DIGITAL TRANSFORMATION FOR THE RETAIL SECTOR

by

PUNEET MANSUKHANI
STUDENT ID - 59160

DISSERTATION
Presented to the Swiss School of Business and Management Geneva
In Partial Fulfillment
Of the Requirements
For the Degree

DOCTOR OF BUSINESS ADMINISTRATION

SWISS SCHOOL OF BUSINESS AND MANAGEMENT GENEVA

FEBRUARY, 2024

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by

PUNEET MANSUKHANI

Supervised by

PROF. GEORGE LATRIDIS

APPROVED BY

DR. LUKA LESKO
Dissertation chair

RECEIVED/APPROVED BY:

Renee Goldstein Osmic
Admissions Director

Dedication

Acknowledgements

ABSTRACT

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PUNEET MANSUKHANI

2024

Dissertation Chair: DR. LUKA LESKO

Co-Chair: DR. LJILJANA KUKEC

Digital transformation in the retail sector represents a comprehensive overhaul of retail operations, leveraging digital technologies to optimize processes, enhance customer experience, and achieve competitive advantage. This transformation encompasses a wide range of technologies, including e-commerce platforms, mobile apps, artificial intelligence (AI), machine learning, big data analytics, and the Internet of Things (IoT), to create seamless omnichannel experiences that bridge the gap between online and physical shopping environments.

The core objective of digital transformation in retail is to respond to changing consumer behaviors and expectations, which are increasingly oriented towards personalized, convenient, and immersive shopping experiences. By integrating digital technologies, retailers can gain insights into customer preferences and behaviors, enabling them to offer tailored recommendations, improve inventory management, and streamline supply chain operations.

Furthermore, digital transformation facilitates the implementation of advanced customer service solutions, such as chatbots and virtual assistants, enhancing customer engagement and support. It also empowers retailers to implement innovative business models, such as subscription services, and explore new revenue streams through data monetization.

However, the journey towards digital transformation is not without challenges. It requires significant investment in technology and skills, a culture shift towards innovation and agility, and

a strategic approach to data security and privacy. Retailers must navigate these challenges carefully, ensuring that their digital transformation initiatives align with overall business goals and deliver tangible value to customers.

In conclusion, digital transformation for the retail sector is not merely an option but a necessity in the digital age. It offers retailers the opportunity to innovate, differentiate, and thrive in a highly competitive and ever-evolving marketplace. Successful digital transformation in retail hinges on a holistic approach that encompasses technology, people, and processes, aimed at enhancing customer satisfaction and driving business growth.

TABLE OF CONTENTS

CHAPTER I: INTRODUCTION

While the widespread use of digital technology has made it an integral part of many fields, the retail industry's particular challenges have put it in the limelight. The epidemic expedited many changes in the industry. Online and omnichannel shopping's meteoric rise, customers' fickle tastes, the push toward hyperpersonalization, and the increasing complexity of supply chains are all factors. Since 2010, retail profit margins have decreased by an average of 3% each year (and as much as 5%-6% in certain sectors) due to these shifts (Accenture. 2015).

Most businesses aren't doing enough to lay the groundwork for the kind of robust technical infrastructure that might boost retail operations in every way. Only a select few businesses have fully multichannel offerings, data use at scale, and established agile work practises. In order to buck the recent trend, shops will need to take bold action and radically alter the structure and management of their IT departments.

Potentially far-reaching effects may result from concerted, ambitious attempts to update technology. TSR was 3.3% higher between 2016 and 2020 for digital leaders in consumer and retail industries compared to laggards. This research lends support to the idea that emerging technologies will play a crucial role in the retail sector's future growth by paving the way for novel customer experiences, goods, and business models including omnichannel retailing and data monetization (Adner, 2006). The health of a retailer's IT system and the viability of its underlying business model may be assessed using a five-point methodology. With this information in hand, retailers may invest in cutting-edge technology in strategic areas, therefore boosting performance across the board.

Small and medium-sized firms (SMEs) account for between 60 and 80 percent of employment and 55 percent of GDP in industrialised nations, as reported by the World Trade Organization (WTO). Official statistics from Portugal indicate consistent results between 2017 and 2018. The evidence suggests that SMEs are crucial to economic growth and should be treated as such. As the effects of Digital Transformation (DT) ripple across industries and types of organisations, it's become evident that adopting and using cutting-edge digital technology is the biggest obstacle firms face today. This is because the Internet and the World Wide Web have assumed such a crucial role in the modern international economy. Businesses that don't change with the times will either fail or be surpassed by more agile competitors (Adner, & Kapoor,2010). It's unclear that the emergence of digital platforms will allow SMEs to maintain their existing foothold in the niche-based economy, thus these companies will need to adapt to the changing nature of their markets. Even though most

SMEs now employ some kind of information technology (IT)—such as personal computers and Internet access—in their operations, they often only use these tools for the most fundamental purposes, such as e-mail communication. However, DT is problematic for SMEs because, in addition to the technical limitations inherent to DT, most of these organisations lack or have limited resources (financial and time) to develop and conduct DT initiatives. And they are completely unprepared for DT because of their lack of knowledge and practise.

RETAILING

Retailing, as a means of connecting with consumers via the medium of products and services, captures advantages from several channels of distribution to generate revenue. Supply chain management is an integral part of retailing since it helps keep the whole retailing operation organised. With this knowledge of the customer's wants, needs, and overall perspective on the goods, the merchant is better able to forge lasting relationships. Since the retail process simplifies the buying experience for the consumer, it is crucial that merchants pay close attention to every detail of their dealings with clients (Al-Debi, et al., 2008). What's included in retailing are things like:

Customers are involved in the retail process because: • retailing is a relationship-building procedure.

- Typically, there is a great deal of business transacted.
- Promotional Methods in Sales
- Important considerations include: • Placement and arrangement.
- There are more options for work thanks to the retail sector.

The procedure is useful for manufacturers since feedback from customers is gathered and utilised to shape future revisions of the product. The word "retailing" is often used to refer to the business practise of selling products and services to customers for use in their homes, either by the individual consumer or by other members of the consumer's immediate family. Over the course of the 20th century, there were significant changes in people's preferred modes of communication, the goods they sought out, and their financial capabilities. The rapid development of technology in the near future, however, has beyond our wildest hopes

(Amit, et al.,2001). Consumers nowadays are more knowledgeable than ever, as seen by the proliferation of innovative payment options, user-generated product evaluations, and 3D virtual stores. The following are some ways that digital technology has altered the retail industry:

Original Products: Many exciting new items have become accessible to buyers as a consequence of the shift to digital. Customers may also have their purchases personalised by the business. Customer satisfaction is crucial in a cutthroat industry where unhappy buyers swiftly move on to a rival.

- Providing excellent customer service is crucial for every successful business, and marketers must work hard to earn their consumers' confidence. In the wake of the onset of digitalization, businesses have prioritised developing a more meaningful connection with their clientele (Anderson, C. (2006).

- Every store strove to lower product prices and increase product availability at optimal times via improvements to its distribution and information systems. The retail industry is investing heavily in supply chain management and IT infrastructure. Nowadays, clients have peace of mind since they can trace their products with a unique identifier.

- Customers are able to make purchases as if they were physically present in shops thanks to augmented reality. In the age of augmented reality, consumers may test out brand new offerings before they buy. Customers won't have to go through the trouble of downloading a corporate app in this case.

- Reducing Transit Times: Customers have shown little patience for delays in receiving their orders. Stores are making efforts to reduce shipping times so that customers get their purchases as soon as possible. Digital transformation makes fast service feasible, which is much needed right now (Blank, S. (2013).

- The term "social shopping" refers to the trend of merchants using social media to sway consumers into making a purchase. Let's say you took a photo of a person wearing a nice pair of shoes and then decided to give them to them. The result is a problem-free process for the users.

- Hyper-personalization: Today's savvy merchants are proactive in their pursuit of client data and use it to their advantage, generating more qualified leads. The great thing about customers is that they are always eager to buy no matter the cost or quality.

DIGITAL TRANSFORMATION

The past several years have seen DT surge to popularity, making it a hot issue in management research and the corporate world. Due to the absence of a unified definition of DT, a variety of conflicting but complimentary formulations have evolved in the academic literature. The DT is based on state-of-the-art digital developments including big data, robotic automation, simulation, system integration (both horizontal and vertical), the IoT, cybersecurity, cloud computing, 3D printing, and augmented reality. Organizations may gain a competitive edge via increased flexibility, durability, and responsiveness as a result of digitization (or DT). Guo points up the potential advantages of digitalization for the adaptability of businesses (Blomkvist, et al.,2015)..

- Low-cost aid in monitoring the environment and making predictions about potential changes.
- making more of the crisis-related business possibilities
- This is because digital technology has a decentralised structure, which allows it to function regardless of location or time zone.
- It makes it possible for the company to reallocate resources in the event of an unexpected crisis.

Digital technology and connections have shown to be vital in the battle against the social and economic consequences of the COVID-19 outbreak. In light of the fact that the COVID-19 pandemic has caught governments, corporations, and whole industries by surprise, the global economy is in danger of collapse. Based on our reading of the studys with DT as their primary focus, we were able to identify a number of recurrent notions and concepts that serve to connect and define the phenomena we were looking at. Studies have shown that DT calls for a change in how businesses are structured, the principles that guide management, the methods by which tasks are carried out, and the outcomes that are produced. In this research, we dissect Matt and Hess's suggested definition of DT methods, which factors in the crucial considerations described above (Bocken, et al.,2013). The term "digital transformation" is used to describe the manner in which digital technology has altered a company's goods, organisational structure, and/or workflow.

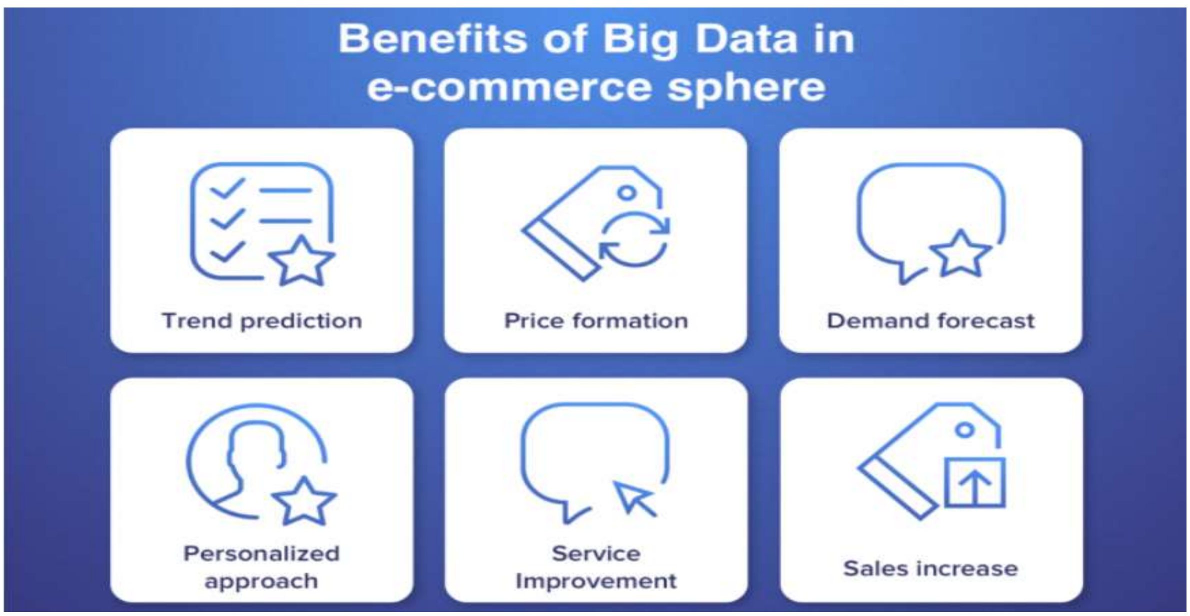
POPULAR DIGITAL TRANSFORMATION TRENDS IN RETAIL?

The retail sector is undergoing a number of digital transformation developments. Several current directions in the digital transition are outlined below. Try to take a peek.

1. **Advantage of Mobile Commerce Is Improved Customer Satisfaction**

Mobile commerce is one of the most well-liked examples of the retail industry's adoption of digital transformation trends. Buying and selling products and services through mobile devices like smartphones and tablets is known as "mobile commerce." There are several benefits to doing business through mobile devices. Businesses may expand their customer base and access new markets thanks to this development. Customers may make purchases from any location, and the experience is streamlined for their benefit (1Brynjolfsson, et al.,2013)..

2. **BIG DATA FOR ENHANCED CHOICE CREATION**



SOURCE-(Bocken, et al.,2013).

Another significant digital transformation trend in retail is the rise of big data. "Big data" describes very vast and complicated datasets that might be challenging to analyse using more conventional techniques.

Using the power of big data, companies may learn about patterns, trends, and consumer behaviour. Decisions, operations, and revenue may all benefit from this data's increased visibility.

3. ARTIFICIAL INTELLIGENCE FOR SMARTER

COMMERCIAL CONCLUSIONS

With AI's meteoric rise throughout industries, it's hard to see the e-commerce market being immune to its potential advantages. Yet, e-commerce has already begun to reap the benefits of this in a number of ways. It's been put to use in areas such as user profiling, product suggestion engines, chatbots, and even fraud detection.

Using AI, organisations can analyse massive volumes of data rapidly and precisely, leading to better choices. We may then use this data to enhance our customer support, fine-tune our advertising, and optimise our stock levels and pricing strategies.

4. Technology that Uses Augmented Reality to Make Interactions With Customers More Interesting and Fun

There is now, not some distant future, but a period when fantasy and reality merge. The retail sector is reaping huge rewards from the here and now. Customers may examine merchandise in a lifelike 3D setting before making a purchase, all thanks to augmented reality. Having a clearer picture of what they're purchasing helps cut down on returns.

The use of augmented reality in making experiences for customers more dynamic and interesting is another potential use of the technology. Customers may use their smartphones to virtually try out an item in their own living room before making a purchase. As a result, sales and consumer involvement are boosted (1Brynjolfsson, et al.,2018).

5. Internet of Things for Smarter Inventory Management

With each passing day, the globe is more linked, and this is true of more than just people. With the advent of the internet of things (IoT), inanimate objects may join the network and exchange data just like people. In addition to healthcare and industry, it is also being employed in the retail sector.

Maintaining an accurate inventory is essential in the retail industry. It aids in minimising waste while simultaneously maximising efficiency and raising patron happiness. Internet of Things technologies have made this process simpler and more effective than ever before. Sensors and RFID tags are two examples of IoT-enabled technologies that may help organisations keep track of inventory in real time and make more informed choices regarding stock levels (Bucherer, et al.,2012).

6. Blockchain for Improved Security and Transparency

Blockchain, a decentralised technology, is essential to Bitcoin and other cryptocurrencies. By using a distributed database, users may conduct trustworthy, unalterable transactions.

In the retail industry, distributed ledgers are being used for inventory and supply chain management, customer loyalty programmes, and product tracking.

The capabilities of the blockchain may be useful for businesses and their clients.

In the corporate world, it means more safety, more openness, and more productivity.

Customers are able to have more faith in the things they purchase as a result..

7. 3D Printing for Customized Products

The rise of 3D printing is just another innovation made possible by the digital revolution, and it promises great things for the retail sector. It enables businesses to meet customer demand for customised products in real time (Bughin, et al.,2017).

Sellers of personalised and bespoke goods stand to gain the most. Three-dimensional printing allows firms to make one-of-a-kind items quickly and affordably without having to worry about achieving minimum order requirements.

3D printing may be used to create prototypes. It helps in prototyping, which is necessary for ensuring that designs work before going into large production.

8. Voice Commerce for Hands-Free Shopping

Voice shopping, facilitated by the proliferation of products like Amazon Echo and Google Home, is gaining traction. The hands-free shopping experience is quick, simple, and hassle-free.

Buyers may now use their voices to browse stores, compare prices, and make purchases. Those who are too occupied to shop online or in person might greatly benefit from this technology (Buldeo Rai, et al.,2019).

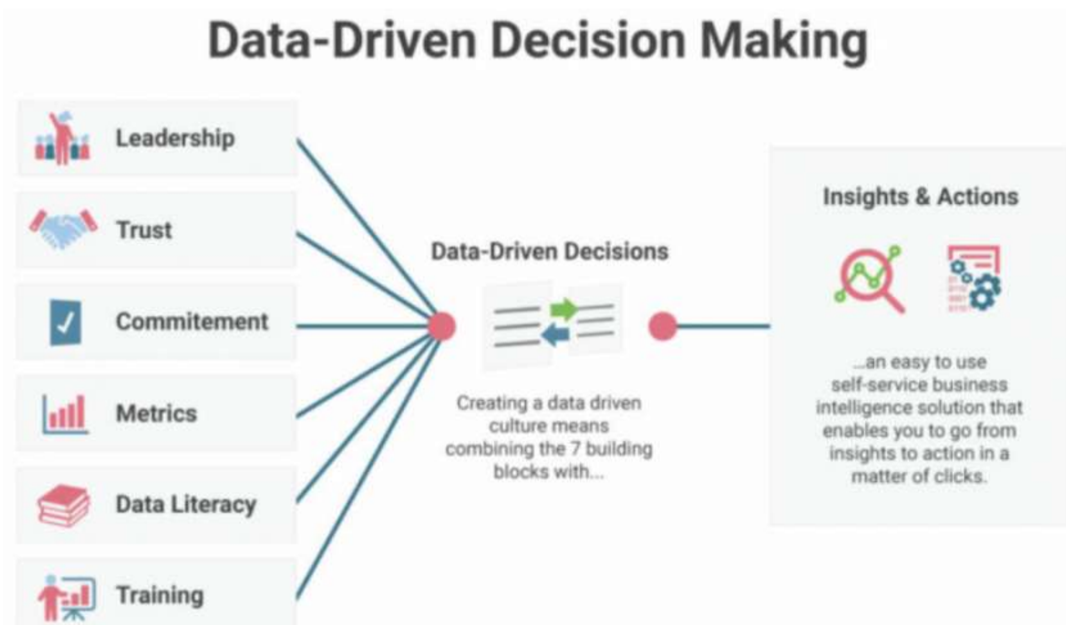
9. Personalization for Improved Customer Experiences

The term "personalization" refers to the practise of adapting one's offerings and interactions with the world to the specific interests and requirements of each consumer.

Businesses in sectors as diverse as healthcare, education, and retail all make use of this technology.

Personalized shopping experiences may be created with the use of personalisation in the retail industry. As an example, online stores may utilise client information to create specific product suggestions and tailor their service to each individual. Customer satisfaction and loyalty may both benefit from this (Cavalcante, et al.,2011).

10. Business Intelligence for Data-Driven Decision Making



SOURCES-(Chesbrough, et al.,2002).

When discussing enterprise-level operations, one often hears the phrase "business intelligence" (BI), which refers to a collection of programmes designed to make the collection, storage, and analysis of data easier. As a consequence of analysing this information, business leaders may make more informed decisions about the company's operations, marketing, and other areas.

With the help of BI, stores can classify their clients more precisely, improve the effectiveness of their marketing campaigns, and increase sales by stocking more of the items their consumers want. Logistics in the supply chain are also improved. By analysing data, businesses may pinpoint supply chain linkages that are susceptible to disruption. As a result, it helps businesses improve their operations and maximise their efficiency (Chesbrough, et al.,2002).

TOOLS FOR DIGITAL TRANSFORMATION IN THE RETAIL INDUSTRY

The retail business primarily employs three technologies for digital transformation: These aids include.

Artificial Intelligence

Offering around-the-clock support is more convenient for clients. With the help of AI, businesses can provide around-the-clock support to their customers. Artificial intelligence chatbots are exemplary of this since they respond instantly to client questions sent through text. In order to pay for conversions and drive new sales, chatbots are a low-cost, rapid response service solution. Further, chatbots provide pre-programmed responses to consumers' inquiries in the same tone as the company. Chatbots are superior to human operators because they never become frustrated by consumers' inquiries.

Machine Learning and Predictive Analysis

Machine learning is a potent tool for building consumer and business loyalty since it allows shops to better understand and predict client needs. Machine learning is the study of using various data sources as inputs to machine learning models with the purpose of making predictions about the future (Chesbrough, 2006). To add to this, the information gathered by ML helps shops:

- Recognize purchasing trends.
- The customer's purchasing patterns must be analysed.
- The ability to provide discounts.

- Adapt your offerings based on client feedback.
- Change prices on the fly and
- Construct forecasts based on past tendencies and current and future consumer preferences.

Unified Commerce

Customers want merchants to be available to them regardless of the channel they choose to use to make a purchase, such as on their computers, mobile phones, tablets, social media platforms, etc. Many shops are turning to unified trading strategies, which allow them to manage all aspects of their operations with a single set of controls, because of this reason. Many methods have been utilised to coordinate their commercial operations prior to the advent of the idea of unified commerce. Rectifying data from several sources requires time and energy. Data storage should be made public and information from many sources should be merged into a single commerce platform to ensure the continued safety and completeness of all stored information (Chesbrough, 2007).

Pillars of digital transformation in the retail industry

A retailer's ability to implement digital transformation in the retail sector depends on mastering these four pillars..

Customer engagement

Since user involvement is at the top of the retail food chain, successful companies must maintain and expand their loyal client base. Improvements in consumer-retailer communication have been made possible by innovations like mobile computing and data analytics. Developed to provide in-depth insights on customer demographics and assess customer data based on behaviour and preferences, customer relationship management systems (CRM) aid in elevating the quality of service provided to consumers by retailers. Using the data collected by the CRM, you can tailor your marketing and sales initiatives to each individual client (Chesbrough, 2010).

Employee empowerment

Giving workers the education, training, and resources, they need to succeed on the job is one example of employee empowerment. In addition to providing insights into customer behaviour and demographics, a CRM provides staff with fast access to customer information so they can sell to and recommend products to consumers.

Optimize operations

One of the four pillars of digital transformation in retail is the improvement of operations. Data-driven decision making, streamlined operations, and improved channel-wide visibility are the primary goals of this initiative. Your company requires functional stability if you're going to provide your customers a consistent experience across all of your channels. The installation of enterprise resource planning software may facilitate the aforementioned fusion. A bird's-eye view of your multi-channel operations, including supply chain, customer service, transactions, purchases, refunds, and more, is made possible by ERP systems, which eliminate the silos between programmes (Christensen, 1997)..

Reimagine your products

Keeping up with the fast-paced introduction of new products and services requires a constant quest for creative applications of cutting-edge technologies. The right apps and hardware are necessary for this, just as they are for the rest of the digital transformation in shopping. Apps and systems that put a premium on predictive analysis may provide the greatest return on investment (ROI). Some systems employ machine learning in tandem with information obtained from ERP, CRM, and business intelligence to predict failures, conduct preventive or remedial actions, and find untapped income and growth prospects (BI).

Wrap Up

The retail sector is undeniably more competitive than it was before. In such a market, the shopper has all the power, and only a personalised or special shopping experience will do to win them over. Despite this, many stores are hesitant to adopt the kinds of technology advances that would enable them to adapt to the changing retail landscape. Adapting to customers' ever-evolving wants and demands is a need for every successful store; you simply cannot force them to run on your timetable (Collis, & Hussey, 2013).

Technology at the core of the retail industry’s transformation

During the last ten years, the retail sector has seen seismic upheavals. Many of these tendencies were accelerated by the COVID-19 epidemic, making it difficult for stores to keep up. Even as internet shopping has become more popular, many brick-and-mortar stores have found it difficult to keep up with the times technologically. When comparing 2019 and 2020, internet sales in Germany increased by 23.0 percent yearly while offline sales increased by just 3.6 percent. And the way customers purchase for goods and interact with companies has also changed, sometimes drastically. Consumers are becoming more channel agnostic, knowledgeable, and connected yet less loyal. Shopping trends in both the food and clothing industries reflect this transition toward more natural, organic, and artisanal ingredients and goods.

E-tailers, who are typically able to create direct ties with businesses, have cornered a sizable portion of the online sales sector, while online marketplaces have emerged as the preeminent platforms (Cope, Meghan. 2010).

2 These shifts put more pressure on traditional stores to have an omnichannel presence.

In order to adapt to these shifts, the retail industry may use technology as a fundamental facilitator in a variety of next-generation retail functions. The smart digital services that support customers' whole decision-making processes can be seamlessly integrated across digital and physical channels thanks to technology. Updating in near-real-time with appealing digital material is possible when paired with trustworthy, individualised offers that have been optimised using cutting-edge analytics. Advanced, real-time management; cross-channel order management; and automated logistics, human resources, and finances are just a few examples of the technological solutions available for the supply chain. Finally, a solid technological basis may broaden the scope of retail business models beyond the main business, allowing for the creation of new income streams, the introduction of new consumer touchpoints, and the collection of more customer data (Demil, & Lecocq, 2010).

We've found that the correct investments may cut the time it takes to bring a digital product or service to market by a third, train employees to create twice as many competitive solutions, and reduce operational expenses by twenty percent. This set of enhancements works together to raise TSR by making businesses more adaptable to their customers' wants and requirements.

