i , a_2^i , a_3^i\right) , i = 1,2,3, \dots , n \qquad (10)$$

In relation (10), the value of A_i indicates the point of view of the i_{th} expert and n is the number of experts.

$$A_{ave} = \left(\frac{1}{n}\sum_{i=1}^{n} a_1^i \ , \ \frac{1}{n}\sum_{i=1}^{n} a_2^i \ , \ \frac{1}{n}\sum_{i=1}^{n} a_3^i \right) , i = 1,2,3, \dots , n \qquad (11)$$

In equation (11), the value of A_{ave} signifies the collective average opinion of the experts. The outcomes of the first survey are detailed in Table 13. Additionally, it's worth highlighting that equation (12), referred to as the Minkowski method, serves to de-fuzzify triangular fuzzy numbers.

$$\gamma = a_1 + \frac{a_3 - a_2}{4} \qquad (12)$$

Table 13: The Findings from the First Survey

No.	Criterion	Content	Mean of Fuzzy Numbers First Round			*Defuzzification First Round*
			First Part	Second Part	Third Part	
1	Purchase Frequency	The frequency of online purchases	0.47	0.72	0.87	***0.50***
2	Purchase Categories	What product categories typically purchase	0.43	0.67	0.87	***0.48***
3	Personalised Recommendation Frequency	Purchasing based on personalised product recommendations	0.37	0.58	0.78	***0.42***
4	Browsing Frequency	How often browse the website or app	0.40	0.62	0.82	***0.45***
5	Product Search Method	How to search for products	0.28	0.53	0.78	***0.35***
6	Search Result Exploration	Applying multiple pages of search results	0.37	0.62	0.85	***0.43***
7	Customer Reviews Importance	The importance of customer reviews in the decision-making process	0.58	0.83	0.93	***0.61***
8	Add to Cart Browsing	Adding products to the cart while browsing	0.18	0.38	0.62	***0.24***
9	Cart Completion Frequency	How often complete the purchase after adding products to a cart	0.18	0.38	0.62	***0.24***
10	Cart Abandonment Factors	The factors influence decisions to abandon a purchase in a cart	0.20	0.38	0.62	***0.26***
11	Save-for-later Frequency	The importance of the "Save for Later" feature	0.12	0.33	0.58	***0.18***
12	Review Left	Leaving a product review online	0.28	0.53	0.75	***0.34***
13	Review Reliability	How much rely on product reviews when making a purchase	0.47	0.72	0.90	***0.51***
14	Review Helpfulness	Helpful information from other customers' reviews	0.57	0.82	0.95	***0.60***
15	Personalised Recommendation Frequency	Receiving personalized product recommendations	0.48	0.73	0.90	***0.53***
16	Recommendation Helpfulness	Finding the recommendations helpful	0.47	0.70	0.90	***0.52***
17	Rating Accuracy	Rating the relevance and accuracy of the recommendations	0.38	0.63	0.82	***0.43***
18	Shopping Satisfaction	Overall shopping satisfaction experience	0.60	0.85	0.97	***0.63***
19	Service Appreciation	The aspects of online services for the most appreciation	0.35	0.60	0.82	***0.40***
20	Improvement Areas	The areas where an online purchasing website can improve	0.37	0.60	0.83	***0.43***

According to Cheng and Lin (Cheng & Lin, 2002), if the variance between the two stages falls below a minimal threshold (0.2), the process is halted. Moving to the second stage of the survey, the previous opinions of each expert and the extent of their differences with the opinions of other experts, along

with a questionnaire, were once again sent to the members of the expert group. The responses collected in the second stage were then scrutinised using equations (11) and (12), akin to the first stage, with the outcomes presented in Table 14.

Table 14: The Findings from the Second Survey

No.	Criterion	Content	Mean of Fuzzy Numbers First Round			*Defuzzification First Round*
			First Part	Second Part	Third Part	
1	Purchase Frequency	The frequency of online purchases	0.47	0.72	0.87	**0.50**
2	Purchase Categories	What product categories typically purchase	0.32	0.55	0.78	**0.38**
3	Personalised Recommendation Frequency	Purchasing based on personalised product recommendations	0.28	0.53	0.77	**0.34**
4	Browsing Frequency	How often browse the website or app	0.37	0.60	0.82	**0.42**
5	Product Search Method	How to search for products	0.30	0.55	0.78	**0.36**
6	Search Result Exploration	Applying multiple pages of search results	0.33	0.57	0.80	**0.39**
7	Customer Reviews Importance	The importance of customer reviews in the decision-making process	0.52	0.77	0.95	**0.56**
8	Add to Cart Browsing	Adding products to the cart while browsing	0.22	0.45	0.70	**0.28**
9	Cart Completion Frequency	How often complete the purchase after adding products to a cart	0.27	0.48	0.70	**0.32**
10	Cart Abandonment Factors	The factors influence decisions to abandon a purchase in a cart	0.35	0.57	0.78	**0.40**
11	Save-for-later Frequency	The importance of the "Save for Later" feature	0.25	0.48	0.70	**0.30**
12	Review Left	Leaving a product review online	0.28	0.53	0.77	**0.34**
13	Review Reliability	How much rely on product reviews when making a purchase	0.50	0.75	0.92	**0.54**
14	Review Helpfulness	Helpful information from other customers' reviews	0.53	0.78	0.92	**0.57**
15	Personalised Recommendation Frequency	Receiving personalized product recommendations	0.47	0.72	0.87	**0.50**
16	Recommendation Helpfulness	Finding the recommendations helpful	0.45	0.70	0.88	**0.50**
17	Rating Accuracy	Rating the relevance and accuracy of the recommendations	0.32	0.57	0.80	**0.38**
18	Shopping Satisfaction	Overall shopping satisfaction experience	0.50	0.75	0.92	**0.54**
19	Service Appreciation	The aspects of online services for the most appreciation	0.35	0.60	0.85	**0.41**
20	Improvement Areas	The areas where an online purchasing website can improve	0.27	0.52	0.75	**0.33**

Through defuzzification of the Mean of Fuzzy Numbers in two rounds, the difference between the outcomes remains comfortably below the threshold, as demonstrated in Table 15.

Table 15: Comparison of Defuzzification Outcomes

No.	Criterion	Content	Defuzzification First Round	Defuzzification Second Round	Difference	*Average*
1	Purchase Frequency	The frequency of online purchases	*0.50*	0.50	0.00	0.504
2	Purchase Categories	What product categories typically purchase	*0.48*	0.38	0.11	0.429
3	Personalised Recommendation Frequency	Purchasing based on personalised product recommendations	*0.42*	0.34	0.08	0.379
4	Browsing Frequency	How often browse the website or app	*0.45*	0.42	0.03	0.435
5	Product Search Method	How to search for products	*0.35*	0.36	0.01	0.352
6	Search Result Exploration	Applying multiple pages of search results	*0.43*	0.39	0.03	0.408
7	Customer Reviews Importance	The importance of customer reviews in the decision-making process	*0.61*	0.57	0.04	0.594
8	Add to Cart Browsing	Adding products to the cart while browsing	*0.24*	0.28	0.04	0.260
9	Cart Completion Frequency	How often complete the purchase after adding products to a cart	*0.24*	0.32	0.08	0.281
10	Cart Abandonment Factors	The factors influence decisions to abandon a purchase in a cart	*0.26*	0.40	0.15	0.331
11	Save-for-later Frequency	The importance of the "Save for Later" feature	*0.18*	0.30	0.13	0.242
12	Review Left	Leaving a product review online	*0.34*	0.34	0.00	0.340
13	Review Reliability	How much rely on product reviews when making a purchase	*0.51*	0.54	0.03	0.527
14	Review Helpfulness	Helpful information from other customers' reviews	*0.60*	0.57	0.03	0.583
15	Personalised Recommendation Frequency	Receiving personalized product recommendations	*0.53*	0.50	0.02	0.515
16	Recommendation Helpfulness	Finding the recommendations helpful	*0.52*	0.50	0.02	0.506
17	Rating Accuracy	Rating the relevance and accuracy of the recommendations	*0.43*	0.38	0.05	0.402
18	Shopping Satisfaction	Overall shopping satisfaction experience	*0.63*	0.54	0.09	0.585
19	Service Appreciation	The aspects of online services for the most appreciation	*0.40*	0.41	0.01	0.408
20	Improvement Areas	The areas where an online purchasing website can improve	*0.43*	0.33	0.10	0.375

Table 15 indicates that the disparity between the fuzzy numbers from the two survey stages was below the threshold (0.2), signifying consensus among the expert group members on all factors. Consequently, the surveying process was concluded.

4.2.3 Determining the Final Factors

After the survey was stopped by the fuzzy Delphi method, we should choose acceptable factors (criteria). If we consider the average defuzzied value as A and call the threshold limit for accepting the index as S, then the desired index is approved under the condition that $A \geq S$.

In this research, I have considered the threshold of 0.5, according to which seven indicators out of the 20 discussed factors are acceptable. These selected factors are specified in Table 16:

Table 16: Selected factors based on Fuzzy Delphi

	F_1	F_2	F_3	F_4	F_5	F_6	F_7
Factors	Purchase Frequency	Customer Reviews Importance	Review Reliability	Review Helpfulness	Personalised Recommendation Frequency	Recommendation Helpfulness	Shopping Satisfaction
Average	0.504	0.594	0.527	0.583	0.515	0.506	0.585
	Worst	**Best**					

4.3 Weighing Factors with the Best-Worst Method

According to the detailed explanations provided, the best-worst (BWM) method is used to weigh the indicators and factors. One notable advantage of this method is its efficiency, requiring fewer comparisons than alternative methods while still producing reliable results.

First step: The factor with the lowest defuzzy average value, referred to as F1 (Purchase Frequency), is identified as the worst factor, while the factor with the highest defuzzy average value, denoted as F2 (Customer Reviews Importance), is considered the best factor.

Table 17 illustrates the relationship between linguistic variables and triangular fuzzy numbers at this stage.

Table 17: Numbers for linguistic terms in the best–worst method

Number	1	2	3	4	5	6	7	8	9
Linguistic Term	Equal	Fairly Quite Better	Quite Better	Extremely Quite Better	Better	Fairly Much Better	Much Better	Extremely Much Better	Fully Better
Fuzzy Number	(1,1,1)	(1,2,3)	(2,3,4)	(3,4,5)	(4,5,6)	(5,6,7)	(6,7,8)	(7,8,9)	(8,9,9)

Next, experts listed in Table 11 have compared the best factor, F2, with other indices, as detailed in Table 18.

Table 18: Pairwise Comparison Between Best Factor and Other Factors

	F_1 Purchase Frequency (Worst)	F_2 Customer Reviews Importance (Best)	F_3 Review Reliability	F_4 Review Helpfulness	F_5 Personalised Recommendation Frequency	F_6 Recommendation Helpfulness	F_7 Shopping Satisfaction
F_2 Customer Reviews Importance (Best)	**Expert 1**						
	(7,8,9)	(1,1,1)	(1,2,3)	(5,6,7)	(4,5,6)	(1,2,3)	(1,2,3)
	Expert 2						
	(7,8,9)	(1,1,1)	(2,3,4)	(3,4,5)	(5,6,7)	(5,6,7)	(1,2,3)
	Expert 3						
	(7,8,9)	(1,1,1)	(7,8,9)	(1,1,1)	(6,7,8)	(4,5,6)	(1,2,3)
	Expert 4						
	(5,6,7)	(1,1,1)	(1,2,3)	(3,4,5)	(1,2,3)	(4,5,6)	(1,1,1)
	Expert 5						
	(8,9,9)	(1,1,1)	(3,4,5)	(6,7,8)	(7,8,9)	(2,3,4)	(3,4,5)
	Expert 6						
	(5,6,7)	(1,1,1)	(2,3,4)	(3,4,5)	(1,2,3)	(1,1,1)	(3,4,5)
	Expert 7						
	(7,8,9)	(1,1,1)	(1,2,3)	(3,4,5)	(1,2,3)	(4,5,6)	(1,1,1)
	Expert 8						
	(5,6,7)	(1,1,1)	(1,2,3)	(1,1,1)	(1,2,3)	(1,1,1)	(2,3,4)
	Expert 9						
	(6,7,8)	(1,1,1)	(2,3,4)	(1,2,3)	(2,3,4)	(3,4,5)	(1,2,3)
	Expert 10						
	(8,9,9)	(1,1,1)	(2,3,4)	(2,3,4)	(6,7,8)	(4,5,6)	(4,5,6)
	Expert 11						
	(6,7,8)	(1,1,1)	(1,1,1)	(2,3,4)	(1,2,3)	(2,3,4)	(2,3,4)
	Expert 12						
	(7,8,9)	(1,1,1)	(3,4,5)	(4,5,6)	(4,5,6)	(3,4,5)	(1,2,3)
	Average of FNumbers						
	(6.5,7.5,8.3)	(1,1,1)	(2.17,3.08,4)	(2.83,3.5,4.3)	(3.25,4.25,5.25)	(2.83,3.67,4.5)	(1.75,2.58,3.41)

Additionally, Table 19 outlines the comparison involving the worst factor, F1, and other indices.

Table 19: Pairwise Comparison Between Worst Factor and Other Factors

	F_1 Purchase Frequency (Worst)																							
F_1 Purchase Frequency (Worst)	Expert 1	(1,1,1)	Expert 2	(1,1,1)	Expert 3	(1,1,1)	Expert 4	(1,1,1)	Expert 5	(1,1,1)	Expert 6	(1,1,1)	Expert 7	(1,1,1)	Expert 8	(1,1,1)	Expert 9	(1,1,1)	Expert 10	(1,1,1)	Expert 11	(1,1,1)	Expert 12	(1,1,1)	Average of FNumbers	(1,1,1)
F_2 Customer Reviews Importance (Best)		(7,8,9)		(7,8,9)		(7,8,9)		(5,6,7)		(8,9,9)		(5,6,7)		(7,8,9)		(5,6,7)		(6,7,8)		(8,9,9)		(6,7,8)		(7,8,9)		(6.5,7.5,8.3)
F_3 Review Reliability		(5,6,7)		(1,2,3)		(2,3,4)		(3,4,5)		(4,5,6)		(2,3,4)		(1,2,3)		(1,2,3)		(2,3,4)		(2,3,4)		(1,2,3)		(2,3,4)		(2.58,3.67,4.91)
F_4 Review Helpfulness		(4,5,6)		(4,5,6)		(5,6,7)		(3,4,5)		(2,3,4)		(1,2,3)		(3,4,5)		(2,3,4)		(3,4,5)		(2,3,4)		(2,3,4)		(4,5,6)		(4.17,5.17,6.17)
F_5 Personalised Recommendation Frequency		(2,3,4)		(1,2,3)		(1,2,3)		(1,2,3)		(2,3,4)		(3,4,5)		(1,2,3)		(1,1,1)		(1,2,3)		(3,4,5)		(1,2,3)		(3,4,5)		(1.92,2.83,3.75)
F_6 Recommendation Helpfulness		(3,4,5)		(2,3,4)		(5,6,7)		(2,3,4)		(4,5,6)		(4,5,6)		(4,5,6)		(2,3,4)		(1,2,3)		(5,6,7)		(2,3,4)		(4,5,6)		(3.33,4.33,5.33)
F_7 Shopping Satisfaction		(7,8,9)		(6,7,8)		(5,6,7)		(5,6,7)		(7,8,9)		(4,5,6)		(7,8,9)		(1,2,3)		(3,4,5)		(7,8,9)		(3,4,5)		(4,5,6)		(5.58,6.58,7.5)

Second step: The next move involved employing the innovative fuzzy best-worst method introduced by Zhang Peng Tian et al. (Tian et al., 2018) to weigh the factors. Applying relation (13) outlined below and relevant equations were formulated.

$$
\begin{aligned}
&Min\ \varepsilon \\
&\left|\frac{(W_B^l \quad W_B^m \quad W_B^u)}{(W_j^l \quad W_j^m \quad W_j^u)} - (W_{Bj}^l \quad W_{Bj}^m \quad W_{Bj}^u)\right| \le \varepsilon \\
&\left|\frac{(W_j^l \quad W_j^m \quad W_j^u)}{(W_W^l \quad W_W^m \quad W_W^u)} - (W_{jW}^l \quad W_{jW}^m \quad W_{jW}^u)\right| \le \varepsilon \qquad (13) \\
&\sum_1^j S(W_j) = 1; \quad S(W_j) = \frac{1}{6}(W_j^l + 4W_j^m + W_j^u), \quad W_j^l \le W_j^m \le W_j^u; \quad W_j^l \ge 0
\end{aligned}
$$

For example, the equations for one of the experts would be as follows (Equation 14).

$$
\begin{aligned}
&Min\ \varepsilon \\
&\left|\frac{(W_6^l \quad W_6^m \quad W_6^u)}{(W_1^l \quad W_1^m \quad W_1^u)} - (7 \quad 8 \quad 9)\right| \le \varepsilon \\
&\left|\frac{(W_6^l \quad W_6^m \quad W_6^u)}{(W_2^l \quad W_2^m \quad W_2^u)} - (1 \quad 2 \quad 3)\right| \le \varepsilon \\
&\left|\frac{(W_6^l \quad W_6^m \quad W_6^u)}{(W_3^l \quad W_3^m \quad W_3^u)} - (5 \quad 6 \quad 7)\right| \le \varepsilon \\
&\left|\frac{(W_6^l \quad W_6^m \quad W_6^u)}{(W_4^l \quad W_4^m \quad W_4^u)} - (4 \quad 5 \quad 6)\right| \le \varepsilon \\
&\left|\frac{(W_6^l \quad W_6^m \quad W_6^u)}{(W_5^l \quad W_5^m \quad W_5^u)} - (1 \quad 2 \quad 3)\right| \le \varepsilon \\
&\left|\frac{(W_6^l \quad W_6^m \quad W_6^u)}{(W_7^l \quad W_7^m \quad W_7^u)} - (1 \quad 2 \quad 3)\right| \le \varepsilon \qquad (14) \\
&\left|\frac{(W_1^l \quad W_1^m \quad W_1^u)}{(W_4^l \quad W_4^m \quad W_4^u)} - (5 \quad 6 \quad 7)\right| \le \varepsilon \\
&\left|\frac{(W_2^l \quad W_2^m \quad W_2^u)}{(W_4^l \quad W_4^m \quad W_4^u)} - (4 \quad 5 \quad 6)\right| \le \varepsilon \\
&\left|\frac{(W_3^l \quad W_3^m \quad W_3^u)}{(W_4^l \quad W_4^m \quad W_4^u)} - (2 \quad 3 \quad 4)\right| \le \varepsilon \\
&\left|\frac{(W_5^l \quad W_5^m \quad W_5^u)}{(W_4^l \quad W_4^m \quad W_4^u)} - (3 \quad 4 \quad 5)\right| \le \varepsilon \\
&\left|\frac{(W_7^l \quad W_7^m \quad W_7^u)}{(W_4^l \quad W_4^m \quad W_4^u)} - (7 \quad 8 \quad 9)\right| \le \varepsilon \\
&\frac{1}{6}(W_1^l + 4W_1^m + W_1^u) + \frac{1}{6}(W_2^l + 4W_2^m + W_2^u) + \frac{1}{6}(W_3^l + 4W_3^m + W_3^u) + \frac{1}{6}(W_4^l + 4W_4^m + W_4^u) + \frac{1}{6}(W_5^l + 4W_5^m + W_5^u) \\
&\quad + \frac{1}{6}(W_6^l + 4W_6^m + W_6^u) + \frac{1}{6}(W_7^l + 4W_7^m + W_7^u) = 1 \\
&W_1^l \le W_1^m \le W_1^u;\ W_1^l \ge 0\ ,\ W_2^l \le W_2^m \le W_2^u;\ W_2^l \ge 0,\quad W_3^l \le W_3^m \le W_3^u;\ W_3^l \ge 0
\end{aligned}
$$

Similar equations need to be formulated for all 12 experts. These equations were then solved using Lingo 20.0 software to determine the value of ε^{*}[7] and the corresponding weights for each expert.

Table 20: Weight of Each Factor for All Experts and Final Average Weight for Each Factor

	F_1 Purchase Frequency (Worst)	F_2 Customer Reviews Importance (Best)	F_3 Review Reliability	F_4 Review Helpfulness	F_5 Personalised Recommendation Frequency	F_6 Recommendation Helpfulness	F_7 Shopping Satisfaction
Expert 1	W_1(0.030,0.032,0.039)	W_2(0.330,0.330,0.341)	W_3(0.107,0.121,0.281)	W_4(0.072,0.089,0.114)	W_5(0.041,0.120,0.190)	W_6(0.092,0.092,0.101)	W_7(0.185,0.185,0.204)
Expert 2	W_1(0.033,0.036,0.036)	W_2(0.304,0.338,0.338)	W_3(0.087,0.088,0.089)	W_4(0.094,0.130,0.150)	W_5(0.040,0.074,0.084)	W_6(0.040,0.058,0.085)	W_7(0.212,0.302,0.302)
Expert 3	W_1(0.028,0.030,0.030)	W_2(0.279,0.304,0.315)	W_3(0.047,0.053,0.059)	W_4(0.219,0.219,0.219)	W_5(0.055,0.064,0.075)	W_6(0.083,0.111,0.160)	W_7(0.219,0.219,0.219)
Expert 4	W_1(0.031,0.036,0.036)	W_2(0.229,0.261,0.261)	W_3(0.153,0.189,0.189)	W_4(0.070,0.097,0.116)	W_5(0.061,0.113,0.117)	W_6(0.053,0.070,0.085)	W_7(0.229,0.261,0.261)
Expert 5	W_1(0.043,0.043,0.043)	W_2(0.327,0.381,0.496)	W_3(0.066,0.112,0.153)	W_4(0.047,0.047,0.068)	W_5(0.043,0.043,0.072)	W_6(0.078,0.110,0.153)	W_7(0.196,0.240,0.310)
Expert 6	W_1(0.037,0.042,0.042)	W_2(0.279,0.321,0.321)	W_3(0.066,0.070,0.086)	W_4(0.079,0.079,0.079)	W_5(0.125,0.125,0.125)	W_6(0.234,0.234,0.234)	W_7(0.097,0.138,0.159)
Expert 7	W_1(0.029,0.032,0.036)	W_2(0.260,0.318,0.318)	W_3(0.082,0.082,0.091)	W_4(0.069,0.069,0.092)	W_5(0.082,0.082,0.091)	W_6(0.077,0.101,0.121)	W_7(0.318,0.318,0.318)
Expert 8	W_1(0.055,0.055,0.055)	W_2(0.219,0.329,0.329)	W_3(0.110,0.110,0.110)	W_4(0.164,0.164,0.164)	W_5(0.110,0.110,0.110)	W_6(0.164,0.164,0.164)	W_7(0.082,0.082,0.110)
Expert 9	W_1(0.057,0.057,0.057)	W_2(0.228,0.342,0.342)	W_3(0.068,0.114,0.171)	W_4(0.114,0.171,0.228)	W_5(0.068,0.086,0.114)	W_6(0.057,0.068,0.114)	W_7(0.114,0.171,0.228)
Expert 10	W_1(0.026,0.026,0.026)	W_2(0.287,0.313,0.313)	W_3(0.131,0.131,0.131)	W_4(0.131,0.131,0.131)	W_5(0.028,0.078,0.093)	W_6(0.104,0.153,0.236)	W_7(0.104,0.156,0.287)
Expert 11	W_1(0.035,0.042,0.072)	W_2(0.337,0.337,0.337)	W_3(0.124,0.124,0.124)	W_4(0.061,0.198,0.199)	W_5(0.100,0.100,0.124)	W_6(0.051,0.054,0.079)	W_7(0.143,0.156,0.165)
Expert 12	W_1(0.028,0.031,0.031)	W_2(0.246,0.301,0.301)	W_3(0.096,0.141,0.141)	W_4(0.073,0.096,0.115)	W_5(0.069,0.096,0.096)	W_6(0.141,0.141,0.218)	W_7(0.171,0.210,0.218)
Average of FNumbers	**W_1(0.036,0.039,0.042)**	**W_2(0.277,0.323,0.334)**	**W_3(0.083,0.111,0.135)**	**W_4(0.099,0.124,0.140)**	**W_5(0.069,0.091,0.108)**	**W_6(0.098,0.113,0.146)**	**W_7(0.173,0.203,0.232)**

Third step: The weights assigned to each factor according to the opinion of each expert, as well as the final average weight for each factor, are presented in Table 20.

The Consistency Ratio was calculated based on the obtained ε^{*} values and the Consistency Index. The values ε^{*}, along with the Consistency Index (CI) and the corresponding Consistency Ratio (CR), are provided in Table 21. The Consistency Ratio (CR) is calculated using equation (4).

Table 21: Consistency Index and Consistency Ratio

	ε^{*}	a_{BW}	CI	CR
Expert 1	2.25834	8	4.47	0.505
Expert 2	1.40185	8	4.47	0.314
Expert 3	2.25834	8	4.47	0.505
Expert 4	1.29844	6	3.00	0.433
Expert 5	2.46887	9	5.23	0.472
Expert 6	1.68338	6	3.00	0.561
Expert 7	1.85995	8	4.47	0.416
Expert 8	1.00000	6	3.00	0.333
Expert 9	1.00000	7	3.73	0.268
Expert 10	3.00000	9	5.23	0.574
Expert 11	1.72508	7	3.73	0.462
Expert 12	1.85995	8	4.47	0.416

[7] $\varepsilon^{*}$is the optimal consistency ratio that ensures the comparisons are as consistent as possible. It is derived by solving the given equation for ξ and using the maximum values to calculate the consistency ratio. This process ensures that the derived weights in the BWM are reliable and consistent, which is crucial for making accurate decisions (Rezaei.J, 2015).

Fourth step: the average weights obtained are fuzzy values. These values are de-fuzzified using equation (5), allowing them to be used in the next subsequent.

In the following, the final weights corresponding to each factor are determined in a defuzzified form and recorded in Table 22.

Table 22: Final Weights Assigned to Each Factor

W_j	W_1	W_2	W_3	W_4	W_5	W_6	W_7
Weight of each Factor	0.039	0.317	0.110	0.123	0.090	0.116	0.203

4.4 THE C-MEANS METHOD FOR DATA CLUSTERING

Clustering algorithms aim to minimise the dissimilarity among samples within a group, seeking high similarity among samples placed in a cluster. The C-Means method, also referred to as the fuzzy C-Means clustering algorithm, is a prominent approach used in data clustering. Unlike hard clustering algorithms, which assign each data point to a single cluster, the C-Means method operates as a soft clustering algorithm, enabling data points to have varying degrees of membership across multiple clusters.

In the C-Means method, the algorithm iteratively adjusts cluster centroids and allocates data points to clusters based on their proximity to these centroids. The degree of membership of each data point to each cluster is determined through a membership function, typically relying on the Euclidean distance between the data point and the cluster centroid. This framework allows for a more flexible and nuanced representation of the underlying data structure, especially beneficial in scenarios where data points may belong to multiple groups concurrently.

In this research, the C-Means clustering algorithm was employed to analyse customer data in e-commerce, focusing on ***gender***, ***age***,and ***purchase frequency.*** This approach facilitated the identification of distinct customer segments based on demographic characteristics and purchasing behaviour. The clustering process revealed detailed patterns within the customer base, enabling the identification of diverse groups. These insights are invaluable for guiding targeted marketing strategies, personalised product recommendations, and customer retention initiatives in e-commerce. Additionally, applying C-means clustering provides important information into online customers' dynamic preferences and behaviours, enhancing decision-making processes. Overall, these segmented groups serve as alternatives for prioritisation in the COPRAS method, based on weighted factors derived from the BWM for the next step.

As previously mentioned, the dataset comprised 602 data records, each associated with multiple variables including purchase date, time of purchase, gender, age, and frequency of purchase.

Following consultations with experts and review of the research literature, the most significant features (gender, age, and frequency of purchase) were selected for final clustering. Utilising MATLAB software and corresponding coding for data modeling, clustering was performed. It should be noted that each factor was numerically modeled in the software to accommodate their diversity. Clustering was conducted for various modes ranging from N=5 to N=8. Based on the results and their interpretation, the optimal mode was determined to be N=5. Subsequently, the final clustering comprised 5 distinct clusters, denoted as A_1, A_2, A_3, A_4, and A_5, each assigned a unique color. The following pie chart (Figure 10) illustrates the clusters. The distribution of data within each cluster is as follows:

- Cluster A1: 29 records (5%)
- Cluster A2: 92 records (15%)
- Cluster A3: 134 records (22%)
- Cluster A4: 146 records (24%)
- Cluster A5: 201 records (37%)

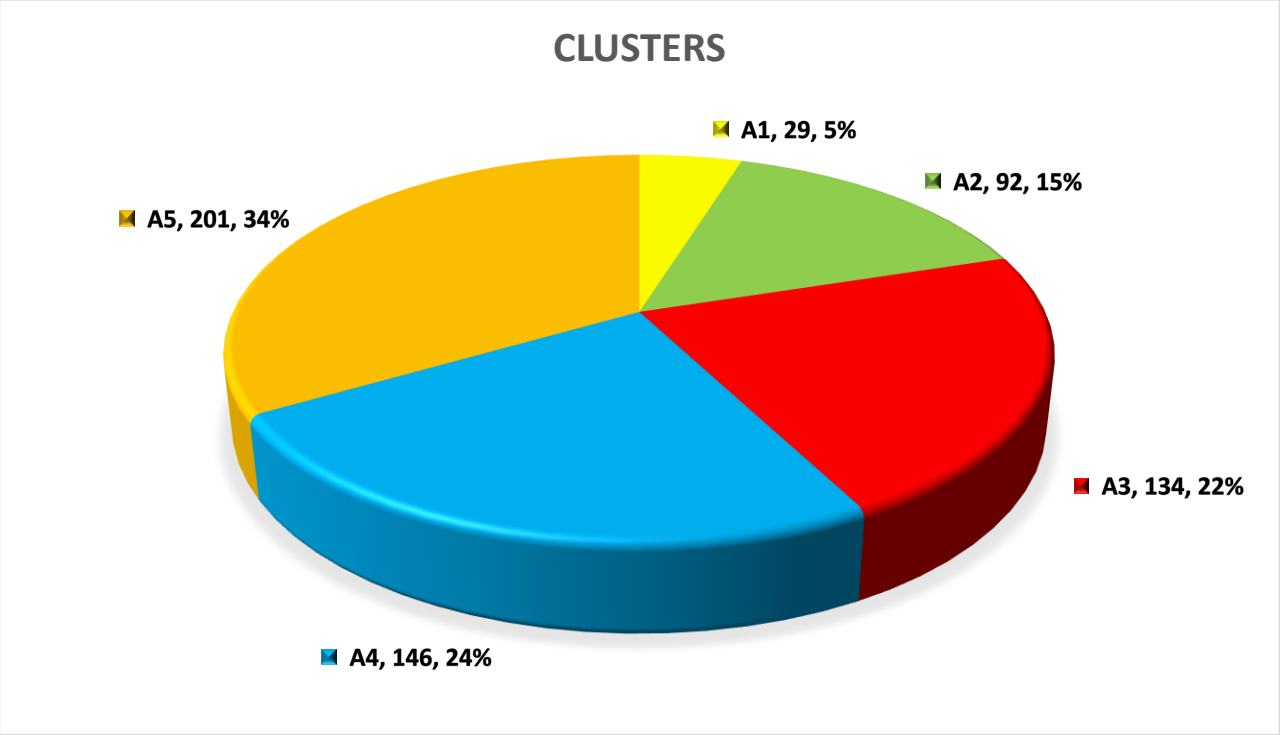

Figure 26: Pie Chart Representation of Final Clustering

In the C-Means method, each member is not strictly assigned to a specific cluster, as membership degrees are distributed across multiple clusters. However, for practical purposes, I opted to consider the highest membership degree for each record, effectively determining its final cluster assignment. This approach facilitates subsequent analysis, particularly when transitioning to the COPRAS method. For instance, consider the first record (customer) out of 602, where the membership degrees for the clusters were as follows:

Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
0.00222205	0.00530068	0.32756007	0.01910327	0.64581394

Given that the highest membership degree corresponds to Cluster 5, denoted as A5, I classify the data under this cluster. This procedure is repeated for all 602 records, finalising the clustering.

Furthermore, in the subsequent discussion, I thoroughly analysed the characteristics of the clusters based on features such as Gender, Age, and Frequency of Purchase, providing insights into the underlying patterns and behaviours within each cluster.

4.4.1 Gender Dynamics within Clusters

Understanding the gender distribution within each cluster sheds light on the diversity of the customer base and helps identify potential trends or preferences. In the following bar chart (Figure 12) depicting clusters A1 to A5, each cluster is showcased separately based on the types of genders represented. Cluster A1 stands out as the smallest cluster, characterised by a nearly equal distribution of females and males, with a minority reporting others or prefer not to say. Conversely, Cluster A5 emerges as the largest cluster, predominantly occupied by females, highlighting the

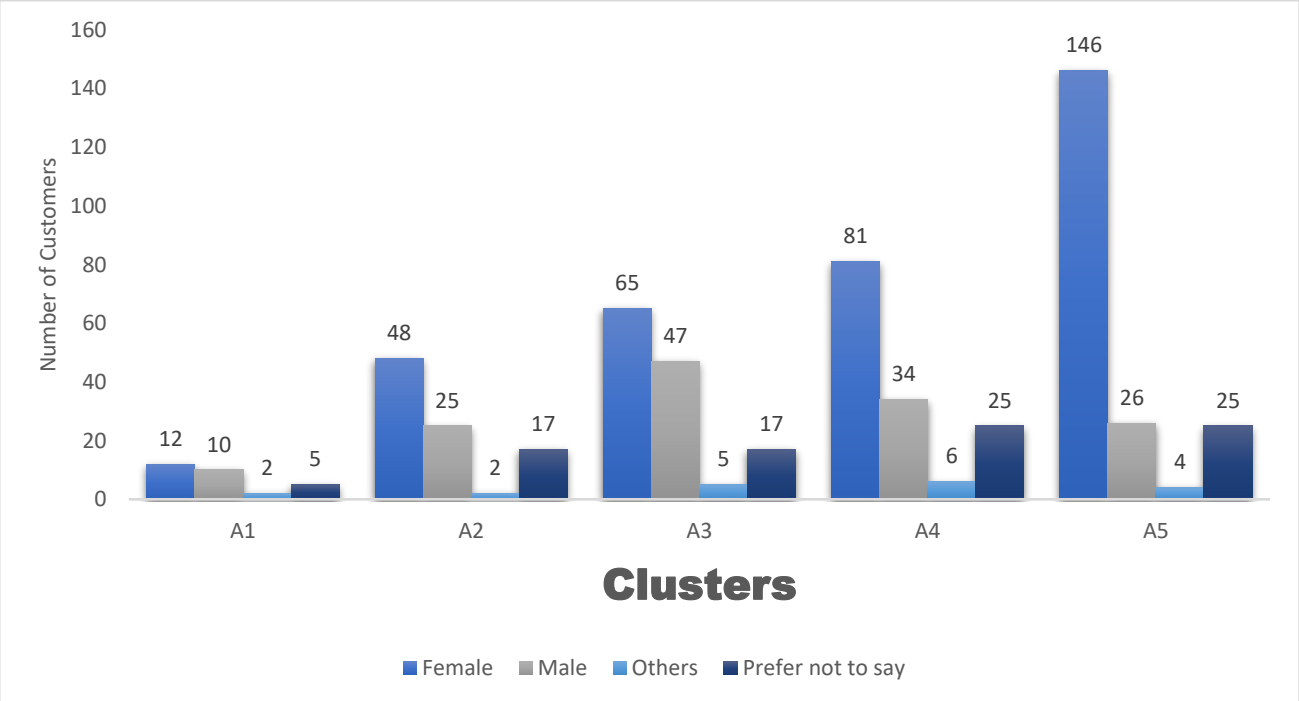

Figure 27: Bar Chart Illustrating Gender Dynamics within Clusters

significance of gender specificity within a cluster. Within Clusters A2, A3, and A4, the dominance of females over males is notably significant.

Examining Cluster A1, this cluster features a relatively balanced gender distribution, with a slight inclination towards females. In Cluster A2, females are notably more prevalent compared to males. The substantial proportion of 'Prefer not to say' responses suggests potential privacy concerns or variability in customer gender identification.

Cluster A3 demonstrates a slightly higher representation of females compared to males. Females dominate Cluster A4, with a significantly higher number compared to males. In Cluster A5, there is a significantly higher number of females compared to males, and the presence of 'Other' and 'Prefer not to say' categories suggests diversity or privacy concerns within this cluster.

Overall, females appear to be the predominant gender across all clusters, with varying degrees of representation. The presence of 'Other' and 'Prefer not to say' categories underscores the importance of inclusivity and privacy considerations in customer segmentation and engagement strategies.

The findings on gender differences in online sales can be discussed in light of substantial literature indicating that men and women exhibit distinct behaviours in online shopping environments. Men are more likely to focus on the utilitarian aspects of online shopping, such as efficiency and convenience. In contrast, women tend to value the hedonic aspects, including the enjoyment of the shopping experience (Garbarino & Strahilevitz, 2004).

This is supported by Dittmar et al. (Dittmar et al., 2004), who found that women are more likely to engage in browsing and window-shopping online, often viewing it as a recreational activity. These differences are crucial for understanding how online sales strategies should be tailored to effectively reach and engage both genders. By identifying and accommodating gender preferences and considerations, businesses can better meet the needs of their diverse customer base.

4.4.2 Frequency of Purchase Analysis within Clusters

Analysing the frequency of purchases within clusters helps explain the shopping behaviours of different customer segments in the e-commerce dataset.

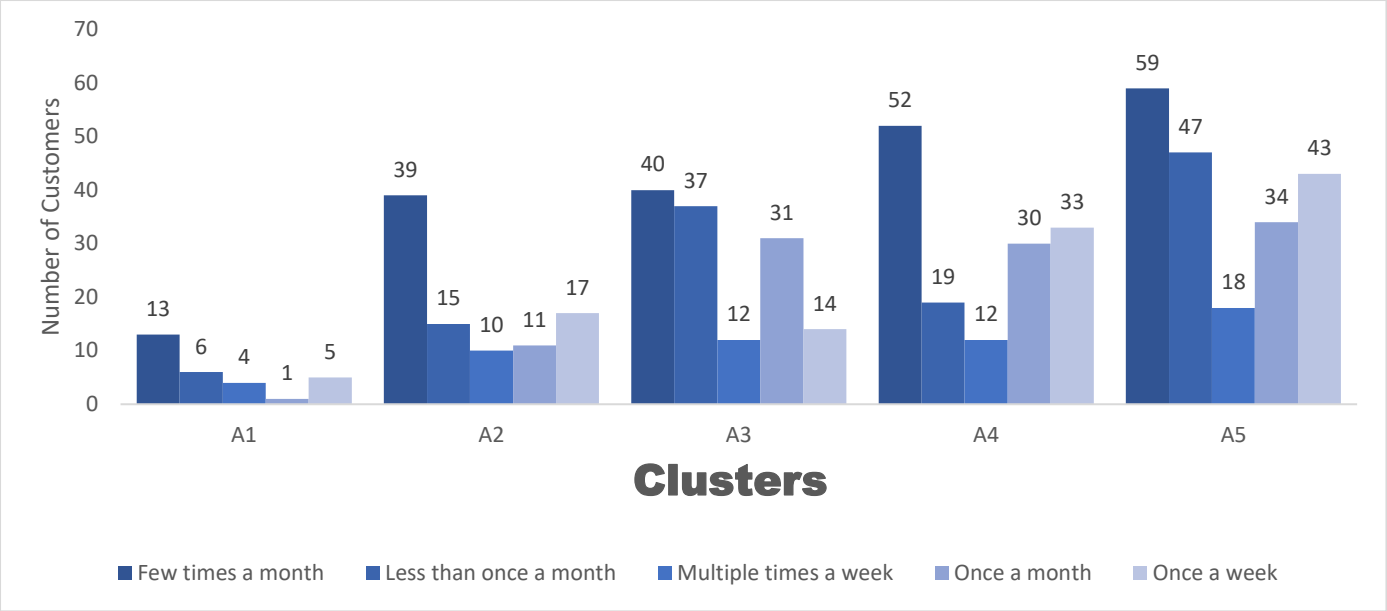

Figure 28: Bar Chart Analysis, Purchase Frequency within Clusters

This provides a detailed examination of the purchasing frequency across clusters (Figure 13).

- ***CLUSTER A1 (29 INDIVIDUALS)***
  - ❖ The majority of customers in Cluster A1 make purchases "Few times a month" or "Less than once a month", with a smaller proportion making purchases "Once a week."
  - ❖ This cluster exhibits a relatively lower frequency of purchases compared to other clusters, indicating potentially less frequent engagement with the e-commerce platform.
- ***CLUSTER A2 (92 INDIVIDUALS)***
  - ❖ Customers in Cluster A2 demonstrate a more evenly distributed frequency of purchases across all categories, with a notable proportion making purchases "Multiple times a week" or "Once a week."
  - ❖ This cluster represents a diverse range of purchasing behaviours, with a significant segment of customers engaging with the platform on a regular basis.
- ***CLUSTER A3 (134 INDIVIDUALS)***
  - ❖ Cluster A3 exhibits a similar pattern to Cluster A2, with a substantial proportion of customers making purchases "Multiple times a week" or "Once a week."
  - ❖ However, this cluster also includes a sizable segment of customers who make purchases "Few times a month" or "Less than once a month", indicating varied engagement levels.
- ***CLUSTER A4 (146 INDIVIDUALS)***
  - ❖ Customers in Cluster A4 display a relatively balanced distribution of purchase frequency across all categories, with no single category dominating.
  - ❖ This cluster represents a diverse mix of purchasing behaviours, with customers engaging with the platform at various frequencies.

- ***CLUSTER A5 (201 INDIVIDUALS)***
  - Cluster A5 stands out for its high frequency of purchases, particularly in the categories of "Few times a month" and "Multiple times a week."
  - This cluster represents a highly engaged segment of customers, likely exhibiting strong loyalty and frequent interactions with the e-commerce platform.

Clusters with higher frequencies of purchases, such as A5, may represent elegant segments for targeted marketing efforts and retention strategies. Conversely, clusters with lower frequencies of purchases, such as A1, may require appropriate approaches to increase engagement and encourage repeat purchases.

Gender differences significantly influence critical success factors in online shopping, such as perceived risk, trust, and others. Research by Bhatnagar et al. (Bhatnagar et al., 2000) indicates that women generally perceive higher levels of risk in online transactions compared to men. This heightened perception of risk among women can affect their trust in online vendors and their overall willingness to make online purchases. Gefen and Straub (2003) further elaborate that women are more likely to trust online vendors who provide detailed product information and have robust customer support (Gefen & Straub, 2003). These insights suggest that online retailers need to address these gender-specific concerns to build trust and reduce perceived risk, particularly among female consumers.

Furthermore, men and women differ in their attitudes towards new technology, with men generally showing higher levels of acceptance and usage of new online shopping technologies (Venkatesh & Morris, 2000). This difference can be attributed to varying levels of self-efficacy and anxiety related to technology use between genders.

Investigating the purchasing frequency across clusters enables e-commerce businesses to optimise marketing strategies, consider product offerings, and enhance customer experiences to meet the diverse needs and preferences of their customer base. By leveraging these ideas, businesses can drive growth, foster customer loyalty, and sustain profitability in the competitive e-commerce landscape.

4.4.3 Age Distribution and Trends across Clusters

This part of the clustering analysis discusses the age distribution across clusters derived from C-Means clustering. The data represents the cumulative number of customers within specific age ranges across five clusters denoted as A1 to A5.

By examining the age distribution within each cluster, I aim to gain insights into the demographic composition and potentially identify patterns or trends that could inform business strategies or research decisions.

Each cluster corresponds to a unique group of customers, with the bars on the chart indicating the total number of customers falling within specific age brackets:

- Cluster A1: Ages 52 to 67, 29 individuals
- Cluster A2: Ages 40 to 50, 92 individuals
- Cluster A3: Ages 24 to 29, 134 individuals
- Cluster A4: Ages 18 to 39, 146 individuals
- Cluster A5: Ages 12 to 28, 201 individuals.

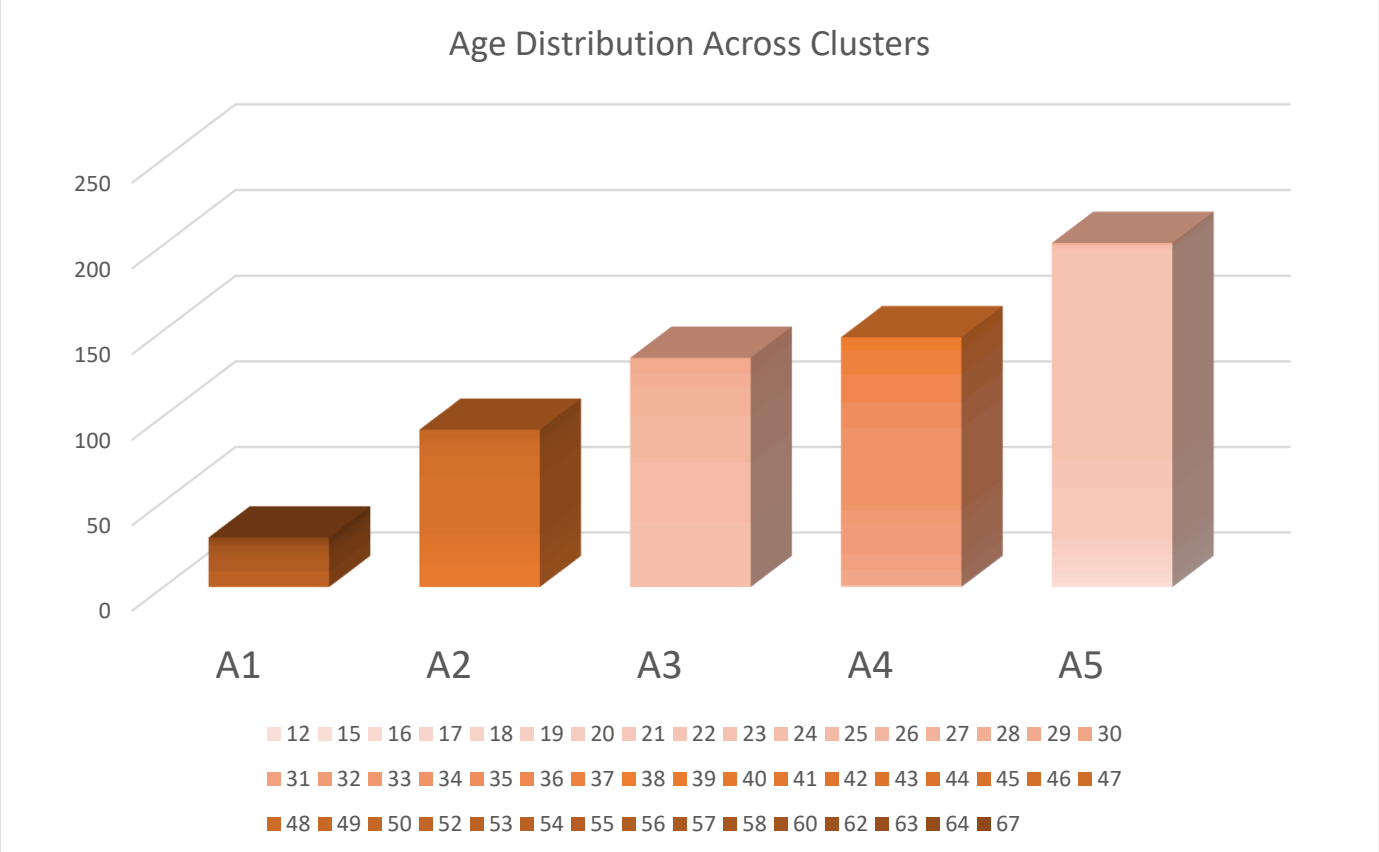

Figure 31: Age Distribution Across Clusters

Upon analysing the age distribution across clusters, several notable trends emerge. Cluster A5 has the largest cumulative number of customers (201 individuals) and represents a younger demographic, with an age range of 12 to 28 years. This suggests a higher concentration of younger customers within this cluster, potentially indicating a segment that is more receptive to products targeted at younger demographics.

On the other hand, Cluster A1 has the smallest cumulative number of customers (29 individuals) and represents an older demographic, with the age range spanning from 52 to 67 years. While this cluster has a smaller customer base, it may still present opportunities for targeted marketing product offerings tailored to older demographics. Clusters A2, A3, and A4 represent varying age distributions, with clusters A2 and A3 predominantly comprising customers in their 20s to 50s, while cluster A4 shows a broader age range from 18 to 39 years.

The analysis of age distribution and trends across clusters reveals significant patterns that align with the existing literature on consumer behaviour across different age groups (Nunan & Di Domenico, 2019). Research indicates that younger consumers, particularly those in the age group of 18-34, are more likely to engage in online shopping due to their higher familiarity and comfort with digital technologies (Smith, 2019). This demographic shows a preference for mobile-friendly shopping experiences and values social media integration in their purchasing decisions. In contrast, older consumers, particularly those aged 55 and above, exhibit more cautious online shopping behaviours, often requiring higher levels of trust and security assurances (Lian & Yen, 2014). Understanding these age-specific trends is essential for tailoring marketing strategies and user interfaces to cater to each age group's distinct preferences and concerns.

The analysis of age distribution across clusters serves as a valuable tool for figuring out the diverse demographic composition of customer segments. By leveraging this understanding to consider strategies and allocate resources effectively, businesses can enhance profitability and maintain a competitive edge in the e-commerce landscape. In the next step, all the characteristics of the clusters is summarised in a table that applies to prioritising them by the COPRAS method.

4.4.4 The Characteristics of Clusters

The preceding sections have provided various visions about the dynamics of customer data records within our e-commerce dataset. From examining gender dynamics to scrutinising purchase frequency and investigating age distribution trends across clusters, I have acquired a thorough understanding of the diverse demographics and behaviours that define our customer base.

Moving forward, I synthesised the characteristics of each cluster, drawing from my analyses of gender dynamics, purchase frequency, and age distribution trends. This comprehensive overview served as a practical resource for prioritisation using the COPRAS method, enabling informed decision-making in the development of sustainable profitability strategies. The characteristics of these clusters are detailed in Table 23.

Table 23: The Characteristics of Clusters

	Cluster Characteristics				
	Number of Purchasers	Gender	Purchase Frequency	Age Range	Cluster Description
A_1	29	Equal distribution of females and males	***MAJORITY:*** "Few times a month" or "Less than once a month"	52 to 67	• The smallest cluster, characterized by a nearly equal distribution of females and males, with a minority reporting "other gender" type or "preferring not to disclose."
A_2	92	Predominantly females	Balanced distribution across categories	40 to 50	• A more evenly distributed frequency of purchases across all categories, with a notable proportion making purchases "Multiple times a week" or "Once a week."
A_3	134	Slightly higher representation of females	Balanced distribution across categories	24 to 29	• A substantial proportion of customers making purchases "Multiple times a week" or "Once a week." However, this cluster also includes a sizable segment of customers who make purchases "Few times a month" or "Less than once a month," indicating varied engagement levels.
A_4	146	Predominantly females	Balanced distribution across categories	18 to 39	• A relatively balanced distribution of purchase frequency across all categories, with single category dominating of "Few times a month."
A_5	201	Females dominate	***MAJORITY:*** "Few times a month" or "Multiple times a week"	12 to 28	• The cluster stands out for its high frequency of purchases, particularly in the categories of "Few times a month" and "Multiple times a week."

4.5 Prioritising Clusters by COPRAS Method

After identifying clusters through the C-Means method and establishing factors using the fuzzy Delphi method and weighing the factors by FBWM, prioritising alternatives requires forming a decision matrix. The fuzzy COPRAS method was chosen for this task due to its ease of use, comprehensive consideration of criteria, and differentiation between negative and positive criteria. The subsequent steps detail the methodology.

First step: Firstly, experts assessed each cluster relative to each decision factor (criterion). The relationship between linguistic variables and triangular fuzzy numbers is outlined in Table 24.

Table 24: Linguistic Variable and Related Fuzzy Number

Linguistic Variable	Fuzzy Number
Very poor / Very light	(0, 1, 2)
Poor / Light	(1, 2, 3)
Mostly poor / Mostly light	(2, 3.5, 5)
Fair	(4, 5, 6)
Mostly good / Mostly difficult	(5, 6.5, 8)
Good / Difficult	(7, 8, 9)
Very good / Very difficult	(8, 9, 10)

The evaluation results, represented in the form of triangular fuzzy numbers by experts, are provided across Tables 25 to 27.

Table 25: Evaluating Options Based on Decision-Making Factors (First Expert)

	F1	F2	F3	F4	F5	F6	F7
	Purchase Frequency	Customer Reviews Importance	Review Reliability	Review Helpfulness	Personalised Recommendation Frequency	Recommendation Helpfulness	Shopping Satisfaction
A1	(2, 3.5, 5)	(7, 8, 9)	(7, 8, 9)	(4, 5, 6)	(1, 2, 3)	(5, 6.5, 8)	(7, 8, 9)
A2	(7, 8, 9)	(5, 6.5, 8)	(1, 2, 3)	(4, 5, 6)	(8, 9, 10)	(5, 6.5, 8)	(5, 6.5, 8)
A3	(5, 6.5, 8)	(5, 6.5, 8)	(2, 3.5, 5)	(5, 6.5, 8)	(7, 8, 9)	(7, 8, 9)	(4, 5, 6)
A4	(4, 5, 6)	(7, 8, 9)	(4, 5, 6)	(5, 6.5, 8)	(7, 8, 9)	(5, 6.5, 8)	(7, 8, 9)
A5	(2, 3.5, 5)	(4, 5, 6)	(4, 5, 6)	(5, 6.5, 8)	(8, 9, 10)	(7, 8, 9)	(7, 8, 9)

Table 26: Evaluating Options Based on Decision-Making Factors (Second Expert)

	F1	F2	F3	F4	F5	F6	F7
	Purchase Frequency	Customer Reviews Importance	Review Reliability	Review Helpfulness	Personalised Recommendation Frequency	Recommendation Helpfulness	Shopping Satisfaction
A1	(4, 5, 6)	(5, 6.5, 8)	(1, 2, 3)	(7, 8, 9)	(0, 1, 2)	(8, 9, 10)	(1, 2, 3)
A2	(5, 6.5, 8)	(7, 8, 9)	(1, 2, 3)	(5, 6.5, 8)	(8, 9, 10)	(5, 6.5, 8)	(4, 5, 6)
A3	(8, 9, 10)	(5, 6.5, 8)	(2, 3.5, 5)	(1, 2, 3)	(5, 6.5, 8)	(7, 8, 9)	(1, 2, 3)
A4	(7, 8, 9)	(4, 5, 6)	(5, 6.5, 8)	(8, 9, 10)	(1, 2, 3)	(5, 6.5, 8)	(5, 6.5, 8)
A5	(4, 5, 6)	(7, 8, 9)	(5, 6.5, 8)	(7, 8, 9)	(5, 6.5, 8)	(5, 6.5, 8)	(8, 9, 10)

Table 27: Evaluating Options Based on Decision-Making Factors (Third Expert)

	F1	F2	F3	F4	F5	F6	F7
	Purchase Frequency	Customer Reviews Importance	Review Reliability	Review Helpfulness	Personalised Recommendation Frequency	Recommendation Helpfulness	Shopping Satisfaction
A1	(2, 3.5, 5)	(4, 5, 6)	(2, 3.5, 5)	(5, 6.5, 8)	(2, 3.5, 5)	(7, 8, 9)	(4, 5, 6)
A2	(4, 5, 6)	(4, 5, 6)	(2, 3.5, 5)	(7, 8, 9)	(5, 6.5, 8)	(5, 6.5, 8)	(2, 3.5, 5)
A3	(7, 8, 9)	(7, 8, 9)	(4, 5, 6)	(2, 3.5, 5)	(4, 5, 6)	(5, 6.5, 8)	(2, 3.5, 5)
A4	(5, 6.5, 8)	(7, 8, 9)	(7, 8, 9)	(7, 8, 9)	(4, 5, 6)	(4, 5, 6)	(8, 9, 10)
A5	(1, 2, 3)	(5, 6.5, 8)	(7, 8, 9)	(8, 9, 10)	(7, 8, 9)	(5, 6.5, 8)	(7, 8, 9)

Second step: A decision-making matrix was constructed using triangular fuzzy numbers to prioritise alternatives with the fuzzy COPRAS method.

The average opinions of experts were applied in this matrix. Additionally, the weights obtained from the fuzzy best-worst method for each factor were incorporated into the calculations. Table 28 displays a decision matrix containing fuzzy numbers, with the symbols (+) denoting positive measures and (-) denoting negative ones.

Table 28: The Average Opinions of Experts

	F1	F2	F3	F4	F5	F6	F7
Factor Type (+/-)	+	+	+	+	+	+	+
A1	(2.66, 4, 5.33)	(5.33, 6.5, 7.66)	(3.33, 4.5, 5.66)	(5.33, 6.5, 7.66)	(1, 2.16, 3.33)	(6.66, 7.83, 9)	(4, 5, 6)
A2	(5.33, 6.5, 7.66)	(5.66, 7, 8.33)	(1.33, 2.5, 3.66)	(5.33, 6.5, 7.66)	(7, 8.16, 9.33)	(5, 6.5, 8)	(3.66, 5, 6.33)
A3	(6.66, 7.83, 9)	(5, 6.5, 8)	(2.66,4, 5.33)	(2.66, 4, 5.33)	(5.33, 6.5, 7.66)	(6.33, 7.5, 8.66)	(2.33, 3.5, 4.66)
A4	(5.33, 6.5, 7.66)	(6, 7, 8)	(5.33, 6.5, 7.66)	(6.66, 7.83, 9)	(4, 5, 6)	(4.66, 6, 7.33)	(6.66, 7.83, 9)
A5	(2.33, 3.5, 4.66)	(5.33, 6.5, 7.66)	(5.33, 6.5, 7.66)	(6.66, 7.83, 9)	(6.66, 7.83, 9)	(5.66, 7, 8.33)	(7.33, 8.33, 9.33)
Sum	(22.31, 28.33, 34.31)	(27.32, 33.5, 39.65)	(17.98, 24, 29.97)	(26.64, 32.66, 38.65)	(23.99, 29.65, 35.32)	(28.31, 34.83, 41.32)	(23.98, 29.66, 35.32)
Weight of Factors	0.039	0.317	0.110	0.123	0.090	0.116	0.203

Third step: The decision matrix has been converted into a normal weight matrix with triangular fuzzy numbers using equation (6). The resulting normal weight matrix is given in Table 29.

Table 29: The Fuzzy-Weighted Normalised Matrix

	F1	F2	F3	F4	F5	F6	F7
Factor Type (+/-)	+	+	+	+	+	+	+
A1	(0.003, 0.006, 0.009)	(0.043, 0.062, 0.089)	(0.012, 0.021, 0.035)	(0.017, 0.024, 0.035)	(0.003, 0.007, 0.012)	(0.019, 0.026, 0.037)	(0.023, 0.034, 0.051)
A2	(0.006, 0.009, 0.013)	(0.045, 0.066, 0.097)	(0.005, 0.011, 0.022)	(0.017, 0.024, 0.035)	(0.018, 0.025, 0.035)	(0.014, 0.022, 0.033)	(0.021, 0.034, 0.054)
A3	(0.008, 0.011, 0.016)	(0.040, 0.062, 0.093)	(0.010,0.018, 0.033)	(0.008, 0.015, 0.025)	(0.014, 0.020, 0.029)	(0.018, 0.025, 0.035)	(0.013, 0.024, 0.039)
A4	(0.006, 0.009,0.013)	(0.048, 0.066, 0.093)	(0.020, 0.030, 0.047)	(0.021, 0.029, 0.042)	(0.010, 0.015, 0.023)	(0.013, 0.020, 0.030)	(0.038, 0.054, 0.076)
A5	(0.002, 0.005, 0.008)	(0.043, 0.062, 0.089)	(0.020, 0.030, 0.047)	(0.021, 0.029, 0.042)	(0.017, 0.024, 0.034)	(0.016, 0.023, 0.034)	(0.042, 0.057, 0.079)

Fourth step: Then, according to equations (7), the values of $\widetilde{S}_i^-$ and $\widetilde{S}_i^+$ are determined for all options. These values are specified in Table 30. It should be noted that in this research, all selected factors have the positive effect on the clusters.