SMALL AND MEDIUM ENTERPRISES

Small and medium-sized enterprises (SMEs) are crucial to the economy because they create employment, advance technology, and ensure social stability. Many small and medium-sized enterprises (SMEs) were hit hard by the global pandemic crisis created by COVID-19 because of their limited resources and the inability to quickly and effectively respond to the crisis. The bulk of customers have shifted their purchasing habits and resorted to online commerce and services, necessitating a response from traditional retail enterprises in order to stay competitive. Small and medium-sized enterprises (SMEs) must adjust to the digital trends that may one day dictate the company culture and organisational structure..

RETAIL TRADE

The rapid expansion of online shopping has resulted in a seismic shift in the business world. It's true that e-commerce was growing in the EU even before the Covid-19 pandemic problem hit, but the restrictions imposed by the epidemic led to explosive expansion and profound effects throughout the economy. Retail SMEs, in contrast to huge corporations, have the agility to swiftly develop formal and flexible procedures to fulfil client demand (E-barometern. 2019). Because of this adaptability and the lack of hierarchical barriers, product and process innovations may be tested on a small scale and resources can be restructured rapidly and efficiently.

DIGITAL CHANNELS

The retail industry as a whole has undergone a fundamental transformation as a consequence of the advent of new distribution channels. The typical sales organisation has abandoned the counter in favour of a large online platform. Distribution channels may be broken down into four broad categories, each with its own own clientele and sets of activities:

- Traditional channels - Shopping in physical stores
- E-commerce - Online shopping
- Multichannel - Shopping using multiple channels (PC, Tablet, Mobile)
- Omnichannel - Engage customers anywhere through a continuous and integrated experience.

The idea of a "omnichannel" sales channel rests on the idea that customers should be able to reach out to companies via any of the several already accessible digital channels (Eisenmann, et al.,2012). With the tremendous change in consumer behaviour and the ubiquitous availability of digital technology, customers are seeking a streamlined and unified purchasing experience, such as that offered by omnichannel. Instead than using separate channels for distribution and sales, as is done in traditional models, omnichannel sales and distribution eliminates these barriers. The effects of digitization on traditional establishments are comparable to those seen by online merchants. One crucial feature of these emerging digital channels is the potential for a reorganisation of the roles of the parties engaged in the company, with customers maybe becoming co-producers and rivals possibly becoming collaborators. As examples of this kind of market disruption, Verhoef points to ING Bank and the prospective conflict between the new Alibaba platform and Maersk, a conventional shipping firm..

Digital transformation strategies

Disruptive technology (DT) is more of a strategy and a shift in mindset than a technological challenge. If DT is to be successful, companies will need to revise their long-term objectives and operational strategy to account for the peculiarities of the digital age. Expanding the scope of this beyond bettering IT is necessary. Most companies' attempts to implement their DT plans fall short because they lack a coherent digital strategy (Eneroth, 2005). Due to the strategic nature of DT, it has far-reaching consequences for business operations. According to Loonam, the five types of business model paradigms made possible by digital technology are: industry reinvention, product/service substitution, the formation of new digital companies, the reconfiguration of value chains, and the rethinking of value propositions. Loonam proposes an organisational architecture that divides managerial responsibilities into four categories, each corresponding to a different aspect of business model thinking. Projects in these areas focus on either strategy, customers, the organisation, or technology. DT strategies consist of generic elements that may be modified to suit a variety of business contexts and organisational structures. A company's long-term objectives and strategies for its digital transformation are sometimes referred to as its "digital strategy." It sets out short-, medium-, and long-term objectives for the company's organisational and cultural makeup, product offerings, and value creation, all through the lens of digitalization.

RESEARCH PROBLEM

If they wish to keep up with the rapid growth of digital platforms and the digital economy, SMEs must immediately begin adopting DT. Although there is a lot of literature on SME DT strategies, much of it is geared toward industrial organisations, leaving retail SME DT and the most successful methodologies for the retail economics sector mostly untapped. As there is currently a dearth of literature on DT in the retail industry, this study's findings will provide credibility to a proposed strategic script model of DT that may be implemented by small and medium-sized businesses (SMEs) (Euchner, & Ganguly, 2014).

RESEARCH AIMS

The level of success that companies have using DT will rely on their own individual tactics, which are unlikely to be universally applicable or applicable across all sectors. It stands to reason, for instance, that a retail SME's strategic tactics for establishing digital channels would vary from those used by an industrial SME. These small and medium-sized enterprises (SMEs) are under intense competitive pressure from both online rivals and the shifting shopping habits of their target consumers.

RESEARCH OBJECTIVES

- To analyse the current extent of digital technology adoption in the retail sector of Noida, including the types of technologies used and the degree of their integration into business operations.
- To Study the Driving Forces and Challenges in Digital Transformation aimed at companies during their digital transformation journey.
- To Study the Impact of Digital Transformation on Customer Experience and Business Performance.
- To Study Workforce Development and Skill Enhancement Strategies related to digital transformation, including employee training, talent acquisition, and fostering a culture of digital literacy and innovation.
- To Study Successful Digital Transformation Case Studies in Noida's Retail Sector

PURPOSE OF RESEARCH

This study details the steps used in conducting the research, examines the methodology and findings, and provides an example from the retail industry to illustrate how organisations' digital transformation success may be measured. The most relevant findings from this study are shown below. Beginning with the literature and interviews with experts and managers in Taiwanese retail firms undertaking digital transformation, this study defines the inputs and outputs for measuring an enterprise's performance in digital transformation (Fitzgerald,et al.,2014). Secondly, we provide a performance evaluation strategy that can be used to any business' digital transformation and help mitigate the risks involved in making this transition. A short introduction establishing the study's context and aims, a detailed description of data exploration and analysis (DEA), a description of the study's methodology, a discussion of the empirical results, and a summary and discussion of the study's implications make up the paper's five sections.

1.6 SIGNIFICANCE OF THE STUDY

Many SMEs worry that they are not ready for the digital revolution. The issue is not a lack of willpower or resources, but rather an absence of the best practises for this kind of organisation. It is widely accepted that the strategy used is a major reason why many digital transformation efforts fail or fall short of their objectives. It's not enough to see digital transformation only as a technological advancement; rather, the whole organisation must undergo a radical makeover. The growth of e-commerce has pushed SMEs into this novel process centred on globalisation and digital business. The goal of this research is to determine what steps a small or medium-sized company (SMB) in the retail industry should take to effectively modify its business model. To help small and medium-sized enterprises (SMEs) choose the best digital approach, this study provides a conceptual model for their digital transformation and describes how to create a prototype script (Golafshani, 2003). The prototype was put to the test by mimicking the real procedures of a small and medium-sized retail company.

1.7 RESEARCH DESIGN

This section will provide a detailed explanation of the study's methodology and research strategy. The approach used has been largely determined by the nature of the study problem and the guiding philosophical viewpoint. The report goes above and above by explaining the rationale behind the study's selection of an explanatory sequential mixed methods research strategy. Structures for data collection, processing, and reporting were also put in place in this section. When compared to the quantitative technique, the qualitative approach has employed a more effective and novel collection of tools to accomplish its objectives. The procedures that were used to add weight to the study's veracity and validity are also explained in detail. The next part delves into the methodological challenges faced by the researchers, including details on when the research was done, how weights were allocated, how the data was merged, and how ethical considerations were factored in (Gray, 2006).

The study's design includes the "methods for data collection, analysis, interpretation, and reporting" in scientific studies. It is a method for connecting the dots between abstract concerns and realistic (but achievable) trials. In other words, the study design specifies the procedures to be followed to collect the required data, analyse the data using the proper methods, and make conclusions regarding the issue under consideration. Robson (2002) outlines the differences between exploratory, descriptive, and explanatory research strategies. He divides things into based on their intended use, since each design is unique. To illustrate the interrelated and organic nature of the world around us, or to build a picture of some element of a situation, person, or event are all possible outcomes of a descriptive research. Given their inability to provide an explanation for an event's occurrence, descriptive studies are best used when investigating novel or uncharted territory. Therefore, when there is a lot of descriptive data available, it's advisable to transition to an explanatory or exploratory research approach (Hagberg, et al.,2016).

Exploratory research is conducted when there is little information available about a phenomenon and the problem is not clearly defined. Intentionally vague so as to encourage readers to go further, rather than serve as a stand-alone primer on the topic. As such, its primary objective is to look into matters that have been overlooked so far. There is no way around the fact that exploratory research will provide the groundwork for future, more definite studies by determining the optimal study design, sample strategy, and data collection method. Explanatory research, on the other hand, seeks to do just the opposite: provide an explanation for and interpretation of the descriptive results. Unlike descriptive research, explanatory research seeks to provide a reason for something. Expanding on descriptive research, an explanatory investigation looks into what causes a phenomenon. Explanatory research seeks to identify and evaluate competing hypotheses in an effort to provide light on the nature of a phenomena. Statistical analysis is used to discover and describe relationships between variables in a phenomenon (Hedman, & Kalling, 2003).

The primary purpose of this research is to examine the aforementioned implications of digital revolution on the retail sector. It achieves so by extrapolating quantitative and qualitative data and then utilising qualitative research to support the assumed relationship. Therefore, the best method is an explanatory research design that seeks to answer the "how" and "why" behind the primary research question. Below, we present more reasoning for why an explanatory research technique was chosen for this inquiry. Reasons for doing the study, or the stance chosen.

Selecting a suitable research design, which is in turn defined by the aims of the study, is necessary for finding answers to the questions raised by a research subject. The primary difficulty encountered in this investigation is a significant open question. Using a causal link between concentration measurements and performance, this study aims to examine the important assumptions concerning industrial concentration. The theoretical test, similar to some other research, involves direct measurements of efficiency to further examine the concentration vs. efficiency issue (Hernant, & Rosengren. 2017). When assessing performance, we also take into account the impact of the well-defined control elements. Therefore, it seems that an explanatory research is the best option when seeking this kind of ad hoc inquiry. The inquiry strategy seeks to clarify a matter by identifying a connection between a problem's underlying causes and a set of contributing factors. The researcher believes that explanatory design is the most effective strategy for addressing the main and secondary research questions of the study.

1.8 Structure of the Thesis

CHAPTERS	SUB HEADINGS
CHAPTER I: INTRODUCTION	1.1 Research Background and Scope 1.2 Research Problem 1.3 Research Aims 1.4 Research Objectives 1.5 Purpose of Research 1.6 Significance of the Study 1.7 Research Design 1.8 Structure of the Thesis 1.8 Structure of the Thesis
CHAPTER II: LITERATURE REVIEW	2.1 Introduction 2.2 The current state of the games industry 2.3 The current state of the mobile games industry 2.4 Business models 2.5 Business models in the gaming industry 2.6 Popularity of the free-to-play model 2.7 Risks of the free-to-play business model 2.8 Challenges faced by startups
CHAPTER III: METHODOLOGY	3.1 Introduction 3.2 Research Questions 3.3 Research Design and Strategy

	3.4 Population and Sample 3.5 Research Instrumentation 3.6 Data Collection Procedures 3.7 Data Analysis 3.8 Coding and analysis 3.9 Methods of validation 3.10 Research Design Limitations 3.11 Conclusion
CHAPTER IV: RESULTS AND FINDINGS	4.1 Introduction 4.2 The Research Case 4.3 Data Analysis 4.4 Summary
CHAPTER V: DISCUSSION, IMPLICATIONS AND RECOMMENDATIONS	5.1 Introduction 5.2 Discussion of Results 5.3 Comparison to other studies 5.4 Limitations 5.5 Recommendations for Future Research 5.6 Conclusion

A disruptive change and transformation process in the retail industry threatens the very existence of Local Owner Operated Retail Outlets (LOOROs) (HDE, 2016, p. 9; IFH, 2015; Heinemann, 2014). Accordingly, the traditional business model of LOOROs is challenged by digitalization pressure imposed by online and offline competitors (Liebmann, 2013; Holden, 2017) as well as by changing shopping habits of their customers (IFH, 2016, p. 33; Statista, 2017). However, to understand the present state of development of the suspended business type LOORO, it is necessary to look back in history: The retail sector is one of the oldest industries in the history of mankind. Archaeological evidence for trade dates back more than

10.000 years to antiquity (Shaw and Jones, 2005, pp. 241-242; Bintliff, 2002, pp. 209-217). Retails core activity, the exchange of goods between people and organizations is named the driving force for development, prosperity and wealth in today´s societies (Niemeier et al., 2012, pp. 10-12; Shaw and Jones, 2005, pp. 241-242). But, despite the rapid development of the retail outlets from simple booths in ancient history to sophisticated and complex shopping malls today, the basic trade process (including the necessary face-to-face interaction) remained untouched for centuries (Coleman, 2006, pp. 19-49, Niemeier, 2012, pp. 10-12).

Only recently, with the advent and the spread of internet-ready devices (stationary and mobile) in private households and organizations in the end of the 20th century, the disruptive transformation process of the retail sector has started to change the trade process fundamentally (Feinleib, 2017, p. 69). Accordingly, the so called "digitalization" has extended a competitive environment for the former locally orientated retailers like LOOROs on a broad scale. On the one hand, the digitalization has introduced new pure e-commerce players to the retail industry, which do not possess physical shops and showrooms (Wolny and Charoensuksai, 2014, p. 317). Furthermore, these pure online players offer a wide range of products and merchandise to low prices via online shops throughout the internet (Feinleib, 2017, pp. 20-22). Unattached to limited catchment areas, shelve spaces and regulated opening hours, these e-commerce players have started to challenge the local retailers traditional business models in their very core (IFH, 2015; Heinemann, 2014). On the other hand, the new digital competition for local retailers is not only imposed by the internet. Already today, formerly pure online players begin to conquer the cities with digital empowered physical stores (Liebmann, 2013; Holden, 2017). And Big-box retail outlets as well as traditional chain stores are digitalizing their stationary business models and offer multichannel sales and services to their local customers' on-site (HDE, 2017, pp. 1-14).

Simultaneously, the available digital information and communication channels and the according devices also enable the local customers to fundamentally change their shopping habits as well as their shopping expectations (IFH, 2016, p. 38). Subsequently, local stationary retailers have to face new shopping behaviors by their customers, i.e., "Showrooming" and its counterpart "Webrooming". Showrooming describes the customer behavior of viewing and evaluating a physical product in-store, but then buying it online. The term Webrooming is used when customers research and evaluate a product online, but then go and buy it in-store (Wolny and Charoensuksai, 2014, p. 318). Accordingly, shopping has become a complex journey in which customers choose the route they take (e.g., which device or sales channel) and which, arguably, needs to be understood by retailers. In the past, research has developed many approaches to map the touchpoints of customers to the retail organization, like service blue printing (e.g., Granbois, 1968; Naumann and Jackson, 1999; Bijmolt et al., 2010) or the many different kinds of the "Customer Decision Journey" (Court et al., 2009). However, today´s multichannel customers research online and offline, switch devices and collect purchase related information wherever possible (see example in Figure 1.1) (Schramm-Klein et al., 2011, p. 8; Wagner, 2015, p. 130).

Channel / Touchpoint			**Stages of the Customer Journey**				
Channel	**Device**	**Touch point**	**Pre-Purchase**			**Purchase**	**Post-Purchase**
			Awareness	**Information**	**Evaluation**		

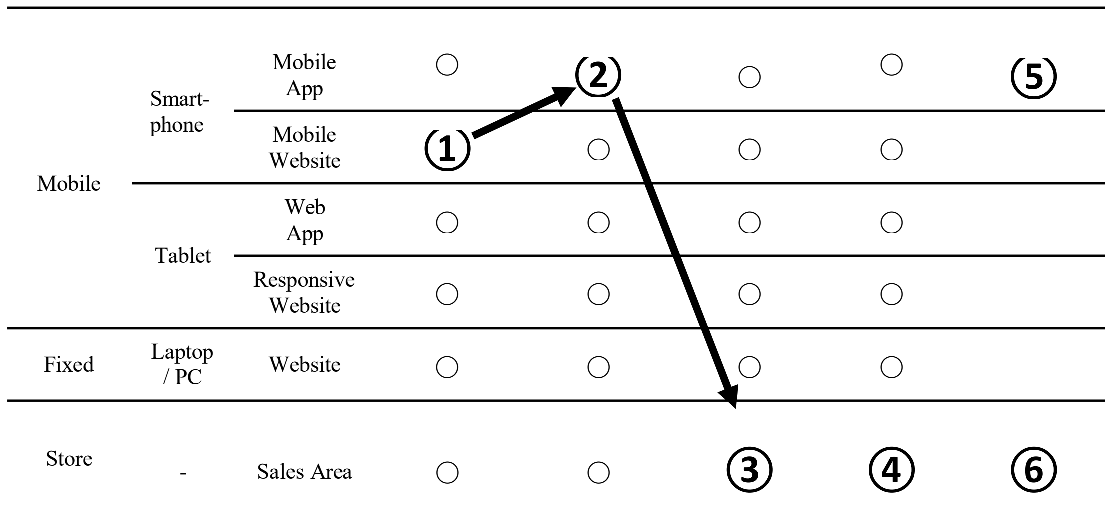
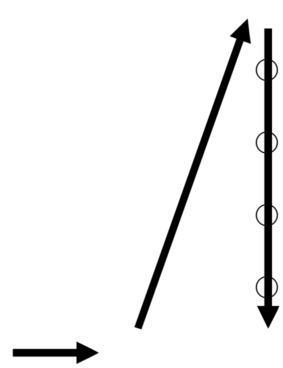


Figure 1.1 Cross-Channel / Cross-Device Customer Journey (Example based on Wagner, 2015)

The triade of digital advanced online and offline competition on the one side as well as changing shopping habits and expectations on the other puts pressure on all local stationary retailers to adapt to the new digital state of the art. However, studies show that not all kinds of retailers are adapting to the new situation in the same pace (IFH, 2016, p. 38; HDE, 2017, p. 9). Especially the small and owner operated retail businesses suffer most under the digital transformation of the local retail sector and seem to be suspended (Simón-Moya et al., 2016, pp. 159-162). Accordingly, the market share of the LOORO business type in Germany has already declined from 26% in 2003 to 17.9% in 2015 (HDE, 2017, p. 9). Furthermore, several independent studies predict a decline in revenues of 30% for LOOROs in Germany over the next four years (IFH, 2015; Heinemann, 2014) and about 50% in the next ten years (Siemssen, 2017).



1.1 Definition of Local Owner Operated Retail Outlets

The main research subject and target group of this dissertation are Local Owner Operated Retail Outlets (LOOROs). As LOOROs are individual businesses which are following individual business models, the aimed field of research was characterized by its high diversity in terms of types and kinds of retailers and their individual and different product and merchandise offers (HDE, 2017, p. 9). Despite the necessary owner involvement, there was no clear definition for LOOROs to build on. Accordingly, a simple framework to define LOOROs has been developed. It was derived from existing market research (e.g., HDE, 2015) and published studies (e.g., IFH, 2015) and used as contrast to larger retail organizations like chain stores, with obviously different background, possibilities and market situations.

Accordingly, a retail store is considered as LOORO if it fulfills the following criteria:

1) It is a local store with existing physical sales area.
2) The owner is involved into the day-to-day operations of the store.
3) The store is independent (not part of a retail chain or a franchise / not more than three subsidiaries).
4) The store is selling consumer goods (e.g., Fast Moving Consumer Goods (FMCG)).
5) The store follows standard opening hours (open at least 8 hours per day, at least five days per week).

1.2 Content and Structure

1.2.1 Research Questions & Methodology

In front of the introduced background, this dissertation aims to deliver a deeper understanding about the current readiness of Local Owner Operated Retail Outlets (LOOROs) for the challenges of the digitalization. Building on the gained insights about the current state of digitalization of LOOROs and the challenges they face in their day-to-day operations, it is aimed to derive possible options for action for LOOROs to regain competitive power and to help them to survive the ongoing disruptive innovation and transformation process of the retail sector. Accordingly, this dissertation aims to give answers to the following overall research questions:

RQ1: *What is the current state of digitalization of local owner operated retail outlets?*

RQ2: *What are possible options for actions for local owner operated retail outlets to regain competitive power and to survive in the digital future?*

CHAPTER 2- LITERATURE REVIEW

In a low growth market environment, the local owner operated retail outlets (LOORO) represented the group with the highest revenue losses in 2014 (HDE, 2015, pp. 3-14). The continued digitalization and further development towards chain stores threatens the very existence of local retail outlets run by their owners. In contrast to this, online retail has been expanding at a growth rate of 17.8 % in 2014 (HDE, 2015, p. 9). According to the German Retail Federation (Handelsverband Deutschland e.V., HDE), online retail will continue to have good growth prospects in the future, especially due to its pioneering digitalization work. But so far, retail is still dominated by in-store sales. However, despite the huge growth rates, the turnover share of e-commerce of retail is still only 11.1% in Germany (Statista, 2014, p. 13). The biggest changes in store-based retail in the last 20 years have been a tendency towards market concentration as chain stores and specialist retailers winning more and more market share from LOOROs. The share of LOOROs among German retail businesses is down from 30% in 1995 to now at only 14% (Ben-Shabat et al., 2015, p. 3).

This development leads us to the question whether the digitalization, which is the key ingredient of online retail and at the same time an important aspect of chain stores, specialist stores and big retail companies, can also open a new development perspective for LOOROs? However, as most of the research into digitalization in retail has concentrated on strategies for implementing digital applications in big organizations, there is a major gap in research into digitalization of small owner-run businesses. In order to address this gap, the authors of this paper have conducted a survey on the current state of digitalization of LOORO in a medium-sized town in Germany. In addition to providing information about the state of digitalization of LOORO, the survey's findings indicate a misalignment or mismatch between the perceived importance of digital services in the future on the one side, and the current implementations and availability of digital services – or even the willingness of LOORO to engage in digitalization – on the other side. This paper aims to be a first contribution to the overall topic. It will discuss and analyze the introduced mismatch on a rather descriptive level and offer the ground work for following empirical studies. Finally, the paper presents the hypothesis that owner-run business are in danger of being alienated from the expectations of their customers and that they seem to underestimate the relevance of service convenience for customers who have already changed their buying behavior in the context of digitalization.

The remainder of this paper is organized as follows: In the third section, we define the field of research and derive a Focal Action-Set (Conway and Steward, 1998, p. 12) based on the Technology-Organization-Environment framework (i.e., Tornatzki and Fleischer, 1990) to identify the main actors of the digital transformation of the retail sector. In the fourth section, we focus on customers as key actors and describe the relevance of convenience for their buying and channel decisions. In the fifth section, we introduce the SERVQUAL approach and the Gap-Model as frameworks for the discussion of the descriptive survey findings provided in the following sixth section. Next to these results of our own survey on retailer expectations regarding digitalization and digital services, the sixth section also contributes findings of a separate study about the change in the customers buying behavior. In the last section, we summarize our findings, provide new research questions and outline exemplary options for LOOROs to digitally support the customer journey.

MAPPING THE LOCAL COMMERCE INNOVATION NETWORK

In the age of digitalization, the retail sector is experiencing major changes. Established structures are eroded, business models are questioned, information asymmetries shift, and power structures among competitors and also between retailers and customers change. Furthermore, limitations of time and space are put into question, and new entrants from other industries introduce innovative ideas and new solutions to customers. The many technology and non-technology-driven changes triggered intense retail business research in general, but the digitalization of LOORO has captured only little attention so far. LOORO are no part of any large retail association or chain store and are very hard to classify as they encompass different owner personalities, different business sectors, different target groups and different business strategies.

To overcome the obstacles of the heterogeneity of LOORO, we start this line of research with designing a conceptual framework to map this special field of interest. To do so, we used the Focal Action-Set approach of Conway and Steward (1998), which guides researchers through the process of selection (abstraction) of specific aspects of the total (social) network surrounding the field of interest. It focuses the attention on the actors of innovation (in this case also transformation) and their relationships to each other. Following the approach of Conway and Steward, two decisions are necessary: The first decision is about the rules of inclusion (which actors to include in the framework) to find a definitional focus. To make this decision, we searched for a well-established theoretical model with regard to the adaption of technologies in comparable (small) companies. Ramdani and Kawalek (2007) developed the following well-structured overview of the most used models in the context of adaption of technologies and innovation in SMEs:

- Technology – Organization – Environment Framework (TOE-Framework)
- Technology Acceptance Model (TAM)
- Theory of Planned Behavior (TPB)
- Combined TAM and TPB
- TAM2
- Diffusion of Innovations Theory
- Resource-Based View
- Stage Theory
- Unified Theory of Acceptance and Use of Technology (UTAUT)

Ramdani and Kawalek (2007) summarized that the listed models typically examine the categories of technology, organization and environment, which also represent the basis categories of the also named TOE-Framework. Hence, for our definitional focus, we chose the Technology-Organization-Environment Framework (TOE-Framework) of Tornatzki and Fleischer (1990) as the theoretical foundation for our coming Focal Action-Set.

The second decision concerned the manner in which the abstraction of the definitional focus is anchored or centered, termed nodal-anchoring. The nodal-anchoring of our network is centered on the technological and innovational decision making by LOORO, which is termed an ego-centered anchoring (Conway and Steward, 1998, p. 7). The graphical output of these thoughts is termed "Actor Positioning Template" and is depicted in Figure 2.1:

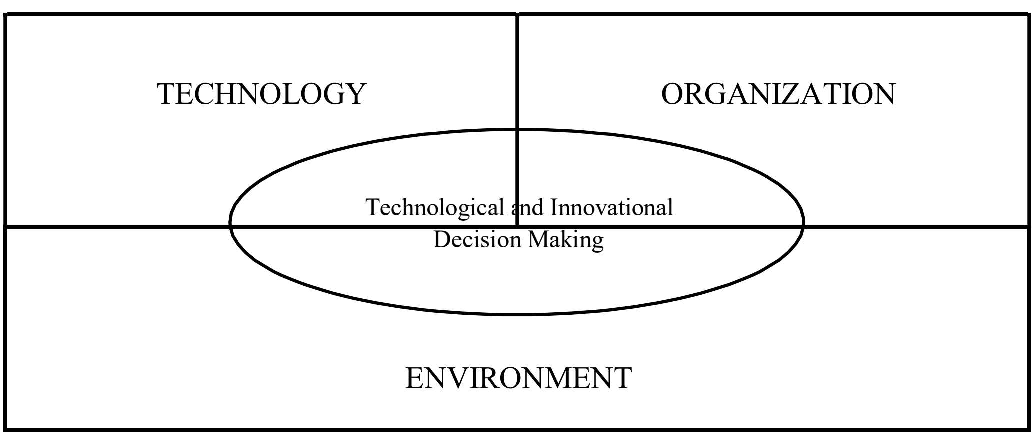


Figure 2.1 TOE-framework based Actor-Positioning Template
(based on Conway and Steward, 1998, p. 12)

The last step in designing the local commerce Focal Action-Set is to place the actors (i.e., transformation drivers) on the Actor-Positioning Template. Therefore, we translated the indicators of the TOE-Framework of Tornatzki and Fleischer (1990) into categories of LOORO transformation drivers: Technology, Owner, Competition, Customers, Suppliers, Urban Infrastructures and Politics. All were placed around the focal actor, the decision-making LOORO (Figure 2.2). With the help of the Focal Action-Set, it is now possible for further research to focus on specific fields of interest in this wide range of actors / drivers.

The last step in mapping an innovation network based on the work of Conway and Steward (1998) is to describe the relationships between the drivers and the focal actor. In this paper, we will focus on the relationship between LOOROs and their customers. We want to get a better understanding of how customer decision-making works and what opportunities evolve in this process. Therefore, we will show in the following that today's customers have changed their shopping behavior and that shopping-convenience is a key factor for shoppers to make their buying decisions and their choice of channel. Accordingly, we will examine the hypothesis that the use of digital services to increase shopping-convenience could be promising for LOOROs, and, regarding to the TOE-Framework and the identified transformation drivers, that the change in shopping behavior should influence the state of digitalization of LOOROs.

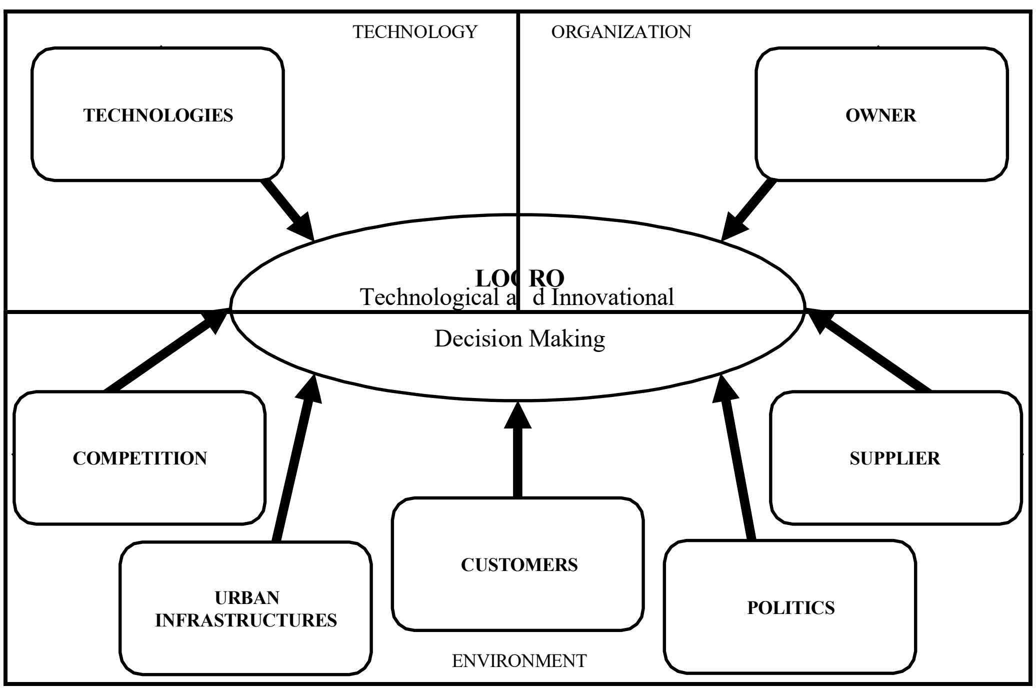


Figure 2.2 Local Commerce Focal Action-Set (Conway and Steward, 1998, p. 12)

CONVENIENCE AS KEY FACTOR INFLUENCING BUYING AND RETAIL CHANNEL DECISIONS

According to Seiders et al. (2007), shopping convenience reflects consumers' perceived time and effort in purchasing or using a service. A number of studies have shown that shopping convenience (e.g., time-saving) has a major influence on buying decisions (e.g., Wolfinbarger, 2001; Berry et al., 2002; Gupta, 2004; Bednarz et al., 2010; Jiang et al., 2013) and retail channel decisions of customers (e.g., Rohm and Swaminathan, 2004; Chang, 2005; Choudhury, 2008; Maity and Dass, 2014). If the products are very similar or even the same, the customer weighs pros and cons (convenience / risk) of different retail channels and then takes his buying decision and channel choice, which is thereby influenced by his personal background (e.g., education level and experience) (Bhatnagar, 2000, p. 3).

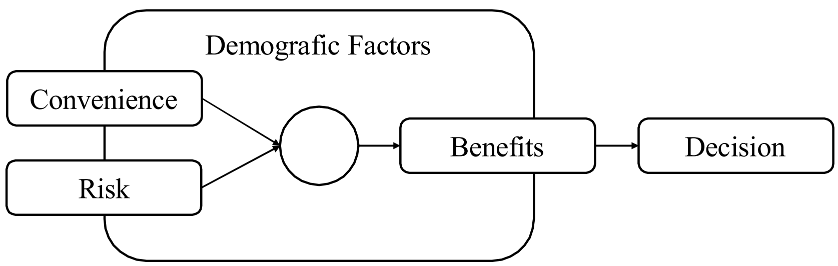


Figure 2.3 Convenience, risk and internet shopping behavior (Bhatnagar, 2000, p. 3)

In the context of retailing, Seiders et al. (2000) suggest four dimensions of convenience, which will guide the further discussion in the following sections:

(1) Access: Consumers may reach a retailer.
(2) Search: Consumers can identify and select products they wish to buy.
(3) Possession: Consumers can obtain desired products.
(4) Transaction: Consumers can effect or amend transactions.

We adapted this classification of shopping convenience for our survey and developed it into a set of digital shopping convenience categories as follows:

1. Online Visibility (Access): This category comprises all questions that refer to visibility online, like through a website (e.g., addressing also search engine optimization (SEO) activities), through search engines, or on digital markets.

2. Digital In-Store Applications (Search): This category refers to all questions related to the product management, like the digitalization of stock management, etc.
3. Delivery and Pick up (Possession): This category deals with delivery services and pick-up options for sold products.
4. Payment and Customer Relationship Management (Transaction): This category refers to questions that focus on e.g., payment methods or customer loyalty efforts, such as customer databases and loyalty schemes.

In the following presentation and discussion of survey results, the mismatch between expectations of the relevance of digitalization and the visible implementation efforts is revealed. Thereby, only a small set of questions / results which is in particular related to the above mentioned categories of digital shopping convenience, will be considered.

Local Commerce and the SERVQUAL Gap-Model

Service quality research has spawned a number of approaches and models (e.g., Cardozo, 1965; Powers, 1988) during its long tradition, such as the SERVQUAL model by Parasuraman et al. (1985). SERVQUAL offers a framework for measuring and managing service quality that encompasses both customer expectations as well as the actual service experience and also defines specific types of gaps that can cause a mismatch between expected and experienced service quality. SERVQUAL allows to conduct research into causes of over- or under-fulfilment of customer expectations using the confirmation / disconfirmation-paradigm amongst other tools. Figure 2.4 shows the SERVQUAL Gap-Model with the several defined types of gaps (Parasuraman et al., 1985, p. 4).

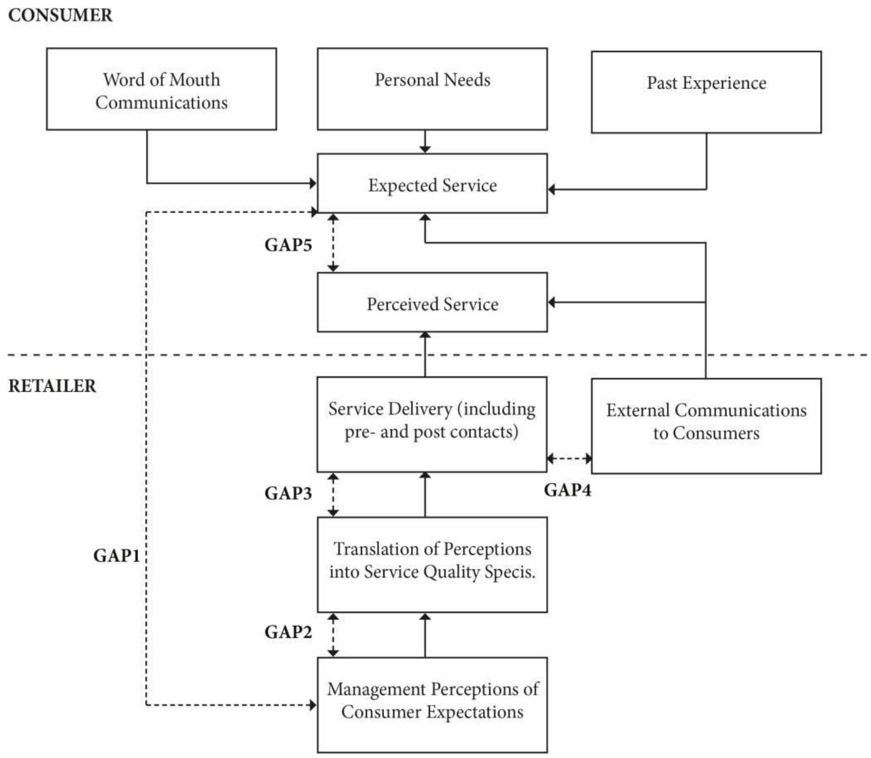


Figure 2.4 Service Quality Model (Parasuraman et al., 1985, p. 4)

We argue that the findings of the two following surveys indicate the existence of Gaps 1 and 2 of the SERVQUAL Gap-Model, increasing the risk of poor service quality in terms of under-fulfilled digital convenience expectations (Gap 5). According to Parasuraman et al. (1985), Gap 5 stands for the "expected service – perceived service gap" and needs to be interpreted as a function of the other gaps: "*The quality that a consumer perceives in a service is a function of the magnitude and direction of the gap between expected service and perceived service."* (Parasuraman et al., 1985, pp. 5-8) Gap 1 then represents the "consumer expectation – management perception gap". This gap represents the discrepancies between executive perceptions of and the actual consumer expectations, leading to improper service decisions and thus contributing to a Gap 5, which would mean negative impact on the service quality from the consumers' viewpoint. Gap 2 finally stands for the "management perception – service quality specification gap". It represents the difficulties of the management to match or exceed with their service specifications the expectations of the consumers, for example due to a lack of awareness, understanding or willingness, and thus also contributes to Gap 5. We neglect the other gaps at this point as they do not refer directly to the focus of this paper.

The following section now focuses on the two studies that reveal clear evidence for changing customer shopping behavior and that LOORO are aware of the importance of digitalization, but that they nevertheless do not feel pressured to take efforts to provide digital services as they do not seem to be fully aware of the changing digital shopping-convenience of their customers.

Changing Shopping Behavior & Retailers' Perception

In 2014, the Institute for Trade Research (IFH) conducted a survey among 411 customers concerning their shopping behavior. This survey took place in the City of Soest, Germany, the same town that we addressed in our survey. The IFH's survey indicates clear evidence of the change in the shopping behavior of today's consumers. It pointed out that 26% of the 411 interviewees indicated that they had changed their high street shopping habits due to new digital retail outlets and that they did less high street shopping than before. A further share of 19.7% stated that they now shop online, but that they so far continued to visit the high street as often as before. This means that a total of 45% of customers have changed their shopping habits already due to the digitalization and the offers of the online retail market (IFH, 2014, p. 38). This also means that in their opting for the online retail channel rather than the high street channel these customers indirectly give on the one hand a negative assessment of shopping convenience of local retail outlets and on the other hand a signal that there is a need to enhance the competitiveness of local retail outlets with regard to digital/non-digital convenience.

In order to investigate the state of digitalization of LOORO in this context, we conducted a survey of local commerce between 10th and 19th February 2015 in the same medium sized German town (46.000 inhabitants / City of Soest). The survey was supported by the society for economic and market promotion (Wirtschaft & Marketing Soest GmbH, WMS) of the town. The WMS provided us with contacts to 135 local businesses that are listed as owner-operated retail outlets on their database. 85 of these 135 businesses fulfilled our definition of a LOORO (e.g., retail store open on business days and with focus on consumer goods). The 85 businesses fulfilling our criteria were contacted personally and invited to take part in the survey. 44 of the contacted business completed all questions on the survey on paper (51.8%). The survey was based on the causality model called Technology Acceptance Model (TAM) (Davis, 1985, p. 24) and the TOE-framework (i.e., Tornatzki and Fleischer, 1990), it consisted of 11 categories with 226 questions.

No.	Question	Answer				
		Very high	High	Average	Low	Very Low
1.	In your opinion, what importance will digitalization have for your business in the future?	10.8%	51.4%	21.6%	10.8%	5.4%
2.	Willingness to work with digital applications?	23.7%	31.6%	31.6%	10.5%	2.6%
3.	How much do your customers expect digital service offerings from you (e.g., online store, apps, internet site)?	5.1%	7.7%	23.1%	35.9%	28.2%

Table 2.1 Exemplary survey questions

The answers of the survey on digitalization in local commerce indicate that there is a gulf between the perception of the relevance of digitalization and the implementation of services or the willingness to consider implementing digital services. This can be illustrated by the following exemplary results: 62.2% of the surveyed retailers stated that digitalization would have a high or a very high relevance for their business in the future (Table 2.1 / Question 1). 55.3% described their willingness to engage with digitalization as high or very high (Table 2.1 / Question 2). Thus, most of the surveyed retailers indicated that digitalization is of a high relevance to them and that they are willing to engage with it. On the other hand, 64.1% of the surveyed retailers assumed that customers would only have a low or even very low expectation of digital services for their business. A further 23.1% did not provide an answer on this question (Table 2.1 / Question 3).

In summary, after defining the field of research and identifying the key actors, we pointed out that despite the more and more difficult market environment most LOORO see digitalization as a topic rather for the future than for today and do not (yet) feel pressured to really engage with it. Using the SERVQUAL Gap-Model and thereby considering two studies conducted in the same German town covering both the retailers' and the customers' perspective, we identified out a growing mismatch between the (digital) shopping-convenience expected by customers and the according offers and activities of the studied retail outlets.

As we argue that the owner-operated retail outlets, which are a major economic factor for high street retail and the town economy can only retain their competitive edge if they manage to tailor their services and products more towards the service expectations of their customers, our advice is to "Mind the Gap." A closer assessment of customer expectations and a closer alignment of (digital) services with those changing expectations seem to be key ingredients for making progress and halting the increasing market share of e-commerce for local businesses.

Future Research and Future Development Options for LOOROs

To address the variety of opportunities for LOOROs in order to increase shopping-convenience through digital services, it is necessary for future research to examine the sales and communication channels. It is almost common business to talk about the seamless integration of all available channels as part of an Omnichannel approach. However, that falls too short in our opinion. In contrast to the company-centric view on channels like web, mobile and in-store, we suggest choosing research on a customer-centric view that explains the digital state of the customer at the touchpoints with the company.

Customer can be met in the following digital states:

1. Offline in-store
2. Offline not in-store
3. Online (fixed) in-store
4. Online (fixed) not in-store
5. Online (mobile) in-store
6. Online (mobile) not in-store

Accordingly, customers who are offline and not in-store could be addressed through traditional marketing and advertising channels. Customers who are offline in-store could be digitally enabled through store facilities to reach the online state (fixed or mobile) in-store so that we can focus on the last four costumer states of our list. Further, to show direct-use cases, Table 2.2 uses the well-established customer journey (Court et al., 2009) to structure exemplary digital options and opportunities for LOORO:

Customer Journey	The customer is			
	In-Store		Not In-Store	
	Online Fixed	**Online Mobile**	**Online Fixed**	**Online Mobile**
	Awareness / Information Phase			
Learning about new brands and products	Digital Displays	Location-Based In-Store Advertising	Search Engine Marketing	Location-Based Marketing
	Consideration / Negotiation Phase			
Searching for additional information on product details	Digital Shelf Extensions	QR-Codes	Search Engine Optimization	Location-Based Recommendations
	Purchase / Agreement Phase			
Completing the purchase	Online Stored Value Payment	Mobile Payment with NFC	Digital Currency	Mobile Payment without NFC
	Fulfilment / Realization Phase			
Obtaining the product	In-Store Pick-Up	Service App	Same Day Delivery	Service App
	Loyalty / Using Phase			
Engaging with the store after sale	Loyalty Cards	In-Store Behavioral Targeting	Customer Relationship Management	Social Media

Table 2.2 Examples of digital capabilities for LOORO on the Customer Journey (based on Court et al., 2009)

This paper aimed at making a first contribution regarding the challenges faced by local commerce in view of digitalization of retail according to their special background and obstacles. It is meant as first step and introduction to the topic. In future, we plan to conduct empirical research on the current state of digitalization and the options of local retailers to address the discovered gaps between their perceptions of and the actual customers' expectations with regard to digital shopping-convenience. Some examples to be studied include mobile payment, digital shelf extensions, online marketing, and co-operative logistics solutions allowing for same-day delivery and how these could be used for digital business model innovations by local retailers.

The retail landscape is experiencing seismic changes. The low growth rate environment puts local owner operated retail outlets (LOORO) under immense pressure (HDE, 2015, p.7). On the German market, the market share of the business model LOORO has fallen from 30% in 1995 to only 14% in 2014 (Ben-Shabat et al., 2015, p.3). In 2014, LOOROs suffered the sharpest decline in turnover of all retail outlets in Germany and the future outlook for LOOROs is also bleak. A further turnover decline of about 30% by 2020 or 2023 has been forecast (IFH, 2015; Heinemann, 2014). Despite the huge growth rates in online retail (17.8% in 2014 (HDE, 2015, p. 9)), the German retail landscape is still dominated by stationary and locally rooted businesses, and LOOROs constitute an important income source for many communities (HDE, 2015, pp. 3-14). Although online retail only had a market share of 11.1% (Statista, 2015) in 2014, it has significantly influenced the whole sector with regard to shopping convenience and service quality (Heinemann and Schwarzl, 2010, pp. 2-10). On the one hand, the growing influence of e-commerce, which manifests itself not just in the online presence of "pure players" but also in an increased digitalization of traditionally stationary retail outlets as well as the changing shopping habits of their customers (IFH, 2014, p. 38, Hudetz et al., 2011, pp. 3-8), has put enormous pressure on LOOROs and has brought retailers with a traditional business models to their knees. On the other hand, a custom-made digitalization strategy tailored to their specific customers also offers potential opportunities to LOOROs with regard to customer satisfaction, competitive advantages, and increased market share (Navickas et al., 2015, p. 4).

However, the diffusion of digital retail services seems to hit a barrier for most LOOROs, as only very minor steps towards digitalization can currently be observed (Bollweg et al. 2015, p. 8). This brings us to the question to what extent LOOROs are ready to face the digitalization challenge. Retail research has shown that increased competition and changed or increased customer expectations normally act as a driver for innovation for small and medium-sized enterprises (SME), as they are traditionally characterized by flexibility in their trade structure. But due to the continued decline of LOOROs, which is forecast to continue and speed up in the next years, it is not known whether LOOROs will be able to weather the digital challenge. This is why we decided to conduct a survey of LOOROs in a medium sized town of 46000 inhabitants about their perception of digitalization and their own position within this development. This survey was then correlated with a third-party survey conducted on shoppers in the same town about their shopping habits and their view on the increased digitalization of retail. Our main research question is, “Do LOOROs realize that digitalization is here to stay and that they will have to adapt to the new retail environment?”

The remainder of this paper is organized as follows: The literature review following in section 3.3 first gives an overview of related studies looking at the adoption of e-business and e-commerce technologies by SMEs. We will then examine the literature body for indications about the impact of the perceived competition and customer expectations on the adoption decision. In section 3.4, we develop the conceptual model concerning the perception of competition and customer expectations regarding the adoption of digitalization in LOORO and derive the hypotheses. The analysis of this model is presented in section 3.5, and the results are discussed in section 3.6. The paper concludes with a summary and an outlook to future research.

Business informatics offers a number of theoretical models for the adoption of innovation and technology in SMEs that have been tested and validated in numerous studies. Ramdani and Kawalek (2007) have identified the following models: Technology – Organization – Environment Framework (TOE-Framework), Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), Combined TAM and TPB, TAM2, Diffusion of Innovation Theory, Resource-Based View, Stage Theory and Unified Theory of Acceptance and Use of Technology (UTAUT). They have shown that in each of the nine models factors from the areas of technology, organization or environment are studied with regard to their influence on the decision to adapt. The Technology-Organization-Environment Framework (TOE-Framework) by Tornatzky and Fleischer (1990) addresses these areas directly and has been tested and validated in several studies. Therefore, we have chosen this model as a basis for our research.

To get an overview about the current state of research using the TOE-Framework in the context of adoption of new technologies in SMEs, we conducted a structured literature review concerning this field. We searched with the keywords “TOE-Framework”, “SME” and “adoption” for journals and conference contributions in the databases of EbscoHost, ScienceDirect and Google Scholar. To reduce our starting collection of 138 Papers we examined all abstracts and selected 22 papers with a clear focus on the TOE-Framework and the adoption of technologies for further investigation. This literature body has been fully analyzed by us and it turned out that 13 of the 22 papers had also a section on SME. In the final 13 papers, we found two kinds of studies fitting to our requirements. The first group was designing general frameworks for examining the adoption of technology in SMEs without defining specific technologies within their model (e.g., Rashid, 2001; Ramdani and

Kawalek, 2007). The second group of studies was very specific and had a clear focus on well-defined technologies, i.e., adoption of e-mail, Internet, EDI, VPN (e.g., Premkumar and Roberts, 1999; Al-Qirim, 2007). Both groups have in common that they adapted the TOE-Framework to the needs of their studies and developed it further by adding new categories or new factors within the predefined TOE categories. Most of the designed models remained close to the original TOE-Framework; just a few nearly doubled the number of examined factors (e.g., Rashid, 2001; Chong, 2008). More visible differences appeared with regard to the use of the term SME in the studies. One group of studies used the term as a universally accepted concept without closer definition (e.g., Zhu et al., 2002). A second group of studies was again very specific and had a clear defined research scope with a definition about e.g., company size, industry classification and area of research (e.g., Rashid, 2001). Most of the studies using TOE presented here have gathered the examined data of their studies directly by taking it from surveys and interviews they conducted themselves. The industries discussed and examined in these studies did not refer to similar business sectors (i.e., Tourism, Manufacturing, E-Commerce).

With regard to our research about the visible change of competition (strong growth of E-Commerce) and the changing shopping habits of customers (i.e., online shopping) we finally examined the influence of the factors of perceived competition and the perceived customer expectations with regard to the decision of adapting to a new environment in the TOE studies of our literature body. Our findings show clearly (see Table 3.1) that, whenever mentioned, the factors competition and customer expectations had a visible positive impact on the adoption of new technologies in SMEs.

Now, concerning our scope of research, the question is why there is no comparable development towards digitalization and new technologies in LOOROs by now. Do LOOROs not perceive any competition and customer expectations regarding digitalization?

RESEARCH FRAMEWORK

In order to pursue our overall research question "Do LOOROs realize that digitalization is here to stay and that they will have to adapt to the new retail environment?" we will examine in more detail the question raised during our literature review: Do LOOROs perceive any competition and customer expectations regarding digitalization?

But first we need to gain a better understanding for the stimulation effects of the factors competition and customer expectation on the adoption process. Both are external factors of the near environment, concerning the three environments model (internal, near and far) of Stapelton (2000). These external factors affect the general environment within a particular SME has to operate (Dholakia and Kshetri, 2004, pp. 2-4). The Stakeholders of the near environment are customers, competitors and suppliers, and these are the main touchpoints of an SME.

With regards to the three environments model, this is the group of external factors that an SME can influence. On the other hand the external factors of the near environment (Customers, Competition and Suppliers) have also significant influence on the SME itself and can shape the environmental situation through their actions (Dholakia and Kshetri, 2004, pp. 2-4). This creates pressure, the SME needs to adapt to the new environmental situation. Otherwise the inability or the unwillingness to adopt or the disbelief in the need to the adoption will lead to a competitive disadvantage (Parasuraman et al., 1985, pp. 6-8). And if so, why does the perception of competition and customer expectations regarding digitalization not lead to the adoption of new technologies in LOOROs in the same way as this perception does in other SMEs?