Table 30: The Table of $\widetilde{S}_i^-$ and $\widetilde{S}_i^+$

	$\widetilde{S}_i^+$	$\widetilde{S}_i^-$
A_1	(0.120, 0.180, 0.268)	(0.000, 0.000, 0.000)
A_2	(0.126, 0.191, 0.289)	(0.000, 0.000, 0.000)
A_3	(0.111, 0.175, 0.270)	(0.000, 0.000, 0.000)
A_4	(0.156, 0.223,0.324)	(0.000, 0.000, 0.000)
A_5	(0.161, 0.230, 0.333)	(0.000, 0.000, 0.000)

Fifth step: The fuzzy relative priority of alternatives (clusters) were determined using relation (8), denoted as $\tilde{Q}_i$. Subsequently, each option was defuzzified using equation (9) to obtain Q_i, representing its relative priority as a numerical value. Finally, the absolute priority of alternatives (clusters), N_i, were calculated using equation (10), with Q_{max}representing the highest value of Q_i.

These values are summarised in Table 31, where N_i ranges from 0 to 100%, indicating the worst and best degree of utility for the clusters.

Table 31: The Final Calculation Table

	$\widetilde{Q}_i$	Q_i	N_i	**Ranking**
A_1	(0.120, 0.180, 0.268)	0.189	77.60	Fourth
A_2	(0.126, 0.191, 0.289)	0.202	82.79	Third
A_3	(0.111, 0.175, 0.270)	0.185	75.96	Fifth
A_4	(0.156, 0.223,0.324)	0.238	97.40	Second
A_5	(0.161, 0.230, 0.333)	0.244	100.00	First

According to Table 30, the priority of each cluster, based on the critical success factors (CSFs) related to online shopping customers in e-commerce, is as follows:

$$A_5 > A_4 > A_2 > A_1 > A_3$$

5 RESULTS & DISCUSSION

This chapter serves as the final section of the present research, focusing on the examination of the results and findings. While the previous chapter provided a general overview of the research findings, a more detailed analysis of each dimension of the research results is necessary. Through thorough examination, one must strive to identify the questions raised in the research and subsequently propose recommendations based on the obtained results in light of the literature.

The ultimate aim of any research is to achieve findings that contribute to an increase in knowledge within the researched field and foster progress in the production or application of science in organisations, companies, and scientific research centres. Following a thorough examination of the results and providing relevant answers to the posed questions, executable and research-oriented recommendations are suggested.

5.1 RESULTS

To explain the findings and results of the research, efforts are made to address the questions raised throughout the study. This research comprises one main question and five related questions, the responses to which will be presented subsequently. The main question is like the cornerstone of the study, guiding the overall investigation, while the related questions provide additional depth and context, allowing for a comprehensive exploration of the research topic. Through systematically addressing these inquiries, a precise understanding of the research outcomes and their implications can be attained. Furthermore, by structuring the inquiry around these questions, the research aims to facilitate a focused analysis, ensuring that each aspect of the study receives appropriate consideration. This approach enhances the clarity and coherence of the findings and enables a more insightful interpretation of the results within the broader context of the research objectives.

Continuing from the preceding chapter's data analysis, I now identify the responses to the research questions. To address the primary inquiry of this thesis, I provide detailed answers to all aspects in the Discussion section with greater precision. In this step, I rigorosely examine each finding, considering its significance, implications, and relevance to the primary research question.

Additionally, any unexpected or conflicting findings is carefully explored to provide insights and potential explanations. By dedicating careful attention to detail in the Discussion section, I aim to ensure that the responses to the primary question are well-supported, grounded in the data, and contribute meaningfully to the research. Furthermore, I integrate relevant literature and theoretical frameworks to provide context and enrich the interpretation of the findings.

5.2 Responses to Related Questions

The following endeavours will furnish precise and targeted responses to inquiries linked with the core subject matter and overarching objectives of the research.

- ***What are the antecedents of customer purchase decisions?***

The identification of antecedents influencing customer purchase decisions is grounded in a thorough examination of existing literature and empirical studies within the field of consumer behaviour. A comprehensive literature review provides valuable perceptions of the various factors that have been identified and studied by researchers.

Through the review of the literature, I investigated key antecedents that have been consistently reported across studies, as well as emerging trends or divergent findings. Moreover, it allows for the synthesis of theoretical frameworks and conceptual models that help explain the complex interplay of factors shaping consumer purchase decisions.

Furthermore, applying a robust database ensures that the research is based on empirical evidence and contributes to advancing knowledge within the field. This evidence-based approach strengthens the credibility and validity of the research findings, enhancing their relevance and applicability to both academic and practical contexts.

Considering the comprehensive and extensive database comprising 602 distinct records with unique data, 23 different factors were selected for further investigation over a specified period.

To establish and validate these criteria, initial sessions were conducted with experts, professionals, and university professors to explore relevant topics and their applicability.

Subsequently, 20 factors received initial validation and were chosen for examination using the fuzzy Delphi method. Due to the limited number of individuals qualified to provide input, 15 experts, including university lecturers and online product sales practitioners, were carefully selected.

Using the fuzzy Delphi method, facilitated by these 15 experts, two rounds of surveys were conducted, resulting in convergent outcomes and the selection of 7 factors for further consideration. These factors included:

- Purchase Frequency
- Customer Reviews Importance
- Review Reliability
- Review Helpfulness
- Personalised Recommendation Frequency
- Recommendation Helpfulness

- Shopping Satisfaction

Among these factors, "Customer Reviews Importance" were identified as having the most significant impact, while "Purchase Frequency" was deemed to have the least impact.

- ***What is the weight of each antecedent for the online customer decisions?***

The weight of each antecedent for online customer decisions refers to the relative importance or influence each factor holds in influencing customer behaviour and decision-making processes in the online domain.

To determine the weight of each antecedent, researchers typically employ statistical techniques such as regression analysis, factor analysis, or machine learning algorithms. These methods help quantify the contribution of each antecedent to customer decisions by examining the strength and direction of their relationships with customer behaviour outcomes.

Additionally, qualitative research methods such as surveys, interviews, and focus groups may be recruited to gather customers' comments regarding the importance of different factors in their decision-making process.

In this research, among numerous options for weighing the factors, the fuzzy best-worst method was employed to accomplish the task. Specifically, the best-worst method, as introduced by Zhang Peng Tian et al. (Tian et al., 2018), was applied to assess and assign weights to the indicators and factors. Equation (13) from the aforementioned methodology was applied, and the weight of each factor was determined through the modelling of equations and conditions using Lingo 20.0 software. The resulting weights for each index are presented in Table 21.

The hierarchy of importance for these factors, based on their respective weights, is as follows:

- Customer Reviews Importance
- Shopping Satisfaction
- Review Helpfulness
- Recommendation Helpfulness
- Review Reliability
- Personalised Recommendation Frequency
- Purchase Frequency

These results were then recruited in the subsequent step, which involved ranking the clusters using FCOPRAS.

- ***What is the optimal grouping of customers with respect to their different recordings and attributes?***

The goal of optimal grouping is to maximise business outcomes. Through rigorous analysis and application of clustering algorithms, researchers can uncover brilliant outcomes that inform strategic decision-making processes and drive business growth.

By employing clustering methods, researchers can identify distinct customer groups exhibiting similar characteristics or behaviours. This facilitates the segmentation of customers into meaningful groups, allowing businesses to consider their strategies and offerings to better meet the needs and preferences of each cluster. Clustering methods also provide information into the underlying structure of customer data, revealing patterns and relationships that may not be immediately apparent through traditional analytical approaches.

The optimal grouping of customers, regarding their various records and attributes, is achieved through the application of clustering techniques, notably C-Means clustering. Clustering methods like C-Means enable the organisation of customers into clusters or segments based on similarities in their recorded data and attributes. These methods utilise algorithms to iteratively assign customers to clusters, aiming to minimise within-cluster variations and maximise between-cluster differences.

The initial dataset comprised 602 distinct records, each representing an online customer and including various informational components. Each of these records consisted of the following corresponding factors: purchase date, purchase time, gender, age, and purchase frequency.

To finalise the clustering process among these factors, those deemed to play a significant role in clustering and hold greater importance than others were identified as follows: gender, age, and purchase frequency.

To model these factors for clustering, they needed to be converted into numerical quantities. Subsequently, with all factors quantified, MATLAB software was employed. Clustering of the final data was performed after modelling the quantitative data. The modelling of factors was conducted for different clustering scenarios, ranging from N = 5 to N = 8. Based on the obtained results, the optimal scenario was determined to be N = 5. Hence, the final clustering comprised 5 distinct clusters, each characterised by unique features, denoted as A_1, A_2, A_3, A_4, and A_5, respectively. Colours, namely yellow, green, red, blue, and orange, were assigned to each cluster accordingly. The resulting final outcome is presented in Table 22.

- ***What is the best approach to rank groups of customers?***

Determining the most suitable method for ranking customer groups rooted in several factors, such as the precise goals of the analysis, the characteristics of the available customer data, and the resources and capabilities of the organisation. Employing a combination of approaches or methodologies can offer a holistic view of customer behaviour and preferences. Ultimately, this integrated approach aids strategic decision-making and resource allocation, leading to enhanced customer value and satisfaction.

In this research, upon identifying the clusters and determining the corresponding factors along with their respective weights, the decision matrix was completed. In the final stage of the proposed framework, the FCOPRAS (Fuzzy COmplex PRoportional ASsessment) method is applied to rank the superior cluster.

Initially, a fuzzy questionnaire related to the indicators was completed comprehensively by a three-member expert group. This fuzzy questionnaire evaluates each cluster related to the desired factors. In the second step, the decision matrix was constructed using triangular fuzzy numbers (TFNs), considering the experts' opinions averages. It is worth mentioning that in the FCOPRAS method, the weight of each criterion must also be considered in calculations. In this matrix, positive and negative criteria are distinguished.

In the third step, the decision matrix, with its positive and negative factors segregated, is transformed into a normalised weight matrix (weight matrix) applying triangular fuzzy numbers, according to Equation (6).

In the fourth step, using Equation (7), the values $\widetilde{\boldsymbol{S}}_{\boldsymbol{i}}^{-}$ and $\widetilde{\boldsymbol{S}}_{\boldsymbol{i}}^{+}$ are determined for all options. In the fifth and final step, to determine the relative importance of each option (cluster), Equation (8) is employed, where the fuzzy relative priority of each option is indicated by $\tilde{Q}_i$. Subsequently, for the defuzzification of each option, Equation (9) is used, resulting in Q_i representing the absolute priority of each option as a single number. Ultimately, the absolute priority of alternatives or N_i is calculated by Equation (10). In Equation (10), Q_{max} denotes the highest value of Q_i. The higher value of N_i is the greater desirability of the option. Finally, the prioritization of the examined clusters is as follows:

$$A5 > A4 > A2 > A1 > A3$$

- ***Based on customer evaluations, what recommendations can be proposed for improving profitability?***

Addressing this question is a significant aspect of the project's objectives, which is rigorously explored in the next part (Discussion). However, based on the results, the recommendations, without considering the clusters, can be summarised as follows:

- ***ENHANCE CUSTOMER REVIEWS IMPORTANCE:*** Given the significant impact of customer reviews on purchase decisions, businesses should prioritise strategies to encourage and highlight positive customer feedback. This can include incentivising customers to leave reviews, responding promptly to reviews (both positive and negative), and actively managing online review platforms (Elwalda et al., 2016; Patil & Rane, 2023).
- ***IMPROVE REVIEW RELIABILITY AND HELPFULNESS:*** Since the reliability and helpfulness of reviews are crucial factors influencing customer decisions, businesses should focus on ensuring the authenticity and usefulness of reviews. Implementing measures to verify the legitimacy of reviews and providing helpful responses to customer inquiries can enhance the credibility of reviews and build trust with potential customers (Agnihotri & Bhattacharya, 2016; Korfiatis et al., 2012).
- ***OPTIMISE PERSONALISED RECOMMENDATIONS:*** Utilise data-driven personalised recommendation algorithms to offer tailored product suggestions to customers. Businesses can provide relevant and timely recommendations by analysing customer preferences and purchase history, increasing the likelihood of purchase and customer satisfaction (Bawack et al., 2022; Raji et al., 2024; Schafer et al., 2001).
- ***MONITOR AND ENHANCE SHOPPING SATISFACTION:*** Continuously monitor customer satisfaction levels throughout the shopping experience and identify areas for improvement. This can include optimising website usability, streamlining the checkout process, providing responsive customer support. Improving overall shopping satisfaction can lead to higher conversion rates and repeat purchases (Duarte et al., 2018; Khalifa & Liu, 2007).
- ***LEVERAGE PERSONALISED RECOMMENDATIONS:*** Since the frequency and helpfulness of personalised recommendations impact customer decisions, businesses should invest in optimising their recommendation systems. This can involve refining algorithms to deliver more accurate recommendations based on customer preferences and behaviour, ultimately increasing sales and customer engagement (Xiao & Benbasat, 2018; Zhou & Zou, 2023).
- ***REWARD AND INCENTIVISE PURCHASE FREQUENCY:*** Implement loyalty programs or rewards schemes to incentivise repeat purchases and increase customer retention. Offering discounts, rewards points, or exclusive offers to frequent buyers can encourage customer loyalty and drive repeat business (Dowling & Uncles, 1997; Lewis, 2004; Magatef & Tomalieh, 2015).

- ***FOCUS ON RECOMMENDATION HELPFULNESS:*** Given the influence of recommendation helpfulness on purchase decisions, businesses should prioritise strategies to increase the perceived helpfulness of recommendations. This can include providing detailed product information, user-generated content such as reviews and ratings, and personalised recommendations based on customer preferences (Maslowska et al., 2017; Ruiz-Mafe et al., 2018).

By focusing on these recommendations and addressing the factors identified as influential in customer purchase decisions, businesses can enhance profitability and drive growth in the online domain. To rigorously tackle the question of "What critical success factors (CSFs) are associated with profitability in e-commerce?", which is the main question of the research, I thoroughly examine all aspects of the research, including the literature review, methodology, and the integration of factors and clusters. This comprehensive analysis is discussed in the next part.

5.3 DISCUSSION

In this section, I explore the critical success factors (CSFs) linked with profitability in e-commerce, drawing from my analysis and insights gathered so far. My goal is to reveal the key antecedents of profitability within the e-commerce landscape, shedding light on both established factors and emerging trends. Through this discussion, I aim to contribute to a comprehensive understanding of the sophisticated dynamics shaping profitability in e-commerce.

5.3.1 Closing Thoughts: Implications for Practitioners

The retail industry has evolved through distinct eras, from Retail 1.0 to the current Retail 4.0. Each phase, marked by technological advancements, has reshaped consumer behaviour and retail landscapes. Retail 1.0 introduced mechanisation and department stores, while Retail 2.0 saw mass production and the rise of suburban malls. With Retail 3.0 came online shopping and digital disruptors, transforming traditional retail models. Retail 4.0 leverages AI, IoT, and Big Data to enhance customer experiences. In the context of this digital era, the study explores critical success factors contributing to e-commerce profitability (Har et al., 2022; Sakrabani & Teoh, 2021).

In the literature review, I explored critical success factors in e-commerce crucial for maximising profits and ensuring the future success of online companies. The outcome results further validate these factors. The following is the wrap-up of the discussion:

1. **User Online Shopping Experience:** The importance of prioritizing high-quality websites and applications that offer convenience, interactivity, customization, and character has been emphasized (Izogo & Jayawardhena, 2018) and the impact of these factors has been

confirmed by the results. Tailoring platforms based on users' experience levels enhances engagement and confidence (Mosteller et al., 2014).

2. **Customer Satisfaction:** Influenced by perceived service quality, especially online convenience, positive experiences foster favorable attitudes and repurchase intentions. Satisfaction acts as a mediator between service convenience and future purchases (Kassim & Asiah Abdullah, 2010; O. Pappas et al., 2014). It is noteworthy that shopping satisfaction which is ranks second among factors analyzed by experts via Fuzzy Delphi methodology.
3. **Product Information:** In some of the questions designed for the experts, the concept of product information was considered. Extensive access to product information online facilitates informed purchase decisions, influenced by factors such as merchant reputation and individual preferences (Bilgihan et al., 2016; Cowley & Mitchell, 2003; Zhang & Wang, 2012).
4. **Trust, Privacy, and Security:** Building trust through competence and integrity is crucial for attracting buyers, as evidenced in certain aspects of the questions (Chang et al., 2013; Fortes et al., 2017; Lăzăroiu et al., 2020). E-trust significantly influences consumer perceptions and transactional willingness, emphasizing reliability in privacy and security assurances (Lăzăroiu et al., 2020; L. Wang et al., 2015).
5. **Price & Perceived Value:** Simplified product searches and heightened price sensitivity challenge assumptions about online pricing. Creating substantial relationship value fosters long-term buyer-seller relationships (H.-W. Kim et al., 2012; Liu & Arnett, 2000; Wu et al., 2014).
6. **Customer Reviews & Feedback:** Online reviews significantly influence purchasing decisions, with three of the seven key factors directly linked to reviews and feedback in the paper. These factors underscore the critical role that customer opinions play in shaping consumer behaviour. Positive reviews can enhance a product's reputation and credibility, while negative feedback can deter potential buyers, highlighting the importance of managing online presence. Furthermore, leveraging social influence data helps optimize marketing strategies and identify opinion leaders (Mudambi & Schuff, 2010; Patil & Rane, 2023; Thakur, 2018; Wei & Lu, 2013).
7. **Shipping and Return Policies:** Lenient return policies enhance satisfaction and loyalty, while positive post-purchase experiences contribute to repeat purchases, as reflected in shopping satisfaction in the outcomes (Bower & Maxham III, 2012; Hjort & Lantz, 2016; Kim & Wansink, 2012; Lantz & Hjort, 2013).

8. **E-Service:** Most factors, such as the importance of customer reviews, the reliability of reviews, and the helpfulness of reviews, as well as the frequency of personalized recommendations and the helpfulness of those recommendations, are integral parts of e-service. Moreover, attributes like speed of delivery and ease of use are important for maintaining high service quality standards. Efficient delivery services ensure customers receive their purchases promptly, enhancing satisfaction and encouraging repeat business (Fared et al., 2021; Rita et al., 2019b; Roy et al., 2018).
9. **Loyalty:** Based on the results, it is evident that loyalty is an integral and indispensable part of e-commerce. Loyalty is influenced by several key factors, including perceived value, customer satisfaction, trust, commitment, and emotional attachment. Loyalty is vital for sustained success, as it encourages repeat purchases, positive word-of-mouth, and long-term customer retention (Anderson & Srinivasan, 2003; Eid, 2011; Peña-García et al., 2018; Zamil et al., 2020).
10. **Switching Behaviour:** Understanding and influencing customer switching behaviour is vital, with factors like service failures and perceived quality significantly impacting revisits and reducing switching intentions (Antón et al., 2007; Geiger et al., 2012; Han et al., 2011).
11. **Cross-Cultural Differences:** Cultural nuances significantly shape e-commerce acceptance and utilization, highlighting the need to understand cross-cultural variations for success in global markets (Peña-García et al., 2018). Different cultures have unique preferences, behaviours, and expectations when it comes to online shopping. For example, payment methods, communication styles, website design preferences, and attitudes toward customer service can vary widely between cultures. Businesses aiming to expand internationally must be aware of these differences and adapt their strategies accordingly (Jarvenpaa et al., 1999; Liao et al., 2008; Tsao et al., 2016).
12. **Cart Interaction:** Cart interaction and cart abandonment considerations encompass not only technical aspects but also cognitive, emotional, and cultural dimensions(Gupta, 2013; Kukar-Kinney et al., 2022). This involves understanding how users interact with the cart interface and the various psychological and cultural factors that shape their decision-making processes. Factors such as ease of navigation, visual appeal, checkout process simplicity, and trustworthiness of the platform contribute to cart abandonment rates. In the paper, all the factors assessed and examined are closely related to cart interaction, highlighting the complexity of online shopping experiences (Kukar-Kinney & Close, 2010; J. Li et al., 2021; Xu & Huang, 2015).

13. **Future Purchase Intentions:** Drawing from both literature review and confirmed results, it becomes apparent that customer satisfaction, service convenience, and online shopping experiences significantly shape future purchase intentions. This emphasizes the interconnectedness of various factors in influencing consumer behaviour, prompting consideration for further research (Gao, 2011; Ginting et al., 2023; Kazancoglu & Aydin, 2018; Kumar et al., 2020; O. Pappas et al., 2014; Y. Zhao et al., 2020).

Contribution to the literature review involved a comprehensive exploration of the retail transformation and the evolutionary journey of e-commerce, investigating its historical roots and contemporary developments. Furthermore, the research endeavoured to dissect and elaborate on the critical success factors that underpin online shopping, offering insights into the aspects influencing its efficacy and sustainability to boost the profitability of online shopping businesses.

5.3.2 From Factor Classification to Cluster Prioritisation: Navigating the Process

Let's look deeper into the analysis, integrating the analyses and providing a comprehensive understanding of the key thoughts derived:

- ***CUSTOMER PURCHASE BEHAVIOUR INSIGHTS***

The analysis underscores the significance of various factors in shaping customer purchase behaviour in online shopping environments. Purchasing frequency, browsing habits, and reliance on customer reviews are critical determinants influencing consumer decision-making processes (Chong et al., 2016; Elwalda et al., 2016; Patil & Rane, 2023). Understanding these factors enables e-commerce platforms to tailor their strategies effectively, meeting customer needs and preferences, thus enhancing overall satisfaction and driving repeat purchases (Fared et al., 2021; Ren & Hong, 2019).

- ***ROLE OF PERSONALISATION AND RECOMMENDATIONS***

Personalization features, particularly personalized product recommendations, wield substantial influence over customer behaviour (Garbarino & Strahilevitz, 2004; Xiao & Benbasat, 2018). The frequency and perceived helpfulness of such recommendations significantly impact purchasing decisions. Leveraging personalized recommendation algorithms empowers e-commerce platforms to enhance user engagement, boost sales conversion rates, and cultivate customer loyalty, thus augmenting overall business performance (Schindler & Bickart, 2012; Zhou & Zou, 2023).

- ***IMPORTANCE OF CUSTOMER REVIEWS***

The analysis emphasizes the pivotal role of customer reviews in the decision-making process (Askalidis & Malthouse, 2016; Hu & Liu, 2004). Factors such as review reliability and helpfulness profoundly influence consumer perceptions and purchasing behaviour. Prioritizing strategies to

encourage and manage customer reviews effectively enhances trust and credibility among users, consequently bolstering the platform's reputation and fostering customer satisfaction (Choi & Leon, 2020; Kashyap et al., 2023; Korfiatis et al., 2012).

- ***SHOPPING SATISFACTION AND SERVICE APPRECIATION***

Shopping satisfaction emerges as a critical factor underpinning customer retention and loyalty (Mofokeng, 2021). Factors such as user experience, service quality, and overall satisfaction with the shopping process contribute significantly to customer satisfaction levels (Pappas, 2018; Rita et al., 2019b). Identifying areas for improvement and addressing them proactively enables e-commerce platforms to enhance service quality, delivering superior shopping experiences and nurturing long-term customer relationships (Cox & Dale, 2001; Sharma & Lijuan, 2015).

- ***IMPLICATIONS FOR BUSINESS STRATEGY***

The insights derived from the analysis hold profound implications for business strategy formulation and optimization. By prioritizing factors based on their weighted averages, businesses can allocate resources effectively and concentrate on initiatives with maximum impact (Asad et al., 2016; Bowles & Peláez, 1995). Strategies aimed at improving customer satisfaction, optimizing product recommendations, and enhancing the reliability of customer reviews yield tangible benefits in terms of revenue growth and market competitiveness (Jannach et al., 2014; Thakur, 2018).

- ***BRIEF OVERVIEW OF RESULTS***

Numerical analyses reveal the weighted importance of various factors, with Customer Reviews (F2) and Shopping Satisfaction (F7) garnering the highest average weights of 0.317 and 0.203, respectively. Moreover, the consistency ratios (CR) calculated for expert opinions range from 0.268 to 0.574, indicating varying degrees of consensus among experts and highlighting the reliability of their assessments. The application of the COPRAS method in cluster prioritization further refines business strategy formulation, enabling a structured approach to resource allocation and decision-making based on cluster characteristics and strategic priorities (Amoozad Mahdiraji et al., 2018a).

By applying these insights effectively, e-commerce platforms can develop targeted strategies to enhance customer satisfaction, drive sales, and foster long-term loyalty in an increasingly competitive marketplace that will lead to maximising profitability (Jiradilok et al., 2014; O. Pappas et al., 2014; Zamil et al., 2020).

5.3.3 Synopsis of Results: Key Insights and Implications

The analysis of the provided results yields a precious understanding of the critical success factors associated with profitability in e-commerce, offering implications for strategic decision-making.

"Customer Reviews Importance" emerges as the most influential factor, highlighting the crucial role of customer feedback in shaping purchasing decisions (Hu & Liu, 2004; Patil & Rane, 2023). This emphasises the necessity for platforms to ensure the reliability and helpfulness of reviews to enhance customer satisfaction and loyalty (Choi & Leon, 2020; Ren & Hong, 2019; Shadkam & O'Hara, 2013). Additionally, "Shopping Satisfaction" emerges as a key determinant of e-commerce success, drawing attention to the need for strategies aimed at improving overall shopping experiences to drive repeat purchases and foster customer relationships (Cox & Dale, 2001; Sharma & Lijuan, 2015).

Among the clusters, A5 emerges as the top-performing segment, demonstrating strong performance across various factors, notably in Review Reliability, Recommendation Helpfulness, and Shopping Satisfaction. With its substantial purchase frequency, Cluster A5 represents a primary target for marketing efforts and retention strategies. The analysis of purchase frequency underscores this cluster's high engagement levels, making it a prime target for revenue generation. Furthermore, the age distribution trends within this cluster offer insights into target demographics, with younger clusters representing potential growth opportunities (Bylok, 2022; Santos et al., 2023).

Additionally, Clusters A4 and A3, although slightly older, demonstrate balanced purchase frequency and predominantly female composition. With a diverse age range and moderate purchase frequency, this segment presents opportunities for targeted promotions based on individual preferences. Efforts to improve review reliability and helpfulness can bolster customer trust and satisfaction (Choi & Leon, 2020; Korfiatis et al., 2012).

Furthermore, Cluster A2, predominantly female with balanced purchase frequencies, represents a valuable market segment. Strategies should focus on maintaining product relevance and recruiting personalized recommendations to drive repeat purchases (Kim & Srivastava, 2007).

In contrast, Cluster A1, exhibits relatively poor performance across all factors, indicating areas for improvement, particularly in Review Reliability and Shopping Satisfaction. Despite its small size and infrequent purchases, this segment warrants attention due to its balanced gender distribution. Tailored marketing campaigns addressing individual preferences and concerns can enhance customer satisfaction and retention (Rane et al., 2023; Rust & Zahorik, 1993).

Regarding the implications of the analysis, e-commerce platforms must prioritize strategies that enhance customer engagement and satisfaction, as noted below:

- ***CUSTOMER REVIEWS IMPORTANCE:*** Platforms should prioritize strategies to enhance the reliability and helpfulness of customer reviews, particularly in clusters with high reliance on reviews for decision-making (Hu & Liu, 2004; Patil & Rane, 2023).

PERSONALISED RECOMMENDATION FREQUENCY AND HELPFULNESS: Leveraging data-driven algorithms to deliver relevant and helpful product recommendations can significantly impact purchase behaviour and satisfaction across all clusters (Bylok, 2022; Choi & Leon, 2020; Korfiatis et al., 2012; Santos et al., 2023).

- ***SHOPPING SATISFACTION:*** Ensuring a seamless and enjoyable shopping experience is paramount for customer retention and loyalty. Strategies should focus on optimizing user interface, navigation, and post-purchase support (Khalifa & Liu, 2007; Mofokeng, 2021; Pappas, 2018; Rita et al., 2019b).

By aligning cluster characteristics with identified CSFs, e-commerce platforms can develop targeted strategies tailored to the needs and preferences of each customer segment. This integrated approach enhances the effectiveness of marketing campaigns, product recommendations, and service delivery, ultimately driving profitability and customer satisfaction. Furthermore, by monitoring and adapting strategies based on evolving customer preferences and feedback, e-commerce platforms can maintain competitiveness and sustain profitability in the dynamic online retail landscape.

6.1.1 Summary of Findings

My study underlines the leading role of customer segmentation and critical success factors (CSFs) in optimizing e-commerce profitability. Applying a data-driven approach to customer segmentation, informed by insights from cluster analysis and CSFs, is significant for guiding strategic decision-making in the e-commerce domain. Continuous monitoring and adaptation of strategies based on evolving customer preferences and market dynamics are essential for maintaining competitiveness and achieving sustained growth in the dynamic e-commerce landscape.

6.1.2 Theoretical and methodological implications

The findings of this study have several theoretical and methodological implications that contribute to the existing body of knowledge in e-commerce research:

- ***THEORETICAL IMPLICATIONS***

The study advances understanding of the critical success factors (CSFs) associated with profitability in e-commerce by empirically examining the influence of customer segmentation on key performance indicators (Colla & Lapoule, 2012; Hjort & Lantz, 2016; Kim & Lee, 2002; Watson et al., 2015) (Khalifa & Liu, 2007; Mofokeng, 2021; Pappas, 2018; Rita et al., 2019b)

By highlighting the significance of customer reviews, recommendation systems, and shopping satisfaction in driving e-commerce success, the study contributes to theoretical frameworks related to customer-centric strategies and marketing effectiveness (Bylok, 2022; Choi & Leon, 2020; Hu & Liu, 2004; Korfiatis et al., 2012; Patil & Rane, 2023; Santos et al., 2023).

The identification of clusters with distinct purchasing behaviours and demographic characteristics enhances theoretical models of customer segmentation and market segmentation strategies in e-commerce contexts.

- ***METHODOLOGICAL IMPLICATIONS***

The study demonstrates the effectiveness of cluster analysis as a methodological approach for segmenting e-commerce customers based on key performance metrics, providing insights into customer behaviour and preferences.