Therefore, we defined a research model with four constructs. The first construct is named "Competition" and is derived from the main sales channels of LOOROs, the local store and the online channel.

It takes the already discussed change in competition for LOOROs (Heinemann and Schwarzl, 2010, pp. 2-10) into the account and is measured by two indicators, the perceived competitive pressure in the local market (C1) and the perceived competitive pressure with the online trade (C2).

The further constructs, "Customer Expectations", "Current Usage" and "Future Usage" represent the digitalization of retail, each with a different scope. To cover this very general and broad category we derived our constructs from the transaction phase logic. We picked digital examples from the basic transaction phases (pre-sales phase, checkout / fulfilment phase and the after-sales phase). Each construct covers at least one example of each phase. For the construct "Customer Expectations" we have chosen frequently used applications and services, for "Current Usage" already widespread applications and services, and for "Future Usage" advancements or evolutions of the "currently used" applications and services (see Table 3.2 Indicators sorted by transaction phase).

The construct "Customer Expectations" measures the perceived change in customer habits and perceived customer expectations regarding digitalization (IFH, 2014, p. 38; Hudetz et al., 2011, pp. 3-6). It consists of four indicators, the acknowledgement of customers using digital applications accompanying their purchases (CE1), the demand of customers regarding an online shop (CE2), regarding customer cards (CE3), and regarding home delivery (CE4).

The constructs "Current Usage" and "Future Usage" measure the adoption and likeliness of the future adoption of digital technologies by LOOROs. The construct "Current Usage" is measured by four indicators, the current usage of basic digital applications like e-mails (CU1), EC-Card (CU2), internet (CU3), and loyalty cards (CU4). The construct "Future Usage" is measured by six indicators, the planed future usage of more advanced digital applications like video telephony (FU1), payment via smartphone (FU2), mobile apps with service (FU3), online shop (FU4), social media (FU5), and customer integration (FU6).

Customer Expectations	Current Usage	Future Usage
PRE-SALES (Search and Information)		
Onlineshop	Homepage Emails	Onlineshop APP Video-Telephony Social Media
CHECKOUT / FULFILMENT (Payment and Delivery)		
Digital Applications Logistics (Home Delivery)	EC-Card	Mobile Payment (via Smartphone)
AFTER SALES (Loyalty and Customer Care)		
Customer Card	Customer Card	Customer Integration

Table 3.2 Indicators sorted by transaction phase

According to the stated relationship of competitive pressure (competition) and the adoption of new technologies in the TOE-Framework (i.e., Tornatzky and Fleischer, 1990) and the proven positive impact by several reviewed TOE based studies about the adoption of new technologies in SME (see Table 3.1 literature review of influencing factors in the TOE-framework), we define our first hypothesis as follows:

H1: *The perceived high competitive pressure has a positive influence on the current usage of digital services by LOOROs.*

To gain more insights into the strategic development of LOOROs, we extend our examination of the current usage of digital services to the planned future usage of digital services and state the following second hypothesis:

H2: *The perceived high competitive pressure has a positive influence on the plans of using digital services in the future.*

Similar to hypothesis 1, we also want to examine the relationship of customer expectations and the adoption of technologies in SME. Customer expectations are not part of the original TOE-Framework, but are frequently used extensions of the TOE-Framework (see Table 3.1 literature review of influencing factors in the TOE-framework). Additionally, customer expectations are a decisive factor in Service Quality Research like the well-known SERVQUAL Gap-Model (Parasuraman et al., 1985, p. 4). The impact on the adoption of new technologies in SMEs is proved by the reviewed TOE based studies depicted in table 3.1 literature review of influencing factors in the TOE-framework. Therefore, we hypothesize:

H3: *The perceived high customer expectation towards digital services has a positive influence on current usage of digital services by LOOROs.*

Corresponding to our extension of the hypothesis 1, we follow this path and also extend hypothesis 3 to gain more long-term insights into the development of LOOROs:

H4: *The perceived high customer expectation towards digital services has a positive influence on the plans of using digital services in the future.*

To examine, if the current usage of digital services seems to be promising for LOOROs, we want to see if there is a positive relationship between current and planned future usage. We assume that in those cases where a LOORO is benefitting from using digital services, they will be likely to use digital services in future. According to that assumption we state the last hypothesis:

H5: *The current usage of digital services by LOOROs has a positive influence on their plans of using digital services in the future.*

The resulting research model is depicted in Figure 3.1. The resulting questionnaire is given in Table 3.3.

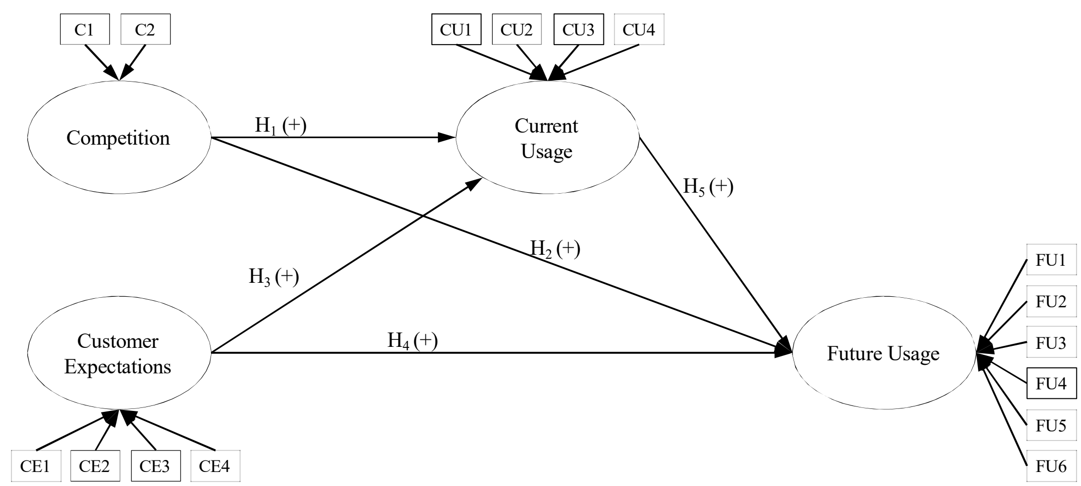


Figure 3.1 Research model

Construct	Indicator	Question
Future Usage	FU1	How would you rate the intention of future use of video telephony as a means of corporate communications for your business?
	FU2	How would you rate the intention of future use of payment by smartphone (mobile wallet, NFC) for your business?
	FU3	How would you rate the intention of future use of an app with service (consultation or sale) for your business?
	FU4	How would you rate the intention of future use of an online shop for your business?
	FU5	How would you rate the intention of future use of social media for your business?
	FU6	How would you rate the intention of future integration of customers in decisions about your product range for your business?
Current Usage	CU1	How would you rate the frequency of current use of e-mails as a means of corporate communications for your business?
	CU2	How would you rate the frequency of current use of EC and credit card payment for your business?
	CU3	How would you rate the frequency of current use of an internet site for your business?
	CU4	How would you rate the frequency of current use of a loyalty card for your business?
Competition	C1	How high is the competitive pressure on the local market?
	C2	How high is the competitive pressure in the online trade?
Customer expectations	CE1	How often do you acknowledge that your customers use digital applications accompanying the purchases in your store?
	CE2	How high is the customer demand for an online shop?
	CE3	How high is the customer demand for loyalty cards?
	CE4	How high is the customers demand for home delivery?

Table 3.3 Questionnaire

ANALYSIS

DATA COLLECTION

The data was gathered in February 2015 in the context of a survey of local owner operated retail outlets (LOOROs) in a medium sized town (46000 inhabitants, City of Soest). The survey was supported by the local business marketing agency (Wirtschaft & Marketing GmbH, WMS) of the town. The WMS agency provided the addresses of 135 retail outlets, of which 85 corresponded to the parameters set for this survey, i.e., local owner operated retail outlets (relevant parameters were normal opening hours, a stationary retail outlet, not a chain store, fast moving consumer goods). Of the 85 LOOROs that were personally invited to take part in the survey, 44 completed the survey in paper form (51.8%) and 8 (9.4%) via an online form. So we received 52 responses in total. All survey questions were measured in a 5-point-Likert-Scale.

In order to analyze the data gathered and to investigate the correlation between the different constructs proposed by the hypotheses, we used structural equation modelling that consists of an outer and an inner model. The outer model, called the measurement model, defines the relations between constructs and indicators, while the inner model, the structural model, represents the relations between the constructs (Fornell and Larcker, 1981 p. 39; Chin, 1998a, pp. 312-318).

We used SmartPLS for the statistical data analysis, which allowed us to use a PLS algorithm and bootstrapping as resampling method (i.e., Ringle et al., 2005). As the PLS algorithm does not calculate all relations at the same time, but only subsets of data (Hair et al., 2014, p. 14), its results are reliable, even for small samples. The minimum sample size is determined by two rules, it is either 10 times the largest number of formative indicators used to measure a single construct or 10 times the largest number of structural paths directed at a particular construct in the structural model (Hair et al., 2014, p. 51). Our model missed the first rule just marginally (6 formative indicators in construct Future Usage) but complies with the requirements of the second rule. With three structural paths as the largest number of structural paths directed at a particular construct of the model, 30 cases would be required and we used 52.

The bootstrapping method, used on 5000 samples and 52 cases, was used to determine significance, loadings, weights and path coefficients (Chin, 1998b, p. 323). In order to ensure that there is no multicollinearity of the indicators, the findings were additionally cross-referenced using SPSS.

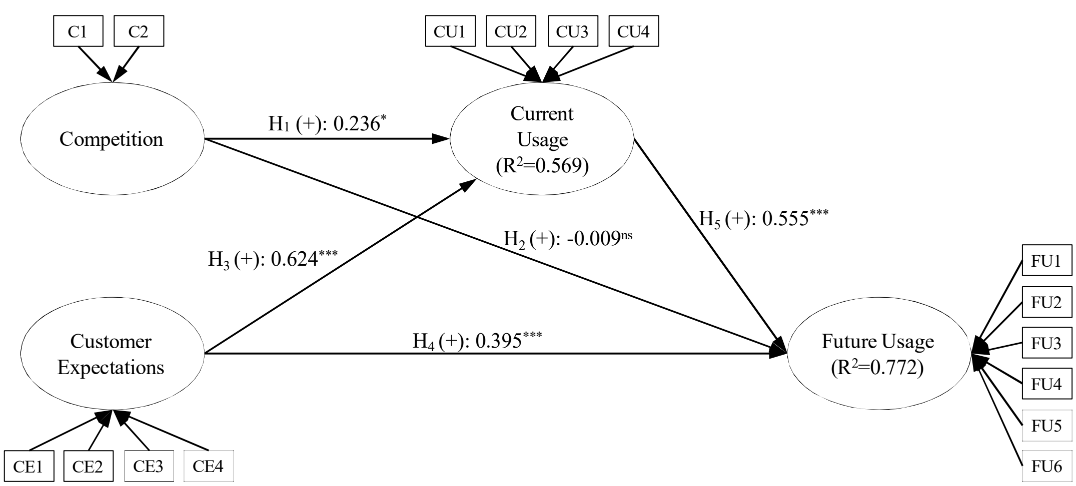


Figure 3.2 Results of the PLS Algorithm

MEASUREMENT MODEL

The two kinds of constructs underlying the measurement model, reflective and formative constructs, have different analysis requirements (Fornell and Bookstein, 1982, p. 442). But as the current model uses only formative constructs, the reflective constructs need not be considered here. The given formative constructs are built by their indicators, which means that a change in one of the indicators will also alter the construct. But an alteration in the construct will not influence its indicators (Bollen and Lennox, 1991, p. 306; Jarvis et al., 2003, p. 200). In order to assess the significance of an indicator, the weights and the t-values have to correspond to the following requirements: The t value of a significant indicator must be higher than 1.65, which corresponds to a significance level of 10% (Hair et al., 2006, pp. 664-670). In order to reach a significance level of 5% (1%), the t-value must be higher than 1.96 (2.57) (Hair et al., 2006, pp. 664-670; Huber et al., 2007, p. 104). In addition, the weights must be higher than 0.1 (Chin, 1998b, p. 324). Table 3.4 show the t-values as well as the corresponding weights for all indicators of our model and also indicates the result with regard to the calculated significance.

For the construct "Future Usage", three (FU2, FU4, FU5) of six indicators are significant having a positive influence. The construct "Current Usage" includes three significant indicators, CU1, CU2 and CU3 each with positive influence. In the construct "Competition" both t-values are higher than 1.96, indicating a 5% level of significance. This again indicates a positive influence of the indicator for the corresponding construct. For the construct "Customer Expectations" only the indicators CE2 and CE3 are significant. The t-value of CE2 is higher than 2.57 (1% level of significance) and the value of CE3 is higher than 1.65 (10% level of significance). The weights of both indicators exceed the threshold of 0.1. In addition to the significance of indicators, the discriminant validity of the formative constructs must be verified. The highest correlation between latent variables is given for the constructs "Current Usage" and "Future Usage" with a value of 0.8357. This does not go beyond the set maximum of 0.9. The analysis conducted using SPSS with regard to multi-collinearity showed that all indicators of the models are sufficiently different and independent of each other.

Construct	Indicator	Weights	*t*-statistic	significance
Future Usage	FU1	0.183	1.366	ns
	FU2	0.431	2.667	***
	FU3	-0.107	0.851	ns
	FU4	0.277	2.145	**
	FU5	0.383	3.218	***
	FU6	0.064	0.629	ns
Current Usage	CU1	0.544	3.261	***
	CU2	0.024	0.301	ns
	CU3	0.273	1.909	*
	CU4	0.495	3.291	***
Competition	C1	0.602	2.241	**
	C2	0.612	2.370	**
Customer Expectations	CE1	0.118	0.853	ns
	CE2	0.807	5.542	***
	CE3	0.245	1.764	*
	CE4	0.175	1.548	ns

ns = not significant; *p<0.10; **p<0.05; ***p<0.01.

Table 3.4 Path coefficients

STRUCTURAL MODEL

In order to validate the model, the constructs were assessed using the variance inflation factor (VIF=1/(1-R^2)) as to potential multicollinearity (Weiber and Mühlhaus, 2010, p. 207). The VIF is lower than the required level of 10, which shows that there is no multicollinearity here either (Diamantopoulos and Winkelhofer, 2001, p. 272; Huber et al., 2007, p. 38). The value of R^2 represents the coefficient of determination, which indicates a substantial influence if the value exceeds 0.67. Above the value of 0.33 a moderate influence of a latent independent variable on the dependent latent variable can be assumed. A weak influence is indicated by an R^2 value of higher than 0.19 (Chin, 1998b, p. 323). Figure 3.2 indicates the values for the different criteria of our model. The coefficient of determination of the construct "Current Usage" is moderate with a value of R^2=0.569 and substantial with a value of R^2=0.772 concerning the construct "Future Usage".

The t-values stated in Table 3.4 and their path coefficients allow conclusions as to the validity of the formulated hypotheses. According to the findings, all relations apart from the one between "Competition" and "Future Usage" (H2) are significant and have t-values of at least 1.65 (Weiber and Mühlhaus, 2010, p. 207).

DISCUSSION

At first sight, the results of our survey are in line with the findings of the other studies reviewed in section 2. The perceived competitive pressure (H1) as well as the perceived customer expectations (H3) influence the current usage of digital technologies by LOOROs positively. Thereby, the explanatory power of the construct "current usage" is moderate, indicating that the current usage could be explained quite satisfactorily. While the influence of the perceived customer expectations on the future usage (H4) was also confirmed at a high significance level (1%), the influence of the perceived competitive pressure on the future usage (H2) was not. As to hypothesis H5, contending that the current usage has a positive impact of the future usage, H5 was also be confirmed with high significance (1%), the competitive pressure indirectly influences the future usage. The main drivers for the usage of digital services are therefore the perceived customer expectations and the already existing use of such services.While this indicates that the LOOROs already engaging in digitalization are satisfied with their current efforts and expect future business increases through digitalization, this could also mean that LOOROs tend to wait before going digital until the pressure of competition is high enough and they are forced to use digital services, or that LOOROs think they are well prepared for the digitalization and their customers' demand for it. To substantiate this assumption, let us have a look at the descriptive statistics of the survey questions (see Table 3.5). In addition to the questionnaire that we used for our research model, we also asked several additional questions (AQ1-AQ4) concerning the status quo of LOOROs and their state of digitalization.

As we can see, about half of the interviewees feel high and very high pressure concerning the local as well as the online market. Following hypothesis H1, this should mean that the current usage of digital services is also quite high. But in fact, this is only the case for e-mail and EC payment. Loyalty cards as well as website are rated high or very high by less than a third. This picture continues when looking at the intention for future usage of digital services. Except for the online shop, less than a quarter of the interviewees indicate a high or very high intention to use digital services in future. The reason for this lies in the perceived customer expectations. Less than one third of LOOROs perceive a high or very high demand of customers for digital services (CE1-CE4 and AQ3-AQ4). But on the other hand, LOOROs feel well prepared for the challenge to digitalize (AQ1 and AQ2) although most of them have very low employee numbers (below ten). Thus, the employee situation is not viewed as barrier to digitalization.

	Question	Answer				
Future Usage		**very high**	**high**	**average**	**low**	**very low**
FU1	How would you rate the intention of future use of video telephony as a means of corporate communications for your business?	1.9%	0%	7.7%	25%	46.2%
FU2	How would you rate the intention of future use of payment by smartphone (mobile wallet, NFC) for your business?	9.6%	11.5%	15.4%	11.5%	36.5%
FU3	How would you rate the intention of future use of an app with service (consultation or sale) for your business?	0%	3.8%	13.5%	17.3%	38.5%
FU4	How would you rate the intention of future use of an online shop for your business?	19.2%	7.7%	17.3%	9.6%	28.8%
FU5	How would you rate the intention of future use of social media for your business?	1.9%	19.2%	25%	15.4%	21.2%
FU6	How would you rate the intention of future integration of customers in decisions about your product range for your business?	3.8%	11.5%	34.6%	11.5%	17.3%
Current Usage		**very high**	**high**	**average**	**low**	**very low**
CU1	How would you rate the frequency of current use of e-mails as a means of corporate communications for your business?	17.3%	23.1%	26.9%	13.5%	7.7%
CU2	How would you rate the frequency of current use of EC and credit card payment for your business?	40.4%	36.5%	7.7%	5.8%	1.9%
CU3	How would you rate the frequency of current use of an internet site for your business?	17.3%	13.5%	23.1%	21.2%	9.6%
CU4	How would you rate the frequency of current use of a loyalty card for your business?	15.4%	7.7%	15.4%	13.5%	30.8%
Competition		**very high**	**high**	**average**	**low**	**very low**
C1	How high is the competitive pressure on the local market?	13.5%	30.8%	28.8%	17.3%	5.8%
C2	How high is the competitive pressure in the online trade?	30.8%	25%	26.9%	9.6%	3.8%
Customer Expectations		**very often**	**often**	**average**	**seldom**	**very seldom**
CE1	How often do you acknowledge that your customers use digital applications accompanying the purchases in your store?	7.7%	17.3%	26.9%	26.9%	11.5%
		very high	**high**	**average**	**low**	**very low**
CE2	How high is the customer demand for an online shop?	7.7%	1.9%	23.1%	17.3%	32.7%
CE3	How high is the customer demand for loyalty cards?	7.7%	11.5%	11.5%	15.4%	40.4%
CE4	How high is the customers demand for home delivery?	17.3	9.6%	17.3%	17.3%	28.8%
Additional Questions		**very high**	**high**	**average**	**low**	**very low**
AQ1	How high is the importance of digitalization for your business?	13.5%	42.3%	19.2%	7.7%	3.8%
		very good	**good**	**average**	**bad**	**very bad**
AQ2	How is your personnel situation regarding the likeliness to work with digital applications?	19.2%	36.5%	23.1%	7.7%	1.9%
		very strong	**strong**	**average**	**weak**	**very weak**
AQ3	How strong do you perceive customer churn toward online trade?	7.7%	13.5%	34.6%	17.3%	9.6%
AQ4	How strong do your customers expect digital service offers (e.g., apps. online shop. website) from you?	5.8%	7.7%	21.2%	30.8%	21.2%

The survey was conducted in German, the questions are translated into English

Table 3.5 Descriptive statistics of survey questions

If we link these results with the customer survey conducted by the Retail Institute at the University of Cologne (Institut für Handelsforschung, IFH) in the same town, we observe an alarming gap. 45% of the shoppers interviewed in that survey indicated that they had changed their shopping habits in favor of more online retail. That means that LOOROs do not seem to perceive the raised expectations of their customers as to digital services.

According to the SERVQUAL Gap-Model based on Parasuraman et al. (1985) (see Figure 3.3), our results suggest Gap 1 (actual customer expectations vs. perceived customer expectations).

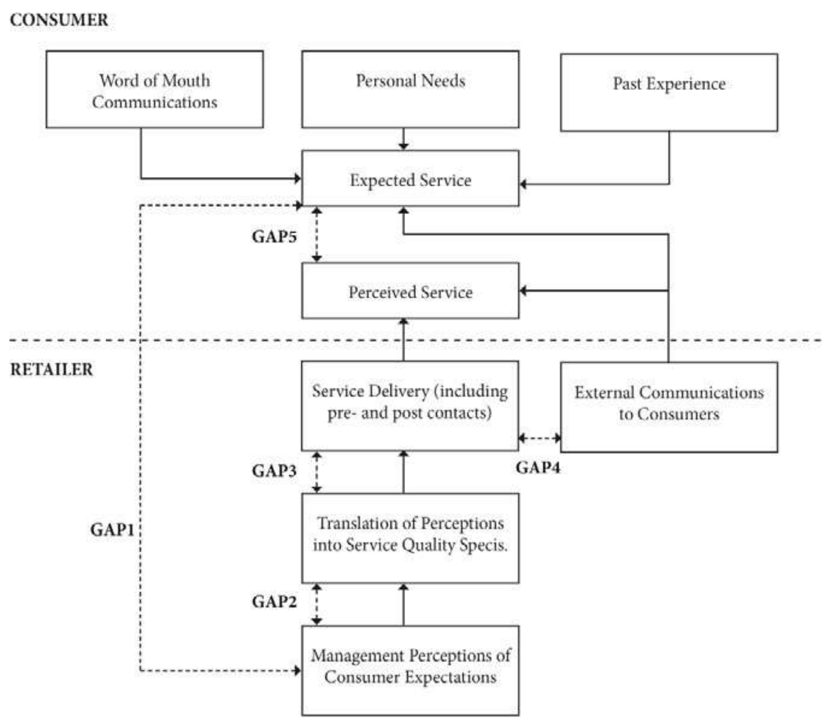


Figure 3.3 SERVQUAL Gap-Model (Parasuraman et al., 1985, p. 4)

This Gap indicates that there is a risk that the services provided by the LOOROs may not correspond to the customer expectations, which will cause customers to have a negative quality perception, as their expectations of digital services provided and the actual services they experience fall short (Gap 5).

In general, the results of our survey are in line with the findings of previous studies based on the TOE-Framework with regard to the adoption of innovation and technology in SMEs. The perception of competition and customer expectations has a positive influence on current usage of digital services and at least the customer expectations also act as a driving force towards the willingness to adopt digital services in the future. If we go back to our main question “Do LOOROs realize that digitalization is here to stay and that they will have to adapt to the new retail environment?”, the picture is ambivalent. On the one hand, LOOROs in general perceive a high importance of digitalization and feel well prepared for this challenge. But on the other hand, they perceive only low customer expectations with regard to digital services. This indicates a growing gap between actual and perceived customer expectations, which has potentially negative implications for the already difficult competitive position of LOOROs. As LOOROs feel high pressure on the local market as well as online, they should be encouraged to assess their digitalization options and make use of them to regain competitiveness (Navickas et al., 2015, p. 4).

For owners and managers of retail outlets several lessons can be learned. This study highlights once again the importance of the perception of customer needs and habits for a successful business. Especially LOOROs seem to lose track of their customers’ needs and wants. Owner and manager needs to take countermeasures and start with a step by step digitalization of their business processes. Facing a multitude of uncertainties, it is recommendable to start with targets within easy reach in the short term, such as search engine visibility and third party sales channels to meet the basic digital needs of their customers (IFH, 2014, p. 38; Hudetz et al., 2011, pp. 3-8). In the long-term, LOOROs should try to develop a digitalization strategy that incorporates their local advantages, like short distance to the customers (using e.g., Location-Based Services) and the opportunity to create a touch and feel customer experiences as well as offering their customers the opportunity to take the products into their possession directly (Navickas et al., 2015, p. 4).

Providers of digital services should consider the findings of this study before tailoring their offers for LOOROs. The big group of not-yet-digitally-developed-LOOROs is a challenging but promising business opportunity for all companies that understand the driving force of digital services for local retail on the one hand and the limitations and obstacles those retailers are in on the other hand. Using digital services to foster the connection between LOOROs and their customers once again is just the first step, enhancing the shopping convenience through channel integration and excellent customer service needs to follow right away.