By incorporating a multi-criteria decision-making framework, the study showcases the application of analytical techniques for prioritizing critical success factors and informing strategic decision-making processes (Zavadskas & Turskis, 2011).

The integration of numerous methods such as fuzzy Delphi, fuzzy BWM, C-means and fuzzy COPRAS the leading methodologies offers a novel methodological approach for handling uncertainty and ambiguity in e-commerce data, providing researchers with tools to analyze complex datasets and derive actionable insights (Amoozad Mahdiraji et al., 2018a; Giannarou & Zervas, 2014; Nayak et al., 2015; Rezaei, 2016).

Overall, the theoretical and methodological implications of this study extend our understanding of e-commerce dynamics and offer a brilliant understanding for researchers, practitioners, and policymakers seeking to enhance business performance in the digital marketplace.

6.1.3 Limitations

By acknowledging the limitations, you demonstrate a critical awareness of the constraints and potential weaknesses of your study, which is an important aspect of academic research. According to my dataset, which included 602 records and encompassed 23 diverse outcomes, the following limitations may influence the results of the project:

- ***CROSS-SECTIONAL NATURE OF DATA:*** Cross-sectional studies, by design, capture a single point in time, which can limit their ability to observe changes and trends over time. This can be particularly limiting in dynamic fields like e-commerce, where customer behaviours and market conditions can evolve rapidly. According to academic literature, cross-sectional studies often fail to account for temporal dynamics and causal relationships, making them less effective for longitudinal analysis and trend forecasting (Levin, 2006; Wang & Cheng, 2020).
- ***GENERALIZABILITY OF FINDINGS:*** The generalizability of findings from e-commerce studies can be constrained by the specific context and sample used. Different industries, regions, and time periods can exhibit unique characteristics that may not be represented in a single study. This variability necessitates caution when applying findings broadly. Literature reviews in consumer behaviour and e-commerce highlight the importance of contextual factors and recommend considering these when extrapolating results to broader populations or different market conditions (Rita & Ramos, 2022; Rosário & Raimundo, 2021).
- ***SAMPLE SIZE AND REPRESENTATIVENESS:*** The size and representativeness of the sample used in e-commerce research can significantly influence the validity and reliability of the findings. Small or non-representative samples may not capture the diversity of the target population, leading to biased results. Studies emphasize the need for adequate sample sizes and representative sampling methods to enhance the credibility and applicability of research findings in e-commerce contexts (Gobo, 2004; Lakens, 2022).

- ***DATA QUALITY:*** Data quality issues, such as missing data, errors, and biases, can impact the accuracy and reliability of research findings. Ensuring high-quality data is critical for robust analysis. Academic sources discuss various strategies to mitigate data quality issues, including rigorous data collection protocols and advanced data cleaning techniques (Batini et al., 2009; Pipino et al., 2002).
- ***FACTOR SELECTION:*** The selection of factors for analysis is crucial, as excluding important variables can lead to incomplete or misleading results. In e-commerce studies, it is essential to capture a comprehensive set of factors influencing profitability and customer behaviour. Literature reviews suggest using multi-faceted approaches to factor selection, incorporating insights from various theoretical frameworks and empirical findings (Cureton & D'Agostino, 2013; Velicer & Jackson, 1990).
- ***CLUSTERING METHODOLOGY:*** The choice of clustering algorithm and the number of clusters can affect the outcomes and interpretations of cluster analysis. Different algorithms may yield different results, and selecting an appropriate method is critical for meaningful insights. Research in this area highlights the importance of validating clustering results using multiple methods and considering the specific characteristics of the data (Kodinariya & Makwana, 2013; Rodriguez et al., 2019).
- ***INTERPRETATION OF RESULTS:*** Interpreting the results of e-commerce studies can be challenging, especially when trying to establish causal relationships. Associations identified in the data may not imply causation, and additional analysis is often required to understand the underlying mechanisms. Academic sources recommend using complementary methods, such as longitudinal studies or experiments, to strengthen causal inferences (Chen & Dhillon, 2003; Colla & Lapoule, 2012).
- ***TEMPORAL FACTORS:*** Temporal factors, such as market trends and external conditions, can influence e-commerce profitability. These factors may change over time, affecting the relevance and applicability of study findings. Literature suggests incorporating temporal analysis and monitoring external trends to contextualize and adapt strategies effectively (Feindt et al., 2002; Xiao et al., 2022).
- ***SCOPE OF ANALYSIS:*** Narrowing the scope of analysis can limit the comprehensive understanding of e-commerce dynamics. While focused studies can provide deep insights into specific aspects, a broader approach may be necessary to capture the full complexity of e-commerce environments. Research highlights the need for balancing depth and breadth in study designs (Gibbs & Kraemer, 2004; Niranjanamurthy et al., 2013).

- ***EXTERNAL VALIDITY:*** The external validity of findings can be limited when studies are conducted in specific contexts or industries. Generalizing results to other sectors or regions requires careful consideration of contextual differences. Academic literature emphasizes the importance of cross-contextual validation and the replication of studies in diverse settings to enhance external validity (Ferguson, 2004; Klassen & Klassen, 2018).

6.1.4 Suggestions for future work

Recommendations for future research based on the findings and limitations of the study is as follows:

- Exploring the integration of emerging technologies such as artificial intelligence and machine learning algorithms to further enhance personalized recommendation systems.
- Conducting longitudinal studies to track the long-term impact of implemented strategies on customer satisfaction, retention, and overall profitability.
- Investigating the effectiveness of alternative loyalty program structures and incentive schemes in driving repeat purchases and fostering customer loyalty.
- Examining the influence of external factors such as market trends, competitive dynamics, and regulatory changes on the efficacy of implemented strategies.
- Exploring cross-channel strategies for customer engagement and retention, including the integration of social media platforms, mobile applications, and email marketing campaigns.
- Investigating the role of user-generated content and social proof mechanisms in shaping consumer perceptions and purchase decisions within the e-commerce context.
- Assessing the scalability and applicability of the proposed strategies across different industry sectors and geographical regions.

Additionally, considering the application of Interval-valued Intuitionistic Fuzzy methodologies (IVIF) could provide a novel approach to analyzing complex and uncertain data within the e-commerce domain. Following IVIF techniques for customer segmentation, sentiment analysis of reviews, and decision-making processes may offer a more comprehensive understanding of customer preferences and behaviours (Zhang & Wang, 2022). Exploring the potential benefits of IVIF in handling ambiguity and uncertainty in e-commerce data could lead to more robust and adaptive strategies for enhancing customer satisfaction and driving profitability. Conducting empirical studies to validate the efficacy of IVIF methodologies in real-world e-commerce settings would be a valuable direction for future research (Büyüközkan & Göçer, 2018; Hashemi et al., 2016).

6.1.5 Closing Statement

In conclusion, the following recommendations serve as important strategies for enhancing e-commerce profitability and customer satisfaction. Prioritize strategies to encourage positive customer feedback by incentivizing reviews and promptly responding to customer feedback. Ensure review authenticity and usefulness through measures to verify legitimacy and provide helpful responses, enhancing credibility and trust. Recruit data-driven recommendation algorithms for tailored product suggestions to increase purchase likelihood and satisfaction. Continuously monitor and improve the shopping experience to enhance customer satisfaction, leading to higher conversion rates. Invest in optimizing recommendation systems based on customer behaviour to drive sales and engagement. Implement loyalty programs to incentivize repeat purchases, fostering loyalty and repeat business. Focus on increasing the perceived helpfulness of recommendations by providing detailed product information and personalized suggestions.

7 REFERENCES

Abdulkareem, K. H., Arbaiy, N., Zaidan, A., Zaidan, B., Albahri, O. S., Alsalem, M., & Salih, M. M. (2021). A new standardisation and selection framework for real-time image dehazing algorithms from multi-foggy scenes based on fuzzy Delphi and hybrid multi-criteria decision analysis methods. *Neural Computing and Applications*, *33*, 1029-1054.

Aboutorab, H., Saberi, M., Asadabadi, M. R., Hussain, O., & Chang, E. (2018). ZBWM: The Z-number extension of Best Worst Method and its application for supplier development. *Expert Systems with Applications*, *107*, 115-125.

Abubakar, A. M., Elrehail, H., Alatailat, M. A., & Elçi, A. (2019). Knowledge management, decision-making style and organizational performance. *Journal of Innovation & Knowledge*, *4*(2), 104-114. https://doi.org/https://doi.org/10.1016/j.jik.2017.07.003

Açıkgöz, A., Günsel, A., Bayyurt, N., & Kuzey, C. (2014). Team climate, team cognition, team intuition, and software quality: The moderating role of project complexity. *Group Decision and Negotiation*, *23*(5), 1145-1176.

Adil, M., Al Ghaswyneh, O. F. M., & Albkour, A. M. (2013). SERVQUAL and SERVPERF: A review of measures in services marketing research. *Global Journal of Management and Business Research Marketing*, *13*(6), 65-76.

Adler, M., & Ziglio, E. (1996). *Gazing into the oracle: The Delphi method and its application to social policy and public health*. Jessica Kingsley Publishers.

Agnihotri, A., & Bhattacharya, S. (2016). Online review helpfulness: Role of qualitative factors. *Psychology & marketing*, *33*(11), 1006-1017.

Akçayır, M., Dündar, H., & Akçayır, G. (2016). What makes you a digital native? Is it enough to be born after 1980? *Computers in Human Behavior*, *60*, 435-440. https://doi.org/https://doi.org/10.1016/j.chb.2016.02.089

Akhavan, P., Barak, S., Maghsoudlou, H., & Antuchevičienė, J. (2015). FQSPM-SWOT for strategic alliance planning and partner selection; case study in a holding car manufacturer company. *Technological and economic development of economy*, *21*(2), 165-185.

Akter, S., & Wamba, S. F. (2016). Big data analytics in E-commerce: a systematic review and agenda for future research. *Electronic Markets*, *26*, 173-194.

Alaloul, W. S., Liew, M. S., & Zawawi, N. A. W. A. (2016). Identification of coordination factors affecting building projects performance. *Alexandria Engineering Journal*, *55*(3), 2689-2698.

Alba, J. W., & Hutchinson, J. W. (1987). Dimensions of consumer expertise. *Journal of Consumer Research*, *13*(4), 411-454.

Alcedo, J., Cavallo, A., Dwyer, B., Mishra, P., & Spilimbergo, A. (2022). *E-commerce during COVID: Stylized facts from 47 economies*.

Aldrich, M. (2011). Online Shopping in the 1980s. *Annals of the History of Computing*, *33*(4), 57-61.

Aldrich, M. (2023). *Internet Online Shopping*. https://www.aldricharchive.co.uk/internet-online-shopping

Alimahomed-Wilson, J., & Reese, E. (2021). *The cost of free shipping: Amazon in the global economy*. Pluto Press.

Alrubaiee, L., & Alkaa'ida, F. (2011). The mediating effect of patient satisfaction in the patients' perceptions of healthcare quality-patient trust relationship. *International Journal of Marketing Studies*, *3*(1), 103.

Alsmadi, M. K. (2018). A hybrid Fuzzy C-Means and Neutrosophic for jaw lesions segmentation. *Ain Shams Engineering Journal*, *9*(4), 697-706.

Ameen, N., Tarhini, A., Reppel, A., & Anand, A. (2021). Customer experiences in the age of artificial intelligence. *Computers in Human Behavior*, *114*, 106548.

Amiri, M., Hashemi-Tabatabaei, M., Ghahremanloo, M., Keshavarz-Ghorabaee, M., Zavadskas, E. K., & Banaitis, A. (2021). A new fuzzy BWM approach for evaluating and selecting a sustainable supplier in supply chain management. *International Journal of Sustainable Development & World Ecology*, *28*(2), 125-142.

Amoozad Mahdiraji, H., Arzaghi, S., Stauskis, G., & Zavadskas, E. K. (2018a). A hybrid fuzzy BWM-COPRAS method for analyzing key factors of sustainable architecture. *Sustainability*, *10*(5), 1626.

Amoozad Mahdiraji, H., Arzaghi, S., Stauskis, G., & Zavadskas, E. K. (2018b). A Hybrid Fuzzy BWM-COPRAS Method for Analyzing Key Factors of Sustainable Architecture. *Sustainability*, *10*(5).

Amoozad Mahdiraji, H., Hafeez, K., Kord, H., & Abbasi Kamardi, A. (2022). Analysing the voice of customers by a hybrid fuzzy decision-making approach in a developing country's automotive market. *Management decision*, *60*(2), 399-425.

Anderson, R. E., & Srinivasan, S. S. (2003). E-satisfaction and e-loyalty: A contingency framework. *Psychology & marketing*, *20*(2), 123-138.

Anderson, R. E., & Swaminathan, S. (2011). Customer satisfaction and loyalty in e-markets: A PLS path modeling approach. *Journal of Marketing Theory and Practice*, *19*(2), 221-234.

Antón, C., Camarero, C., & Carrero, M. (2007). The mediating effect of satisfaction on consumers' switching intention. *Psychology & marketing*, *24*(6), 511-538.

Arkes, H. R., Dawes, R. M., & Christensen, C. (1986). Factors influencing the use of a decision rule in a probabilistic task. *Organizational behavior and human decision processes*, *37*(1), 93-110.

Asad, M. M., Mohajerani, N. S., & Nourseresh, M. (2016). Prioritizing factors affecting customer satisfaction in the internet banking system based on cause and effect relationships. *Procedia economics and finance*, *36*, 210-219.

Ashraf, A. R., Thongpapanl, N., & Auh, S. (2014). The application of the technology acceptance model under different cultural contexts: The case of online shopping adoption. *Journal of International Marketing*, *22*(3), 68-93.

Askalidis, G., & Malthouse, E. C. (2016). The value of online customer reviews. Proceedings of the 10th ACM Conference on Recommender Systems,

Atanassov, K. T., & Atanassov, K. T. (1999). *Intuitionistic fuzzy sets*. Springer.

Babakus, E., & Boller, G. W. (1992). An empirical assessment of the SERVQUAL scale. *Journal of business research*, *24*(3), 253-268.

Bai, B., Law, R., & Wen, I. (2008). The impact of website quality on customer satisfaction and purchase intentions: Evidence from Chinese online visitors. *International journal of hospitality management*, *27*(3), 391-402.

Bai, Y., Yao, Z., & Dou, Y.-F. (2015). Effect of social commerce factors on user purchase behavior: An empirical investigation from renren. com. *International Journal of Information Management*, *35*(5), 538-550.

Baird, B. F. (1991). *Managerial decisions under uncertainty: An introduction to the analysis of decision making* (Vol. 4). John Wiley & Sons.

Bakos, J. Y. (1997). Reducing buyer search costs: Implications for electronic marketplaces. *Management science*, *43*(12), 1676-1692.

Bamfield, J. (2013a). Retail futures 2018. In: Report for the Centre for Retail Research.

Bamfield, J. (2013b). Retail futures 2018: Shop numbers, online and the high street: A guide to retailing in 2018. *Centre for Retail Research Limited*, *16*(2), 5-14.

Baourakis, G., Kourgiantakis, M., & Migdalas, A. (2002). The impact of e-commerce on agro-food marketing: The case of agricultural cooperatives, firms and consumers in Crete. *British food journal*, *104*(8), 580-590.

Barnes, S. J., & Vidgen, R. (2001). An evaluation of cyber-bookshops: the WebQual method. *International Journal of electronic commerce*, *6*(1), 11-30.

Barnes, S. J., & Vidgen, R. T. (2002). An integrative approach to the assessment of e-commerce quality. *J. Electron. Commer. Res.*, *3*(3), 114-127.

Batini, C., Cappiello, C., Francalanci, C., & Maurino, A. (2009). Methodologies for data quality assessment and improvement. *ACM computing surveys (CSUR)*, *41*(3), 1-52.

Bawack, R. E., Wamba, S. F., Carillo, K. D. A., & Akter, S. (2022). Artificial intelligence in E-Commerce: a bibliometric study and literature review. *Electronic Markets*, *32*(1), 297-338.

Behling, O., Gifford, W. E., & Tolliver, J. M. (1980). Effects of grouping information on decision making under risk. *Decision Sciences*, *11*(2), 272-283.

Benlahbib, A. (2020). Aggregating customer review attributes for online reputation generation. *IEEE Access*, *8*, 96550-96564.

Berners-Lee, T., Cailliau, R., Groff, J. F., & Pollermann, B. (1992). World-Wide Web: the information universe. *Internet Research*, *2*(1), 52-58.

Berry, L. L., Seiders, K., & Grewal, D. (2002). Understanding service convenience. *Journal of marketing*, *66*(3), 1-17.

Bezdek, J. C. (2013). *Pattern recognition with fuzzy objective function algorithms*. Springer Science & Business Media.
Bezdek, J. C., Ehrlich, R., & Full, W. (1984). FCM: The fuzzy c-means clustering algorithm. *Computers & geosciences*, *10*(2-3), 191-203.
Bezos, J. (1998). *Amazon. com*. Purdue University Public Affairs Video Archives.
Bhatnagar, A., Misra, S., & Rao, H. R. (2000). On risk, convenience, and Internet shopping behavior. *Communications of the ACM*, *43*(11), 98-105.
Bhattacharya, A., Mohapatra, P., Kumar, V., Dey, P. K., Brady, M., Tiwari, M. K., & Nudurupati, S. S. (2014). Green supply chain performance measurement using fuzzy ANP-based balanced scorecard: a collaborative decision-making approach. *Production Planning & Control*, *25*(8), 698-714.
Bierman, D. J., Destrebecqz, A., & Cleeremans, A. (2005). Intuitive decision making in complex situations: Somatic markers in an artificial grammar learning task. *Cognitive, Affective, & Behavioral Neuroscience*, *5*, 297-305.
Bigne, E., Ruiz, C., & Sanz, S. (2005). The impact of internet user shopping patterns and demographics on consumer mobile buying behaviour. *Journal of electronic commerce research*, *6*(3), 193.
Bilgihan, A. (2016). Gen Y customer loyalty in online shopping: An integrated model of trust, user experience and branding. *Computers in Human Behavior*, *61*, 103-113.
Bilgihan, A., Kandampully, J., & Zhang, T. (2016). Towards a unified customer experience in online shopping environments: Antecedents and outcomes. *International Journal of Quality and Service Sciences*, *8*(1), 102-119.
Bleier, A., & Eisenbeiss, M. (2015). The importance of trust for personalized online advertising. *Journal of retailing*, *91*(3), 390-409.
Blut, M. (2016). E-service quality: development of a hierarchical model. *Journal of retailing*, *92*(4), 500-517.
Blut, M., Chowdhry, N., Mittal, V., & Brock, C. (2015). E-service quality: A meta-analytic review. *Journal of retailing*, *91*(4), 679-700.
Bonifield, C., Cole, C., & Schultz, R. L. (2010). Product returns on the internet: a case of mixed signals? *Journal of business research*, *63*(9-10), 1058-1065.
Bordoloi, S., Fitzsimmons, J. A., & Fitzsimmons, M. J. (2019). *Service management: operations, strategy, information technology*. McGraw-Hill.
Boukis, A. (2020). Exploring the implications of blockchain technology for brand–consumer relationships: a future research agenda. *Journal of Product & Brand Management*, *29*(3), 307-320.
Bower, A. B., & Maxham III, J. G. (2012). Return shipping policies of online retailers: Normative assumptions and the long-term consequences of fee and free returns. *Journal of marketing*, *76*(5), 110-124.
Bowles, J. B., & Peláez, C. E. (1995). Fuzzy logic prioritization of failures in a system failure mode, effects and criticality analysis. *Reliability engineering & system safety*, *50*(2), 203-213.
Branca, T. A., Fornai, B., Colla, V., Murri, M. M., Streppa, E., & Schröder, A. J. (2020). The challenge of digitalization in the steel sector. *Metals*, *10*(2), 288.
Broekhuizen, T. L. J., Broekhuis, M., Gijsenberg, M. J., & Wieringa, J. E. (2021). Introduction to the special issue – Digital business models: A multi-disciplinary and multi-stakeholder perspective. *Journal of business research*, *122*, 847-852. https://doi.org/https://doi.org/10.1016/j.jbusres.2020.04.014
Brown, A. D., & Jones, M. R. (1998). Doomed to failure: Narratives of inevitability and conspiracy in a failed IS project. *Organization studies*, *19*(1), 73-88.
Brown, M., Pope, N., & Voges, K. (2003). Buying or browsing? An exploration of shopping orientations and online purchase intention. *European Journal of marketing*, *37*(11/12), 1666-1684.
Brubaker, R. (2013). *The limits of rationality*. Routledge.
Brucks, M. (1985). The effects of product class knowledge on information search behavior. *Journal of Consumer Research*, *12*(1), 1-16.
Brunelli, M., & Rezaei, J. (2019). A multiplicative best–worst method for multi-criteria decision making. *Operations Research Letters*, *47*(1), 12-15.
Bryman, A., & Bell, E. (2011). Business research methods 3rd ed. New York. In: Oxford Press. Bui, K. VT (2002). First-generation college students at a four.
Brynjolfsson, E., Hu, Y., & Rahman, M. S. (2009). Battle of the retail channels: How product selection and geography drive cross-channel competition. *Management science*, *55*(11), 1755-1765.

Bui, T. D., Tsai, F. M., Tseng, M.-L., & Ali, M. H. (2020). Identifying sustainable solid waste management barriers in practice using the fuzzy Delphi method. *Resources, conservation and recycling*, *154*, 104625.

Buldeo Rai, H. (2021). The net environmental impact of online shopping, beyond the substitution bias. *Journal of Transport Geography*, *93*, 103058. https://doi.org/https://doi.org/10.1016/j.jtrangeo.2021.103058

Burnham, T. A., Frels, J. K., & Mahajan, V. (2003). Consumer switching costs: A typology, antecedents, and consequences. *Journal of the academy of marketing science*, *31*(2), 109-126.

Burt, S., & Sparks, L. (2003). E-commerce and the retail process: a review. *Journal of Retailing and Consumer Services*, *10*(5), 275-286.

Burton, J. W., Stein, M. K., & Jensen, T. B. (2020). A systematic review of algorithm aversion in augmented decision making. *Journal of behavioral decision making*, *33*(2), 220-239.

Busari, A., & Spicer, D. (2015). The role of intuitive and analytical cognitive style towards leadership effectiveness: Exploration from Malaysian government-link-companies. Proceedings of,

Büyüközkan, G., & Göçer, F. (2018). An extension of ARAS methodology under interval valued intuitionistic fuzzy environment for digital supply chain. *Applied Soft Computing*, *69*, 634-654.

Bylok, F. (2022). Examining the impact of trust on the e-commerce purchase intentions of young consumers in Poland. *Journal of Internet Commerce*, *21*(3), 364-391.

Cai, S., & Xu, Y. (2006). Effects of outcome, process and shopping enjoyment on online consumer behaviour. *Electronic Commerce Research and Applications*, *5*(4), 272-281.

Cai, Y., & Cude, B. J. (2016). Online Shopping. In J. J. Xiao (Ed.), *Handbook of Consumer Finance Research* (pp. 339-355). Springer International Publishing. https://doi.org/10.1007/978-3-319-28887-1_28

Calvo-Porral, C., & Lévy-Mangin, J.-P. (2015). Switching behavior and customer satisfaction in mobile services: Analyzing virtual and traditional operators. *Computers in Human Behavior*, *49*, 532-540.

Calvo-Porral, C., & Lévy-Mangin, J.-P. (2018). From “foodies” to “cherry-pickers”: A clustered-based segmentation of specialty food retail customers. *Journal of Retailing and Consumer Services*, *43*, 278-284.

Cantrill, J., Sibbald, B., & Buetow, S. (1996). The Delphi and nominal group techniques in health services research. *International Journal of pharmacy practice*, *4*(2), 67-74.

Cao, L., & Li, L. (2015). The impact of cross-channel integration on retailers’ sales growth. *Journal of retailing*, *91*(2), 198-216.

Cao, Y., Ajjan, H., & Hong, P. (2018). Post-purchase shipping and customer service experiences in online shopping and their impact on customer satisfaction: An empirical study with comparison. *Asia Pacific Journal of Marketing and Logistics*, *30*(2), 400-416.

Casalo, L. V., Flavián, C., & Guinalíu, M. (2007). The influence of satisfaction, perceived reputation and trust on a consumer's commitment to a website. *Journal of Marketing Communications*, *13*(1), 1-17.

Cash, J. I., & Konsynski, B. R. (1985). IS redraws competitive boundaries. *Harvard business review*, *63*(2), 134-142.

Čereška, A., Podvezko, V., & Zavadskas, E. K. (2016). Operating characteristics analysis of rotor systems using MCDM methods. *Studies in Informatics and Control*, *25*(1), 60.

Čereška, A., Zavadskas, E. K., Cavallaro, F., Podvezko, V., Tetsman, I., & Grinbergienė, I. (2016). Sustainable assessment of aerosol pollution decrease applying multiple attribute decision-making methods. *Sustainability*, *8*(7), 586.

Chan, J. C., Jiang, Z., & Tan, B. C. (2009). Understanding online interruption-based advertising: Impacts of exposure timing, advertising intent, and brand image. *IEEE Transactions on Engineering Management*, *57*(3), 365-379.

Chan, P. (2022). An empirical study on data validation methods of Delphi and general consensus. *Data*, *7*(2), 18.

Chandra, S., & Kumar, K. N. (2018). EXPLORING FACTORS INFLUENCING ORGANIZATIONAL ADOPTION OF AUGMENTED REALITY IN E-COMMERCE: EMPIRICAL ANALYSIS USING TECHNOLOGY-ORGANIZATION-ENVIRONMENT MODEL. *Journal of electronic commerce research*, *19*(3).

Chang, H. H., & Chen, S. W. (2009). Consumer perception of interface quality, security, and loyalty in electronic commerce. *Information & Management*, *46*(7), 411-417.

Chang, M. K., Cheung, W., & Tang, M. (2013). Building trust online: Interactions among trust building mechanisms. *Information & Management*, *50*(7), 439-445.

Chang, Y.-W., & Polonsky, M. J. (2012). The influence of multiple types of service convenience on behavioral intentions: The mediating role of consumer satisfaction in a Taiwanese leisure setting. *International journal of hospitality management*, *31*(1), 107-118.

Chaudhuri, S., & Terlep, S. (2018). The Next Big Threat to Consumer Brands (Yes, Amazon's Behind It). *The Wall Street Journal*.

Cheema, A., & Papatla, P. (2010). Relative importance of online versus offline information for Internet purchases: Product category and Internet experience effects. *Journal of business research*, *63*(9-10), 979-985.

Chek, Y. L., & Ho, J. S. Y. (2016). Consumer electronics E-retailing: why the alliance of vendors' E-service quality, trust and trustworthiness matters. *Procedia-Social and Behavioral Sciences*, *219*, 804-811.

Chen, A., Lu, Y., & Wang, B. (2017). Customers' purchase decision-making process in social commerce: A social learning perspective. *International Journal of Information Management*, *37*(6), 627-638.

Chen, C.-T. (2000). Extensions of the TOPSIS for group decision-making under fuzzy environment. *Fuzzy Sets and Systems*, *114*(1), 1-9.

Chen, J. V., Yen, D. C., Pornpriphet, W., & Widjaja, A. E. (2015). E-commerce web site loyalty: A cross cultural comparison. *Information Systems Frontiers*, *17*, 1283-1299.

Chen, M.-K., & Wang, S.-C. (2010). The use of a hybrid fuzzy-Delphi-AHP approach to develop global business intelligence for information service firms. *Expert Systems with Applications*, *37*(11), 7394-7407.

Chen, S.-J., & Hwang, C.-L. (1992). Fuzzy multiple attribute decision making methods. In *Fuzzy multiple attribute decision making: Methods and applications* (pp. 289-486). Springer.

Chen, S. C., & Dhillon, G. S. (2003). Interpreting dimensions of consumer trust in e-commerce. *Information technology and management*, *4*, 303-318.

Chen, S. J., & Chang, T. Z. (2003). A descriptive model of online shopping process: some empirical results. *International Journal of Service Industry Management*, *14*(5), 556-569.

Chen, W., Giger, M. L., & Bick, U. (2006). A fuzzy c-means (fcm)-based approach for computerized segmentation of breast lesions in dynamic contrast-enhanced mr images1. *Academic radiology*, *13*(1), 63-72.

Chen, Y.-H., Hsu, I.-C., & Lin, C.-C. (2010). Website attributes that increase consumer purchase intention: A conjoint analysis. *Journal of business research*, *63*(9-10), 1007-1014.

Chen, Y.-Y. (2012). Why do consumers go internet shopping again? Understanding the antecedents of repurchase intention. *Journal of Organizational Computing and Electronic Commerce*, *22*(1), 38-63.

Chen, Z., Shu, W., Guo, H., & Pan, C. (2021). The Spatial Characteristics of Sustainable Development for Agricultural Products E-Commerce at County-Level: Based on the Empirical Analysis of China. *Sustainability*, *13*(12).

Cheng, C.-H., & Lin, Y. (2002). Evaluating the best main battle tank using fuzzy decision theory with linguistic criteria evaluation. *European journal of operational research*, *142*(1), 174-186.

Chiou, J.-S., & Droge, C. (2006). Service quality, trust, specific asset investment, and expertise: Direct and indirect effects in a satisfaction-loyalty framework. *Journal of the academy of Marketing Science*, *34*(4), 613-627.

Chiu, C. M., Chang, C. C., Cheng, H. L., & Fang, Y. H. (2009). Determinants of customer repurchase intention in online shopping. *Online information review*, *33*(4), 761-784.

Cho, J. E., & Hu, H. (2009). The effect of service quality on trust and commitment varying across generations. *International Journal of Consumer Studies*, *33*(4), 468-476.

Choi, H. S., & Leon, S. (2020). An empirical investigation of online review helpfulness: A big data perspective. *Decision Support Systems*, *139*, 113403.

Chong, A. Y. L., Li, B., Ngai, E. W., Ch'Ng, E., & Lee, F. (2016). Predicting online product sales via online reviews, sentiments, and promotion strategies: A big data architecture and neural network approach. *International Journal of Operations & Production Management*, *36*(4), 358-383.

Chou, S., Chen, C.-W., & Lin, J.-Y. (2015). Female online shoppers: Examining the mediating roles of e-satisfaction and e-trust on e-loyalty development. *Internet Research*, *25*(4), 542-561.