As always, some limitations of our study have to be acknowledged. First of all, the sample size of the survey with 52 participants is rather small. This brings us to the question to what extent the results of this study can be generalized. The respondents form quite a representative group concerning the city where the survey was conducted. 38.5% of all retail outlets and 61.1% of the town's LOOROs responded to the survey. This makes the survey representative for the town and lets us generalize the results to cities of the same size and in a similar regional situation (rural). The town is about 35 km and approximately 45 minutes by car away from Germany's biggest urban area, the Ruhr Area. However, the picture may change in big cities so that the survey is only partly generalizable. Secondly, the survey covers only a small share of conceivable measures of digitalization. In particular, the usage of social media functions was barely touched on. Several measures like channel integration, in-store applications, in-store analytics, real time interaction management, could also be taken into account. But as LOOROs are already reluctant to use the simple measures of digitalization that we surveyed, we can assume that these more sophisticated measures are currently not taken into account either. However, in future studies, more detailed questions concerning the specific scope and direction of digitalization should and will be used.

FUTURE OUTLOOK

With regard to the findings of this research we suggest the following areas of future research:

1. "What are the barriers of digitalization of LOOROs within in the organization? How strong is the impact of limited capital, limited human resources, limited education, and limited time for strategic planning on the current state of digitalization?"
2. "How realistic is the perception of LOOROs as to the digital competence of their business?"
3. "What are the technological and non-technological options for LOOROs with regard to digitalization and what are the potential risks and opportunities of its implementation?"
4. "What are the most promising digital services and are there special digital services that can be a competitive "local" advantage for LOOROs in the competition with e-commerce?"
5. "What are best practices in LOOROs and what type of options and what type of actions can be derived from them?"

6. Customer Research (Survey) on the questions: "What are the products services and offers that motivate customers to continue to buy in the cities?

7. Identifying Product characteristics and categories that are most promising for LOOROs.

Integrating the previously mentioned fields of future research, we suggest further to repeat the already conducted survey with an extended sample through surveying LOOROs from a bigger region or area. To gain more generalizability as well as to learn more about the differences of LOOROs in urban and rural areas, the sample should be adjusted to the size (small / medium / big) and the location (urban / rural area) of the surveyed cities.

The digital transformation of all parts of the society and of the retail industry in particular poses tremendous challenges to local owner operated retail outlets (LOOROs), which are characterized by a small-sized store area, a limited number of staff and high owner-involvement in the day-to-day business operations (Bollweg et al., 2015, p. 8). Although the overall retail market is growing, the share of LOOROs in Germany constantly declined and hardly reached 18% anymore in 2015 (HDE, 2016, p. 9). Forecasts are even more worrying and predict a decline in revenue of up to 50% within the next ten years (i.e., IFH, 2015; Heinemann, 2014; Siemssen, 2017). Besides strong price and service competition induced by (new) online competitors, reasons for this development are the changing shopping habits of customers, who are getting accustomed to online shopping and services more and more (IFH, 2016, p. 33; Statista, 2017b), and the strategic turnaround of online and offline competitors. While formerly pure online players begin to conquer the cities with physical stores (Liebmann, 2013; Holden, 2017), big-box retail outlets and chain stores are digitalizing their business models and offer multichannel sales and services to their local customers (HDE, 2017, p. 9). All of these factors pressure LOOROs to rethink and adapt their traditional business models.

However, despite their limited resources (e.g., lack of time and knowledge, as well as of human and financial resources, etc.), LOOROs are not defenselessly exposed to this development. Many digital tools and applications, like e.g., digital inventory management systems, online shops, customer relationship management systems (CRM), or also marketing automation tools, could also help them to overcome their inherent restrictions (Bollweg et al., 2015, p. 9) and support them in developing locational advantages in an omnichannel environment (Navickas et al., 2015, p. 4). But as other SME and especially other micro-enterprises (ME), LOOROs still hesitate to actively face the digital transformation and seem reluctant to digitalize their business (Bollweg et al., 2016, p. 13; Pantano and Viasonne, 2014, p. 3). This paper investigates this phenomenon and aims at a better understanding of the reasons why LOOROs hesitate to digitalize their infrastructure and their business processes. Only with such an understanding, options for actions can be derived for shop owners, politicians and city representatives, on how to help local retail grow digital and turn into omnichannel Local Commerce. In particular, this study focuses on the interplay of the internal (organizational) and external (environmental) factors that impact the technology adoption of LOOROs. For this, we conducted a survey among 223 LOOROs from 26 cities to answer the following research questions:

RQ1: *How do internal (organizational) and external (environmental) factors influence the digitalization process of LOOROs?*

RQ2: *Why are LOOROs hesitating to digitalize their business?*

The remainder of this paper is organized as follows: In section 4.3, we discuss the theoretical background based on a structured literature analysis concerning influencing factors on the current use of digitalization in SME retail. In section 4.4, we develop a research framework and a conceptual model based on related theory and the analyzed literature. In section 4.5, we describe the survey design and provide an overview of the results. Subsequently, we discuss our findings in section 4.6, and finally point out implications in order to answer the initial research questions.

THEORETICAL BACKGROUND SME RETAIL

METHODOLOGY / STRUCTURED LITERATURE ANALYSIS

Although the relevance and importance of small retailers for city centers, their infrastructure, local economies, or for the labor market is often emphasized by policy and studies (e.g., HDE, 2016, pp. 3-14; IFH, 2016, p. 9), research concerning the technology adoption of micro retailers (ME) like LOOROs is scarce. A reason could be the high diversity of the retail sector that hinders the collection of a sufficient number of retailers to obtain significant and representative results (Bollweg, 2015, p. 5). For this, our structured literature analysis (Webster and Watson, 2002, pp. 3-11) (see Table 4.1) focused on research about SME retail outlets and the adoption of technology by SMEs in general as an equivalent for LOOROs and ME retailers. Doing so, structural differences of SME retail outlets and LOOROs have to be taken into account in the following. We used the databases EbscoHost, IEEE, and ScienceDirect and restricted the search to the years from 2000 to 2017. After deleting all duplicate findings, we received a total of 219 unique papers. Analyzing the title and abstract, we were able to reduce our literature body to 51 publications. Last-mentioned were read completely and in turn yielded a final set of twelve relevant papers that coped with internal and/or external factors influencing the adoption of new technologies.

Time frame: 2000 to 2017	EbscoHost	IEEE	ScienceDirect
Total download: 219 paper	64	51	104
After title and abstract analysis: 51 paper	16	9	26
After full analysis: 12 paper	1	4	7

Table 4.1 Literature analysis

1.2.2 Internal and External Influence Factors of SME Retail

In contrast to the industry sector, the term SME is rather undefined in the retail sector. Mainly, the number of employees is used as a size indicator. While Savrul et al. (2014) follow the definition of the EU commission (EU recommendation 2003/361), other authors limit SMEs to the size of 100 employees (e.g., Rahayu and Day (2015); Kabanda and Brown (2017): <100 employees; Mehrtens et al. (2001): 3-80 employees; Maduku et al. (2016): <50 employees). Also concerning the business types, the papers differ. Kurnia et al. (2015) for example analyzed SME retail chains, while others, like Amin and Hussin (2014), or Kabanda and Brown (2017), focused on single-location outlets.

No.	Author / Year	Internal Factors (Attitude)	Internal Factors (Organization)	External Factors (Environment)
1.	Mehrtens et al. (2001)	Attitude	Organizational Readiness	External Pressure
2.	Erosa (2009)	Prior Use	-	External Pressure
3.	Vize et al. (2013)	Attitude, Prior Use	-	External Pressure
4.	Pantano and Viasonne (2014)	Attitude, Prior Use	Organizational Readiness, Available Resources	-
5.	Pantano (2014)	Attitude, Prior Use	Organizational Readiness	-
6.	Amin and Hussin (2014)	Current Use	Organizational Readiness	External Pressure, Available Resources
7.	Savrul et al. (2014)	Prior Use	Organizational Readiness	External Pressure
8.	Kurnia et al. (2015)	-	Organizational Readiness	External Pressure
9.	Rahayu and Day (2015)	Attitude	Organizational Readiness	External Pressure, Available Resources
10.	Osei et al. (2016)	-	-	External Pressure
11.	Maduku et al. (2016)	Current Use, Prior Use	Organizational Readiness	External Pressure, Available Resources
12.	Kabanda and Brown (2017)	Prior Use	Organizational Readiness	External Pressure

Table 4.2 Categories of influencing factors based on the literature analysis

However, a commonality is the classification of factors influencing the innovation and technology adoption process into the three categories (1) internal attitudinal factors, (2) internal organizational factors, and (3) external environmental factors (see Table 2). In this line, Mehrtens et al. (2001) who focused on internet adoption found that the internal and external factors "perceived benefits", "organizational readiness", and "external pressure" significantly influence a company's decision to adopt technology. Erosa (2009) investigated the role of prior use on technology adoption. As internal factors, she used risk perception, advantages of IT use, and the owner's perspective. In addition, external technological influence was considered as an external factor. Results show that low use and low use intentions have a negative impact on the actual use of technology. Pantano and Viasonne (2014) present a push-pull approach based on the external push of technology and the pull of retailers' internal demand. In particular, the internal factors have a high impact. The diffusion of technology-based innovation is mainly influenced by retailers' expectations and their propensity to invest. Amin and Hussin (2014) applied an extension of the "Technology-Organization-Environment Framework" to examine technology adoption and showed that technology adoption is a process passing certain stages instead of being a one-level process. Kurnia et al. (2015) combined the Diffusion of Innovation Theory with the National Institutions Perspective to examine the effect of internal factors based on attitudes and several external factors on the technology adoption process. They distinguished external factors of the industry (competition), the nation (government), and the overall environment (society), and showed the importance of the context of retailers for digital development.

Research Framework & Conceptual Model

Internal and External Influence Factors

While in large firms, decisions are highly influenced by internal groups and are subject to collective, collaborative scrutiny and testing, the decision situation of LOOROs is quite different. As LOOROs are micro-enterprises (Erosa, 2009, p. 1) that often face structural shortage of internal and external resources (Bollweg et al., 2016, p. 13), the owners are intensely involved in the day-to-day business operations and simultaneously act as the executive manager, salesman, and storekeeper (Venkatesh, 2006, pp. 497 - 500). The owner is the company's sole decision maker, who is said to be more influenced by external factors than by (not existing) internal hierarchical structures (Liberman-Yaconi et al., 2010, p. 80). However, to understand why LOOROs hesitate to digitalize, and to derive options for action for LOOROs, both external environmental as well as internal organizational factors influencing the decisions of LOORO owners to use digital tools and applications for their business need to be examined. Internal factors are – to a certain extent – under the control of the owner (Vize et al., 2013, pp. 10-11; Rahayu and Day, 2015, pp. 143-146). They can be categorized into factors from the organizational-level and from the individual-level (attitudinal) (Erosa, 2009, p. 2; Amin and Hussin, 2014, p. 3). The organizational-level comprises factors concerning the readiness, such as the availability of internal resources (e.g., human resources, motivation, time and knowledge), as well as the overall organizational commitment towards digitalization. As we focus on the owner as the sole decision maker, factors of the internal organizational-level thus represent "internal external factors" (Marcati et al., 2008, pp. 1579-1580). The individual-level concerns factors like attitude, intentions, and prior and current usage of digital tools and approaches (Erosa, 2009, p. 2; Amin and Hussin, 2014, p. 3; Maduku et al., 2016, pp. 712-713).

In contrast to internal factors, external factors cannot be controlled by the company. These factors can be subdivided into factors related to the competitive environment, governmental regulations, pressure from value chain partners (e.g., suppliers and customers), and the availability of external resources (Vize et al., 2013, pp. 10-11; Rahayu and Day, 2015, pp. 143-146; Kabanda and Brown, 2017, p. 123; Kurnia et al. 2015, p. 1907). Focusing on an owner-centric examination and based on the individual level of the owner's personal attitudes (Marcati et al., 2008, p. 1583), approaches commonly used to explain the technology adoption of small, medium, and large enterprises on the organizational level like the Technology-Organization-Environment Framework (TOE) are not fully suitable (Ramdani and Kawalek, 2007, pp. 412-413). Therefore, this study uses the Stimulus-Organism-Response Model (S-O-R Model), which focuses on the individual level (Vize et al., 2013, p. 16; Rahayu and Day, 2015, pp. 143-146; Kabanda and Brown, 2017, pp. 123-124; Kurnia et al., 2015, p. 1907).

STIMULUS-ORGANISM-RESPONSE MODEL

The Stimulus-Organism-Response Model (S-O-R) of Mehrabian and Russel (1974) originates from the environmental psychology field (Woodworth 1923, p. 244) and is often used in marketing research to examine the customer response to a situational or environmental (external) stimulus. For example, Wang et al. (2011) investigate the impact of web aesthetics with its two dimensions aesthetic formality and aesthetic appeal on psychological reactions of online consumers with the help of the S-O-R model. Lee and Widdows (2011) analyzed the impact of high-technology attributes and Zhang et al. (2014) examined the influence of technological environments and virtual customer experience on customer motivation to participate in social commerce. The main idea behind the S-O-R model is that environmental processes and changes, called stimuli (S), are perceived by an organism (O) and instigate (emotional) reactions of the organism called behavioral response (R) (see Figure 4.1).

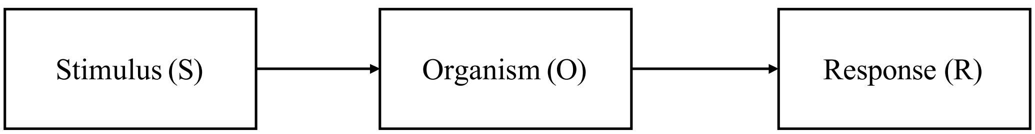


Figure 4.1 S-O-R Model

Based on the environmental psychology, three basic dimensions of emotional responses to the perception of the encountered environments are used: pleasure, arousal and dominance (the PAD-Scale). Thereby, pleasure is described purely in terms of positive or negative feelings, arousal as a feeling state that concerns mental activity, and dominance as a feeling of control and behavior restrictions caused by physical or social barriers (Mehrabian and Russel, 1974, pp. 216-217). However, despite of its contributions to the research on consumer behavior, the S-O-R framework is often criticized for its bipolar measurement when using the PAD-Scale (Kim et al., 2016, pp. 1-2), as it allows the joint occurrence of pleasant and unpleasant states (Westbrook, 1987, p. 259). For this, a unipolar view linking the three dimensions to one joint model is proposed to be more suitable (Bakker et al., 2014, pp. 2-6; Westbrook, 1987, p. 259). Pleasure, arousal, and dominance can be seen as affective (feeling), cognitive (thinking), and conative (acting) responses. Then, these responses can be unified as one joint measure for the organism (Bakker et al., 2014, pp. 2-6).

1.2.3 Conceptual Model

The discussed joint measurement of attitudes is similar to the common measurement of attitudes in Information Systems (IS) theories and related research. Here, a broad range of theories about technology adoption, acceptance and implementation, extent of usage, effectiveness, success, and satisfaction is available (Ramdani and Kawalek, 2007, p. 414). Two streams can be distinguished: Technology centered theories focus on the characteristics of the technology itself and the diffusion through different channels (i.e., Rogers, 1995). These theories are helpful for explaining technology adoption outcomes on an organizational level. In contrast, decision maker centered theories focus on the individual level and analyze human behavior and its impact on the decision-making process regarding technology adoption and use (e.g., Ajzen, 1991; Davis et al., 1989). In this regard, the Theory of Reasoned Action (TRA) (i.e., Ajzen and Fishbein, 1977) and its successor, the Theory of Planned Behavior (TPB) (i.e., Ajzen, 1991) state that attitudes, control beliefs, and subjective norms influence behavioral intention, which in turn influences actual behavior.

Davis et al. (1989) applied TRA / TPB to the individual level of technology adoption behavior in his well-known Technology Adoption Model (TAM). Over the last two decades, researchers extended this view, examined antecedent as well as moderating factors and incorporated alternative belief factors into their research models, like TAM2 or the UTAUT Model, while keeping the core structure (behavioral intention influences actual behavior) of TAM (Ramdani and Kawalek, 2007, pp. 412-413). Furthermore, researchers integrated the TRA / TPB core (attitudes have impact on intentions) into theories of related disciplines. E.g., Koufaris (2002) used constructs from TAM to examine consumer behavior in combination with flow and environmental psychology in an integrated theoretical framework. Accordingly, the organism, namely the owner as the decision maker in LOOROs, is captured by the TRA / TBP logic that the attitude towards a technology influences the intention to use it in order to mimic the thought process of a decision maker (Bakker et al., 2014, pp. 2-6). This thought process is triggered by internal and external stimuli. We postulate that the perception of organizational resource availability and the perception of external pressures can both be seen as such environmental stimuli leading to the organism's emotional reactions (Wang et al., 2011, pp. 47-48). Finally, the usage of the technology is the stimulated organism's emotional response. To frame the ambiguity of the umbrella term digitalization into an operational understanding, we structure the digital tools and applications based on the operational view of the management process of business models: 1) The digitalization of the front-end sales channels, where we find all digitalization efforts with direct customer touch points, and 2) the digitalization of the administrative back-end, invisible to the customer (Enders and Jelassi, 2000, pp. 544-546).

HYPOTHESES DEVELOPMENT

STIMULUS (S) TO ORGANISM (O)

According to the resource-based view (RBV), firm resources are heterogeneous and immobile (Barney, 1991, pp. 105-109). Differences in market performance are fundamentally due to the distinctive resources and capabilities that are valuable, rare, inimitable and non-substitutable (Barney, 1991, pp. 105-109; Wernerfelt, 1984, p. 172). For a company's future competitiveness, prosperity, and development, the availability of resources is decisive. Companies with limited access to resources (e.g., human resources) and with insufficient infrastructures (e.g., capacities) are reluctant to invest in tools and applications that could create a competitive advantage (Barney, 1991, p. 112). The RBV categorizes resources into tangible and intangible resources and distinguishes between resources on the organizational and individual level. As we focus on the owners of LOOROs (research on the individual-level), resources from the organizational level can be seen as external factors (or stimuli), so-called internal external factors (structural resources from the organizational-level; internal factors of the LOORO but external from the owner's point of view) (Liberman-Yaconi et al., 2010, p. 80). The availability of the tangible organizational infrastructure is represented by the availability of general resources (AI1), of necessary capacities (AI2), and of an IT-Infrastructure (AI3) (Wernerfelt, 1984, p. 173). To investigate the influence of the available infrastructure on an organism's (O) emotional reactions (attitudes towards digitalization) we hypothesize:

H1: *The availability of infrastructure has a positive influence on the attitude towards the digitalization.*

The availability of the intangible organizational human resources is represented by the available innovative strength regarding digitalization (HR1), available competences for digitalization (HR2), and available motivation for digitalization (HR3) (Wernerfelt, 1984, p. 173). To investigate the influence of the availability of human resources on an organism's (O) emotional reactions (attitudes towards digitalization), we hypothesize:

H2: *The availability of human resources has a positive influence on the attitude towards the digitalization.*

Several studies have shown that external environmental pressures have an impact on the adaption of technology among companies (e.g., Amin and Hussin, 2014; Savrul et al., 2014; Kurnia et al., 2015; Rahayu and Day, 2015; Osei et al., 2016; Maduku et al., 2016). The "Three-Environment Theory" offers a structural understanding of the origins of external influences (Stapleton, 2000, pp. 24-30). Correspondingly, external pressures comprise influences from the near and far environment. To avoid repetition, we neglect the application of technological pressure (like in push and pull theory) as the primary influence indicator, as technology is already the theme and research subject of all indicators, especially in the organism (O) and response (R) sections. The near (specific) environment is formed by influences of competitors and customers that exert a direct impact on the examined organization. The perceived pressure of the competitors is represented by the perception of the own development compared to the development of the competitors (PC1), the perception of the need for own development to stay competitive (PC2) and the perception of external pressure towards digitalization to stay competitive (PC3) (Stapleton, 2000, p. 26). Accordingly, we hypothesize:

H3: *Perceived pressure from competitors towards digitalization has a positive influence on the attitude towards digitalization.*

The perceived pressure of the customers is represented by the perception of customer actions (CP1), the perception of customer pressure (CP2), the perception of customer expectations (CP3) (Stapleton, 2000, p. 28). Accordingly, we hypothesize:

H4: *Perceived pressure from customers towards digitalization has a positive influence on the attitude towards digitalization.*

The far environment is defined by the government and socio-political conditions (Melville et al., 2004, p. 286). Thus, the perceived society pressure is represented by the perception of the importance of digitalization (SP1) in general, the perception of governmental pressure (SP2) and the perception of societal expectations (SP3) (Stapleton, 2000, p. 28). Accordingly, we hypothesize:

H5: *Perceived pressure from politics and society towards digitalization has a positive influence on the attitude towards digitalization.*

1.2.3.1 Organism (O) to Response (R)

In the traditional S-O-R models, the organism (O) is represented by the PAD-Scale and its measure of pleasure, arousal and dominance. Despite the undoubted contributions of the S-O-R model for consumer research, the PAD-Scale itself is questionable (Bakker et al., 2014, pp. 2-6) and was often criticized due to its bipolar conceptualization (Kim et al., 2016 pp. 1-2; Westbrook, 1987, p. 259). Therefore, this study replaces the PAD-scale with the core blocks of the established models of TRA/TPB, and TAM, using only one joint construct for the attitude instead of the triad of feeling, thinking, and acting used by Mehrabian and Russel (1974). The attitude as well as control beliefs and subjective norms do not influence actual behavior directly, but rather influence the behavioral intention (intention to use), which in turn influences the actual behavior (current use) (Ajzen, 1991, p. 182; Davis et al., 1989, p. 984). Accordingly, we use the core constructs of the TRA / TPB / TAM theory for the organism section: “Attitude towards Digitalization” and “Intention to use Digitalization”. Attitudes are viewed as predispositions to respond in a consistent favorable or unfavorable manner toward an object or situation, in this study, to the availability of organizational resources and the perception of external environmental pressure. Measures of the construct are oriented to the ones of TRA / TPB / TAM theory: Assessment of digitalization (A1), the ease to learn (A2) and the expected effectiveness of digitalization (A3) (Ajzen, 1991, pp. 181-182; Davis et al., 1989, p. 984). To investigate the influence of attitudes on behavioral intentions to use digitalization, we hypothesize:

H6: *A positive attitude towards digitalization has a positive influence on the intention to use digitalization.*

Behavioral intentions are said to influence actual behavior and therefore to have direct impact on the current use of digital tools and applications (Ajzen, 1991, pp. 181-182; Davis et al., 1989, p. 984). Hence, we hypothesize:

H7: *A high intention to use digitalization has a positive influence on its current use.*

To frame the ambiguity of the umbrella term digitalization into an operational understanding, we separate the back-end from the front-end activities (Enders and Jelassi, 2000, pp. 544-546). The back-end activities of retailers represent all activities without customer touch points; front-end activities are all activities with customer touch points and vary regarding their level of customer interaction (Wirtz et al., 2016, p. 11; Enders and Jelassi, 2000, pp. 544-546). Accordingly, we divide the (behavioral) intentions ("Intention to Use") and the actual behavior ("Current Use") towards digitalization into the two dimensions administration and sales. Thus, we extend the above stated hypotheses 6 and 7 as follows:

H6a: *A positive attitude towards digitalization has a positive influence on the intention to use digital administration.*

H6b: *A positive attitude towards digitalization has a positive influence on the intention to use digital sales channels.*

H7a: *A high intention to use digital administration has a positive influence on the current use of digital administration.*

H7b: *A high intention to use digital sales channels has a positive influence on the current use of digital sales channels.*

As representation of the intention to use and the hereinafter current use of digital tools and applications among the stated business areas, we derived sets of frequently used digital tools and applications based on recent studies on technological trends in the retail sector (Statista, 2016).

Digital Sales Channels	online shop (US1)	3rd party marketplaces (US2)	in-store applications (US3)	online advertisement (US4)
Digital Administration	software for administration (UA1)	inventory management System (UA2)	digital communication channels (UA3)	digital payment systems (UA4)

Table 4.3 Indicators based on frequently used digital tools and applications (Statista, 2016)

The resulting conceptual model is depicted in Figure 4.2.