Chu, H.-C., & Hwang, G.-J. (2008). A Delphi-based approach to developing expert systems with the cooperation of multiple experts. *Expert Systems with Applications*, *34*(4), 2826-2840.

Chua, A. Y., & Banerjee, S. (2015). Understanding review helpfulness as a function of reviewer reputation, review rating, and review depth. *Journal of the Association for Information Science and Technology*, *66*(2), 354-362.

Chuang, Y.-F., & Tai, Y.-F. (2016). Research on customer switching behavior in the service industry. *Management Research Review*, *39*(8), 925-939.
Clark, J., & Van Oorschot, P. C. (2013). SoK: SSL and HTTPS: Revisiting past challenges and evaluating certificate trust model enhancements. 2013 IEEE Symposium on Security and Privacy,
Clarke III, I. (2008). Emerging value propositions for m-commerce. *Journal of Business Strategies*, *25*(2), 41-57.
Clemes, M. D., Gan, C., & Zhang, D. (2010). Customer switching behaviour in the Chinese retail banking industry. *International Journal of Bank Marketing*, *28*(7), 519-546.
Colla, E., & Lapoule, P. (2012). E-commerce: exploring the critical success factors. *International Journal of Retail & Distribution Management*, *40*(11), 842-864.
Connolly, R., & Bannister, F. (2008). Factors influencing Irish consumers' trust in internet shopping. *Management Research News*, *31*(5), 339-358.
Corritore, C. L., Kracher, B., & Wiedenbeck, S. (2003). On-line trust: concepts, evolving themes, a model. *International journal of human-computer studies*, *58*(6), 737-758.
Coulthard, L. J. M. (2004). A review and critique of research using SERVQUAL. *International Journal of Market Research*, *46*(4), 479-497.
Cowley, E., & Mitchell, A. A. (2003). The moderating effect of product knowledge on the learning and organization of product information. *Journal of Consumer Research*, *30*(3), 443-454.
Cox, J., & Dale, B. G. (2001). Service quality and e-commerce: an exploratory analysis. *Managing service quality: An international journal*, *11*(2), 121-131.
Creswell, J. (2018). How amazon steers shoppers to its own products. *The New York Times*, *23*.
Crisp, J., Pelletier, D., Duffield, C., Adams, A., & Nagy, S. (1997). The delphi method? *Nursing research*, *46*(2), 116-118.
Cureton, E. E., & D'Agostino, R. B. (2013). *Factor analysis: An applied approach*. Psychology press.
Dabholkar, P. A. (1996). Consumer evaluations of new technology-based self-service options: an investigation of alternative models of service quality. *International Journal of research in Marketing*, *13*(1), 29-51.
Daft, R. (1995). Organization theory and decision. *St. Paul, MN: West Publishing Co*.
Dalkey, N., & Helmer, O. (1963). An experimental application of the Delphi method to the use of experts. *Management science*, *9*(3), 458-467.
Dannenberg, P., Fuchs, M., Riedler, T., & Wiedemann, C. (2020). Digital transition by COVID-19 pandemic? The German food online retail. *Tijdschrift voor economische en sociale geografie*, *111*(3), 543-560.
Darley, W. K., Blankson, C., & Luethge, D. J. (2010). Toward an integrated framework for online consumer behavior and decision making process: A review. *Psychology & marketing*, *27*(2), 94-116.
de Mooij, M., & Hofstede, G. (2011). Cross-Cultural Consumer Behavior: A Review of Research Findings. *Journal of International Consumer Marketing*, *23*(3-4), 181-192. https://doi.org/10.1080/08961530.2011.578057
Dean Jr, J. W., & Sharfman, M. P. (1993). Procedural rationality in the strategic decision-making process. *Journal of Management Studies*, *30*(4), 587-610.
Dekimpe, M. G., Geyskens, I., & Gielens, K. (2020). Using technology to bring online convenience to offline shopping. *Marketing letters*, *31*, 25-29.
DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: a ten-year update. *Journal of management information systems*, *19*(4), 9-30.
DeLone, W. H., & McLean, E. R. (2004). Measuring e-commerce success: Applying the DeLone & McLean information systems success model. *International Journal of electronic commerce*, *9*(1), 31-47.
Deutsch, M. (1958). Trust and suspicion. *Journal of conflict resolution*, *2*(4), 265-279.
Devaraj, S., Fan, M., & Kohli, R. (2002). Antecedents of B2C channel satisfaction and preference: validating e-commerce metrics. *Information Systems Research*, *13*(3), 316-333.
Dhiman, H. S., & Deb, D. (2020). Fuzzy TOPSIS and fuzzy COPRAS based multi-criteria decision making for hybrid wind farms. *Energy*, *202*, 117755.
Diaz, T. (2021). The evolution of retailing: a look back and a look ahead.
Diehl, K., & Poynor, C. (2010). Great expectations?! Assortment size, expectations, and satisfaction. *Journal of marketing research*, *47*(2), 312-322.
Dittmar, H., Long, K., & Meek, R. (2004). Buying on the Internet: Gender differences in on-line and conventional buying motivations. *Sex roles*, *50*, 423-444.

Doney, P. M., Cannon, J. P., & Mullen, M. R. (1998). Understanding the influence of national culture on the development of trust. *Academy of management review*, *23*(3), 601-620.
Dorn, C., Burkhart, T., Werth, D., & Dustdar, S. (2010). Self-adjusting recommendations for people-driven ad-hoc processes. Business Process Management: 8th International Conference, BPM 2010, Hoboken, NJ, USA, September 13-16, 2010. Proceedings 8,
Dowling, G. R., & Uncles, M. (1997). Do customer loyalty programs really work? *Sloan management review*, *38*, 71-82.
Duarte, P., e Silva, S. C., & Ferreira, M. B. (2018). How convenient is it? Delivering online shopping convenience to enhance customer satisfaction and encourage e-WOM. *Journal of Retailing and Consumer Services*, *44*, 161-169.
Duarte, P. A. d. O., & Silva, S. C. (2020). The role of consumer-cause identification and attitude in the intention to purchase cause-related products. *International Marketing Review*, *37*(4), 603-620.
Duckstein, L. (1995). *Fuzzy rule-based modeling with applications to geophysical, biological, and engineering systems* (Vol. 8). CRC press.
Dunn, J. C. (1973). A fuzzy relative of the ISODATA process and its use in detecting compact well-separated clusters.
Ecer, F. (2014). A hybrid banking websites quality evaluation model using AHP and COPRAS-G: a Turkey case. *Technological and economic development of economy*, *20*(4), 758-782.
Eid, M. I. (2011). Determinants of e-commerce customer satisfaction, trust, and loyalty in Saudi Arabia. *Journal of electronic commerce research*, *12*(1), 78.
Eisenfuhr, F. (2011). Decision making. In: New York, NY: Springer.
Eisenhardt, K. M., & Zbaracki, M. J. (1992). Strategic decision making. *Strategic Management Journal*, *13*(S2), 17-37.
Elbanna, S. (2006). Strategic decision-making: Process perspectives. *international Journal of Management reviews*, *8*(1), 1-20.
Elbeltagi, I., & Agag, G. (2016). E-retailing ethics and its impact on customer satisfaction and repurchase intention: a cultural and commitment-trust theory perspective. *Internet Research*, *26*(1), 288-310.
Elizabeth Lloyd, A., YK Chan, R., SC Yip, L., & Chan, A. (2014). Time buying and time saving: effects on service convenience and the shopping experience at the mall. *Journal of services Marketing*, *28*(1), 36-49.
Elliot, S., & Fowell, S. (2000). Expectations versus reality: a snapshot of consumer experiences with Internet retailing. *International Journal of Information Management*, *20*(5), 323-336.
Ellis, R. (1988). Professional competence and quality assurance in the caring professions. *(No Title)*.
Elwalda, A., Lü, K., & Ali, M. (2016). Perceived derived attributes of online customer reviews. *Computers in Human Behavior*, *56*, 306-319.
Engel, J. F., Blackwell, R. D., & Miniard, P. W. (1986). *Consumer behavior*. Dryden Press.
Eriksson, N., & Stenius, M. (2020). Changing behavioral patterns in grocery shopping in the initial phase of the COVID-19 crisis—A qualitative study of news articles.
Escursell, S., Llorach-Massana, P., & Roncero, M. B. (2021). Sustainability in e-commerce packaging: A review. *Journal of cleaner production*, *280*, 124314. https://doi.org/https://doi.org/10.1016/j.jclepro.2020.124314
Falk, L. K., Sockel, H., & Chen, K. (2005). E-commerce and consumer's expectations: What makes a website work. *Journal of Website Promotion*, *1*(1), 65-75.
Fared, M. A., Darmawan, D., & Khairi, M. (2021). Contribution of E-Service Quality to Repurchase Intention with Mediation of Customer Satisfaction: Study of Online Shopping Through Marketplace. *Journal of Marketing and Business Research (MARK)*, *1*(2), 93-106.
Fedirko, O., Zatonatska, T., Dluhopolskyi, O., & Londar, S. (2021). The impact of e-commerce on the sustainable development: case of Ukraine, Poland, and Austria. IOP Conference Series: Earth and Environmental Science,
Feindt, S., Jeffcoate, J., & Chappell, C. (2002). Identifying success factors for rapid growth in SME e-commerce. *Small business economics*, *19*, 51-62.
Ferguson, L. (2004). External validity, generalizability, and knowledge utilization. *Journal of Nursing Scholarship*, *36*(1), 16-22.
Fishburn, P. C. (1978). A survey of multiattribute/multicriterion evaluation theories. Multiple Criteria Problem Solving: Proceedings of a Conference Buffalo, NY (USA), August 22–26, 1977,

Fitzgerald, D. R., Mohammed, S., & Kremer, G. O. (2017). Differences in the way we decide: The effect of decision style diversity on process conflict in design teams. *Personality and Individual Differences*, *104*, 339-344.
Flacandji, M., & Krey, N. (2020). Remembering shopping experiences: the shopping experience memory scale. *Journal of business research*, *107*, 279-289.
Fortes, N., Rita, P., & Pagani, M. (2017). The effects of privacy concerns, perceived risk and trust on online purchasing behaviour. *International Journal of Internet Marketing and Advertising*, *11*(4), 307-329.
Fukuyama, F. (1995). Trust: The Social Virtues and the Creation of Prosperity, New York: Free Press, Chapter 9.
Fung, V. K., & Fung, W. K. (2001). Yoram (Jerry) Wind. *Competing in a Flat World: Building Enterprises for a Borderless World*.
Gao, F. (2011). A study of online purchase intention: based on the perspective of customer trust. 2011 International Conference on Management and Service Science,
Gao, J., Zhang, C., Wang, K., & Ba, S. (2012). Understanding online purchase decision making: The effects of unconscious thought, information quality, and information quantity. *Decision Support Systems*, *53*(4), 772-781.
Garbarino, E., & Strahilevitz, M. (2004). Gender differences in the perceived risk of buying online and the effects of receiving a site recommendation. *Journal of business research*, *57*(7), 768-775.
Gefen, D. (2000). E-commerce: the role of familiarity and trust. *Omega*, *28*(6), 725-737.
Gefen, D. (2002). Customer loyalty in e-commerce. *Journal of the association for information systems*, *3*(1), 2.
Gefen, D., & Straub, D. (2003). Managing user trust in B2C e-services. *e-Service*, *2*(2), 7-24.
Geiger, I., Durand, A., Saab, S., Kleinaltenkamp, M., Baxter, R., & Lee, Y. (2012). The bonding effects of relationship value and switching costs in industrial buyer–seller relationships: An investigation into role differences. *Industrial Marketing Management*, *41*(1), 82-93.
Giannakos, M. N., Pateli, A. G., & Pappas, I. O. (2011). Identifying the direct effect of experience and the moderating effect of satisfaction in the greek online market. *International Journal of E-Services and Mobile Applications (IJESMA)*, *3*(2), 39-58.
Giannarou, L., & Zervas, E. (2014). Using Delphi technique to build consensus in practice. *International Journal of Business Science & Applied Management (IJBSAM)*, *9*(2), 65-82.
Gibbs, J. L., & Kraemer, K. L. (2004). A cross-country investigation of the determinants of scope of e-commerce use: an institutional approach. *Electronic Markets*, *14*(2), 124-137.
Ginting, Y., Chandra, T., Miran, I., & Yusriadi, Y. (2023). Repurchase intention of e-commerce customers in Indonesia: An overview of the effect of e-service quality, e-word of mouth, customer trust, and customer satisfaction mediation. *International Journal of Data and Network Science*, *7*(1), 329-340.
Gitlin, M. (2011). *eBay: The company and its founder*. ABDO.
Gobo, G. (2004). Sampling, representativeness and generalizability. *Qualitative research practice*, *405*, 426.
Gommans, M., Krishman, K. S., & Scheffold, K. B. (2001). From brand loyalty to e-loyalty: A conceptual framework. *Journal of Economic & Social Research*, *3*(1).
Goodnight, G. T., & Green, S. (2010). Rhetoric, risk, and markets: The dot-com bubble. *Quarterly journal of speech*, *96*(2), 115-140.
Gounaris, S., Dimitriadis, S., & Stathakopoulos, V. (2010). An examination of the effects of service quality and satisfaction on customers' behavioral intentions in e-shopping. *Journal of services Marketing*, *24*(2), 142-156.
Gremler, D. D., Gwinner, K. P., & Brown, S. W. (2001). Generating positive word-of-mouth communication through customer-employee relationships. *International Journal of Service Industry Management*, *12*(1), 44-59.
Grewal, D., & Lindsey-Mullikin, J. (2006). The moderating role of the price frame on the effects of price range and the number of competitors on consumers' search intentions. *Journal of the academy of Marketing Science*, *34*, 55-62.
Griffis, S. E., Rao, S., Goldsby, T. J., & Niranjan, T. T. (2012). The customer consequences of returns in online retailing: An empirical analysis. *Journal of Operations Management*, *30*(4), 282-294.
Guaita Martínez, J. M., Puertas, R., Martín Martín, J. M., & Ribeiro-Soriano, D. (2022). Digitalization, innovation and environmental policies aimed at achieving sustainable production. *Sustainable Production and Consumption*, *32*, 92-100. https://doi.org/https://doi.org/10.1016/j.spc.2022.03.035

Guo, B., & Zhou, S. (2017). What makes population perception of review helpfulness: an information processing perspective. *Electronic Commerce Research*, *17*, 585-608.
Guo, H., Liu, Y., Shi, X., & Chen, K. Z. (2021). The role of e-commerce in the urban food system under COVID-19: Lessons from China. *China Agricultural Economic Review*, *13*(2), 436-455.
Guo, H., Wang, L., Liu, X., & Pedrycz, W. (2020). Information granulation-based fuzzy clustering of time series. *IEEE transactions on cybernetics*, *51*(12), 6253-6261.
Guo, S., & Zhao, H. (2017). Fuzzy best-worst multi-criteria decision-making method and its applications. *Knowledge-Based Systems*, *121*, 23-31.
Gupta, A. (2014). E-Commerce: Role of E-Commerce in today's business. *International Journal of Computing and Corporate Research*, *4*(1), 1-8.
Gupta, H. (2018). Assessing organizations performance on the basis of GHRM practices using BWM and Fuzzy TOPSIS. *Journal of environmental management*, *226*, 201-216.
Gupta, S. (2013). Online shopping cart application.
Habibi, A., Jahantigh, F. F., & Sarafrazi, A. (2015). Fuzzy Delphi technique for forecasting and screening items. *Asian Journal of Research in Business Economics and Management*, *5*(2), 130-143.
Hallowell, R. (1996). The relationships of customer satisfaction, customer loyalty, and profitability: an empirical study. *International Journal of Service Industry Management*, *7*(4), 27-42.
Han, H., & Hyun, S. S. (2013). Image congruence and relationship quality in predicting switching intention: Conspicuousness of product use as a moderator variable. *Journal of Hospitality & Tourism Research*, *37*(3), 303-329.
Han, H., Kim, W., & Hyun, S. S. (2011). Switching intention model development: Role of service performances, customer satisfaction, and switching barriers in the hotel industry. *International journal of hospitality management*, *30*(3), 619-629.
Han, W. (2021). Purchasing Decision-Making Process of Online Consumers. 2021 International Conference on Public Relations and Social Sciences (ICPRSS 2021),
Har, L. L., Rashid, U. K., Te Chuan, L., Sen, S. C., & Xia, L. Y. (2022). Revolution of retail industry: from perspective of retail 1.0 to 4.0. *Procedia Computer Science*, *200*, 1615-1625.
Harren, V. A. (1979). A model of career decision making for college students. *Journal of vocational behavior*, *14*(2), 119-133.
Hartson, R., & Pyla, P. S. (2012). *The UX Book: Process and guidelines for ensuring a quality user experience*. Elsevier.
Hasan, B. (2016). Perceived irritation in online shopping: The impact of website design characteristics. *Computers in Human Behavior*, *54*, 224-230. https://doi.org/https://doi.org/10.1016/j.chb.2015.07.056
Hashemi, S. S., Hajiagha, S. H. R., Zavadskas, E. K., & Mahdiraji, H. A. (2016). Multicriteria group decision making with ELECTRE III method based on interval-valued intuitionistic fuzzy information. *Applied mathematical modelling*, *40*(2), 1554-1564.
Häubl, G., & Trifts, V. (2000). Consumer decision making in online shopping environments: The effects of interactive decision aids. *Marketing science*, *19*(1), 4-21.
Havinga, M., Hoving, M., & Swagemakers, V. (2016). Alibaba: a case study on building an international imperium on information and E-Commerce. *Multinational Management: A Casebook on Asia's Global Market Leaders*, 13-32.
Heins, C. (2023). The impact of COVID-19 on the grocery retail industry: Innovative approaches for contactless store concepts in Germany. *foresight*, *25*(3), 349-366.
Hernández, B., Jiménez, J., & Martín, M. J. (2010). Customer behavior in electronic commerce: The moderating effect of e-purchasing experience. *Journal of business research*, *63*(9-10), 964-971.
Heskett, J. L., Jones, T. O., Loveman, G. W., Sasser, W. E., & Schlesinger, L. A. (1994). Putting the service-profit chain to work. *Harvard business review*, *72*(2), 164-174.
Hester, P. T., Velasquez, M., & Hester, P. T. (2013). An analysis of multi-criteria decision making methods mission creep view project systemic thinking view project an analysis of multi-criteria decision making methods. *Int J Oper Res*, *10*.
Hjort, K., & Lantz, B. (2012). (R) e-tail borrowing of party dresses: an experimental study. *International Journal of Retail & Distribution Management*, *40*(12), 997-1012.
Hjort, K., & Lantz, B. (2016). The impact of returns policies on profitability: A fashion e-commerce case. *Journal of business research*, *69*(11), 4980-4985.

Hodgetts, H. M., Vachon, F., Chamberland, C., & Tremblay, S. (2017). See no evil: Cognitive challenges of security surveillance and monitoring. *Journal of applied research in memory and cognition*, *6*(3), 230-243.

Hodgkinson, G. P., Sadler-Smith, E., Burke, L. A., Claxton, G., & Sparrow, P. R. (2009). Intuition in organizations: Implications for strategic management. *Long Range Planning*, *42*(3), 277-297.

Holland, C., Lockett, G., & Blackman, I. (1992). Planning for electronic data interchange. *Strategic Management Journal*, *13*(7), 539-550.

Holloway, B. B., Wang, S., & Parish, J. T. (2005). The role of cumulative online purchasing experience in service recovery management. *Journal of Interactive Marketing*, *19*(3), 54-66.

Hong, H., Xu, D., Wang, G. A., & Fan, W. (2017). Understanding the determinants of online review helpfulness: A meta-analytic investigation. *Decision Support Systems*, *102*, 1-11.

Hou, A. C., Chern, C.-C., Chen, H.-G., & Chen, Y.-C. (2011). 'Migrating to a new virtual world': Exploring MMORPG switching through human migration theory. *Computers in Human Behavior*, *27*(5), 1892-1903.

Hough, J. R., & Ogilvie, D. (2005). An empirical test of cognitive style and strategic decision outcomes. *Journal of Management Studies*, *42*(2), 417-448.

Howard, J. A., & Sheth, J. N. (1969). The theory of buyer behavior. *New York*, *63*, 145.

Hsia, T.-L., Wu, J.-H., & Li, E. Y. (2008). The e-commerce value matrix and use case model: A goal-driven methodology for eliciting B2C application requirements. *Information & Management*, *45*(5), 321-330.

Hsieh, J.-K., Hsieh, Y.-C., Chiu, H.-C., & Feng, Y.-C. (2012). Post-adoption switching behavior for online service substitutes: A perspective of the push–pull–mooring framework. *Computers in Human Behavior*, *28*(5), 1912-1920.

Hsieh, M.-T., & Tsao, W.-C. (2014). Reducing perceived online shopping risk to enhance loyalty: a website quality perspective. *Journal of Risk Research*, *17*(2), 241-261.

Hsieh, T.-Y., Lu, S.-T., & Tzeng, G.-H. (2004). Fuzzy MCDM approach for planning and design tenders selection in public office buildings. *International journal of project management*, *22*(7), 573-584.

Hsin Chang, H., & Wang, H. W. (2011). The moderating effect of customer perceived value on online shopping behaviour. *Online information review*, *35*(3), 333-359.

Hsu, C.-C., & Sandford, B. A. (2019). The Delphi technique: making sense of consensus. *Practical assessment, research, and evaluation*, *12*(1), 10.

Hsu, C. L., Chen, M. C., Chang, K. C., & Chao, C. M. (2010). Applying loss aversion to investigate service quality in logistics: A moderating effect of service convenience. *International Journal of Operations & Production Management*, *30*(5), 508-525.

Hsu, Y.-L., Lee, C.-H., & Kreng, V. B. (2010). The application of Fuzzy Delphi Method and Fuzzy AHP in lubricant regenerative technology selection. *Expert Systems with Applications*, *37*(1), 419-425.

Hu, M., & Liu, B. (2004). Mining and summarizing customer reviews. Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining,

Huang, A. H., Chen, K., Yen, D. C., & Tran, T. P. (2015). A study of factors that contribute to online review helpfulness. *Computers in Human Behavior*, *48*, 17-27.

Huang, G.-H., Korfiatis, N., & Chang, C.-T. (2018). Mobile shopping cart abandonment: The roles of conflicts, ambivalence, and hesitation. *Journal of business research*, *85*, 165-174.

Hüseyinoğlu, I. Ö. Y., Galipoğlu, E., & Kotzab, H. (2017). Social, local and mobile commerce practices in omni-channel retailing: Insights from Germany and Turkey. *International Journal of Retail & Distribution Management*, *45*(7/8), 711-729.

Hwang, C.-L., & Lin, M.-J. (2012). *Group decision making under multiple criteria: methods and applications* (Vol. 281). Springer Science & Business Media.

Ignat, B., & Chankov, S. (2020). Do e-commerce customers change their preferred last-mile delivery based on its sustainability impact? *The International Journal of Logistics Management*, *31*(3), 521-548.

Ingaldi, M., & Ulewicz, R. (2019). How to Make E-Commerce More Successful by Use of Kano's Model to Assess Customer Satisfaction in Terms of Sustainable Development. *Sustainability*, *11*(18).

Ishikawa, A., Amagasa, M., Shiga, T., Tomizawa, G., Tatsuta, R., & Mieno, H. (1993). The max-min Delphi method and fuzzy Delphi method via fuzzy integration. *Fuzzy sets and systems*, *55*(3), 241-253.

Ittner, C. D., & Larcker, D. F. (1998). Are nonfinancial measures leading indicators of financial performance? An analysis of customer satisfaction. *Journal of accounting research*, *36*, 1-35.

Izogo, E. E., & Jayawardhena, C. (2018). Online shopping experience in an emerging e-retailing market. *Journal of Research in Interactive Marketing*, *12*(2), 193-214.
Jahan, A., & Edwards, K. (2013). VIKOR method for material selection problems with interval numbers and target-based criteria. *Materials & Design*, *47*, 759-765.
Jain, V., Malviya, B., & Arya, S. (2021). An overview of electronic commerce (e-Commerce). *Journal of Contemporary Issues in Business and Government*, *27*(3), 665-670.
Jaller, M., & Pahwa, A. (2020). Evaluating the environmental impacts of online shopping: A behavioral and transportation approach. *Transportation Research Part D: Transport and Environment*, *80*, 102223.
Janakiraman, N., Syrdal, H. A., & Freling, R. (2016). The effect of return policy leniency on consumer purchase and return decisions: A meta-analytic review. *Journal of retailing*, *92*(2), 226-235.
Janis, I. L., & Mann, L. (1977). *Decision making: A psychological analysis of conflict, choice, and commitment*. Free press.
Jannach, D., Zanker, M., & Fuchs, M. (2014). Leveraging multi-criteria customer feedback for satisfaction analysis and improved recommendations. *Information Technology & Tourism*, *14*, 119-149.
Jarvenpaa, S. L., Tractinsky, N., & Saarinen, L. (1999). Consumer trust in an Internet store: A cross-cultural validation. *Journal of Computer-Mediated Communication*, *5*(2), JCMC526.
Jato-Espino, D., Castillo-Lopez, E., Rodriguez-Hernandez, J., & Canteras-Jordana, J. C. (2014). A review of application of multi-criteria decision making methods in construction. *Automation in Construction*, *45*, 151-162. https://doi.org/https://doi.org/10.1016/j.autcon.2014.05.013
Javad, M. O. M., Darvishi, M., & Javad, A. O. M. (2020). Green supplier selection for the steel industry using BWM and fuzzy TOPSIS: A case study of Khouzestan steel company. *Sustainable Futures*, *2*, 100012.
Jayaram, A. (2017). Smart Retail 4.0 IoT Consumer retailer model for retail intelligence and strategic marketing of in-store products. *Proceedings of the 17th international business horizon-INBUSH ERA-2017, Noida, India*, *9*.
Jiang, L. A., Yang, Z., & Jun, M. (2013). Measuring consumer perceptions of online shopping convenience. *Journal of Service management*, *24*(2), 191-214.
Jiradilok, T., Malisuwan, S., Madan, N., & Sivaraks, J. (2014). The impact of customer satisfaction on online purchasing: A case study analysis in Thailand. *Journal of Economics, Business and Management*, *2*(1), 5-11.
Johnston, H. R., & Vitale, M. R. (1988). Creating competitive advantage with interorganizational information systems. *MIS quarterly*, 153-165.
Jones, M. A., Reynolds, K. E., & Arnold, M. J. (2006). Hedonic and utilitarian shopping value: Investigating differential effects on retail outcomes. *Journal of business research*, *59*(9), 974-981.
Jun, M., Yang, Z., & Kim, D. (2004). Customers' perceptions of online retailing service quality and their satisfaction. *International Journal of Quality & Reliability Management*, *21*(8), 817-840.
Kacprzyk, J., & Zadrożny, S. (2001). Computing with words in intelligent database querying: standalone and Internet-based applications. *Information Sciences*, *134*(1-4), 71-109.
Kahraman, C., Onar, S. C., & Oztaysi, B. (2015). Fuzzy multicriteria decision-making: a literature review. *International journal of computational intelligence systems*, *8*(4), 637-666.
Kamble, S. S., Gunasekaran, A., Ghadge, A., & Raut, R. (2020). A performance measurement system for industry 4.0 enabled smart manufacturing system in SMMEs-A review and empirical investigation. *International journal of production economics*, *229*, 107853.
Kandra, A. (2000). Shipping Charges: Who Foots the Bill? *PC World*, *18*(9), 39-39.
Kansra, P., & Jha, A. K. (2016). Measuring service quality in Indian hospitals: an analysis of SERVQUAL model. *International Journal of Services and Operations Management*, *24*(1), 1-17.
Kaplan, A., Skogstad, A., & Girshick, M. A. (1949). The Prediction of Social and Technological Events. P-93. The RAND Corporation, Santa Monica, CA. In.
Kaptein, M., & Eckles, D. (2012). Heterogeneity in the effects of online persuasion. *Journal of Interactive Marketing*, *26*(3), 176-188.
Karimi, S., Papamichail, K. N., & Holland, C. P. (2015). The effect of prior knowledge and decision-making style on the online purchase decision-making process: A typology of consumer shopping behaviour. *Decision Support Systems*, *77*, 137-147.
Karimi, S., & Wang, F. (2017). Online review helpfulness: Impact of reviewer profile image. *Decision Support Systems*, *96*, 39-48.

Kashyap, R., Kesharwani, A., & Ponnam, A. (2023). Measurement of online review helpfulness: A formative measure development and validation. *Electronic Commerce Research*, *23*(4), 2183-2216.
Kassim, N., & Asiah Abdullah, N. (2010). The effect of perceived service quality dimensions on customer satisfaction, trust, and loyalty in e-commerce settings: A cross cultural analysis. *Asia Pacific Journal of Marketing and Logistics*, *22*(3), 351-371.
Kaufmann, L., Kreft, S., Ehrgott, M., & Reimann, F. (2012). Rationality in supplier selection decisions: The effect of the buyer's national task environment. *Journal of Purchasing and Supply Management*, *18*(2), 76-91.
Kawaf, F., & Tagg, S. (2017). The construction of online shopping experience: A repertory grid approach. *Computers in Human Behavior*, *72*, 222-232.
Kaynama, S. A., & Black, C. I. (2000). A proposal to assess the service quality of online travel agencies: An exploratory study. *Journal of professional services marketing*, *21*(1), 63-88.
Kazancoglu, I., & Aydin, H. (2018). An investigation of consumers' purchase intentions towards omni-channel shopping: A qualitative exploratory study. *International Journal of Retail & Distribution Management*, *46*(10), 959-976.
Keaveney, S. M. (1995). Customer switching behavior in service industries: An exploratory study. *Journal of marketing*, *59*(2), 71-82.
Keaveney, S. M., & Parthasarathy, M. (2001). Customer switching behavior in online services: An exploratory study of the role of selected attitudinal, behavioral, and demographic factors. *Journal of the academy of marketing science*, *29*(4), 374-390.
Kennedyd, S. I., Marjerison, R. K., Yu, Y., Zi, Q., Tang, X., & Yang, Z. (2022). E-commerce engagement: A prerequisite for economic sustainability—An empirical examination of influencing factors. *Sustainability*, *14*(8), 4554.
Khalifa, M., & Liu, V. (2007). Online consumer retention: contingent effects of online shopping habit and online shopping experience. *European Journal of Information Systems*, *16*, 780-792.
Khan, A., Rezaei, S., & Valaei, N. (2022). Social commerce advertising avoidance and shopping cart abandonment: A fs/QCA analysis of German consumers. *Journal of Retailing and Consumer Services*, *67*, 102976. https://doi.org/https://doi.org/10.1016/j.jretconser.2022.102976
Kim, C., Galliers, R. D., Shin, N., Ryoo, J.-H., & Kim, J. (2012). Factors influencing Internet shopping value and customer repurchase intention. *Electronic Commerce Research and Applications*, *11*(4), 374-387.
Kim, H.-W., Xu, Y., & Gupta, S. (2012). Which is more important in Internet shopping, perceived price or trust? *Electronic Commerce Research and Applications*, *11*(3), 241-252.
Kim, J., Fiore, A. M., & Lee, H.-H. (2007). Influences of online store perception, shopping enjoyment, and shopping involvement on consumer patronage behavior towards an online retailer. *Journal of Retailing and Consumer Services*, *14*(2), 95-107.
Kim, J., & Lee, J. (2002). Critical design factors for successful e-commerce systems. *Behaviour & Information Technology*, *21*(3), 185-199.
Kim, J., & Wansink, B. (2012). How retailers' recommendation and return policies alter product evaluations. *Journal of retailing*, *88*(4), 528-541.
Kim, S., & Stoel, L. (2004). Apparel retailers: website quality dimensions and satisfaction. *Journal of Retailing and Consumer Services*, *11*(2), 109-117.
Kim, Y. A., & Srivastava, J. (2007). Impact of social influence in e-commerce decision making. Proceedings of the ninth international conference on Electronic commerce,
Kitapci, O., Akdogan, C., & Dortyol, I. T. (2014). The impact of service quality dimensions on patient satisfaction, repurchase intentions and word-of-mouth communication in the public healthcare industry. *Procedia-Social and Behavioral Sciences*, *148*, 161-169.
Kittell-Limerick, P. (2005). *Perceived barriers to completion of the academic doctorate: A Delphi study*. Texas A&M University-Commerce.
Klassen, R. M., & Klassen, J. R. (2018). Self-efficacy beliefs of medical students: a critical review. *Perspectives on medical education*, *7*, 76-82.
Klein, N. M., & Yadav, M. S. (1989). Context effects on effort and accuracy in choice: An enquiry into adaptive decision making. *Journal of Consumer Research*, *15*(4), 411-421.
Kocak, H., Caglar, A., & Oztas, G. Z. (2018). Euclidean best–worst method and its application. *International Journal of Information Technology & Decision Making*, *17*(05), 1587-1605.

Kodinariya, T. M., & Makwana, P. R. (2013). Review on determining number of Cluster in K-Means Clustering. *International Journal*, *1*(6), 90-95.
Kohli, R., Devaraj, S., & Mahmood, M. A. (2004). Understanding determinants of online consumer satisfaction: A decision process perspective. *Journal of management information systems*, 115-135.
Köksalan, M., Wallenius, J., & Zionts, S. (2016). An early history of multiple criteria decision making. *Multiple Criteria Decision Analysis: State of the Art Surveys*, 3-17.
Köksalan, M. M., Wallenius, J., & Zionts, S. (2011). *Multiple criteria decision making: from early history to the 21st century*. World Scientific.
Kollmann, T., Kuckertz, A., & Kayser, I. (2012). Cannibalization or synergy? Consumers' channel selection in online–offline multichannel systems. *Journal of Retailing and Consumer Services*, *19*(2), 186-194.
Koo, D. M., Kim, J. J., & Lee, S. H. (2008). Personal values as underlying motives of shopping online. *Asia Pacific Journal of Marketing and Logistics*, *20*(2), 156-173.
Kooti, F., Lerman, K., Aiello, L. M., Grbovic, M., Djuric, N., & Radosavljevic, V. (2016). Portrait of an online shopper: Understanding and predicting consumer behavior. Proceedings of the ninth ACM international conference on web search and data mining,
Korfiatis, N., García-Bariocanal, E., & Sánchez-Alonso, S. (2012). Evaluating content quality and helpfulness of online product reviews: The interplay of review helpfulness vs. review content. *Electronic Commerce Research and Applications*, *11*(3), 205-217.
Kotler, P., & Keller, K. L. (2006). *Marketing Management*. Pearson Prentice Hall. https://books.google.co.nz/books?id=Bm_DQgAACAAJ
Kotler, P., & Keller, K. L. (2006). Marketing Management, Perarson Prenntice Hall. In: Pearson Education International.
Kukar-Kinney, M., & Close, A. G. (2010). The determinants of consumers' online shopping cart abandonment. *Journal of the academy of Marketing Science*, *38*, 240-250.
Kukar-Kinney, M., Scheinbaum, A. C., Orimoloye, L. O., Carlson, J. R., & He, H. (2022). A model of online shopping cart abandonment: Evidence from e-tail clickstream data. *Journal of the academy of Marketing Science*, *50*(5), 961-980.
Kumar, K., & Van Dissel, H. G. (1996). Sustainable collaboration: Managing conflict and cooperation in interorganizational systems. *MIS quarterly*, 279-300.
Kumar, R., Sachan, A., & Dutta, T. (2020). Examining the impact of e-retailing convenience dimensions on behavioral intention: The mediating role of satisfaction. *Journal of Internet Commerce*, *19*(4), 466-494.
Kuo, Y.-F. (2003). A study on service quality of virtual community websites. *Total Quality Management & Business Excellence*, *14*(4), 461-473.
Kuo, Y.-F., & Hou, J.-R. (2017). Oppositional brand loyalty in online brand communities: Perspectives on social identity theory and consumer-brand relationship. *Journal of electronic commerce research*, *18*(3), 254.
Kwark, Y., Chen, J., & Raghunathan, S. (2014). Online product reviews: Implications for retailers and competing manufacturers. *Information Systems Research*, *25*(1), 93-110.
Ladhari, R. (2009). A review of twenty years of SERVQUAL research. *International Journal of Quality and Service Sciences*, *1*(2), 172-198.
Lahdelma, R., Salminen, P., & Hokkanen, J. (2000). Using multicriteria methods in environmental planning and management. *Environmental management*, *26*, 595-605.
Lakens, D. (2022). Sample size justification. *Collabra: psychology*, *8*(1), 33267.
Landeta, J. (2006). Current validity of the Delphi method in social sciences. *Technological forecasting and social change*, *73*(5), 467-482. https://doi.org/https://doi.org/10.1016/j.techfore.2005.09.002
Lantz, B., & Hjort, K. (2013). Real e-customer behavioural responses to free delivery and free returns. *Electronic Commerce Research*, *13*, 183-198.
Larichev, O. (2000). Decision-making theory and methods. *Moscow: Logos (in Russian)*.
Laudon, K. C., & Traver, C. G. (2020). *E-commerce 2019: Business, technology, society*. Pearson.
Lăzăroiu, G., Neguriţă, O., Grecu, I., Grecu, G., & Mitran, P. C. (2020). Consumers' decision-making process on social commerce platforms: Online trust, perceived risk, and purchase intentions. *Frontiers in Psychology*, *11*, 890.

Le-Hoang, P. V. (2020). The relationship between online convenience, online customer satisfaction, buying intention and electronic word-of-mouth. *Independent Journal of Management & Production*, *11*(7), 2943-2966.
Le, D.-N., Van Le, C., Tromp, J. G., & Nguyen, G. N. (2018). Emerging technologies for health and medicine: virtual reality, augmented reality, artificial intelligence, internet of things, robotics, industry 4.0.
Learning, L. (2020). Introduction to retailing. *The evolution of retail. Portland: Module of Retail Management*.
Lee, G. G., & Lin, H. F. (2005). Customer perceptions of e-service quality in online shopping. *International Journal of Retail & Distribution Management*, *33*(2), 161-176.
Lee, J.-M., & Rha, J.-Y. (2016). Personalization–privacy paradox and consumer conflict with the use of location-based mobile commerce. *Computers in Human Behavior*, *63*, 453-462.
Lee, K.-W., Tsai, M.-T., & Lanting, M. C. L. (2011). From marketplace to marketspace: Investigating the consumer switch to online banking. *Electronic Commerce Research and Applications*, *10*(1), 115-125.
Lee, M. K., & Turban, E. (2001). A trust model for consumer internet shopping. *International Journal of electronic commerce*, *6*(1), 75-91.
Lee, P.-M. (2002). Behavioral model of online purchasers in e-commerce environment. *Electronic Commerce Research*, *2*, 75-85.
Lee, S. M. (2018). Innovation: from small “i” to large “I”. *International Journal of Quality Innovation*, *4*(1), 1-10.
Lee, S. M., & Lee, D. (2020). “Untact”: a new customer service strategy in the digital age. *Service Business*, *14*(1), 1-22.
Lee, T. H., & Hsieh, H.-P. (2016). Indicators of sustainable tourism: A case study from a Taiwan's wetland. *Ecological Indicators*, *67*, 779-787.
Leiner, B. M., Cerf, V. G., Clark, D. D., Kahn, R. E., Kleinrock, L., Lynch, D. C., Postel, J., Roberts, L. G., & Wolff, S. (2009). A brief history of the Internet. *ACM SIGCOMM computer communication review*, *39*(5), 22-31.
Łęski, J. (2003). Towards a robust fuzzy clustering. *Fuzzy sets and systems*, *137*(2), 215-233.
Leung, D., Law, R., & Lee, H. A. (2011). The perceived destination image of Hong Kong on Ctrip. com. *International journal of tourism research*, *13*(2), 124-140.
Levin, K. A. (2006). Study design III: Cross-sectional studies. *Evidence-based dentistry*, *7*(1), 24-25.
Lewis, M. (2004). The influence of loyalty programs and short-term promotions on customer retention. *Journal of marketing research*, *41*(3), 281-292.
Lewis, P. H. (1994). Attention shoppers: Internet is open. *The New York Times*, *12*(1).
Li, J., Luo, X., Lu, X., & Moriguchi, T. (2021). The double-edged effects of e-commerce cart retargeting: does retargeting too early backfire? *Journal of marketing*, *85*(4), 123-140.
Li, Y.-M., Wu, C.-T., & Lai, C.-Y. (2013). A social recommender mechanism for e-commerce: Combining similarity, trust, and relationship. *Decision Support Systems*, *55*(3), 740-752.
Li, Y., Chu, X., Tian, D., Feng, J., & Mu, W. (2021). Customer segmentation using K-means clustering and the adaptive particle swarm optimization algorithm. *Applied Soft Computing*, *113*, 107924.
Lian, J.-W., & Yen, D. C. (2014). Online shopping drivers and barriers for older adults: Age and gender differences. *Computers in Human Behavior*, *37*, 133-143.
Liao, H., Proctor, R. W., & Salvendy, G. (2008). Content preparation for cross-cultural e-commerce: a review and a model. *Behaviour & Information Technology*, *27*(1), 43-61. https://doi.org/10.1080/01449290601088424
Liao, T.-H., & Keng, C.-J. (2013). Online shopping delivery delay: Finding a psychological recovery strategy by online consumer experiences. *Computers in Human Behavior*, *29*(4), 1849-1861.
Lim, H., & Dubinsky, A. J. (2004). Consumers' perceptions of e-shopping characteristics: an expectancy-value approach. *Journal of services Marketing*, *18*(7), 500-513.
Lim, J. S., & O'Connor, M. (1996). Judgmental forecasting with time series and causal information. *International Journal of Forecasting*, *12*(1), 139-153.
Lim, Y. J., Osman, A., Salahuddin, S. N., Romle, A. R., & Abdullah, S. (2016). Factors influencing online shopping behavior: the mediating role of purchase intention. *Procedia economics and finance*, *35*, 401-410.
Lin, C. C. (2003). A critical appraisal of customer satisfaction and e-commerce. *Managerial Auditing Journal*, *18*(3), 202-212.

Ling, K. C., Chai, L. T., & Piew, T. H. (2010). The effects of shopping orientations, online trust and prior online purchase experience toward customers' online purchase intention. *International business research*, *3*(3), 63.
Linstone, H. A., & Turoff, M. (1975). *The delphi method*. Addison-Wesley Reading, MA.
Lissitsa, S., & Kol, O. (2016). Generation X vs. Generation Y – A decade of online shopping. *Journal of Retailing and Consumer Services*, *31*, 304-312. https://doi.org/https://doi.org/10.1016/j.jretconser.2016.04.015
Liu, C., & Arnett, K. P. (2000). Exploring the factors associated with Web site success in the context of electronic commerce. *Information & Management*, *38*(1), 23-33.
Liu, X., He, M., Gao, F., & Xie, P. (2008). An empirical study of online shopping customer satisfaction in China: a holistic perspective. *International Journal of Retail & Distribution Management*, *36*(11), 919-940.
Liu, Y., Soroka, A., Han, L., Jian, J., & Tang, M. (2020). Cloud-based big data analytics for customer insight-driven design innovation in SMEs. *International Journal of Information Management*, *51*, 102034.
Liu, Z., & Park, S. (2015). What makes a useful online review? Implication for travel product websites. *Tourism Management*, *47*, 140-151.
Loiacono, E. T., Watson, R. T., & Goodhue, D. L. (2002). WebQual: A measure of website quality. *Marketing theory and applications*, *13*(3), 432-438.
Løken, E. (2007). Use of multicriteria decision analysis methods for energy planning problems. *Renewable and Sustainable Energy Reviews*, *11*(7), 1584-1595. https://doi.org/https://doi.org/10.1016/j.rser.2005.11.005
Loureiro, S. M., Cavallero, L., & Miranda, F. J. (2018). Fashion brands on retail websites: Customer performance expectancy and e-word-of-mouth. *Journal of Retailing and Consumer Services*, *41*, 131-141.
Lu, X., Ba, S., Huang, L., & Feng, Y. (2013). Promotional marketing or word-of-mouth? Evidence from online restaurant reviews. *Information Systems Research*, *24*(3), 596-612.
Lu, Y., Zhao, L., & Wang, B. (2010). From virtual community members to C2C e-commerce buyers: Trust in virtual communities and its effect on consumers' purchase intention. *Electronic Commerce Research and Applications*, *9*(4), 346-360.
Lunenburg, F. C. (2010). The decision making process. National Forum of Educational Administration & Supervision Journal,
Luo, J., Ba, S., & Zhang, H. (2012). The effectiveness of online shopping characteristics and well-designed websites on satisfaction. *MIS quarterly*, 1131-1144.
Luo, X., & Bhattacharya, C. B. (2006). Corporate social responsibility, customer satisfaction, and market value. *Journal of marketing*, *70*(4), 1-18.
Magatef, S. G., & Tomalieh, E. F. (2015). The impact of customer loyalty programs on customer retention. *International Journal of Business and Social Science*, *6*(8), 78-93.
Mahdiraji, H. A., Kazimieras Zavadskas, E., Kazeminia, A., & Abbasi Kamardi, A. (2019). Marketing strategies evaluation based on big data analysis: a CLUSTERING-MCDM approach. *Economic research-Ekonomska istraživanja*, *32*(1), 2882-2892.
Maity, M., & Dass, M. (2014). Consumer decision-making across modern and traditional channels: E-commerce, m-commerce, in-store. *Decision Support Systems*, *61*, 34-46.
Malhotra, N. K. (1983). On'Individual differences in search behavior for a nondurable'. *Journal of Consumer Research*, *10*(1), 125-131.
Malone, T. W., Yates, J., & Benjamin, R. I. (1987). Electronic markets and electronic hierarchies. *Communications of the ACM*, *30*(6), 484-497.
Marceda Bach, T., da Silva, W. V., Mendonça Souza, A., Kudlawicz-Franco, C., & da Veiga, C. P. (2020). Online customer behavior: perceptions regarding the types of risks incurred through online purchases. *Palgrave Communications*, *6*(1), 1-12.
March, J. G. (1994). *Primer on decision making: How decisions happen*. Simon and Schuster.
Martensen, A., Gronholdt, L., & Kristensen, K. (2000). The drivers of customer satisfaction and loyalty: cross-industry findings from Denmark. *Total quality management*, *11*(4-6), 544-553.
Maslowska, E., Malthouse, E. C., & Viswanathan, V. (2017). Do customer reviews drive purchase decisions? The moderating roles of review exposure and price. *Decision Support Systems*, *98*, 1-9.
Mason, A., Narcum, J., & Mason, K. (2020). Changes in consumer decision-making resulting from the COVID-19 pandemic. *Journal of Customer Behaviour*, *19*(4), 299-321.

Mason, K. J., & Alamdari, F. (2007). EU network carriers, low cost carriers and consumer behaviour: A Delphi study of future trends. *Journal of air transport management*, *13*(5), 299-310.
McCole, P., Ramsey, E., & Williams, J. (2010). Trust considerations on attitudes towards online purchasing: The moderating effect of privacy and security concerns. *Journal of business research*, *63*(9-10), 1018-1024.
McKnight, D. H., & Chervany, N. L. (2001). What trust means in e-commerce customer relationships: An interdisciplinary conceptual typology. *International Journal of electronic commerce*, *6*(2), 35-59.
Melis, K., Campo, K., Breugelmans, E., & Lamey, L. (2015). The impact of the multi-channel retail mix on online store choice: does online experience matter? *Journal of retailing*, *91*(2), 272-288.
Mergel, I., Rethemeyer, R. K., & Isett, K. (2016). Big data in public affairs. *Public Administration Review*, *76*(6), 928-937.
Meyer, H. (1999). Many happy returns. *The Journal of Business Strategy*, *20*(4), 27.
Meyer, S. (2020). The history and evolution of retail stores: from mom and pop to online shops. *Ecommerce News*.
Michaud Trevinal, A., & Stenger, T. (2014). Toward a conceptualization of the online shopping experience. *Journal of Retailing and Consumer Services*, *21*(3), 314-326. https://doi.org/https://doi.org/10.1016/j.jretconser.2014.02.009
Mir, M. A., Ghazvinei, P. T., Sulaiman, N., Basri, N., Saheri, S., Mahmood, N., Jahan, A., Begum, R., & Aghamohammadi, N. (2016). Application of TOPSIS and VIKOR improved versions in a multi criteria decision analysis to develop an optimized municipal solid waste management model. *Journal of environmental management*, *166*, 109-115.
Mishra, R., Singh, R. K., & Koles, B. (2021). Consumer decision-making in Omnichannel retailing: Literature review and future research agenda. *International Journal of Consumer Studies*, *45*(2), 147-174.
Mofokeng, T. E. (2021). The impact of online shopping attributes on customer satisfaction and loyalty: Moderating effects of e-commerce experience. *Cogent Business & Management*, *8*(1), 1968206.
Mohd-Any, A. A., Winklhofer, H., & Ennew, C. (2015). Measuring users' value experience on a travel website (e-value) what value is cocreated by the user? *Journal of Travel Research*, *54*(4), 496-510.
Moisander, J., Närvänen, E., & Valtonen, A. (2020). Interpretive marketing research: Using ethnography in strategic market development. In *Marketing management* (pp. 237-253). Routledge.
Moore, W. L., & Lehmann, D. R. (1980). Individual differences in search behavior for a nondurable. *Journal of Consumer Research*, *7*(3), 296-307.
Morales, J., Montes, R., Zermeno, N., Duran, J., & Herrera, F. (2018). The use of fuzzy linguistic information and fuzzy delphi method to validate by consensus a questionnaire in a blended-learning environment. International conference on information processing and Management of Uncertainty in knowledge-based systems,
Mosavi, S. M., Sangari, M. S., & Keramati, A. (2018). An integrative framework for customer switching behavior. *The Service Industries Journal*, *38*(15-16), 1067-1094.
Mosteller, J., Donthu, N., & Eroglu, S. (2014). The fluent online shopping experience. *Journal of business research*, *67*(11), 2486-2493.
Mousavizadeh, M., Kim, D. J., & Chen, R. (2016). Effects of assurance mechanisms and consumer concerns on online purchase decisions: An empirical study. *Decision Support Systems*, *92*, 79-90.
Mudambi, S. M., & Schuff, D. (2010). Research note: What makes a helpful online review? A study of customer reviews on Amazon. com. *MIS quarterly*, 185-200.
Mukhopadhyay, S. K., & Setaputra, R. (2007). A dynamic model for optimal design quality and return policies. *European journal of operational research*, *180*(3), 1144-1154.
Mullen, P. M. (2003). Delphi: myths and reality. *Journal of health organization and management*, *17*(1), 37-52.
Na, D. Y. (2011). The what, why, and how of mobile applications. *Connectivity and the User Experience*, *11*(1), 20-26.
Narang, M., Joshi, M., & Pal, A. (2021). A hybrid fuzzy COPRAS-base-criterion method for multi-criteria decision making. *Soft Computing*, *25*, 8391-8399.
Nayak, J., Naik, B., & Behera, H. (2015). Fuzzy C-means (FCM) clustering algorithm: a decade review from 2000 to 2014. Computational Intelligence in Data Mining-Volume 2: Proceedings of the International Conference on CIDM, 20-21 December 2014,

Negash, S., Ryan, T., & Igbaria, M. (2003). Quality and effectiveness in web-based customer support systems. *Information & Management*, *40*(8), 757-768.

Ngoc Thuy, P. (2011). Using service convenience to reduce perceived cost. *Marketing Intelligence & Planning*, *29*(5), 473-487.

Niranjanamurthy, M., Kavyashree, N., Jagannath, S., & Chahar, D. (2013). Analysis of e-commerce and m-commerce: advantages, limitations and security issues. *International Journal of Advanced Research in Computer and Communication Engineering*, *2*(6), 2360-2370.

Nisar, T. M., & Prabhakar, G. (2017). What factors determine e-satisfaction and consumer spending in e-commerce retailing? *Journal of Retailing and Consumer Services*, *39*, 135-144.

Nöjd, S., Trischler, J. W., Otterbring, T., Andersson, P. K., & Wästlund, E. (2020). Bridging the valuescape with digital technology: A mixed methods study on customers' value creation process in the physical retail space. *Journal of Retailing and Consumer Services*, *56*, 102161.

Nunan, D., & Di Domenico, M. (2019). Older consumers, digital marketing, and public policy: A review and research agenda. *Journal of Public Policy & Marketing*, *38*(4), 469-483.

Nutt, P. (1989). Making tough choices. In: Jossey-Bass, San Francisco, CA.

Nutt, P. C. (2003). Why decisions fail: Avoiding the blunders and traps that lead to debacles. In: Academy of Management Briarcliff Manor, NY 10510.

Nutt, P. C. (2008). Investigating the success of decision making processes. *Journal of Management Studies*, *45*(2), 425-455.

O. Pappas, I., G. Pateli, A., N. Giannakos, M., & Chrissikopoulos, V. (2014). Moderating effects of online shopping experience on customer satisfaction and repurchase intentions. *International Journal of Retail & Distribution Management*, *42*(3), 187-204.

Ogilvie, S. (2011). *Institutions and European trade: Merchant guilds, 1000–1800*. Cambridge University Press.

Oh, H., Animesh, A., & Pinsonneault, A. (2016). Free versus for-a-fee. *MIS quarterly*, *40*(1), 31-56.

Oláh, J., Kitukutha, N., Haddad, H., Pakurár, M., Máté, D., & Popp, J. (2019). Achieving Sustainable E-Commerce in Environmental, Social and Economic Dimensions by Taking Possible Trade-Offs. *Sustainability*, *11*(1).

Oliveira, A. (2007). A discussion of rational and psychological decision-making theories and models: The search for a cultural-ethical decision-making model. *Electronic journal of business ethics and organization studies*, *12*(2), 12-17.

Oliver, R. L. (1999). Whence consumer loyalty? *Journal of marketing*, *63*(4_suppl1), 33-44.

Olsen, S. O. (2007). Repurchase loyalty: The role of involvement and satisfaction. *Psychology & marketing*, *24*(4), 315-341.

P. Riquelme, I., & Román, S. (2014). Is the influence of privacy and security on online trust the same for all type of consumers? *Electronic Markets*, *24*, 135-149.

Pacini, R., & Epstein, S. (1999). The interaction of three facets of concrete thinking in a game of chance. *Thinking & Reasoning*, *5*(4), 303-325.

Pappas, I. O. (2018). User experience in personalized online shopping: a fuzzy-set analysis. *European Journal of marketing*, *52*(7/8), 1679-1703.

Pappas, I. O., Kourouthanassis, P. E., Giannakos, M. N., & Chrissikopoulos, V. (2016). Explaining online shopping behavior with fsQCA: The role of cognitive and affective perceptions. *Journal of business research*, *69*(2), 794-803.

Pappas, I. O., Kourouthanassis, P. E., Giannakos, M. N., & Chrissikopoulos, V. (2017). Sense and sensibility in personalized e-commerce: How emotions rebalance the purchase intentions of persuaded customers. *Psychology & marketing*, *34*(10), 972-986.

Parasuraman, A., Zeithaml, V. A., & Berry, L. (1988). SERVQUAL: A multiple-item scale for measuring consumer perceptions of service quality. *1988*, *64*(1), 12-40.

Parasuraman, A., Zeithaml, V. A., & Malhotra, A. (2005). ES-QUAL: A multiple-item scale for assessing electronic service quality. *Journal of service research*, *7*(3), 213-233.

Park, C.-H., & Kim, Y.-G. (2006). The effect of information satisfaction and relational benefit on consumers' online shopping site commitments. *Journal of Electronic Commerce in Organizations (JECO)*, *4*(1), 70-90.

Park, C., & Jun, J. K. (2003). A cross-cultural comparison of Internet buying behavior: Effects of Internet usage, perceived risks, and innovativeness. *International Marketing Review*, *20*(5), 534-553.

Park, C. H., & Kim, Y. G. (2003). Identifying key factors affecting consumer purchase behavior in an online shopping context. *International Journal of Retail & Distribution Management*, *31*(1), 16-29.
Park, I., Cho, J., & Rao, H. R. (2012). The effect of pre-and post-service performance on consumer evaluation of online retailers. *Decision Support Systems*, *52*(2), 415-426.
Park, J., Lennon, S. J., & Stoel, L. (2005). On-line product presentation: Effects on mood, perceived risk, and purchase intention. *Psychology & marketing*, *22*(9), 695-719.
Patil, D. R., & Rane, N. L. (2023). Customer experience and satisfaction: importance of customer reviews and customer value on buying preference. *International Research Journal of Modernization in Engineering Technology and Science*, *5*(3), 3437-3447.
Patton, J. R. (2003). Intuition in decisions. *Management decision*, *41*(10), 989-996.
Pauwels, K., Leeflang, P. S., Teerling, M. L., & Huizingh, K. E. (2011). Does online information drive offline revenues?: Only for specific products and consumer segments! *Journal of retailing*, *87*(1), 1-17.
Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International Journal of electronic commerce*, *7*(3), 101-134.
Pavlou, P. A., & Fygenson, M. (2006). Understanding and predicting electronic commerce adoption: An extension of the theory of planned behavior. *MIS quarterly*, 115-143.
Payne, J. W., Bettman, J. R., & Johnson, E. J. (1988). Adaptive strategy selection in decision making. *Journal of experimental psychology: Learning, Memory, and Cognition*, *14*(3), 534.
Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). *The adaptive decision maker*. Cambridge university press.
Peña-García, N., Gil-Saura, I., & Rodríguez-Orejuela, A. (2018). E-loyalty formation: A cross-cultural comparison of Spain and Colombia. *Journal of electronic commerce research*, *19*(4), 336-356.
Peštek, A., Resić, E., & Nožica, M. (2011). Model of trust in e-transactions. *Economic research-Ekonomska istraživanja*, *24*(3), 131-146.
Peters, G., Crespo, F., Lingras, P., & Weber, R. (2013). Soft clustering–fuzzy and rough approaches and their extensions and derivatives. *international Journal of Approximate reasoning*, *54*(2), 307-322.
Peterson, R. A., Balasubramanian, S., & Bronnenberg, B. J. (1997). Exploring the implications of the Internet for consumer marketing. *Journal of the academy of Marketing Science*, *25*, 329-346.
Petitjean, F., Ketterlin, A., & Gançarski, P. (2011). A global averaging method for dynamic time warping, with applications to clustering. *Pattern recognition*, *44*(3), 678-693.
Pipino, L. L., Lee, Y. W., & Wang, R. Y. (2002). Data quality assessment. *Communications of the ACM*, *45*(4), 211-218.
Pitta, D., Franzak, F., & Fowler, D. (2006). A strategic approach to building online customer loyalty: integrating customer profitability tiers. *Journal of consumer marketing*, *23*(7), 421-429.
Plous, S. (1993). *The psychology of judgment and decision making*. Mcgraw-Hill Book Company.
Poddar, A., Donthu, N., & Wei, Y. (2009). Web site customer orientations, Web site quality, and purchase intentions: The role of Web site personality. *Journal of business research*, *62*(4), 441-450.
Pohekar, S. D., & Ramachandran, M. (2004). Application of multi-criteria decision making to sustainable energy planning—A review. *Renewable and sustainable energy reviews*, *8*(4), 365-381.
Prensky, M. (2001). Digital natives, digital immigrants part 2: Do they really think differently? *On the horizon*.
Publishing, O. (2011). *OECD guide to measuring the information society 2011*. Organisation for Economic Co-operation and Development.
Qalati, S. A., Vela, E. G., Li, W., Dakhan, S. A., Hong Thuy, T. T., & Merani, S. H. (2021). Effects of perceived service quality, website quality, and reputation on purchase intention: The mediating and moderating roles of trust and perceived risk in online shopping. *Cogent Business & Management*, *8*(1), 1869363.
Qiu, J., Lin, Z., & Li, Y. (2015). Predicting customer purchase behavior in the e-commerce context. *Electronic Commerce Research*, *15*, 427-452.
Quelch, J. A., & Klein, L. R. (1996). The Internet and international marketing. *MIT Sloan Management Review*, *37*(3), 60.
Qureshi, I., Fang, Y., Ramsey, E., McCole, P., Ibbotson, P., & Compeau, D. (2009). Understanding online customer repurchasing intention and the mediating role of trust–an empirical investigation in two developed countries. *European Journal of Information Systems*, *18*, 205-222.

Raji, M. A., Olodo, H. B., Oke, T. T., Addy, W. A., Ofodile, O. C., & Oyewole, A. T. (2024). E-commerce and consumer behavior: A review of AI-powered personalization and market trends. *GSC Advanced Research and Reviews*, *18*(3), 066-077.