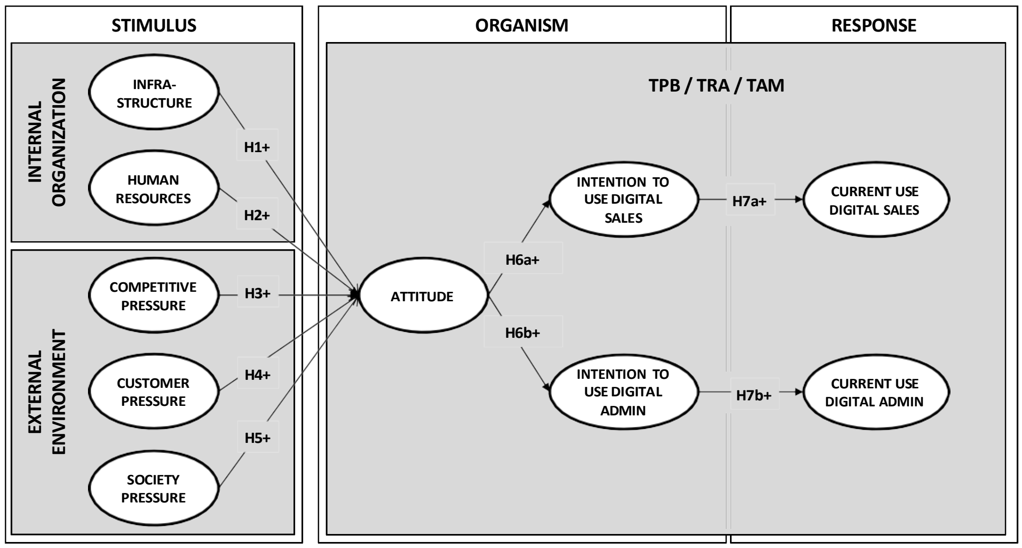


Figure 4.2 Conceptual model

1.3 Analysis

1.3.1 Data Collection

Between May and July 2016, we conducted a survey among LOOROs in 26 cities in the South Westphalia region in Germany. Following informed consent and stating the purpose of the research, the approximate duration, and a statement that participation is voluntary and anonymous, the analyzed questionnaire contained two opening questions (retail industry, no. of employees) and 34 individual questions measured on a 5-point-Likert-Scale. It was answered by 124 participants via an online form and by 119 participants on paper. In total, 243 questionnaires were submitted, including 223 questionnaires with full data sets. For the analysis of the collected data and the evaluation of the research model, we used SmartPLS 2.0 (i.e., Ringle et al., 2005). Bootstrapping was done with 5,000 samples and 223 cases, determining the significance of weights, loadings and path coefficients. For the multicollinearity tests of the formative constructs, we used SPSS.

1.3.2 Measurement Model

The research model has one reflective construct ("Attitude towards Digitalization"). The other nine constructs are formative, so that different analyses are needed (Fornell and Bookstein, 1982, p. 442). The significance of the constructs' indicators is assessed by their loadings (reflective constructs) that should be greater than 0.7 (greater than 0.6 is acceptable) or weights (formative constructs) that should be greater than 0.1 (Jarvis et al., 2003, pp. 200-205) and their t-values. An indicator is significant if its t-value is greater than 1.65. This corresponds to a significance level of 10%.

ns = not significant; *p<0.10; **p<0.05; ***p<0.01.

Construct	Indicator	Loading / Weight	t-statistics	Significance	VIF	R^2
Available Infrastructure	AI1	0.394	2.595	***		
	AI2	0.661	4.440	***	-	-
	AI3	0.219	2.003	**		
Available Human Resources	HR1	0.023	0.369	ns		
	HR2	0.404	5.316	***	-	-
	HR3	0.671	9.302	***		
Perceived Competitive Pressure	PC1	0.345	2.039	**		
	PC2	0.115	1.072	ns	-	-
	PC3	0.895	9.720	***		
Perceived Customer Pressure	CP1	0.176	1.592	ns		
	CP2	0.797	8.841	***	-	-
	CP3	0.591	5.166	***		
Perceived Society Pressure	SP1	0.591	4.183	***		
	SP2	0.538	4.669	***	-	-
	SP3	0.501	3.865	***		
Attitude	A1	**0.839**	30.990	***		
	A2	**0.794**	23.629	***	1.64	0.664
	A3	**0.805**	22.202	***		
Intention Digital Admin	IA1	0,084	1,075	ns		
	IA2	0,473	2,552		-	0.084
	IA3	0,605	4,876	***		
	IA4	0,272	1,514	ns		
Intention Digital Sales	IS1	0,063	0,933	ns		
	IS2	0,381	2,196		-	0.049
	IS3	0,714	4,623	***		
	IS4	0,010	0,144	ns		
Current Use D. Admin	CA1	0,115	1,378	ns		
	CA2	0,491	2,756		-	**0.772**
	CA3	0,555	4,309	***		
	CA4	0,302	1,640	ns		
Current Use D. Sales	CS1	0,053	0,800	ns		
	CS2	0,351	2,021		-	**0.812**
	CS3	0,748	5,014	***		
	CS4	0,039	0,571	ns		

Table 4.4 Bootstrapping and model validation

In order to reach a significance level of 5% (1%), the t-value must be greater than 1.96 (2.57) (Hair et al. 2006, pp. 664-670). Table 4.4 shows the t-values as well as the corresponding loadings / weights for all indicators of our model and further indicates the result regarding the calculated significances. Concerning the reflective construct, all indicators (A1, A2, A3) are significant. As the AVE (Average Variance Extracted) is 0.6609 (minimum > 0.5) and the composite reliability is 0.8539 (min. 0.7), the model fits to the convergence criteria.

The discriminant validity of the constructs is also given. The model complies with the Fornell-Larcker criterion: Its highest squared construct correlation is meeting with 0.557 the AVE maximum of 0.5 and the loadings of the reflective indicators are significantly higher than their cross loadings as compared to the other constructs. The internal consistency is given, as the reflective construct exceeds the critical value of 0.7 for Cronbach's Alpha. Attitude towards Digitalization: 0.7432 (Hair et al., 2006, pp. 664-670). The prediction validity Q^2 is with 0.3201 higher than the minimum of 0 (Hair et al., 2014, pp. 102-103). The results of the formative constructs are as follows: For the construct "Available Infrastructure" (AI1, AI2, AI3), three indicators have significant influences. For the construct "Available Human Resources", two (HR2, HR3) of the three indicators have significant positive influences. For the construct "Perceived Competitive Pressure", two (PC1, PC3) of the three indicators have significant influences. For the construct "Perceived Customer Pressure", two (CP2, CP3) of the three indicators have significant influences. For the construct "Perceived Society Pressure", three (SP1, SP2, SP3) of the three indicators have significant influences. The construct "Intention to Use Digital Sales Channels" comprises two of four significant indicators: IS2, IS3. For the construct "Intention to Use Digital Administration" two of four indicators have significant positive influences (IA2, IA3). The construct "Current Use of Digital Sales Channel" includes two of four significant indicators: CS2, CS3. And finally, for the construct "Current Use of Digital Administration" two of four indicators are significant: CA2, CA3 (see Table 4.4). In addition to the significance of indicators, the discriminant validity of the formative constructs must be verified. The highest correlation between the latent variables is given for the constructs "Intention to Use Digital Sales Channels" and "Current Use of Digital Sales Channels" with a value of 0.9016. This does match the maximum of 0.9, so that the criterion regarding the discriminant validity is met (Hair et al., 2014, p. 96). The analysis conducted using SPSS with regard to multicollinearity showed that all indicators of the models are sufficiently different and independent of each other (Hair et al., 2014, p. 125).

1.3.3 Structural Model

In order to validate the model, the constructs with two or more influencing factors (only Attitude) were assessed using the variance inflation factor ($VIF=1/(1-R^2)$) as to potential multicollinearity (Weiber and Mühlhaus, 2010, p. 207). The VIF of "Attitude towards Digitalization" (1.64) is lower than the required level of 5 and stays even below 3.333 which shows that there is no multicollinearity (Diamantopoulos and Siguaw, 2006, pp. 271-272). The value of R^2 represents the coefficient of determination which indicates a substantial influence if the value exceeds 0.67. A value higher than 0.33 implies that a moderate influence of a latent independent variable on the dependent latent variable can be assumed. A weak influence is indicated by an R^2 value of higher than 0.19 (Van der Heijden et al., 2003, p. 44). The coefficients of determination of the endogen constructs are all substantial: "Current Use of Digital Sales Channels" R^2=0.813, "Current Use of Digital Administration" R^2=0.773, "Intention to Use Sales" R^2=0.054, "Intention to Use Admin" R^2=0.088, "Attitude" R^2=0.672. The t-values depicted in Table 4.4 and their path coefficients allow conclusions as to the validity of the formulated hypotheses. In sum, all stated hypotheses are significant. The results of the hypotheses are as follows: H1, "Available Infrastructure" has a positive influence on the "Attitude towards digitalization" (H1– effect size f^2=0.12; effect size scale: >0.02 = low, >0.15 = medium, >0.35 = high) (Cohen, 1988, p. 81). H2, "Available Human Resources" has a positive influence on the "Attitude towards digitalization" (H2– effect size f^2=0.38). H3, "Perceived Competitive Pressure" has a positive influence on the "Attitude towards digitalization" (H3– effect size f^2=0.03). H4, "Perceived Customer Pressure" has a positive influence on the "Attitude towards digitalization" (H4– effect size f^2=0.04). H5, "Perceived Society Pressure" has a positive influence on the "Attitude towards digitalization" (H5– effect size f^2=0.01). H6a, a positive "Attitude towards Digitalization" has a positive influence on the "Intention to Use Digital Sales Channels" (The effect size of 3a, b and 4a, b are not computable due to the model design). H6b, a positive "Attitude towards Digitalization" has a positive influence on the "Intention to Use Digital Administration". H7a, a high "Intention to Use Digital Sales Channels" has a positive influence on the "Current Use of Digital Sales Channels". H7b, a high "Intention to Use Digital Administration" has a positive influence on the "Current Use of Digital Administration". Figure 4.3 shows all significant relations with a t-value of at least 1.65 (Fornell and Bookstein, 1982, pp. 444-445).

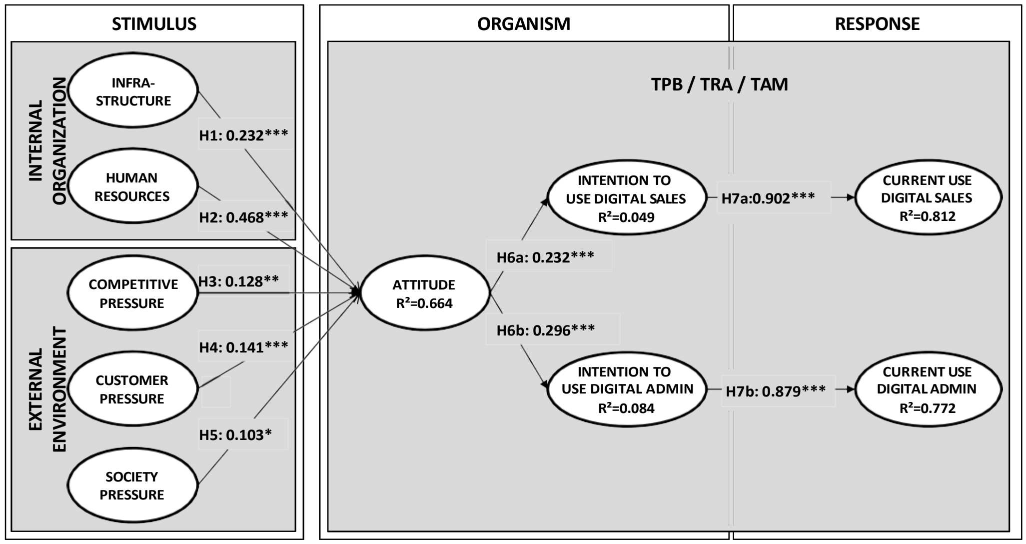


Figure 4.3 Results (*p<0.10; **p<0.05; ***p<0.01)

1.4 Conclusion

1.4.1 Results & Discussion

This study sheds light on the internal states of the owners of LOOROs and on the impact of internal organizational and external environmental influence factors on the current usage of digital tools and applications. The results of our survey among 223 LOOROs in 26 cities in Germany are very satisfactory. The explanatory power of the model is on a high level at 77.2% and 81.2%. All hypotheses could be confirmed of which only two have a significance level of 10% (H5) and 5% (H3). That means that there is a causal chain between the examined external stimuli (organizational and environmental) and usage intention and subsequently current use of digital tools and applications via attitude.

Concerning the first research question, "*How do internal (organizational) and external (environmental) factors influence the digitalization process of LOOROs?",* our results show a highly significant impact of "Available Organizational Infrastructures" as well as "Available Human Resources" (first, internal organizational stimuli) on attitude and therefore on intention and actual use (see Figure 4.3). But for the organizational infrastructure, the descriptive results show only a low infrastructural readiness of LOOROs. Additionally, the results indicate a high uncertainty among LOOROs regarding the readiness of their existing infrastructure expressed by high neutral responses. Only 31% of the respondents agreed or strongly agreed that they have sufficient "infrastructural resources" to face the digitalization challenge. 43% of the respondents were neutral. Additionally, only 28% confirmed that they have sufficient "capacities", while 42% answered neutral. Finally, only 26% stated that they have a sufficient "IT-Infrastructure" for the challenges of the digitalization (28% answered neutral). However, for the "Availability of Human Resources", our findings show slightly better results. The respondents found their available human resources to have enough "competencies" (44%) and to be "motivated" enough to handle digitalization (58%).

Regarding the external environment (second stimuli), all examined factors also have an impact on the attitude towards digitalization, as all hypotheses could be confirmed (H3, H4, H5). Surprisingly, LOOROs perception of the pressures from the near environment (Customers and Competitors) and far environment (Society) is contradicting the visible digital developments of the external environments. Despite the ongoing digital transformation LOOROs only perceive low pressures. For the "Perceived Competitive Pressure" our results show that the perception of the "own development" compared to the digital development of the competitors (40%) is on a medium to low level. Furthermore, only 54% of the owners of LOOROs perceive a need to participate in the digital transition of retail to stay competitive. With regards to the "Perceived Customer Pressure" towards digitalization, only 11% of the owners perceive "explicit customer expectations" with regards to digitalization. 54% of the respondents at least consider the option that their customers could have according expectations. Finally, the examination of the "Perceived Society Pressure" showed that 85% consider digitalization to be important, while only 56% think that the "society expects digitalization" from them. Furthermore, only 37% feel that the "government is pressuring" them towards digitalization.

Concerning the organism of the model, which is influenced by the examined stimuli, the owners of LOOROs expressed an overall positive attitude towards digitalization. Nearly 60% (addition of strongly agree and agree) have answered that "digitalization is good" (A1) and "easy to learn" (A2) and 52% that digitalization will "increase their effectiveness" (A3). Subsequently, our findings for the "Intention to Use" and the "Current Use of Digitalization" are emphasizing the consequences of LOOROs' perception of the internal organizational and external environmental influence factors: LOOROs still hesitate to adopt digital technologies and communicate only a low intention to do so in the future. Concerning the usage of digital tools and application on the sales channels, LOOROs report on low usage intentions, with just 12.6% of them confirming their intention to sell on third-party e-marketplaces (IS2). Only 8% of the respondents expressed their intention to use in-store applications (IS3). Further, only 28% of the owners indicated their intention to use an own online shop (IS1), but surprisingly, nearly 41% stated that they plan to use online advertisement in the future (IS4).

Finally, the results for the response section of the model are in line with the low intentions and the significance of the indicators from the organism and are showing also an overall low "Current Use" of digital tools and applications among LOOROs. Just 9% make use of third-party e-marketplaces (CS2) to sell their products so far and only 2.3% reported a use of in-store applications (CS3). Only 13% of LOOROs operate their own online shop (CS1) and 22.4% use online advertisement (CS4). With respect to the use of digital tools and applications for administrative purposes, the respondents expressed slightly stronger intentions, with 59% of them intending to use administrative software (IA1), 62% planning to use inventory management systems (IA2), and 41% seeking to use digital payment systems (IA4). Concerning the "Current Use", our results show that 58.3% of owners of LOORO already use administration software (CA1), 56.1% use digital inventory management systems (CA2) and 35% use digital payment systems (CA4). With only 2%, the lowest usage was reported for digital In-Store Application (CA3).

Concerning the second research question, "*Why are LOOROs hesitating to digitalize their business?",* our results show that LOOROs are facing a shortage of available infrastructure and human resources, and, even more important, that they face a situation of uncertainty. It appears that LOOROs hold and wait with their decision towards digitalization, as they do not know whether their own available infrastructure is sufficient or not and in which technologies to invest. Studies about technology adoption decision making under uncertainty explain this behavior and show that adopters (in this case LOOROs) rarely face a dichotomous choice, to invest now or never, but rather they choose among a series of options to either invest now or postpone the decision (Purvis et al., 1995, pp. 541-542). However, our results show that LOOROs are aware of the importance of digitalization and the external influences. Surprisingly, they do not perceive customer expectations and thus do not see a need to react to digitalization efforts of competitors. The shop owners seem to be disconnected from their near and far environment, leading to erroneous self-assessments and their services losing touch to the relevant competitive environment and customer expectations (Parasuraman et al., 1988, p. 4; Bollweg et al., 2015, p. 8; Pantano, 2014, p. 6). If LOOROs are digitalizing their business, they seem to be more open to digital solutions that improve their day-to-day business operations directly (pace of work, convenience) when compared to digital tools and applications for the actual sales process (Bollweg et al., 2015, p. 11; Navickas et al., 2015, p. 4).

MANAGERIAL IMPLICATIONS

The above results bring about important implications for the owners / managers of LOOROs: First of all, LOOROs seem to be decoupled from their near and far environment. They rarely perceive any pressure towards digitalization neither from their customers or competitors, nor from the society who all have already adapted to the digital age and are getting more and more accustomed to digital sales and services channels (Müller-Seitz et al., 2009, pp. 37-38). To reconnect LOOROs with the environmental developments, the owner / manager have to work most importantly on the perception of the current and potential customer needs and expectations (Grewal et al., 2017, pp. 4-5; Parasuraman et al., 1988, p. 4). Secondly, LOOROs neglect opportunities of digital sales channels and are subsequently inexperienced with the according tools and applications. To first experience the digital world, LOOROs should start using online sales and marketing channels with low entry barriers, like third-party platforms (also local shopping platforms), to keep in touch with existing customers, explore new markets and to get started in the e-commerce arena (Standing et al., 2010, pp. 49-50). Thirdly, LOOROs face a phase of uncertainty and thus remain passive. In fact, opposite behavior would make much more sense: LOOROs should continuously analyze and track the digital developments and actively seek for opportunities (Pantano, 2014, p. 6). In doing so they should make use of digital tools and applications with their analytical capabilities and their abilities to help, control and improve important business processes (Cohen et al., 2016, p. 25). Finally, LOOROs seem to be lost in digitalization, their erroneous perception of the external developments indicates a need for an external (public or governmental) push to support the necessary internal turn around for LOOROs to regain competitive power.

RESEARCH IMPLICATIONS

This study also has several theoretical implications. The integration of the constructs derived from TRA/ TPB and TAM in the S-O-R Model lead to valid results. The new model thus could serve as a toolbox for future research on micro enterprises. Furthermore, the resulting model contributes to 1) the scarce literature on the technology adoption of ME retailers with insights about the current state of digitalization of local owner operated retail outlets, and 2) to the technology adoption research by means of an examination of the internal organizational and external environmental influence factors. The new model includes an improved organism (O) section (resulting from the integration of TRA / TPB core constructs) as well as an extended response (R) section and a usage-related examination.

LIMITATIONS & FUTURE RESEARCH

When interpreting and evaluating the above findings, the following limitations need to be taken into account: 1) LOOROs are not easy to survey and although we collected data from 223 LOOROs in 26 cities, the rather small sample size limits the explanatory power of our findings. 2) This study is based on the context of the German retail industry, where LOOROs have a high market share and are traditionally well established and anchored in society. Therefore, the results cannot simply be adapted to other countries with their specific retail cultures.

Future research would be valuable on at least the following aspects: 1) Technology: Although we looked at tools from several business areas, systematic research is needed to identify promising technologies and digital tools and applications (including e-commerce channels and online marketing strategies) that can help LOOROs improve their businesses and win back competitive power. 2) Technology adoption under uncertainty: As the examined external and internal factors do not cover all factors that are influencing LOOROs' in their decision-making, further studies should investigate what other factors may impact the technology adoption process. Additionally, more research on how to overcome the high uncertainty of local shop owners is needed, as this uncertainty currently clearly hinders the technology adoption of LOOROs. 3) Public and governmental support: Research is needed on how the public can trigger (subsidies, regulations) the digital development of LOOROs.

DRIVERS AND BARRIERS OF THE DIGITALIZATION OF LOCAL OWNER OPERATED RETAIL OUTLETS: A CASE OF RETAILERS IN RURAL AREAS OF GERMANY

Local owner operated retail outlets (LOOROs), which are characterized by a small-sized store area, a limited number of staff and high owner-involvement in the day-to-day business operations, are challenged by the transformation of the retail industry (Bollweg et al., 2015, p. 3). Although LOOROs are operating in a growing market environment, they are pressured to adapt their traditional business model to the intense competitive environment of the retail sector (Simón-Moya et al., 2016, pp. 159-162). The market share of the LOORO business type in Germany has already declined from 26% in 2003 to 17.9% in 2015 (HDE, 2016, p. 9). Furthermore, several independent studies predict a decline in revenues of 30% for LOOROs in Germany over the next four years (e.g., IFH, 2015; Heinemann, 2014) and about 50% in the next ten years (i.e., Siemssen, 2017). It is expected, that this development impacts most heavily on the rural areas of the country. Factors contributing to the decline include strong price and service competition from the online trade and the expansion of pure online players that have so far focused solely on online retail to physical stores in the city (Liebmann, 2013; Holden, 2017). Furthermore, big-box retail outlets and chain stores have started to digitalize their business models and offer multichannel sales and services to their local customers (HDE, 2017, p. 9). Customers, on the other hand, have changed their shopping habits: they are already used to online shopping and digital services. Accordingly, their shopping frequency in city centers is diminishing (IFH, 2016, p. 38; Statista, 2017b). However, LOOROs are not defenselessly exposed to the threats of the digital age: digital tools and applications allow them to overcome their inherent limitations (e.g., lack of time, adequate knowledge, human resources and finances, etc.) (Bollweg et al., 2015, p. 3). Additionally, the use of integrated digital infrastructures that enhance locational advantages in the digital world, enable LOOROs to regain competitive power (Li et al., 2016, p. 28; Navickas et al., 2015, p. 4). Examples of digital applications include digital inventory management systems, online shops, customer relationship management systems (CRM) and marketing automation. Despite all opportunities, several studies show that LOOROs, like other small- and medium-sized enterprises (SME) and micro-enterprises (ME), still hesitate to adopt digital tools for their own business (Bollweg et al., 2016, p. 13; Pantano and Viasonne, 2014, p. 3). This paper aims to address this phenomenon by providing a better understanding of the reasons why LOOROs and other SME retailers hesitate to develop a digital infrastructure that could possibly promote their business success. We want to identify options for action and give insights on how to support the digital development of LOOROs in rural areas by examining the internal and external influence factors that have an impact on the technology adoption of local retail outlets in the region of South Westphalia, Germany.

The region of South Westphalia is consisting of Sauerland, Siegerland, Soester Börde and some smaller sub-regions. South Westphalia itself is a region in the federal state North Rhine-Westphalia (NRW). The mostly rural region of South Westphalia is the most sparsely populated region of the federal state NRW and therefore an ideal area for the examination of the upcoming challenges for local retail. Accordingly, this paper aims to answer the following research questions:

RQ1: *What are the drivers and barriers of the digitalization of LOOROs?*

RQ2: *What are potential starting points for LOOROs to grow into digitalization and get ready for the digital future?*

This study is structured as follows: In section 5.3, we discuss the theoretical background based on a structured literature analysis concerning influencing factors on the current use of digitalization in SME retail. In the sections 5.4 and 5.5, we develop a research framework and a conceptual model based on related theory and the results of our literature analysis. In section 5.6, we describe the survey design and provide an overview of the results. Furthermore, we determine the current state of digitalization of LOOROs based on the descriptive and statistical results of the survey, and the assessment of the drivers and barriers of digitalization. Subsequently, we discuss our findings in section 5.7 and point out implications and conclude in section 5.8 in order to answer the initial research questions.

1.5 Theoretical Background SME Retail

1.5.1 Methodology / Structured Literature Analysis

To review and elaborate prior research, we conducted a structured literature analysis (Webster and Watson, 2002, pp. 3-11) (see Table 5.1). While research provided a wide range of publications in the last two decades, focusing on the reluctant innovation and technology adoption of SMEs from the production industry, research concerning the technology adoption of micro retailers (ME) like LOOROs is scarce. This is surprising because many studies point out the importance of small retailers for the local economies, the labor market and traditional infrastructures of city centers (e.g., HDE, 2016, pp. 3-14; IFH, 2016, p. 3). However, high diversity in the retail sector and the resulting difficulty in obtaining an adequate number of retailers to reach a meaningful sample size could explain the low research output on this subject (Bollweg et al., 2015, p. 8). To overcome this shortage of literature, we focused on research about SME retail outlets and the adoption of technology by SMEs in general as an equivalent for LOOROs and ME retailers. Nevertheless, we will highlight the structural differences of SME retail outlets and LOOROs in the discussion and in the development of the research framework and the conceptual model. Accordingly, we searched for journal and conference contributions from 2000 to 2017 in the databases of EbscoHost, IEEE and ScienceDirect. In the first step of the analysis, we deleted all duplicate findings and received a total of 219 unique papers. Following with a title and abstract analysis, we were able to reduce our literature body to 51 publications. Last-mentioned were read completely and in turn yielded a final set of 12 papers.