Rane, N. L., Achari, A., & Choudhary, S. P. (2023). Enhancing customer loyalty through quality of service: Effective strategies to improve customer satisfaction, experience, relationship, and engagement. *International Research Journal of Modernization in Engineering Technology and Science*, *5*(5), 427-452.

Rasheed, F. A., & Abadi, M. F. (2014). Impact of service quality, trust and perceived value on customer loyalty in Malaysia services industries. *Procedia-Social and Behavioral Sciences*, *164*, 298-304.

Rasiulis, R., Ustinovichius, L., Vilutienė, T., & Popov, V. (2016). Decision model for selection of modernization measures: public building case. *Journal of civil engineering and management*, *22*(1), 124-133.

Ravald, A., & Grönroos, C. (1996). The value concept and relationship marketing. *European Journal of marketing*, *30*(2), 19-30.

Reagan, J. R., & Singh, M. (2020). Management 4.0: Cases and Methods for the 4th Industrial Revolution.

Reinartz, W., Wiegand, N., & Imschloss, M. (2019). The impact of digital transformation on the retailing value chain. *International Journal of research in Marketing*, *36*(3), 350-366.

Ren, G., & Hong, T. (2019). Examining the relationship between specific negative emotions and the perceived helpfulness of online reviews. *Information Processing & Management*, *56*(4), 1425-1438.

Rezaei, J. (2015). Best-worst multi-criteria decision-making method. *Omega*, *53*, 49-57.

Rezaei, J. (2016). Best-worst multi-criteria decision-making method: Some properties and a linear model. *Omega*, *64*, 126-130. https://doi.org/https://doi.org/10.1016/j.omega.2015.12.001

Rezaei, J., Kothadiya, O., Tavasszy, L., & Kroesen, M. (2018). Quality assessment of airline baggage handling systems using SERVQUAL and BWM. *Tourism Management*, *66*, 85-93.

Richards, T. J., Hamilton, S. F., & Empen, J. (2017). Attribute search in online retailing. *American Journal of Agricultural Economics*, *99*(1), 1-18.

Rieger, W. G. (1986). Directions in Delphi developments: Dissertations and their quality. *Technological forecasting and social change*, *29*(2), 195-204.

Rita, P., Oliveira, T., & Farisa, A. (2019a). The impact of e-service quality and customer satisfaction on customer behavior in online shopping. *Heliyon*, *5*(10), e02690.

Rita, P., Oliveira, T., & Farisa, A. (2019b). The impact of e-service quality and customer satisfaction on customer behavior in online shopping. *Heliyon*, *5*(10).

Rita, P., & Ramos, R. F. (2022). Global Research Trends in Consumer Behavior and Sustainability in E-Commerce: A Bibliometric Analysis of the Knowledge Structure. *Sustainability*, *14*(15).

Ritter, S. M., & Dijksterhuis, A. (2014). Creativity—the unconscious foundations of the incubation period. *Frontiers in human neuroscience*, *8*, 215.

Ritter, T., & Pedersen, C. L. (2020). Digitization capability and the digitalization of business models in business-to-business firms: Past, present, and future. *Industrial Marketing Management*, *86*, 180-190.

Rodriguez, L. A. (2022). *Ventas online: Los pilares del canal online: satisfacción, seguridad y promoción colectiva*

Rodriguez, M. Z., Comin, C. H., Casanova, D., Bruno, O. M., Amancio, D. R., Costa, L. d. F., & Rodrigues, F. A. (2019). Clustering algorithms: A comparative approach. *PloS one*, *14*(1), e0210236.

Rosário, A., & Raimundo, R. (2021). Consumer Marketing Strategy and E-Commerce in the Last Decade: A Literature Review. *Journal of Theoretical and Applied Electronic Commerce Research*, *16*(7), 3003-3024.

Rout, K., Sahoo, P. R., Bhuyan, A., Tripathy, A., & Smrutirekha. (2022). Online grocery shopping behavior during COVID-19 pandemic: An interdisciplinary explanation. *Cogent Business & Management*, *9*(1), 2084969.

Rowe, G., & Wright, G. (1999). The Delphi technique as a forecasting tool: issues and analysis. *International Journal of Forecasting*, *15*(4), 353-375.

Rowley, J. (2000). Product search in e-shopping: a review and research propositions. *Journal of consumer marketing*, *17*(1), 20-35.

Roy Dholakia, R., & Zhao, M. (2010). Effects of online store attributes on customer satisfaction and repurchase intentions. *International Journal of Retail & Distribution Management*, *38*(7), 482-496.

Roy, S. K., Shekhar, V., Lassar, W. M., & Chen, T. (2018). Customer engagement behaviors: The role of service convenience, fairness and quality. *Journal of Retailing and Consumer Services*, *44*, 293-304.
Rubin, D., Martins, C., Ilyuk, V., & Hildebrand, D. (2020). Online shopping cart abandonment: A consumer mindset perspective. *Journal of consumer marketing*, *37*(5), 487-499.
Ruiz-Mafe, C., Chatzipanagiotou, K., & Curras-Perez, R. (2018). The role of emotions and conflicting online reviews on consumers' purchase intentions. *Journal of business research*, *89*, 336-344.
Rust, R. T., & Zahorik, A. J. (1993). Customer satisfaction, customer retention, and market share. *Journal of retailing*, *69*(2), 193-215.
Sadler-Smith, E. (2007). *Inside intuition*. Routledge.
Saffie, N. A. M., & Rasmani, K. A. (2016). Fuzzy delphi method: Issues and challenges. 2016 International Conference on Logistics, Informatics and Service Sciences (LISS),
Saha, S. K., Duarte, P., Silva, S. C., & Zhuang, G. (2021). Supporting sustainability by promoting online purchase through enhancement of online convenience. *Environment, Development and Sustainability*, *23*, 7251-7272.
Saha, S. K., Duarte, P., Silva, S. C., & Zhuang, G. (2023). The role of online experience in the relationship between service convenience and future purchase intentions. *Journal of Internet Commerce*, *22*(2), 244-271.
Sakrabani, P., & Teoh, A. P. (2021). Retail 4.0 adoption and firm performance among Malaysian retailers: the role of enterprise risk management as moderator. *International Journal of Retail & Distribution Management*, *49*(3), 359-376.
Sánchez-García, I., & Currás-Pérez, R. (2011). Effects of dissatisfaction in tourist services: The role of anger and regret. *Tourism Management*, *32*(6), 1397-1406.
Santos, J. (2003). E-service quality: a model of virtual service quality dimensions. *Managing service quality: An international journal*, *13*(3), 233-246.
Santos, V., Augusto, T., Vieira, J., Bacalhau, L., Sousa, B. M., & Pontes, D. (2023). E-commerce: issues, opportunities, challenges, and trends. *Promoting organizational performance through 5G and agile marketing*, 224-244.
Saunders, M., Lewis, P., & Thornhill, A. (2007). Research methods. *Business Students 4th edition Pearson Education Limited, England*, *6*(3), 1-268.
Saunders, M., Lewis, P., & Thornhill, A. (2009). *Research methods for business students*. Pearson education.
Sauter, V. L. (1999). Intuitive decision-making. *Communications of the ACM*, *42*(6), 109-115.
Schafer, J. B., Konstan, J. A., & Riedl, J. (2001). E-commerce recommendation applications. *Data mining and knowledge discovery*, *5*, 115-153.
Schindler, R. M., & Bickart, B. (2012). Perceived helpfulness of online consumer reviews: The role of message content and style. *Journal of Consumer Behaviour*, *11*(3), 234-243.
Schmidt, J. B., & Spreng, R. A. (1996). A proposed model of external consumer information search. *Journal of the academy of Marketing Science*, *24*, 246-256.
Schmidt, S., Cantallops, A. S., & dos Santos, C. P. (2008). The characteristics of hotel websites and their implications for website effectiveness. *International journal of hospitality management*, *27*(4), 504-516.
Schoenfeld, A. H. (2010). *How we think: A theory of goal-oriented decision making and its educational applications*. Routledge.
Scholz, M., Franz, M., & Hinz, O. (2017). Effects of decision space information on MAUT-based systems that support purchase decision processes. *Decision Support Systems*, *97*, 43-57.
Scott, S. G., & Bruce, R. A. (1995). Decision-making style: The development and assessment of a new measure. *Educational and psychological measurement*, *55*(5), 818-831.
Seal, K. (1990). Decision-makers rely on honed intuition. *Hotel and Motel Management*, *205*.
Seefeldt, D., & Thomas III, W. G. (2009). What is digital history? A look at some exemplar projects.
Seiders, K., Berry, L. L., & Gresham, L. G. (2000). Attention, retailers! How convenient is your convenience strategy? *MIT Sloan Management Review*, *41*(3), 79.
Shadkam, M., & O'Hara, J. (2013). Social commerce dimensions: The potential leverage for marketers. *Journal of Internet Banking and Commerce*, *18*(1), 1.
Shankar, V. (2018). How artificial intelligence (AI) is reshaping retailing. *Journal of retailing*, *94*(4), vi-xi.
Sharma, G., & Lijuan, W. (2015). The effects of online service quality of e-commerce Websites on user satisfaction. *The electronic library*, *33*(3), 468-485.

Sharma, K. (2020). A surge in e-commerce market in India after COVID-19 pandemic. *Gap gyan-a global journal of social sciences*, *3*(4), 54-57.
Shen, C.-C., & Chiou, J.-S. (2010). The impact of perceived ease of use on Internet service adoption: The moderating effects of temporal distance and perceived risk. *Computers in Human Behavior*, *26*(1), 42-50.
Shen, X.-L., Li, Y.-J., Sun, Y., & Wang, N. (2018). Channel integration quality, perceived fluency and omnichannel service usage: The moderating roles of internal and external usage experience. *Decision Support Systems*, *109*, 61-73.
Shin, D. D. (2019). Blockchain: The emerging technology of digital trust. *Telematics and informatics*, *45*, 101278.
Shocker, A. D., Ben-Akiva, M., Boccara, B., & Nedungadi, P. (1991). Consideration set influences on consumer decision-making and choice: Issues, models, and suggestions. *Marketing letters*, *2*, 181-197.
Sieck, W. R., & Arkes, H. R. (2005). The recalcitrance of overconfidence and its contribution to decision aid neglect. *Journal of behavioral decision making*, *18*(1), 29-53.
Siering, M., Muntermann, J., & Rajagopalan, B. (2018). Explaining and predicting online review helpfulness: The role of content and reviewer-related signals. *Decision Support Systems*, *108*, 1-12.
Simakov, V. (2020). History of formation of e-commerce enterprises as subjects of innovative entrepreneurship. *Three Seas Economic Journal*, *1*(1), 84-90.
Singh, A. (2014). Supplier evaluation and demand allocation among suppliers in a supply chain. *Journal of Purchasing and Supply Management*, *20*(3), 167-176.
Sismeiro, C., & Bucklin, R. E. (2004). Modeling purchase behavior at an e-commerce web site: A task-completion approach. *Journal of marketing research*, *41*(3), 306-323.
Skulmoski, G. J., Hartman, F. T., & Krahn, J. (2007). The Delphi method for graduate research. *Journal of Information Technology Education: Research*, *6*(1), 1-21.
Słowiński, R. (1986). A multicriteria fuzzy linear programming method for water supply system development planning. *Fuzzy Sets and Systems*, *19*(3), 217-237. https://doi.org/https://doi.org/10.1016/0165-0114(86)90052-7
smallbusiness.chron.com. (2020, September 10, 2020). *Concept of Consumer-Switching Behavior*. Chron Contributor.
Smink, A. R., Frowijn, S., van Reijmersdal, E. A., van Noort, G., & Neijens, P. C. (2019). Try online before you buy: How does shopping with augmented reality affect brand responses and personal data disclosure. *Electronic Commerce Research and Applications*, *35*, 100854.
Smith, A. (2019). *Consumer behaviour and analytics*. Routledge.
Smith, A. D., & Rupp, W. T. (2003). Strategic online customer decision making: leveraging the transformational power of the Internet. *Online information review*, *27*(6), 418-432.
Smith, M. D., & Brynjolfsson, E. (2001). Consumer decision-making at an Internet shopbot: Brand still matters. *The Journal of Industrial Economics*, *49*(4), 541-558.
Smolka, K. M., Verheul, I., Burmeister–Lamp, K., & Heugens, P. P. (2018). Get it together! Synergistic effects of causal and effectual decision–making logics on venture performance. *Entrepreneurship Theory and Practice*, *42*(4), 571-604.
Soni, V. D. (2020). Emerging roles of artificial intelligence in ecommerce. *International Journal of trend in scientific research and development*, *4*(5), 223-225.
Soopramanien, D. (2011). Conflicting attitudes and scepticism towards online shopping: The role of experience. *International Journal of Consumer Studies*, *35*(3), 338-347.
Soutjis, B., Cochoy, F., & Hagberg, J. (2017). An ethnography of Electronic Shelf Labels: The resisted digitalization of prices in contemporary supermarkets. *Journal of Retailing and Consumer Services*, *39*, 296-304.
Srinivasan, S. S., Anderson, R., & Ponnavolu, K. (2002). Customer loyalty in e-commerce: an exploration of its antecedents and consequences. *Journal of retailing*, *78*(1), 41-50.
Steel, W., Daglish, T., Marriott, L., Gemmell, N., & Howell, B. (2013). E-Commerce and its effect upon the Retail Industry and Government Revenue.
Stewart, T. J. (1992). A critical survey on the status of multiple criteria decision making theory and practice. *Omega*, *20*(5-6), 569-586.

Su, Q., & Chen, L. (2015). A method for discovering clusters of e-commerce interest patterns using click-stream data. *Electronic Commerce Research and Applications*, *14*(1), 1-13. https://doi.org/https://doi.org/10.1016/j.elerap.2014.10.002
Subramoniam, R., Huisingh, D., Chinnam, R. B., & Subramoniam, S. (2013). Remanufacturing Decision-Making Framework (RDMF): research validation using the analytical hierarchical process. *Journal of Cleaner Production*, *40*, 212-220.
Suh, B., & Han, I. (2003). The impact of customer trust and perception of security control on the acceptance of electronic commerce. *International Journal of electronic commerce*, *7*(3), 135-161.
Sulich, A., Sołoducho-Pelc, L., & Ferasso, M. (2021). Management Styles and Decision-Making: Pro-Ecological Strategy Approach. *Sustainability*, *13*(4).
Susiang, M. I. N., Suryaningrum, D. A., Masliardi, A., Setiawan, E., & Abdillah, F. (2023). Enhancing customer experience through effective marketing strategies: The context of online shopping. *SEIKO: Journal of Management & Business*, *6*(2), 437-447.
Szmidt, E., & Kacprzyk, J. (2001). Entropy for intuitionistic fuzzy sets. *Fuzzy Sets and Systems*, *118*(3), 467-477.
Szmidt, E., & Kacprzyk, J. (2002). Using intuitionistic fuzzy sets in group decision making. *Control and cybernetics*, *31*(4), 1055-1057.
Tamošaitienė, J., & Gaudutis, E. (2013). Complex assessment of structural systems used for high-rise buildings. *Journal of civil engineering and management*, *19*(2), 305-317.
Tang, H., & Lin, X. (2019). Curbing shopping cart abandonment in C2C markets—An uncertainty reduction approach. *Electronic Markets*, *29*, 533-552.
Taylor, D. G., & Strutton, D. (2010). Has e-marketing come of age? Modeling historical influences on post-adoption era Internet consumer behaviors. *Journal of business research*, *63*(9-10), 950-956.
Taylor, K. (2019). The retail apocalypse is far from over as analysts predict 75,000 more store closures. *Business Insider*, *9*.
Teshnizi, S. H., Aghamolaei, T., Kahnouji, K., Teshnizi, S. M. H., & Ghani, J. (2018). Assessing quality of health services with the SERVQUAL model in Iran. A systematic review and meta-analysis. *International Journal for Quality in Health Care*, *30*(2), 82-89.
Tetlock, P. E., Peterson, R. S., & Berry, J. M. (1993). Flattering and unflattering personality portraits of integratively simple and complex managers. *Journal of Personality and Social Psychology*, *64*(3), 500.
Thakur, R. (2018). Customer engagement and online reviews. *Journal of Retailing and Consumer Services*, *41*, 48-59.
Thorne, P. (1990). Another critique of pure reason. *International Management*, *45*, 68.
Tiago, F., Gil, A., Stemberger, S., & Borges-Tiago, T. (2021). Digital sustainability communication in tourism. *Journal of Innovation & Knowledge*, *6*(1), 27-34.
Tian, Z.-p., Wang, J.-q., & Zhang, H.-y. (2018). An integrated approach for failure mode and effects analysis based on fuzzy best-worst, relative entropy, and VIKOR methods. *Applied Soft Computing*, *72*, 636-646.
Tonietto, J., & Carbonneau, A. (2004a). A multicriteria climatic classification system for grape-growing regions worldwide. *Agricultural and Forest Meteorology*, *124*(1), 81-97. https://doi.org/https://doi.org/10.1016/j.agrformet.2003.06.001
Tonietto, J., & Carbonneau, A. (2004b). A multicriteria climatic classification system for grape-growing regions worldwide. *Agricultural and Forest Meteorology*, *124*(1-2), 81-97.
Torkayesh, A. E., Deveci, M., Karagoz, S., & Antucheviciene, J. (2023). A state-of-the-art survey of evaluation based on distance from average solution (EDAS): Developments and applications. *Expert Systems with Applications*, *221*, 119724.
Tran, V. D. (2020). The relationship among product risk, perceived satisfaction and purchase intentions for online shopping. *The Journal of Asian Finance, Economics and Business*, *7*(6), 221-231.
Trautman, L. J. (2015). E-Commerce, cyber, and electronic payment system risks: lessons from PayPal. *UC Davis Bus. LJ*, *16*, 261.
Trevinal, A. M., & Stenger, T. (2014). Toward a conceptualization of the online shopping experience. *Journal of Retailing and Consumer Services*, *21*(3), 314-326.
Triantaphyllou, E., & Lin, C.-T. (1996). Development and evaluation of five fuzzy multiattribute decision-making methods. *international Journal of Approximate reasoning*, *14*(4), 281-310.
Triantaphyllou, E., & Triantaphyllou, E. (2000). *Multi-criteria decision making methods*. Springer.

Tsai, H.-C., Lee, A.-S., Lee, H.-N., Chen, C.-N., & Liu, Y.-C. (2020). An application of the fuzzy Delphi method and fuzzy AHP on the discussion of training indicators for the regional competition, Taiwan national skills competition, in the trade of joinery. *Sustainability*, *12*(10), 4290.

Tsao, W.-C., Hsieh, M.-T., & Lin, T. M. (2016). Intensifying online loyalty! The power of website quality and the perceived value of consumer/seller relationship. *Industrial Management & Data Systems*, *116*(9), 1987-2010.

Tsao, W.-C., & Tseng, Y.-L. (2011). The impact of electronic-service quality on online shopping behaviour. *Total Quality Management & Business Excellence*, *22*(9), 1007-1024.

Tseng, F.-C., Cheng, T., Li, K., & Teng, C.-I. (2017). How does media richness contribute to customer loyalty to mobile instant messaging? *Internet Research*, *27*(3), 520-537.

Turanoglu Bekar, E., Cakmakci, M., & Kahraman, C. (2016). Fuzzy COPRAS method for performance measurement in total productive maintenance: a comparative analysis. *Journal of Business Economics and Management*, *17*(5), 663-684.

Turel, O., & Connelly, C. E. (2013). Too busy to help: Antecedents and outcomes of interactional justice in web-based service encounters. *International Journal of Information Management*, *33*(4), 674-683.

Turoff, M., & Linstone, H. A. (2002). The Delphi method-techniques and applications.

Turow, J. (2017). *The aisles have eyes: How retailers track your shopping, strip your privacy, and define your power*. Yale University Press.

Udo, G. J., Bagchi, K. K., & Kirs, P. J. (2010). An assessment of customers'e-service quality perception, satisfaction and intention. *International Journal of Information Management*, *30*(6), 481-492.

Uhl, M. W. (2011). Explaining US consumer behavior with news sentiment. *ACM Transactions on Management Information Systems (TMIS)*, *2*(2), 1-18.

Uzelac, B., Bauer, F., Matzler, K., & Waschak, M. (2016). The moderating effects of decision-making preferences on M&A integration speed and performance. *The International Journal of Human Resource Management*, *27*(20), 2436-2460.

Van den Poel, D., & Buckinx, W. (2005). Predicting online-purchasing behaviour. *European journal of operational research*, *166*(2), 557-575.

Van Leekwijck, W., & Kerre, E. E. (1999). Defuzzification: criteria and classification. *Fuzzy Sets and Systems*, *108*(2), 159-178.

Van Riel, A. C., Liljander, V., & Jurriens, P. (2001). Exploring consumer evaluations of e-services: a portal site. *International Journal of Service Industry Management*, *12*(4), 359-377.

Vargo, S. L., & Lusch, R. F. (2004). Evolving to a new dominant logic for marketing. *Journal of marketing*, *68*(1), 1-17.

Vargo, S. L., & Lusch, R. F. (2008). Service-dominant logic: continuing the evolution. *Journal of the academy of Marketing Science*, *36*, 1-10.

Vargo, S. L., & Lusch, R. F. (2016). Institutions and axioms: an extension and update of service-dominant logic. *Journal of the academy of Marketing Science*, *44*, 5-23.

Velicer, W. F., & Jackson, D. N. (1990). Component analysis versus common factor analysis: Some issues in selecting an appropriate procedure. *Multivariate behavioral research*, *25*(1), 1-28.

Venkatesh, V., & Morris, M. G. (2000). Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior. *MIS quarterly*, 115-139.

Venkatraman, N., & Zaheer, A. (1990). Electronic integration and strategic advantage: a quasi-experimental study in the insurance industry. *Information Systems Research*, *1*(4), 377-393.

Vidal, E., & Mitchell, W. (2013). When Do First Entrants Become First Survivors? *Long Range Planning*, *46*(4), 335-347. https://doi.org/https://doi.org/10.1016/j.lrp.2013.06.006

Wallenius, J., Dyer, J. S., Fishburn, P. C., Steuer, R. E., Zionts, S., & Deb, K. (2008). Multiple criteria decision making, multiattribute utility theory: Recent accomplishments and what lies ahead. *Management Science*, *54*(7), 1336-1349.

Walton, S. History of Walmart.

Wang, L., Law, R., Guillet, B. D., Hung, K., & Fong, D. K. C. (2015). Impact of hotel website quality on online booking intentions: eTrust as a mediator. *International journal of hospitality management*, *47*, 108-115.

Wang, M., Sun, Y., & Sweetapple, C. (2017). Optimization of storage tank locations in an urban stormwater drainage system using a two-stage approach. *Journal of environmental management*, *204*, 31-38.

Wang, S., Cheah, J.-H., Lim, X.-J., Leong, Y. C., & Choo, W. C. (2022). Thanks COVID-19, I'll reconsider my purchase: Can fear appeal reduce online shopping cart abandonment? *Journal of Retailing and Consumer Services*, *64*, 102843.
Wang, W., Dong, C., Dong, W., Yang, C., Ju, T., Huang, L., & Ren, Z. (2016). The design and implementation of risk assessment model for hazard installations based on AHP–FCE method: A case study of Nansi Lake Basin. *Ecological Informatics*, *36*, 162-171.
Wang, W., Pedrycz, W., & Liu, X. (2015). Time series long-term forecasting model based on information granules and fuzzy clustering. *Engineering Applications of Artificial Intelligence*, *41*, 17-24.
Wang, X., & Cheng, Z. (2020). Cross-sectional studies: strengths, weaknesses, and recommendations. *Chest*, *158*(1), S65-S71.
Wang, Y., Ma, H.-S., Yang, J.-H., & Wang, K.-S. (2017). Industry 4.0: a way from mass customization to mass personalization production. *Advances in manufacturing*, *5*, 311-320.
Wang, Y., & Ruhe, G. (2007). The cognitive process of decision making. *International Journal of Cognitive Informatics and Natural Intelligence (IJCINI)*, *1*(2), 73-85.
Wang, Y. D., & Emurian, H. H. (2005). An overview of online trust: Concepts, elements, and implications. *Computers in Human Behavior*, *21*(1), 105-125.
Wassouf, W. N., Alkhatib, R., Salloum, K., & Balloul, S. (2020). Predictive analytics using big data for increased customer loyalty: Syriatel Telecom Company case study. *Journal of Big Data*, *7*, 1-24.
Watson, G. F., Beck, J. T., Henderson, C. M., & Palmatier, R. W. (2015). Building, measuring, and profiting from customer loyalty. *Journal of the academy of Marketing Science*, *43*, 790-825.
Wei, P.-S., & Lu, H.-P. (2013). An examination of the celebrity endorsements and online customer reviews influence female consumers' shopping behavior. *Computers in Human Behavior*, *29*(1), 193-201.
Weinman, J. (2015). The cloud and the economics of the user and customer experience. *IEEE Cloud Computing*, *2*(6), 74-78.
Wigand, R. T. (1997). Electronic commerce: Definition, theory, and context. *The information society*, *13*(1), 1-16.
Williamson, O. E., & Mueller, D. C. (1986). The Economic Institutions of Capitalism. *Antitrust Bulletin*.
Wind, Y. J., & Mahajan, V. (2002). *Digital marketing: global strategies from the world's leading experts*. John Wiley & Sons.
Winterman, D., & Kelly, J. (2013). Online shopping: The pensioner who pioneered a home shopping revolution. *BBC. https://www. bbc. co. uk/news/magazine-24091393*.
Wirtz, J., Xiao, P., Chiang, J., & Malhotra, N. (2014). Contrasting the drivers of switching intent and switching behavior in contractual service settings. *Journal of retailing*, *90*(4), 463-480.
Wolfinbarger, M., & Gilly, M. C. (2001). Shopping online for freedom, control, and fun. *California Management Review*, *43*(2), 34-55.
Wolfinbarger, M., & Gilly, M. C. (2003). eTailQ: dimensionalizing, measuring and predicting etail quality. *Journal of retailing*, *79*(3), 183-198.
Wright, R. (2020, 20 June 2020). The challenges, the opportunities: past Covid-19 Lockdown retail trends.
Wu, J.-J., Chen, Y.-H., & Chung, Y.-S. (2010). Trust factors influencing virtual community members: A study of transaction communities. *Journal of business research*, *63*(9-10), 1025-1032.
Wu, J.-J., Hwang, J.-N., Sharkhuu, O., & Tsogt-Ochir, B. (2018). Shopping online and off-line? Complementary service quality and image congruence. *Asia Pacific Management Review*, *23*(1), 30-36.
Wu, K.-L., & Yang, M.-S. (2002). Alternative c-means clustering algorithms. *Pattern recognition*, *35*(10), 2267-2278.
Wu, L.-Y., Chen, K.-Y., Chen, P.-Y., & Cheng, S.-L. (2014). Perceived value, transaction cost, and repurchase-intention in online shopping: A relational exchange perspective. *Journal of business research*, *67*(1), 2768-2776.
Wu, L. L., & Lin, J. Y. (2006). The quality of consumers' decision-making in the environment of e-commerce. *Psychology & marketing*, *23*(4), 297-311.
Wu, Q., Zhou, L., Chen, Y., & Chen, H. (2019). An integrated approach to green supplier selection based on the interval type-2 fuzzy best-worst and extended VIKOR methods. *Information Sciences*, *502*, 394-417. https://doi.org/https://doi.org/10.1016/j.ins.2019.06.049
Xiao, B., & Benbasat, I. (2018). An empirical examination of the influence of biased personalized product recommendations on consumers' decision making outcomes. *Decision Support Systems*, *110*, 46-57.

Xiao, Y., He, W., Zhu, Y., & Zhu, J. (2022). A click-through rate model of e-commerce based on user interest and temporal behavior. *Expert Systems with Applications*, *207*, 117896.
Xie, K., Wu, Y., Xiao, J., & Hu, Q. (2016). Value co-creation between firms and customers: The role of big data-based cooperative assets. *Information & Management*, *53*(8), 1034-1048.
Xie, K. L., & Kwok, L. (2017). The effects of Airbnb's price positioning on hotel performance. *International journal of hospitality management*, *67*, 174-184.
Xu, X., Wu, J.-H., & Li, Q. (2020). What drives consumer shopping behavior in live streaming commerce? *Journal of electronic commerce research*, *21*(3), 144-167.
Xu, Y., & Huang, J.-S. (2015). Factors influencing cart abandonment in the online shopping process. *Social Behavior and Personality: an international journal*, *43*(10), 1617-1627.
Yan, R. (2009). Product categories, returns policy and pricing strategy for e-marketers. *Journal of Product & Brand Management*, *18*(6), 452-460.
Yang, L., Xu, M., & Xing, L. (2022). Exploring the core factors of online purchase decisions by building an E-Commerce network evolution model. *Journal of Retailing and Consumer Services*, *64*, 102784.
Yang, Y., Yang, L., Chen, H., Yang, J., & Fan, C. (2020). Risk factors of consumer switching behaviour for cross-border e-commerce mobile platform. *International Journal of Mobile Communications*, *18*(6), 641-664.
Yang, Z. (2001). Consumer perceptions of service quality in Internet-based electronic commerce.
Yang, Z., Jiang, S., Yu, F., Pedrycz, W., Yang, H., & Hao, Y. (2022). Linear Fuzzy Information-Granule-Based Fuzzy $ C $-Means Algorithm for Clustering Time Series. *IEEE transactions on cybernetics*.
Yang, Z., & Jun, M. (2002). Consumer perception of e-service quality: from internet purchaser and non-purchaser perspectives. *Journal of Business Strategies*, *19*(1), 19-42.
Yazdani, M., Alidoosti, A., & Zavadskas, E. K. (2011). Risk analysis of critical infrastructures using fuzzy COPRAS. *Economic research-Ekonomska istraživanja*, *24*(4), 27-40.
Yeo, V. C. S., Goh, S.-K., & Rezaei, S. (2017). Consumer experiences, attitude and behavioral intention toward online food delivery (OFD) services. *Journal of Retailing and Consumer Services*, *35*, 150-162.
Yin, X., Wang, H., Xia, Q., & Gu, Q. (2019). How social interaction affects purchase intention in social commerce: A cultural perspective. *Sustainability*, *11*(8), 2423.
Yoon, K. P., & Hwang, C.-L. (1995). *Multiple attribute decision making: an introduction*. Sage publications.
Yoseph, F., Ahamed Hassain Malim, N. H., Heikkilä, M., Brezulianu, A., Geman, O., & Paskhal Rostam, N. A. (2020). The impact of big data market segmentation using data mining and clustering techniques. *Journal of Intelligent & Fuzzy Systems*, *38*, 6159-6173. https://doi.org/10.3233/JIFS-179698
Yu, L., Wang, S., & Lai, K. K. (2009). An intelligent-agent-based fuzzy group decision making model for financial multicriteria decision support: The case of credit scoring. *European Journal of Operational Research*, *195*(3), 942-959. https://doi.org/https://doi.org/10.1016/j.ejor.2007.11.025
Yu, R. (2017). Looking back on 40 years of retail- top tips for the future.
Zadeh, L. (1965). Fuzzy sets. *Inform Control*, *8*, 338-353.
Zadeh, L. A. (1997). Toward a theory of fuzzy information granulation and its centrality in human reasoning and fuzzy logic. *Fuzzy sets and systems*, *90*(2), 111-127.
Zamil, A., Al Adwan, A., & Vasista, T. (2020). Enhancing customer loyalty with market basket analysis using innovative methods: a python implementation approach. *International Journal of Innovation, Creativity and Change*, *14*(2), 1351-1368.
Zangana, H. M., & Abdulazeez, A. M. (2023). Developed Clustering Algorithms for Engineering Applications: A Review. *International Journal of Informatics, Information System and Computer Engineering (INJIISCOM)*, *4*(2), 147-169.
Zarbakhshnia, N., Soleimani, H., & Ghaderi, H. (2018). Sustainable third-party reverse logistics provider evaluation and selection using fuzzy SWARA and developed fuzzy COPRAS in the presence of risk criteria. *Applied Soft Computing*, *65*, 307-319.
Zavadskas, E. K., & Antucheviciene, J. (2007). Multiple criteria evaluation of rural building's regeneration alternatives. *Building and Environment*, *42*(1), 436-451. https://doi.org/https://doi.org/10.1016/j.buildenv.2005.08.001
Zavadskas, E. K., Kaklauskas, A., & Šarka, V. (1994). The new method of multicriteria complex proportional assessment of projects.
Zavadskas, E. K., & Turskis, Z. (2011). Multiple criteria decision making (MCDM) methods in economics: an overview. *Technological and economic development of economy*, *17*(2), 397-427.