Time frame: 2000 to 2017	**EbscoHost**	**IEEE**	**ScienceDirect**
Total download: 219 paper	64	51	104
After title and abstract analysis: 51 paper	16	9	26
After full analysis: 12 paper	1	4	7

Table 5.1 Literature analysis

1.5.2 SME Retail

The term SME retail is rather undefined compared to the term SME used by the production industry. There is no clear and common scale for SME retail suitable for the business types in the retail industry. However, the reviewed papers and studies using the term SME retail mainly classified the examined retailers using the number of employees as a size indicator. Apart from Savrul et al. (2014) (50-249 employees), all other publications considered retail businesses with less than 100 employees as SME retailers. For example, Rahayu and Day (2015) and Kabanda and Brown (2017) analyzed businesses with less than 100 employees. Mehrtens et al. (2001) examined companies within a range from three to 80 employees and Maduku et al. (2016) reduced the sample to companies with less than 50 employees. Furthermore, the reviewed studies showed differences regarding the business types selected for the examination of SME retailers. Some of the studies concentrated their analysis on SME retail chains (e.g., Kurnia et al. 2015), while others had a focus on single-location outlets (e.g., Amin and Hussin, 2014; Kabanda and Brown, 2017).

Despite data sample diversity in terms of the sample size and examination group, the reviewed studies shared one major commonality: the special role of owners / managers of the SME retailers. SMEs are mainly owned and operated autonomously and most of the operating capital is provided by the owners who in turn control and manage the company (Savrul et al., 2014). Subsequently, in SMEs a strategic decision is highly dependent on the owners. A positive attitude of the owners towards change creates an organizational environment that is receptive to innovation (Amin and Hussin, 2014, pp. 4-5). Accordingly, the owners need to communicate the role of innovation within the SME organization's overall strategy and to emphasize the significance of creativity and innovation to subordinates as well as offering rewards for innovative initiatives to encourage change (Maduku et al., 2016, p. 714). A further characteristic of SME retailers is the structural shortage of internal and external resources (Rahayu and Day, 2015, pp. 143-146). Reluctant technology adoption in retail often depends on limited financial resources and incompetence (Erosa, 2009, p. 4). Additionally, many non-adopter SMEs lack the necessary infrastructure and procedures to adopt digital technology (Kurnia et al., 2015, p. 1907; Kabanda and Brown, 2017, p. 123).

Like the entire retail industry, SME retail is frequently subjected to disruptive innovation (Pantano, 2014, p. 6). SME retailers are pressured by digitally enabled changes of their value chain partners (customers and suppliers), as well as by the competitive environment (multichannel chain stores and pure online trade). Current advancements in technology can enhance the whole value chain, from the consumers' shopping activity to the retailers' job. However, the current strategy of retailers towards technologies does not satisfy customers' expectations (Pantano and Viassone, 2014, p. 3). Customers have already changed their shopping habits and make use of digital sales channels and services and the high convenience of digital services has changed their expectations with regards to services and shopping in local stores. The gap between the service expectations and the current state of digitalization of SME retailers depends on high technological challenges and uncertainties for retailers. Due to the high complexity of digital systems, SME retailers struggle to implement new technologies (Erosa, 2009, p. 1). Accordingly, prior inexperience is negatively correlated to technology adoption in SMEs (Vize et al., 2013, pp. 12-16). Once implemented, SME retailers have problems ensuring system security (Amin and Hussin, 2014, p. 4). In terms of micro and small store formats, technology is an enhancing factor regarding competitiveness, but it is not perceived as attractive to customers (Erosa, 2009, p. 4). It is uncertain whether SMEs retailers can adapt to the digital age on their own. Industry standards are needed to create more certainty for SME retailers so that technology will last (Kurnia et al., 2015, p. 1907). The public sector, governments and other institutions need to support SMEs to reach out to their customers and enable them to succeed in a competitive world (Osei et al., 2016, p. 421). Despite all mentioned challenges, the majority of research also identifies opportunities for SME retail and suggests that retailers should adapt to the digital age. Advanced technology may support firms in extracting knowledge from clients and attracting and maintaining existing ones (Pantano, 2014, p. 6).

1.5.3 Internal and External Influence Factors

Prior examinations of SME retailers lay in the intersection of entrepreneurship, marketing, information science, computer science and psychology. The investigation of certain factors with influence on the current and future development of SME retailers is an interdisciplinary commonality. The influencing factors of innovation and technology adoption process are mainly classified into two types: 1) internal and 2) external factors (see Table 5.2). Mehrtens et al. (2001) examined internet adoption, and argued that a company's decision to adopt technology is influenced by internal and external factors based on attributes of innovation: perceived benefits, organizational readiness and external pressure. The study concludes that these factors have significant effects on the adoption process. Erosa (2009) examined the effects of prior use on technology adoption in SME retail. For measurement, she used three categories of internal factors: risk perception, advantages of IT use and the owner's perspective as well as one category of external factors: external technology influences. The study highlights the negative impact of low use and low use intentions on the actual use of technology by SME retailers in Mexico and the U.S. Pantano and Viasonne (2014) present a push-pull approach based on the external push of technology as well as on the pull of retailer internal demand. The results highlight the high impact of internal factors and reveal that the diffusion of technology-based innovation is influenced by retailers' expectations and their propensity to invest.

No.	Author / Year	Examined Internal Factors	Examined External Factors
1.	Mehrtens et al. (2001)	Attitude, Organizational Readiness	External Pressure
2.	Erosa (2009)	Prior Use	External Pressure
3.	Vize et al. (2013)	Attitude, Prior Use	External Pressure
4.	Pantano and Viasonne (2014)	Attitude, Organizational Readiness, Prior Use	Available Resources
5.	Pantano (2014)	Attitude, Organizational Readiness, Prior Use	-
6.	Amin and Hussin (2014)	Organizational Readiness, Prior Use	External Pressure, Available Resources
7.	Savrul et al. (2014)	Organizational Readiness, Prior Use	External Pressure
8.	Kurnia et al. (2015)	Organizational Readiness	External Pressure
9.	Rahayu and Day (2015)	Attitude, Organizational Readiness	External Pressure, Available Resources
10.	Osei et al. (2016)	-	External Pressure
11.	Maduku et al. (2016)	Organizational Readiness, Prior Use	External Pressure, Available Resources
12.	Kabanda and Brown (2017)	Organizational Readiness, Prior Use	External Pressure

Table 5.2 Categories of influencing factors based on the literature analysis

Amin and Hussin (2014) applied the "Technology-Organization-Environment Framework", extended by a stage-process to the examination of technology adoption among SME retailers to highlight that technology adoption is not a one-level process, but rather a process that has to go through certain stages. Kurnia et al. (2015) used a model based on the Diffusion of Innovation Theory combined with the National Institutions Perspective to examine the effect of internal factors based on attitudes and external factors of the industry (competition), the nation (government) and the overall environment (society), on the technology adoption process. Their results highlight the importance of the context of retailers for digital development.

1.6 Research Framework & Conceptual Model

1.6.1 Drivers and Barriers of the Decision Making Process of LOOROs

LOOROs are in fact micro-enterprises (Erosa, 2009, p. 1) in which the owners are intensively involved in the day-to-day business operations. These small businesses often face structural shortages of internal and external resources (Bollweg et al., 2016, p. 13). In large firms, decisions are subject to collective, collaborating scrutiny and testing, and are influenced by internal groups to a much higher degree than in micro-enterprises. In LOOROs, the owner is the executive manager, salesman, and storekeeper in personal union (Venkatesh, 2006, pp. 497-500). Hence, the owner-managers of LOOROs are the company's key decision-makers and they are more influenced by external factors than by (not existing) internal structures (Liberman-Yaconi et al., 2010, p. 80). To determine options for action for LOOROs, this study aims to examine the external and internal influence factors that have an impact (as driver or barrier) on the owners of LOOROs and their use of digital tools and applications for their business. Internal factors are controlled by the retailer (Vize et al., 2013, pp. 11-12; Rahayu and Day, 2015, pp. 143-146) and can be subdivided into factors from the organizational-level and from the individual-level (Erosa, 2009, p. 2; Amin and Hussin, 2014, p. 3). On the organizational-level, research has examined factors concerning organizational readiness, such as the availability of internal resources (e.g., human resources, motivation, time and current state of education), as well as the overall organizational commitment towards digitalization. On the individual-level, research has analyzed factors concerning the attitude, intentions, use and the usage experience of owners who have a key role in the innovation process of SME retail (Erosa, 2009, p. 4; Amin and Hussin, 2014, pp. 2-5; Maduku et al., 2016, pp. 717-718). External factors are factors that are out of the direct control of SMEs. These factors are related to the competitive environment, governmental regulations, pressure from value chain partners (e.g., suppliers and customers) and the availability of external resources (Vize et al., 2013, pp. 11-12; Rahayu and Day, 2015, pp. 143-146; Kabanda and Brown, 2017, pp. 123-124; Kurnia et al., 2015, p. 1907).

Based on the characteristics discussed above, this study will scrutinize the impact of the organizational level as an external factor (so called internal external factors) to focus on an owner-centric examination based on the individual level of the owner's personal attitudes (Marcati et al., 2008, p. 1583). Subsequently, common small, medium and large enterprise-related technology adoption approaches operating on the organizational level (e.g., the Technology-Organization-Environment Framework (TOE)) are unsuitable (Ramdani and Kawalek, 2007, p. 414). This study's research framework will be built on the Stimulus-Organism-Response Model (S-O-R Model) that operates on the individual level. To synthesize the findings of our literature analysis, we will utilize the following terms for our examination: 1) influence factors, for all measurable internal and external influencers of the innovation and technology adoption process (Vize et al., 2013, pp. 11-12; Rahayu and Day, 2015, pp. 143-146; Kabanda and Brown, 2017, p. 123; Kurnia et al., 2015, p. 1907) and 2) drivers and barriers as contribution-attributes for these factors, with regards to the direction of the impact on the examined innovation process (Harland et al., 2007, pp. 1238-1241).) We postulate that the examined influence factors have an inherent duality. They can either be a driving element which stimulates development towards the observed outcome or a barrier that slows down processes and overall development (see Table 5.3).

	Internal Factors		**External Factors**
Drivers	Individual Level	Positive Attitude Towards Use High Use Intentions High Usage	High Availability of External Resources High Perceived External Pressure
	Organizational Level	High Availability of Internal Resources High Perceived Internal Pressure	
Barriers	Individual Level	Negative Attitude Towards Use Low Use Intentions Low Usage	Low Availability of External Resources Low Perceived External Pressure
	Organizational Level	Low Availability of Internal Resources Low Perceived Internal Pressure	

Table 5.3 Overview internal and external drivers and barriers of technology adoption based on the literature analysis

1.6.2 Theory and adaptation of the Stimulus-Organism-Response Model

The Stimulus-Organism-Response Model (S-O-R) of Mehrabian and Russel (1974) originates from the environmental psychology field (Woodworth, 1929, p. 244) and is often used in marketing research to examine the customer response to a situational or environmental (external) stimulus. For example, Wang et al. (2011) investigate the impact of web aesthetics with its two dimensions aesthetic formality and aesthetic appeal on psychological reactions of online consumers with the help of the S-O-R model. Lee and Widdows (2011) analyzed the impact of high-technology attributes and Zhang et al. (2014) examined the influence of technological environments and virtual customer experience on customer motivation to participate in social commerce. The main idea behind the S-O-R model is that environmental processes and changes, called stimuli (S), are perceived by an organism (O) and instigate (emotional) reactions of the organism called behavioral response (R) (see Figure 5.1).

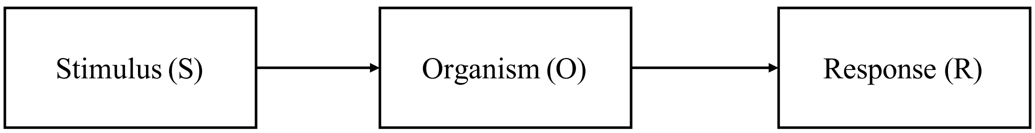


Figure 5.1 S-O-R Model

Despite contributions of the S-O-R framework to the research of consumer behavior, Kim et al. (2016) pointed out that there is an issue with its PAD-Scale, which measures consumers' emotional responses to environmental stimuli on bipolar continua. Westbrook (1987) criticized the bipolar conceptualization of the PAD-Scale for allowing the joint occurrence of pleasant and unpleasant states and proposed a unipolar view as more suitable. In an attempt to overcome this issue, one of the latest reviews of the “PAD-Scale” by Bakker et al. (2014) also highlighted that three dimensions of the PAD-Scale can be linked to one joint model of attitudes: pleasure, arousal and dominance can be respectively affective (feeling), cognitive (thinking) and conative (acting) responses. According to Bakker et al. (2014), the triad of feeling, thinking and acting can be unified as one joint measure for the organism (O). This suggestion of a joint measurement of attitudes is in line with the application of attitude constructs in Information Systems (IS) theories and related research.

1.6.3 Conceptual Model

The discussed joint measurement of attitudes is similar to the common measurement of attitudes in Information Systems (IS) theories and related research. Here, a broad range of theories about technology adoption, acceptance and implementation, extent of usage, effectiveness, success, and satisfaction is available (Ramdani and Kawalek, 2007, p. 414).

Two streams can be distinguished: Technology centered theories focus on the characteristics of the technology itself and the diffusion through different channels (i.e., Rogers, 1995). These theories are helpful for explaining technology adoption outcomes on an organizational level. In contrast, decision maker centered theories focus on the individual level and analyze human behavior and its impact on the decision-making process regarding technology adoption and use (e.g., Ajzen, 1991, Davis et al., 1989). In this regard, the Theory of Reasoned Action (TRA) (i.e., Ajzen and Fishbein, 1977) and its successor, the Theory of Planned Behavior (TPB) (i.e., Ajzen, 1991) state that attitudes, control beliefs, and subjective norms influence behavioral intention, which in turn influences actual behavior. Davis et al. (1989) applied TRA / TPB to the individual level of technology adoption behavior in his well-known Technology Adoption Model (TAM). Over the last two decades, researchers extended this view, examined antecedent as well as moderating factors and incorporated alternative belief factors into their research models, like TAM2 or the UTAUT Model, while keeping the core structure (behavioral intention influences actual behavior) of TAM (Ramdani and Kawalek, 2007, pp. 412-413). Furthermore, researchers integrated the TRA / TPB core (attitudes have impact on intentions) into theories of related disciplines. E.g., Koufaris (2002) used constructs from TAM to examine consumer behavior in combination with flow and environmental psychology in an integrated theoretical framework.

Accordingly, the organism, namely the owner as the decision maker in LOOROs, is captured by the TRA / TBP logic that the attitude towards a technology influences the intention to use it in order to mimic the thought process of a decision maker (Bakker et al., 2014, pp. 2-6). This thought process is triggered by internal and external stimuli. We postulate that the perception of organizational resource availability and the perception of external pressures can both be seen as such environmental stimuli leading to the organism's emotional reactions (Wang et al., 2011, pp. 47-48). Finally, the usage of the technology is the stimulated organism's emotional response. To frame ambiguity of the umbrella term digitalization into an operational understanding, we structure the variety of possible digital tools and applications based on the operational view of the business model management process (Wirtz et al., 2016, p. 11; Enders and Jelassi, 2000, pp. 544-546) into four categories of key digital business activities in the retail industry: 1) digital administration, 2) digital marketing activities, 3) digital sales channels and 4) digital services. Accordingly, these four categories will subdivide the organism (O) and the response (R) sections of the model. Finally, we extend the examination of the response (R) section by investigating the relationships between the stated usage segments (Wirtz et al., 2016, p. 11; Enders and Jelassi, 2000, pp. 544-546) to understand the impact of (prior) use of the precursory business areas on the current use of the following business area (Taylor and Todd, 1995, pp. 561-563).

2. Carrot-or-Stick: How to Trigger the Digitalization of Local Owner Operated Retail Outlets?

2.1 Introduction

In a growing market environment, local owner operated retail outlets (LOOROs) are pressured to adapt their own business models to the intense competitive situation in the retail sector. LOOROs, which are characterized by a small-sized store area, a limited number of staff and high owner-involvement in the day-to-day business operations, are challenged by the industry transformation (Bollweg et al., 2015, p. 8). In Germany, the market share of the business type LOORO has declined from 26% to 18.5% between the years 2003 and 2014 (HDE, 2016, p. 9). Additionally, several independent studies predict a decline in revenues of 30% in the next four years in Germany (IFH, 2015; HDE, 2017, pp. 3-14). Responsible for this development is on the one hand the online trade that challenges LOOROs with strong price and service competition, while, at the same time, former purely internet-based retailers have started expanding its operations by means of physical stores in city centers to conquer the last bastion of brick and mortar retail, the customers in the high streets. Moreover, big-box retail outlets and chain stores have started to digitalize their business models and offer multichannel sales and services to their local customers (Liebmann, 2013). Customers, on the other hand, have changed their buying habits: they are already used to online shopping and digital services so that their shopping frequency in city centers is declining (IFH, 2016, p. 38). To sum it up, pure online retailers, big-box retail outlets and chain stores as well as changing customer shopping habits and a decline in shoppers' frequencies in the high streets are threatening the very existence of LOOROs. However, LOOROs are not defenselessly exposed to the threats of the digital age. Digital tools and applications to handle administrative tasks (e.g., digital inventory management systems, customer relationship management systems and marketing tools) and to enable digital interaction with the customers across the sales channels (e.g., via online shops, e-marketplaces, in-store applications, digital shelf extensions) allow LOOROs to overcome their inherent limitations (e.g., lack of time, lack of knowledge, lack of human resources, lack of finance, etc.) and to regain competitive power (Navickas et al., 2015, p. 4). Despite all opportunities, studies show that LOOROs, like other small- and medium-sized enterprises (SME), still hesitate to adopt digital tools for their own business (Navickas et al., 2015, p. 4; Bollweg et al., 2016, p. 13).

The transformation of the retail sector and the slow but steady dying of the small, owner-operated retailers is not just a matter of the LOOROs themselves. Abandoned high streets and empty city centers are potential threats to the traditional infrastructures and might have a negative impact on related industries (gastronomy, tourism, and many more) as well as on the local job markets. Therefore, politicians, city managers and the retail lobbies seek for triggers to support the local structures and to push the digitalization efforts of the local retailers in this uncertain phase of industry transformation. With regards to the Economic Theory of Regulations (ET), the government and the public sector use two types of measures to foster the desired development: 1) Subsidies including measures that add or improve access to resources for development (e.g., grants, loans, loan guarantees, vouchers, contracts, etc.) and 2) Regulations including measures that create pressure towards desired development (e.g., legal, economic and social regulations, public information, taxes, liability, etc.) (Salamon and Elliot, 2002, pp. 1-47; Migué, 1977, pp. 213-221). The application of this two-sided toolbox is called the "Government´s Carrot-and-Stick Approach" (i.e., Andreoni et al., 2002).

The purpose of this study is to examine the impact of subsidy (carrot: offering resources) and regulation (stick: creating pressure) based triggers to foster the use of digital tools and applications among LOOROs. Therefore, we want to understand:

RQ1: *Are LOOROs receptive for triggers based on resources (carrot) and pressure (stick)?*

And furthermore:

RQ2: *What are promising measures for a "Carrot-And-Stick" approach to foster the current use of digital tools and applications among LOOROs?*

To achieve meaningful results, we conducted a survey among 223 owners of LOOROs of 26 comparable cities (rural region and population below 100,000 inhabitants) in Germany. The results of this study offer insights for the public sector on how to promote the digitalization of LOOROs as well as insights for owners of LOOROs on promising starting points for their own digital development. Our results contribute to the body of knowledge on two levels: 1) insights on the effects of "Available Resources" (Carrot) and "Perceived Pressures" (Stick) on the intention to use and the current usage of digital tools and applications in the front-end and back-end activities of LOOROs and 2) insights on the orchestration of an efficient and effective "Carrot-And-Stick" approach.

The remainder of this paper is structured as follows: In section 6.3, we provide an overview about the related theory with regards to subsidies and regulations. In section 6.4, we develop a conceptual model based on the above-mentioned theories to address our research question. In section 6.5, we describe the survey conducted and provide the statistical analysis. Further, we discuss our findings in section 6.6 and point out research, managerial and political implications in section 6.7. Finally, we conclude in section 6.8 in order to answer the initial research question, to highlight limitations and to point out future research opportunities.

2.2 Theoretical Background

This study is addressing an intensively discussed area: the implication of governmental and public interventions with regards to technology adoption among commercial industries. Beside politicians and citizens also economists support controversial viewpoints about the use of public resources and powers to improve the economic status of members of the public (private or corporations) e.g., Keynesianism vs. Monetarism. As this study does not aim to resolve this controversy neither to argue for one or the other, we draw the attention towards literature that explains subsidies (carrot) and regulations (stick) and exposes implications for the technology adoption.

The Economic Theory of Regulation regarded market failure as the motivating reason for enacting regulations. Once established, regulatory bodies were supposed to lessen or eliminate the inefficiencies engendered by the market failure (Peltzmann et al., 1989, pp. 4-5). The available measures for the government and the public sector to foster the desired development are divided into subsidies and regulations (Salamon and Elliot, 2002, pp. 1-47; Migué, 1977, pp. 213-221). Subsidies are state transfers to members of the public which are either in kind or of monetary nature. Regulations are considered as the employment of legal instruments for the implementation of social-economic policy objectives (Aktan and Dokuzcesmeler, 2016, p. 305). The counterpart to regulation is deregulation; it means the state's withdrawal of its legal powers to direct the economic conduct (e.g., pricing, market entry) of members of the public. A fully functional market is a pre-requisite for the successful implementation of deregulation (Peltzmann et al., 1989, pp. 4-5).

Existing IS research neglects the examination of impacts of subsidies (carrot) and regulations (stick) on the technology adoption at an industry and firm level. A structured literature search in the databases of ScienceDirect, EbscoHost and Google Scholar remained fruitless. Minor effects of governmental regulations are discussed in technology adoption models like the "Technology-Organization-Environment-Framework (TOE)" without differentiating the governmental toolbox into subsidies and regulations (e.g., Tornatzky and Fleischer, 1990). These models process governmental regulations as given parameters companies are required to comply with (Petrova and Wang, 2013, p. 2; Rahayu and Day, 2015, pp. 143-146). However, extensive research on subsidies and regulations is done at an industry-level in highly regulated markets (e.g., renewable energy and agriculture) (e.g., Kalkuhl et al., 2013, Latruffe et al., 2013). For the research on highly regulated markets, we discovered two main examination areas: 1) impact of subsidies and regulations on consumer prices and 2) the impact on industry growth. None of the reviewed literature was related to the impacts of governmental triggered technology adoption among economic groups at the firm level. The lack of research in this direction might be attributable to the favorable market conditions in the retail sector over the past decades. Nowadays, the retail market is jeopardized because of the challenges of the digital age and is failing due to financial and technological imbalances (Liebmann, 2013, IFH, 2016, p. 38). The existence of market failure is often the reason that self-regulatory organizations and governments intervene in a particular market (Tornatzky and Fleischer, 1990, pp. 177-195). Therefore, the government and the public sector are seeking triggers to lessen the imbalances of the market; this research takes a step towards identifying these triggers.

2.3 Conceptual Model & Research Framework

To support current public efforts and which in turn foster LOOROs and their current state of digitalization, this study aims to examine the possible external triggers of the governmental "carrot-and-stick approach" to push the use of digital tools and applications among LOOROs. Therefore, we examine whether and how "available resources" (carrot) and "perceived pressures" (stick) influence the owners of local retail outlets to use digital technologies. To frame the ambiguity of the umbrella term digitalization into an operational understanding, we structure the digital tools and applications based on the operational view of the management process of business models: 1) The digitalization of the front-end sales channels where we collect all digitalization efforts with direct customer touch points, and 2) the digitalization of the administrative back-end, invisible to the customer (Enders and Jelassi, 2000, pp. 544-546).

LOOROs are in fact micro-enterprises where owners are intensively involved in the day-to-day operations and which have to handle a structural shortage of internal and external resources (Bollweg et al., 2016, p. 13). Due to these characteristics, common small, medium and large enterprise-related technology adoption approaches (e.g., the Technology-Organization-Environment Framework (TOE), Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), Combined TAM and TPB, TAM2, Diffusion of Innovations Theory, and many more) are not suitable (Ramdani and Kawalek, 2007, pp. 412-

413). In large firms decisions are subject to collective, collaborating scrutiny and testing, and are influenced by others to a much higher degree than in micro-enterprises. In LOOROs the owner is the executive manager, salesman, and storekeeper in personal union. Hence, the owner-managers of LOOROs are the company's key decision makers who are in turn rather influenced by external factors than by internal structures (Liberman-Yaconi, 2010, p. 80). To meet these characteristics this study will exclude the impacts of the organizational level from the research model and focuses on an owner-centric examination based on the individual level of the owner´s personal characteristics.