Zavadskas, E. K., Turskis, Z., & Kildienė, S. (2014). State of art surveys of overviews on MCDM/MADM methods. *Technological and economic development of economy*, *20*(1), 165-179.
Zavadskas, E. K., Turskis, Z., Vilutienė, T., & Lepkova, N. (2017). Integrated group fuzzy multi-criteria model: Case of facilities management strategy selection. *Expert Systems with Applications*, *82*, 317-331.
Zeithaml, V. A., Berry, L. L., & Parasuraman, A. (1996). The behavioral consequences of service quality. *Journal of marketing*, *60*(2), 31-46.
Zeleny, M. (2012). *Multiple criteria decision making Kyoto 1975* (Vol. 123). Springer Science & Business Media.
Zeng, M., & Reinartz, W. (2003). Beyond online search: The road to profitability. *California Management Review*, *45*(2), 107-130.
Zeng, W., & Li, H. (2006). Relationship between similarity measure and entropy of interval valued fuzzy sets. *Fuzzy Sets and Systems*, *157*(11), 1477-1484.
Zhang, H., & Wang, L. (2022). The service quality evaluation of agricultural e-commerce based on interval-valued intuitionistic fuzzy GRA method. *Journal of Mathematics*, *2022*, 1-10.
Zhang, K. Z., Cheung, C. M., & Lee, M. K. (2012). Online service switching behavior: The case of blog service providers. *Journal of electronic commerce research*, *13*(3), 184.
Zhang, P., & Wang, C. (2012). The evolution of social commerce: an examination from the people, business, technology, and information perspective. *Wang Chingning & Ping Zhang (2012), the evolution of social commerce: an examination from the people, business, technology, and information perspective, communications of the AIS (CAIS)*, *31*, 105-127.
Zhang, Z., Wen, F., Sun, Z., Guo, X., He, T., & Lee, C. (2022). Artificial intelligence-enabled sensing technologies in the 5G/internet of things era: from virtual reality/augmented reality to the digital twin. *Advanced Intelligent Systems*, *4*(7), 2100228.
Zhao, K., Zhao, X., & Deng, J. (2015). Online price dispersion revisited: How do transaction prices differ from listing prices? *Journal of management information systems*, *32*(1), 261-290.
Zhao, X., Louca, R., Hu, D., & Hong, L. (2020). The difference between a click and a cart-add: learning interaction-specific embeddings. Companion Proceedings of the Web Conference 2020,
Zhao, Y., Wang, L., Tang, H., & Zhang, Y. (2020). Electronic word-of-mouth and consumer purchase intentions in social e-commerce. *Electronic Commerce Research and Applications*, *41*, 100980.
Zheng, X., Lee, M., & Cheung, C. M. (2017). Examining e-loyalty towards online shopping platforms: The role of coupon proneness and value consciousness. *Internet Research*, *27*(3), 709-726.
Zhou, B., & Zou, T. (2023). Competing for recommendations: The strategic impact of personalized product recommendations in online marketplaces. *Marketing science*, *42*(2), 360-376.
Zhou, K., Martin, A., Pan, Q., & Liu, Z.-g. (2015). Median evidential c-means algorithm and its application to community detection. *Knowledge-Based Systems*, *74*, 69-88.
Zhou, L., Dai, L., & Zhang, D. (2007). Online shopping acceptance model-A critical survey of consumer factors in online shopping. *Journal of electronic commerce research*, *8*(1).
Zhu, F. X., Wymer, W., & Chen, I. (2002). IT-based services and service quality in consumer banking. *International Journal of Service Industry Management*, *13*(1), 69-90.
Zhu, G., Wu, Z., Wang, Y., Cao, S., & Cao, J. (2019). Online purchase decisions for tourism e-commerce. *Electronic Commerce Research and Applications*, *38*, 100887.

8 APPENDIX

8.1 ETHICAL APPROVAL DOCUMENT

WAIKATO MANAGEMENT SCHOOL
TE RAUPAPA

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Hamidreza Kord
By email: hamidrezakordd@gmail.com

1 May 2024

Dear Hamidreza

Ethics Application WMS 23/143
Sustaining E-Commerce Profitability: A Hybrid Quantitative Investigation into Critical Success Factors (CSFs)

The above research project, as outlined in your submitted application, has been granted Ethical Approval for Research by the Waikato Management School Human Research Ethics Committee.

Please note: should you make changes to the project outlined in the approved ethics application; you may need to reapply for ethics approval.

Best wishes for your research.

Kind regards,

Amanda Sircombe

Amanda Sircombe
WMS Research and Postgraduate Manager

8.2 FUZZY DELPHI QUESTIONNAIRE

Researcher: *Hamidreza Kord (Postgraduate Student- Master of Management Studies)*

Supervisors: *Dr Antoine Gilbert-Saad, Prof Frank Scrimgeour*

University: *The University of Waikato*

Dear [Participant's Name],

I hope this message finds you well.

I am a postgraduate student at the University of Waikato, New Zealand, conducting research on online shopping behaviours, under the supervision of ***Dr. Antoine Gilbert-Saad*** and ***Prof. Frank Scrimgeour***. As a part of my study, I need to gather the opinions of other experts hence seeking your valuable input.

My research aim is to identify key aspects of customer behaviour in e-commerce, focusing on value creation, sustainable profitability, and other success factors for e-commerce. Your input will provide valuable insights that can help enhance online shopping experiences and improve services offered by online retailers.

Your responses are confidential and will only be used for research purposes. If you have any questions or need assistance, please do not hesitate to reach out to me at hk214@students.waikato.ac.nz or hamidrezakordd@gmail.com

Your participation is greatly appreciated.

Sincerely,

Hamidreza Kord

Thank you for your participation in my study on online shopping trends.

- Leveraging your expertise and wealth of experience, it is highly appreciated to determine the significance of each of the following customer behaviours when they are selecting and finalising their online purchasing via a website or app.

Success Factors Through Online Shopping: Understanding Customer Behaviour

No	*Criterion*	*Content*	*Not Important*	*Slightly Important*	*Important*	*Fairly Important*	*Very Important*
01	**Purchase Frequency**	The frequency of online purchases					
02	**Purchase Categories**	What product categories typically purchase					
03	**Personalised Recommendation Frequency**	Purchasing based on personalised product recommendations					
04	**Browsing Frequency**	How often browse the website or app					
05	**Product Search Method**	How to search for products					
06	**Search Result Exploration**	Applying multiple pages of search results (vs. focus on the first page)					
07	**Customer Reviews Importance**	The importance of customer reviews in the decision-making process					
08	**Add to Cart Browsing**	Adding products to the cart while browsing					
09	**Cart Completion Frequency**	How often complete the purchase after adding products to a cart					
10	**Cart Abandonment Factors**	The factors influence decisions to abandon a purchase in a cart					

Success Factors Through Online Shopping: Understanding Customer Behaviour

No	*Criterion*	*Content*	*Not Important*	*Slightly Important*	*Important*	*Fairly Important*	*Very Important*
11	**Save-for-later Frequency**	The importance of the "Save for Later" feature					
12	**Review Left**	Leaving a product review online					
13	**Review Reliability**	How much rely on product reviews when making a purchase					
14	**Review Helpfulness**	Helpful information from other customers' reviews					
15	**Personalised Recommendation Frequency**	Receiving personalized product recommendations					
16	**Recommendation Helpfulness**	Finding the recommendations helpful					
17	**Rating Accuracy**	Rating the relevance and accuracy of the recommendations					
18	**Shopping Satisfaction**	Overall shopping satisfaction experience					
19	**Service Appreciation**	The aspects of online services for the most appreciation					
20	**Improvement Areas**	The areas where an online purchasing website can improve					

8.3 BEST WORST METHOD (BWM) QUESTIONNAIRE

Dear [Participant's Name],

I would like to express my sincere gratitude for your willingness to participate in this study. Your contribution will be instrumental in advancing our understanding of online purchasing trends and behaviours.

In the first step of my research, I applied the Fuzzy Delphi method to assess the significance of 20 factors in the field of purchasing behaviours for online customers. After two rounds, I stopped the Fuzzy Delphi process upon achieving the required consistency in expert opinion, with a difference between the two rounds of less than 0.1, well below the acceptance threshold of 0.5.

Consequently, the total number of factors was reduced from 20 to just 7 (F_1 to F_7), as indicated in the table below (Table 31). This streamlined selection facilitates management's decision-making process by focusing on a reduced set of key factors.

Table 32: Selected factors based on Fuzzy Delphi

	F_1	F_2	F_3	F_4	F_5	F_6	F_7
Factors	Purchase Frequency	Customer Reviews Importance	Review Reliability	Review Helpfulness	Personalised Recommendation Frequency	Recommendation Helpfulness	Shopping Satisfaction
Average	0.504	0.594	0.527	0.583	0.515	0.506	0.585
	Worst	**Best**					

However, the resulting weights for the seven factors ranged from 0.504 to 0.594, offering limited insight into which factors are relatively more critical. This lack of differentiation prompted me to employ the Fuzzy Best-Worst Method (FBWM) approach.

In this approach, I leveraged the outcomes of the fuzzy Delphi method, designating F_2 (with the highest average defuzzified value among the seven factors) as the 'Best' or most significant factor, and F_1 (with the lowest average) as the 'Worst' or least important factor.

Using the BWM, I conduct pairwise comparisons for the seven chosen factors, employing fuzzy linguistic terms as defined in Table 32. The numerical values assigned in the table range from 1 to 9, reflecting the relative importance of one factor over another. A value of 1 denotes equal importance, while 9 signifies the maximum importance of one factor over the other.

Table 33:Numbers for linguistic terms in the best–worst method

Number	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Linguistic Term	Equal	Fairly Quite Better	Quite Better	Extremely Quite Better	Better	Fairly Much Better	Much Better	Extremely Much Better	Fully Better

Without further ado, let's begin the survey.

As an expert, could you kindly indicate your preference for the F_2 (best factor) over others by assigning a number between 1 and 9, referring to the linguistic terms provided in Table 33. When comparing F_2 (best factor) to other factors, please assign a higher number if F_2 is considered more important than the other factors.

A: In every box, just use the dropdown and assign an appropriate number/linguistic term by comparing F_2 with the other factors.

*Table 34: Pairwise Comparison Questionnaire: Assessing Preference for **the Best Factor***

	F_1 (Worst)	**F_2 (Best)**	**F_3**	**F_4**	**F_5**	**F_6**	**F_7**
	Purchase Frequency	**Customer Reviews Importance**	**Review Reliability**	**Review Helpfulness**	**Personalised Recommendation Frequency**	**Recommendation Helpfulness**	**Shopping Satisfaction**
F_2 Customer Reviews Importance (Best)	Choose an item.	1- Equal	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.

For the last step, please determine your preference for the other factors over F_1 (the worst factor) by selecting a number between 1 and 9, referring to the linguistic terms provided in Table 34. Similarly, when comparing other factors to F_1 (the worst factor), allocate a higher number if the other factors are considered more important than F_1.

B: In every box, just use the dropdown and assign an appropriate number/linguistic term by comparing other factors with F_1.

*Table 35: Pairwise Comparison Questionnaire: Assessing Preference for **the Worst Factor***

		F_1 Purchase Frequency (Worst)
F_1 (Worst)	Purchase Frequency	1- Equal
F_2 (Best)	Customer Reviews Importance	Choose an item.
F_3	Review Reliability	Choose an item.
F_4	Review Helpfulness	Choose an item.
F_5	Personalised Recommendation Frequency	Choose an item.
F_6	Recommendation Helpfulness	Choose an item.
F_7	Shopping Satisfaction	Choose an item.

8.4 COPRAS METHOD EXPERT ASSESSMENT FORM

Dear [Participant's Name],

I trust this message finds you in good spirits. I wanted to take a moment to express my sincere appreciation for your invaluable contributions to my work thus far. Your expertise has truly enriched the research process, and I am grateful for the insights you have shared along the way.

As I move into the final and perhaps most crucial phase of my thesis, I find myself once again in need of your expertise. The Complex Proportional Assessment (COPRAS) method represents a significant step, and I believe your guidance will be essential in ensuring its success. Your insights have been invaluable, and I am confident that with your support, I can navigate this stage with confidence.

Thank you once again for your ongoing support. I look forward to continuing our collaboration as I work towards the completion of my thesis.

RECAP OF PREVIOUS STAGES

In the first step of my research, I applied the Fuzzy Delphi method to assess the significance of 20 factors in the field of purchasing behaviours for online customers. Following two rounds of expert consultation, I concluded the Fuzzy Delphi process upon achieving the desired consensus among experts. Upon defuzzifying the collective average opinions gathered over the two rounds, the discrepancy between the numerical values assigned to each factor was less than 0.1. This discrepancy fell well below the established acceptance threshold of 0.5, indicating a high level of agreement among experts.

Consequently, after reducing the number of factors from 20 to just 7 (F1 to F7), I applied the best-worst method (BWM) for weighing factors. The experts compared the best and worst factors with others using linguistic variables and fuzzy numbers.

In the subsequent steps, equations were formulated for each expert's questionnaire to weigh the factors using the fuzzy best-worst method. These equations were solved to determine the weights for each expert.

The "Consistency Ratio" was calculated based on the obtained values to ensure reliability. Finally, the average weights for each factor are determined and de-fuzzified for further use. The final weights for each factor are recorded in the following table.

Table 36: Weights of selected factors based on FBWM

Factors	**F_1**	**F_2**	**F_3**	**F_4**	**F_5**	**F_6**	**F_7**
	Purchase Frequency (Worst)	Customer Reviews Importance (Best)	Review Reliability	Review Helpfulness	Personalised Recommendation Frequency	Recommendation Helpfulness	Shopping Satisfaction
Weights	**W_1**	**W_2**	**W_3**	**W_4**	**W_5**	**W_6**	**W_7**
	0.039	**0.317**	**0.110**	**0.123**	**0.090**	**0.116**	**0.203**

To make the COPRAS Matrix, the C-Means method was used for clustering e-commerce customer data based on ***gender***, ***age***, and ***purchase frequency***. It revealed detailed patterns in customer behaviour, aiding in targeted marketing and retention strategies. The dataset comprised 602 records with significant features identified as gender, age, and purchase frequency.

Using MATLAB, 5 clusters (A1 to A5) were formed, with each record assigned based on its highest membership degree. Gender dynamics show female predominance across clusters. Purchase frequency varies, from infrequent, A1, to very frequent, A5. Age distribution ranges from older, A1 to younger, A5.

Prioritising Clusters by COPRAS Method

After identifying clusters using the C-Means method, establishing factors through the fuzzy Delphi method, and weighing them with FBWM, prioritizing alternatives involves creating a decision matrix. The fuzzy COPRAS method, chosen for its simplicity and careful consideration of criteria, guides this process. Your assessment of each cluster against the decision factor is crucial. Please note that the relationship between linguistic variables and triangular fuzzy numbers is outlined in the following table.

Table 37:Numbers for linguistic terms

Number	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Linguistic Term	Very Poor / Very Light	Poor / Light	Mostly Poor / Mostly Light	Fair	Mostly Good / Mostly Difficult	Good / Difficult	Very Good / Very Difficult

I have prepared the matrix, in each row, there are A1 to A5 clusters with their features and characteristics, also, in each column, there are factors with their weights.

As an expert, could you kindly evaluate each cluster against each factor by assigning a number between 1 and 7, referring to the linguistic terms provided. When comparing a cluster to factors, please assign a higher number if that factor is considered more important for the cluster (there is a dropdown in each box for your convenience).

Sincerely Yours,
Hamidreza Kord

Table 38: COPRAS Matrix for Evaluation

Factors & Weights / Clusters & Characteristics		F_1 Purchase Frequency W_1 =0.039	F_2 Customer Reviews Importance W_2 =0.317	F_3 Review Reliability W_3 =0.110	F_4 Review Helpfulness W_4 =0.123	F_5 Personalised Recommendation Frequency W_5 =0.090	F_6 Recommendation Helpfulness W_6 =0.116	F_7 Shopping Satisfaction W_7 =0.203
• No. of Purchasers: 29 • Age Range 52 to 67 • The smallest cluster • Purchase Frequency: Majority of "Few times a month" or "Less than once a month" • characterized by a nearly equal distribution of females and males, with a minority reporting "other gender" type or "preferring not to disclose."	A_1	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
• No. of Purchasers: 92 • Age Range 40 to 50 • Predominantly females • Purchase Frequency: Balanced distribution across categories • A more evenly distributed frequency of purchases across all categories, with a notable proportion making purchases "Multiple times a week" or "Once a week."	A_2	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
• No. of Purchasers: 134 • Age Range 24 to 29 • Slightly higher representation of females • Purchase Frequency: Balanced distribution across categories • A substantial proportion of customers making purchases "Multiple times a week" or "Once a week." However, this cluster also includes a sizable segment of customers who make purchases "Few times a month" or "Less than once a month," indicating varied engagement levels.	A_3	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
• No. of Purchasers: 146 • Age Range 18 to 39 • Predominantly females • Purchase Frequency: Balanced distribution across categories • A relatively balanced distribution of purchase frequency across all categories, with single category dominating of "Few times a month."	A_4	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
• No. of Purchasers: 201 • Age Range 12 to 28 • The biggest cluster • Females dominate • Purchase Frequency: Majority of "Few times a month" or "Multiple times a week" • The cluster stands out for its high frequency of purchases, particularly in the categories of "Few times a month" and "Multiple times a week."	A_5	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.

8.5 LINGO SOFTWARE MODELLING FOR ONE OF THE PARTICIPANTS

min=e;

@abs(WL2/WU1-7)<=e;@abs(WM2/WM1-8)<=e;@abs(WU2/WL1-9)<=e;

@abs(WL2/WU3-1)<=e;@abs(WM2/WM3-2)<=e;@abs(WU2/WL3-3)<=e;

@abs(WL2/WU4-5)<=e;@abs(WM2/WM4-6)<=e;@abs(WU2/WL4-7)<=e;

@abs(WL2/WU5-4)<=e;@abs(WM2/WM5-5)<=e;@abs(WU2/WL5-6)<=e;

@abs(WL2/WU6-1)<=e;@abs(WM2/WM6-2)<=e;@abs(WU2/WL6-3)<=e;

@abs(WL2/WU7-1)<=e;@abs(WM2/WM7-2)<=e;@abs(WU2/WL7-3)<=e;

@abs(WL3/WU1-5)<=e;@abs(WM3/WM1-6)<=e;@abs(WU3/WL1-7)<=e;

@abs(WL4/WU1-4)<=e;@abs(WM4/WM1-5)<=e;@abs(WU4/WL1-6)<=e;

@abs(WL5/WU1-2)<=e;@abs(WM5/WM1-3)<=e;@abs(WU5/WL1-4)<=e;

@abs(WL6/WU1-3)<=e;@abs(WM6/WM1-4)<=e;@abs(WU6/WL1-5)<=e;

@abs(WL7/WU1-7)<=e;@abs(WM7/WM1-8)<=e;@abs(WU7/WL1-9)<=e;

(1/6)*((WL1+4*WM1+WU1)+(WL2+4*WM2+WU2)+(WL3+4*WM3+WU3)+(WL4+4*WM4+WU4)+(WL5+4*WM5+WU5)+(WL6+4*WM6+WU6)+(WL7+4*WM7+WU7))=1;

WL1-WM1<=0;WM1-WU1<=0;WL1>=0;

WL2-WM2<=0;WM2-WU2<=0;WL2>=0;

WL3-WM3<=0;WM3-WU3<=0;WL3>=0;

WL4-WM4<=0;WM4-WU4<=0;WL4>=0;

WL5-WM5<=0;WM5-WU5<=0;WL5>=0;

WL6-WM6<=0;WM6-WU6<=0;WL6>=0;

WL7-WM7<=0;WM7-WU7<=0;WL7>=0;

8.6 LINGO SOFTWARE RESULT FOR ONE OF THE PARTICIPANTS

LINGO/WIN64 20.0.23 (5 Sep 2023), LINDO API 14.0.5099.295

Licensee info: Eval Use Only

License expires: 13 SEP 2024

Local optimal solution found.

Objective value:	2.258343
Infeasibilities:	0.1243297E-05
Total solver iterations:	31
Elapsed runtime seconds:	0.20

Model Class:	NLP

Total variables:	22
Nonlinear variables:	21
Integer variables:	0

Total constraints:	56
Nonlinear constraints:	33

Total nonzeros:	156
Nonlinear nonzeros:	66

Variable	Value	Reduced Cost
E	2.258343	0.000000
WL1	0.3031661E-01	0.000000
WL2	0.3304312	0.000000
WL3	0.1066775	0.000000
WL4	0.7198218E-01	0.000000
WL5	0.4132970E-01	0.000000
WL6	0.9154038E-01	0.000000
WL7	0.1845706	0.000000

WM1	0.3221099E-01	0.000000
WM2	0.3304312	0.000000
WM3	0.1205224	0.000000
WM4	0.8831146E-01	0.000000
WM5	0.1199872	0.000000
WM6	0.9154038E-01	0.000000
WM7	0.1852257	0.000000
WU1	0.3890986E-01	0.000000
WU2	0.3413148	0.000000
WU3	0.2806816	0.000000
WU4	0.1138106	0.000000
WU5	0.1897223	0.000000
WU6	0.1014108	0.000000
WU7	0.2043842	0.000000

Row	Slack or Surplus	Dual Price
1	2.258343	-1.000000
2	0.7661202	0.000000
3	0.4116222E-05	0.1336306
4	0.4983817E-07	0.000000
5	2.081097	0.000000
6	1.516686	0.000000
7	2.058840	0.000000
8	0.1616848	0.000000
9	0.1723636E-07	0.3663693
10	-0.2780226E-07	0.000000
11	0.2588436E-07	0.000000
12	0.1222964E-01	0.000000
13	0.5000569E-07	0.000000
14	-0.1243297E-05	0.000000
15	0.6486656	0.000000

16	1.529772	0.000000
17	1.641627	0.000000
18	2.042281	0.000000
19	1.107580	0.000000
20	-0.1211127E-05	0.000000
21	-0.8214826E-06	0.000000
22	0.4983792E-07	0.000000
23	0.1083153	0.000000
24	-0.8214826E-06	0.5000001
25	0.1241129E-01	0.000000
26	1.320534	0.000000
27	1.533303	0.000000
28	0.3118892E-03	0.000000
29	1.610969	0.000000
30	1.100242	0.000000
31	0.6033993	0.000000
32	0.1886217E-02	0.000000
33	0.8731791E-02	0.000000
34	0.4983792E-07	0.000000
35	0.000000	0.000000
36	0.1894375E-02	0.000000
37	0.6698876E-02	0.000000
38	0.3031661E-01	0.000000
39	0.000000	0.000000
40	0.1088360E-01	0.000000
41	0.3304312	0.000000
42	0.1384499E-01	0.000000
43	0.1601591	0.000000
44	0.1066775	0.000000
45	0.1632928E-01	0.000000
46	0.2549918E-01	0.000000

47	0.7198218E-01	0.000000
48	0.7865752E-01	0.000000
49	0.6973508E-01	0.000000
50	0.4132970E-01	0.000000
51	0.000000	0.000000
52	0.9870403E-02	0.000000
53	0.9154038E-01	0.000000
54	0.6550820E-03	0.000000
55	0.1915850E-01	0.000000
56	0.1845706	0.000000

8.7 MATLAB CODE FOR C-MEANS

```
data = readtable(filename);


% Extract the columns you want for clustering by column index
% Assuming 'Age' is the first column, 'Gender' is the second column, and 'Purchase Frequency' is the third column
X = data(:, 1:3});


% Number of clusters
c = 5;


% Run Fuzzy C-Means clustering
options = [2.0, NaN, NaN, NaN];
[centers, U] = fcm(X, c, options);


% Get cluster assignments based on maximum membership
[~, clusterAssignments] = max(U, [], 2);


% Initialize a cell array to store cluster sets and memberships
clusterSets = cell(c, 1);
clusterMemberships = cell(c, 1);


% Iterate through clusters
for i = 1:c
    % Find logical indices for data points belonging to cluster i
    clusterIndices = (clusterAssignments == i);


    % Check if there are data points in the cluster
    if any(clusterIndices)
        % Use logical indices to extract data points and memberships
        clusterData = X(clusterIndices, :);
```

```
        clusterMembership = U(clusterIndices, i);

        % Store cluster data and membership values
        clusterSets(Aboutorab et al.) = clusterData;
        clusterMemberships(Aboutorab et al.) = clusterMembership;
    end
end

% Visualization (3D scatter plot with cluster coloring)
figure;

% Iterate through clusters, assign a unique color, and plot data points
for i = 1:c
    % Check if the cluster has data points
    if ~isempty(clusterSets(Aboutorab et al.))
        % Plot cluster data with a unique color
        scatter3(clusterSets(Aboutorab et al.)(:, 1), clusterSets(Aboutorab et al.)(:, 2),
clusterSets(Aboutorab et al.)(:, 3), 10, i, 'filled');
        hold on;
    end
end

% Plot cluster centers
scatter3(centers(:, 1), centers(:, 2), centers(:, 3), 100, 'k', 'filled');
hold off;

% Set title and labels
title('3D Scatter Plot with Cluster Coloring');
xlabel('Age');
ylabel('Gender');
zlabel('Purchase Frequency');
```

8.8 A LETTER TO THE EDITOR

Dear Editor,

I am writing to submit my manuscript titled "Sustaining E-Commerce Profitability: A Hybrid Quantitative Investigation into Critical Success Factors (CSFs)" for consideration for publication in “Management Decision Journal”. This research addresses the dynamic and crucial factors influencing customer satisfaction and profitability in the e-commerce sector, employing advanced methodological frameworks.

- *Significance of the Research*

In today's digital landscape, e-commerce has not only transformed consumer behaviour but has also reshaped the retail industry. Understanding the factors that contribute to profitability in this highly competitive market is essential for businesses aiming to thrive. This study identifies and prioritises critical success factors (CSFs) using fuzzy Delphi, fuzzy BWM, C-means clustering, and fuzzy COPRAS methods. By analysing 602 customer records, the research classifies purchasing behaviours and demographic characteristics, providing actionable insights into customer satisfaction, review systems, recommendation systems, and personalised shopping experiences.

- Persuasive Reasons for Publication

INNOVATIVE METHODOLOGICAL APPROACH: The study employs a combination of advanced analytical techniques that manage the uncertainty and complexity inherent in e-commerce data. This hybrid approach is relatively novel in the field and demonstrates significant potential for broader application in other domains of consumer research.

PRACTICAL IMPLICATIONS: The findings offer valuable implications for e-commerce businesses, highlighting the importance of customer reviews, personalised shopping experiences, and recommendation systems in driving profitability. These insights can help practitioners develop more effective strategies to enhance customer engagement and satisfaction.

COMPREHENSIVE ANALYSIS: The thorough analysis of customer records not only identifies key success factors but also clusters purchasing behaviours and demographic characteristics, offering a nuanced understanding of different customer segments. This level of detail is critical for businesses aiming to tailor their strategies to specific consumer groups.

FUTURE RESEARCH DIRECTIONS: The study acknowledges its limitations, such as the cross-sectional nature of the data and sample size constraints, and provides clear directions for future research. This

includes integrating emerging technologies, conducting longitudinal studies, and developing cross-channel strategies to further enhance customer engagement and profitability.

- Potential Journals for Publication:

Given the interdisciplinary nature of this research, I believe it would be well-suited for publication in journals such as:

- Journal of Retailing and Consumer Services
- Electronic Commerce Research and Applications
- Journal of Business Research
- International Journal of Electronic Commerce

These journals are known for publishing high-quality research on e-commerce, consumer behaviour, and retailing, and would provide an appropriate platform for disseminating the findings to a wide audience of scholars and practitioners.

Thank you for considering my submission. I look forward to the possibility of contributing to the ongoing discourse in this vital area of research.

Sincerely,

Hamidreza Kord