The framework of the model is built on the S-O-R Model. The origin of the S-O-R Model lies in the field of environmental psychology. Mehrabian and Russel (1974) postulate that environmental stimuli (S) lead to emotional reactions of the organism (O) which finally drives behavioral response (R). To describe human perception of their encountered environments, the original S-O-R Model used three emotional dimensions: pleasure, arousal and dominance (the PAD-Scale). In the field of environmental psychology, pleasure, arousal and dominance are conceived as three basic dimensions of emotional responses that indicate peoples' state of feeling. Mehrabian and Russel (1974) described pleasure purely in terms of positive or negative feelings. Arousal is described as a feeling state that concerns mental activity and dominance as a feeling of control and behavior restrictions caused by physical or social barriers (Mehrabian and Russell, 1974, pp. 216-217)

In marketing research the S-O-R Model is usually used to examine the response of customers to a situational or environmental stimulus e.g., colors in a store environment or music while online shopping. Wang et al. (2011) used an S-O-R approach to examine how the two dimensions of web aesthetics, aesthetic formality and aesthetic appeal influence online consumers' psychological reactions. Moreover, Lee and Widdows (2011) applied an S-O-R based model to investigate how high-technology attributes influence consumer responses. By means of S-O-R Zhang et al. (2014) examined the motivation of customers to participate in social commerce and the impact of technological environments and virtual customer experience. Despite the contribution of the S-O-R framework to the research of consumer behavior, Kim et al. (2016) and other research papers point out that there is an issue with its PAD-Scale which measures consumers' emotional responses to environmental stimuli on bipolar continua. Several studies criticize the bipolar conceptualization for allowing the joint occurrence of pleasant and unpleasant states and propose a unipolar view as more suitable (Westbrook, 1987 p. 259; Russell and Carroll, 1999, pp. 25-26; Stangor et al., 2013, pp. 160-196). In an attempt to overcome this issue, the latest reviews of the "PAD-Scale" by Bakker et al. (2014) had highlighted that the three dimensions of the PAD-Scale can be linked to one joint model of attitudes: pleasure, arousal and dominance can be respectively affective (feeling), cognitive (thinking) and conative (acting) responses. According to Bakker et al. (2014), the triad of feeling, thinking and acting can be unified as one joint measure for the organism (O) (Bakker et al., 2014, pp. 2-6).

This finding stands in line with the long history of information systems research about the use of technology in organizations. IS research has provided a broad range of theories with regard to technology adoption, acceptance and implementation, extent of usage, effectiveness, success as well as satisfaction (Ramdani and Kawalek, 2007, p. 414). Some of the perspectives are regarded as theories about diffusion of technology and discuss the adoption of technology through different channels (i.e., Rogers, 1995). Other perspectives focus on human behavior and its impact on the decision-making process towards the adoption and usage of technology (e.g., Ajzen, 1991; Davis et al., 1989). While related theories of technology diffusion are helpful to explain technology adoption outcomes on an organizational level behavioral theories contrarily focus on the individual analysis level where human behavior has its impact. The Theory of Reasoned Action (TRA) (i.e., Ajzen and Fishbein, 1977) and its successor the Theory of Planned Behavior (TPB) by Ajzen (1991) stated that attitudes, control beliefs and subjective norms influence behavioral intention, what in turn influences the actual behavior. Davis et al. (1989) applied TRA / TPB to the individual level of technology adoption behavior in his well-known "Technology Adoption Model (TAM)". According to Davis, two key constructs influence an individual's intention to use a technology namely the "Perceived Usefulness" and "Perceived Ease of Use". Over the last two decades researchers extended this view, examined antecedent as well as moderating factors and incorporated alternative belief factors into their research models like the TAM2 or the UTAUT Model while keeping the core structures (behavioral intention influences actual behavior). Furthermore, researchers used the TRA / TPB as core framework and integrated theory of related disciplines. Koufaris (2002) used constructs from information systems (TAM), marketing (Consumer Behavior), and psychology (Flow and Environmental Psychology) in an integrated theoretical framework of online consumer behavior to examine how emotional and cognitive responses to visiting a Web-based store for the first time can influence online consumers' intention to return (Koufaris, 2002, pp. 206-213).

Accordingly, we build our research framework on the S-O-R framework and extend its organism (O) section with the integration of the core constructs of TRA, TPB and TAM, namely “attitude”, “behavioral intention” and “actual behavior”.

Stimulus (S): Despite the growing competition from the online trade, digitalized advanced big box retail outlets and chain stores as well as changing customer habits towards digital channels LOOROs still hesitate to use digital tools and applications to regain competitive power (Navickas et al., 2015, p. 4; Bollweg et al., 2016, p. 13). To support LOOROs, politicians, city managers and the retail lobbies seek for triggers to push the digitalization efforts of the local retailers. The toolbox of the public sector comprises two types of measures to promote the desired development: 1) Subsidies (adding resources) and 2) Regulations (creating pressure) (Salamon and Elliot, 2002, pp. 1-47): the “Government´s Carrot-and-Stick Approach” (i.e., Andreoni et al., 2002). The prospects of success of the applicable measures (adding resources or creating pressure) are related to the state of the availability of resources and the perception of pressure among the aimed target group. In detail, a state of high available resources and a low perception of pressure would have a lower impact on the prospects of success. Vice versa, a state of low available resources and a high perception of pressures would be promising for the prospects of success of the applied measures (Salamon and Elliot, 2002, pp. 1-47).

To examine the potential effectiveness of the discussed measures, this study investigates the current availability of resources and the perception of pressures among LOOROs as well as their impact on the usage of digital tools and applications. Mehrabian and Russel (1974) state that environmental stimuli (S) lead to emotional reaction of the organism (O). The perception of the availability of resources and the perception of external pressures can be both seen as comparable environmental stimuli that lead to comparable emotional reactions of the organism. According to Bakker et al. (2014), we will link the commonly used PAD-Scale in the organism (O) block to a joint model of attitudes to avoid the joint occurrence of pleasant and unpleasant states.

Our measurement of the “Available Resources” is based on the resource categories of the Resource-Based View. These categories are representing tangible and intangible goods and can be translated into the availability of financial resources (R1), the availability of the necessary capacities (R2), the availability of the needed knowledge (R3) and the availability of time (R4) (Wernerfelt, 1984, p. 173). To investigate the influence of available resources on the emotional reactions of the organism (O) block of the research model, we hypothesize:

H1: *The availability of resources has a positive influence on the attitude towards the digitalization.*

Regarding the effectiveness of measures that use pressure to foster digital developments among LOOROs, this study also investigates the current state of the perception of external pressures and their influence on the organism (O) of the research model. Our measurement of the "Perceived Pressure" is derived from the "Three-Environment Theory" (Stapleton, 2000, p. 28). Correspondingly, external pressures comprise influences from the near and far environment. As described in the Three-Environment Theory, the near (specific) environment is formed by influences of competitors (EP1 – competitive pressure), customers (EP2 - customer pressure) and suppliers who exert a direct impact on the examined organization. The far (general) environment is formed by influences of politics (EP3 – legal pressure), society (EP4 – society pressure), technological and economic pressures (Stapleton, 2000, p. 28). With respect to the discussed background we are mainly covering the economic pressure with the investigation of the financial resources but we neglect the suppliers' pressure (based on offer and demand) and the technological pressure (push and pull) due to our research scope of potential triggers for the public sector. Accordingly, we hypothesize:

H2: *Perceived pressure towards digitalization has a positive influence on the attitude towards the digitalization.*

Organism (O): In the traditional S-O-R models the (O) is represented by the PAD-Scale and its measure of pleasure, arousal and dominance. Despite the undoubted contributions of the S-O-R model for consumer research, the PAD-Scale itself is questionable (Bakker et al., 2014, pp. 2-6). To address the criticism about the bipolar conceptualization, namely the joint occurrence of pleasant and unpleasant states in the PAD-Scale (Kim et al., 2016, pp. 1-2; Westbrook, 1987, p. 259), this study integrates the core blocks of the established TRA/TPB theory that derives from the well-known Technology Acceptance Model (TAM). In contrast to the suggested triade of feeling, thinking, and acting by Bakker et al. (2014), TRA/TPB theory separates the internal state of acting (behavior) from the measurement of the attitude (feeling and thinking). TRA/TPB theory states that attitudes, control beliefs and subjective norms do not directly influence actual behavior. Furthermore, it states that attitudes influence the behavioral intention (intention to use) which in turn influences the actual behavior (current use) (Ajzen, 1991, p. 182; Davis et al., 1989, p. 984).

Our joint measurement of the attitude towards digitalization is based on TRA / TPB theory. The feeling is represented by the measurement of the subjective norm towards digitalization (A1) and the ease of use (A2). The thinking is covered by the expected future developments

(A3) and the expected effectiveness of the digitalization (A4) (Ajzen, 1991, pp. 181-182; Davis et al., 1989, p. 984). According to the introduced relationships of the TRA/TPB theory we state the following hypotheses for both of our examination areas (front-end and back-end):

H3a: *A positive attitude towards digitalization has a positive influence on the intention to use digital sales channels (front-end).*

H3b: *A positive attitude towards digitalization has a positive influence on the intention to use the digital tools in the administration (back-end).*

Our measurement (behavioral) intention to use digitalization in both examination areas (front-end and back-end activities) is based on the operational view of the management process of business models for brick and mortar retail stores (Enders and Jelassi, 2000, pp. 544-546). For the front-end (intention to use digital sales channels), it covers the possible online and offline sales channels such as an own online shop (IS1), the presence on third-party e-marketplaces (IS2) and the use of in-store applications (IS3) as well as the online marketing activities (IS4) (Enders and Jelassi, 2000, pp. 544-546).

Our measurement for the back-end (intention to use digital tools and applications in the administration) covers all digital support activities with no direct customer touch points (Enders and Jelassi, 2000, pp. 544-546). As there are: the use of soft-ware for administration (IA1), the use of inventory management systems (IA2), the use of digital communication channels (IA3) and the use of digital payment systems (IA4).

According to TRA/TPB theory attitudes influence the behavioral intentions what in turn influences the actual behavior, we consequently state the following hypotheses (Ajzen, 1991, pp. 181-182; Davis et al., 1989, p. 984):

H4a: *A high intention to use digital sales channels has a positive influence on the current use of digital sales channels.*

H4b: *A high intention to use the digital tools in the administration has a positive influence on the current use of the digital tools in the administration.*

Response (R): The usage of digitalization either in front-end or back-end activities is measured as indirect response to the examined stimuli, “Available Resources” and “Perceived Pressures”. It is the last step in the already introduced chain of relationships, stated by the TRA/TPB theory (Ajzen, 1991, p. 182; Davis et al., 1989, p. 984). Our last measurement of the current use of digitalization for both examination areas shares the same theoretical structure with the intentional constructs (Enders and Jelassi, 2000, pp. 544-546). Instead of behavioral intentions we examine the actual behavior. For the “Current Use of digital Sales Channels” we cover the already introduced possible online and offline sales channels: online shop (US1), third-party e-marketplaces (US2), in-store applications (US3) and online advertisement (US4). For the “Current Use of digital Administration” we cover the back-end activities of the LOOROs namely the use of software for administration (UA1), the use of inventory management System (UA2), the use of digital communication channels (UA3) and the use of digital payment systems (UA4).

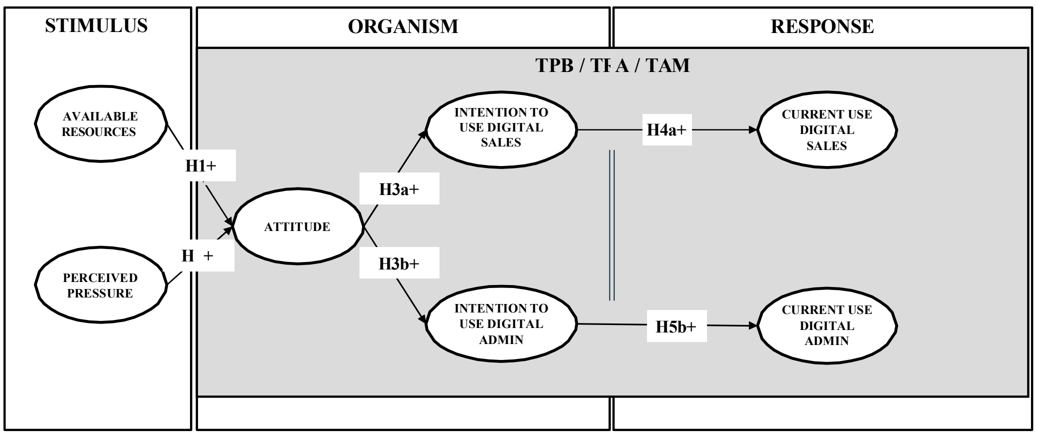


Figure 6.1 Research model

2.4 Analysis

2.4.1 Data Collection

As part of the research project “Future Lab Retail South Westphalia 2020” we conducted a survey among LOOROs (May and July 2016) of the 26 partner cities of the region of South Westphalia in Germany. The questionnaire contained 42 questions with a 5-point-Likert-Scale and was answered by 124 participants via an online form and by 119 participants on paper. In total 243 questionnaires were submitted with 223 full data sets. For the analysis of the collected data and the evaluation of the research model we used SmartPLS (i.e., Ringle et al., 2005). Bootstrapping was done with 5000 samples and 223 cases, determining the significance of weights, loadings and path coefficients. SPSS was used for the multicollinearity tests of the formative constructs.

2.4.2 Measurement Model

The research model has one reflective construct (“Attitude towards Digitalization”). The other six constructs are formative so that different analyses are needed (Fornell and Bookstein, 1982, p. 442). The significance of the constructs’ indicators is assessed by their loadings (reflective constructs) that should be greater than 0.7 (greater than 0.6 is acceptable) or weights (formative constructs) that should be greater than 0.1 (Jarvis et al., 2003, p. 200-205) and their t-values. An indicator is significant if its t-value is greater than 1.65. This corresponds to a significance level of 10%. In order to reach a significance level of 5% (1%). the t-value must be greater than 1.96 (2.57) (Hair et al., 2006, pp. 664-670). Table 6.1 shows the t-values as well as the corresponding loadings / weights for all indicators of our model and also indicates the result with regards to the calculated significance. Concerning the reflective construct, all indicators are significant. The AVE (Average Variance Extracted) is 0.5750 (minimum > 0.5) and the composite reliability is 0.8428 (min. 0.7) so that the model fits to the convergence criteria. The discriminant validity of the constructs is also given. The model complies with the Fornell-Larcker criterion: Its highest squared construct correlation is with 0.3 below the maximum of 0.5 and the loadings of the reflective indicators are significantly higher than their cross loadings as compared to the other constructs. The internal consistency is given as the reflective construct exceeds the critical value of 0.7 for Cronbach’s Alpha. Attitude towards Digitalization: 0.7515 (Hair et al., 2006, pp. 664-670). The prediction validity Q2 is with 0.4323 higher than the minimum of 0 (Hair et al., 2014, 102-103).

The results of the formative constructs are as follows: For the construct "Available Resources", two (R2, R4) of the six indicators have significant positive influences. The construct "Perceived External Pressure" includes three of four significant indicators: EP2, EP3 and EP4. The construct “Intention to Use Digital Sales Channels” comprises two of four significant indicators: IS2, IS3. For the construct “Intention to Use Digital Administration” three of four indicators have significant positive influences (IA2, IA3, and IA4). The construct “Current Use of Digital Sales Channel” includes three of four significant indicators: US2, US3 and US4. And finally, for the construct “Current Use of Digital Administration” three of four indicators are significant: UA2, UA3, UA4 (see Table 6.1). In addition to the significance of indicators, the discriminant validity of the formative constructs must be verified. The highest correlation between the latent variables is given for the constructs "Intention to Use Digital Sales Channels" and "Current Use of Digital Sales Channels" with a value of 0.8995. This does not exceed the set maximum of 0.9 so that the criterion regarding the discriminant validity is met (Hair et al., 2014, pp. 102-103). The analysis conducted using SPSS with regard to multicollinearity showed that all indicators of the models are sufficiently different and independent of each other (Hair et al., 2014, p. 125).

ns = not significant; *p<0.10; **p<0.05; ***p<0.01.

Indicator	**Loading** / Weight	*t*-statistics	Significance	VIF	R²
R1	0.0104	0.089	ns		
R2	0.8274	9.6099	***		
R3	-0.0342	0.2392	ns	-	-
R4	0.4094	2.4363	**		
EP1	-0.0634	0.4512	ns		
EP2	0.3257	2.2084	**		
EP3	-0.573	3.8501	***	-	-
EP4	0.7678	6.7553	***		
A1	**0.8284**	31.6562	***		
A2	**0.7428**	17.973	***		
A3	**0.6412**	10.046	***	**1.64**	0.398
A4	**0.8114**	9.3633	***		
IS1	0.0771	0.85	ns		
IS2	0.3918	2.4835	**		
IS3	0.6875	4.8411	***	-	0.067
IS4	0.0153	0.1447	ns		
IA1	0.5818	5.5666	***		
IA2	0.3082	1.831	*		
IA3	0.0734	0.8627	ns	-	0.111
IA4	0.4783	3.1103	***		
US1	0.0606	0.6482	ns		
US2	0.3614	2.2645	**		
US3	0.7284	5.3362	***	-	**0.809**
US4	-0.0193	0.2012	ns		
UA1	0.5358	4.8738	***		
UA2	0.331	1.9906	**		
UA3	0.1082	1.266	ns	-	**0.770**
UA4	0.4949	3.2791	***		

Table 6.1 Path coefficient

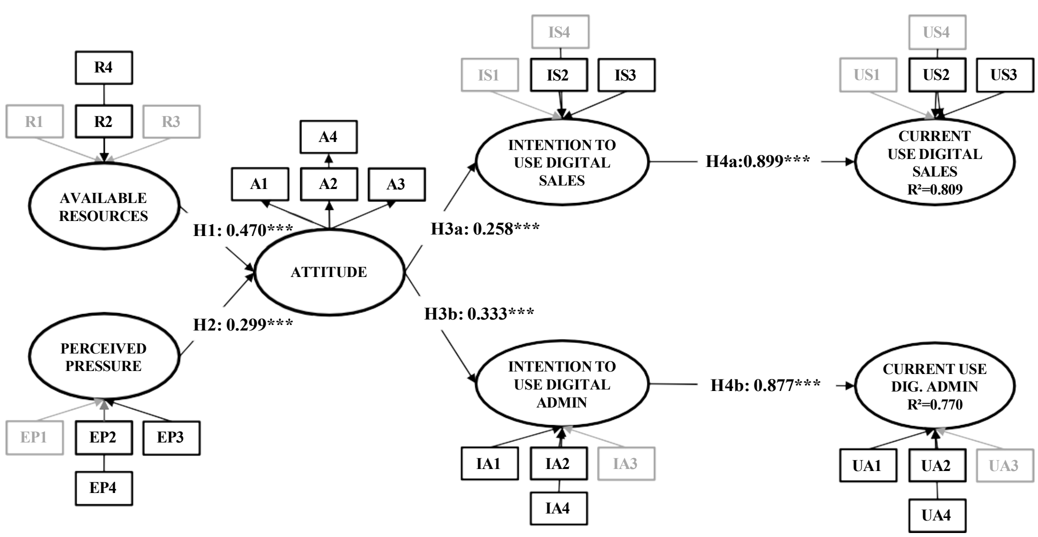


Figure 6.2 Research model & analysis

CHAPTER4 - DATA ANALYSIS

The purpose of this chapter was to describe the data analysis and present the results of the study. This chapter had presented the results of both descriptive and inferential statistical analyses performed on the data obtained through field survey. First, the relevant descriptive statistical tools like mean and standard deviation and cross tabulations were applied to part-A,B,C D, and E in the questionnaire. Second, inferential statistical were presented.

4.1 Descriptive Statistics (Sample Description)

Retail managers and/or retail IT professionals familiarised and/or working with big data retail business analytics in food and grocery, apparel, consumer durables and entertainment retailing in the cities of Delhi/NCR were invited to participate in the survey through self-administered structured questionnaire as well as online (survey monkey) survey method. A total of six hundred thirty retail managers/IT Professionals were surveyed. Out of which, five hundred and eighty hundred questionnaires were rendered usable and rest were found unusable due to incomplete data. This is an approximately 92 percent response rate.

Results for demographics of the samples (full sample and sector-wise) shown in Table-4.1 appears to be relatively consistent and representative of the target audience of four types of retail sectors considered in the study. The following sub sections present the data analysis about respondent's demographic, designation, experience and expertise in the domain areas concerned.

Table 4.1: Respondents' Profile

Description		Total sample n=580	Apparel sector (n=180)	Food &Grocery sector (n=155)	Consumer durable sector (n=140)	Entertainment sector (n=105)	For χ^2Value at 5% level of significance
Gender	Male	445 (76.7)	130 (72.2)	120 (77.42)	110 (78.57)	85 (80.95)	$\chi 2$ =2.217, df3, p>0.05
	Female	135 (23.3)	50 (27.78)	35 (22.58)	30 (21.43)	20 (19.05)	
Age in Years	25-35	120 (20.69)	43 (23.89)	35 (22.58)	25 (17.86)	20 (19.05)	$\chi 2$ =20.05, df9, p< 0.025
	35-45	250 (43.10)	66 (36.67)	57 (36.77)	55 (39.29)	39 (36.14)	
	45-55	144 (24.83)	45 (25.00)	34 (21.94)	40 (28.57)	28 (26.67)	
	55 – 65	66 (11.38)	26 (14.44)	29 (18.71)	20 (14.29)	18 (17.14)	
Marital Status	Married	493 (85.00)	153 (85.00)	131 (84.52)	119 (85.00)	90 (85.71)	$\chi 2$ =5.096, df3, p> 0.05
	Unmarried	87 (15.00)	27 (15.00)	76 (49.03)	21 (15.00)	25 (23.81)	
Education	Degree	377 (65.00)	177(66.11)	101 (65.16)	91 (66.43)	68 (64.76)	$\chi 2$ =30.76, df3, p< 0.001
	PG & above	203(35.00)	63(16.1)	54 (34.84)	49 (33.57)	37 (35.24)	
Designation	Top/Adman.	290(50.00)	91 (50.56)	78 (50.32)	72(51.43)	53 (50.48)	$\chi 2$ =1.008, df 9, p > 0.05
	Middle/Exec.	232 (40.00)	73 (40.56)	62 (40.00)	53(37.86)	42 (40.00)	
	Lower level	29(5.00)	9(5.00)	7(4.52)	8(5.71)	5(4.76)	
	Operative	29(5.00)	7 (3.89)	8(5.16)	7(5.00)	5(4.76)	
Expertise	CRM	203(35.00)	63(35.46)	54 (34.84)	51(36.43)	37(35.24)	$\chi 2$ =0.608, df 9, p > 0.05
	LSCM	116(20.00)	36 (20.00)	31(20.00)	28(20.00)	21(20.00)	
	ICT	116(20.00)	36 (19.44)	31 (20.00)	29(20.71)	21(20.00)	
	Merchandising	87 (15.00)	28(15.56)	23 (14.84)	20(14.29)	16 (15.24)	
	RCOM	58(10.00)	18(9.44)	16(10.32)	12(8.57)	10(9.52)	
Experience	< 5 years	59 (10.17)	19 (10.56)	15 (9.68)	15(10.71)	10 (9.52)	$\chi 2$ =20.59, df9, p< 0.025
	5-10	116(20.00)	35(19.44)	31(20.00)	29(20.71)	32(30.48)	
	10 -15	174(30.00)	53(29.44)	47(30.32)	42 (30.00)	42(40.00)	
	>15 years	231(39.83)	73(40.56)	62(40.00)	54(38.57)	21(20.00)	

Source: Primary data

Note: Values given in parenthesis are calculated in percentage of their column totals.

4.1.1 Respondents' Profiles

All the respondents were retail managers, IT professionals and business analysts consisted of 445 male (56.7%) and 135 female (23.3%) with an average age of 37 years (range 25-65). Majority of the respondents (85%) were married. The majority (65%) of the respondents are graduates with technical and IT background. Majority of the respondents (50%) are from top /Administrative level, followed by middle/executive level (40 %). Majority of the respondents (35 %) have expertise in customer service and customer relationship management, followed by information and communication technology and logistics and supply chain management with 20 percent each. About 40 percent of the respondents have more than 15 years of experience in use of big data retail business analytics in their respective domain areas, specifically customer relationship management followed by respondents with 10-15 years of experience, specifically in L&SCM and ICT. The Chi-square test statistic results at 5% level of significance shown in Table 4.1 revealed that respondents' age ($\chi 2$ = 20. 05, df 9, $p < 0.025$), education ($\chi 2$ = 30. 76, df 6, $p < 0.001$), and their experience ($\chi 2$ = 20. 59, df 9, $p < 0.025$), are significantly diverse with type of retail organisation in contrast to the respondents' gender, marital status, designation and expertise which are not significant with the type of retail sector considered in the research. The Chi-square results implied that retail managers in the age group of 35-45 with PG qualification and more than fifteen years of experience have significant association with type of retail sector. Retail managers' choice of retail sector using big data retail business analytics are significantly differed with their age, educational qualification and years of experience. Retail managers' age, education and experience are not independent of type of retail sector.

4.1.2 Responses to question "Do you trust that your organization is working on big Data?"

Results shown in Table-4.2 reveal that, overall, 90.5 percent of respondents have trust in retail organisation's working on big data analytics in various business functions. 92 percent of respondents from apparel retailing have trust in organisation's working on big data analytics, followed by consumer durable retailing (91%), food and grocery (90%) and entertainment retailing (89.5%). The Chi-square statistic results ($\chi 2$ = 0.90, df 3, $p > 0.05$) indicate that there is no difference in the distribution of responses to the outcome variable among the comparison groups. There is no difference among retail managers' trust in four types of retail organisations' working on big data. The results shown in Figure 4.1, by and large, are explicitly implied that respondents have high levels of trust in their retail organisations' working on big data analytics.

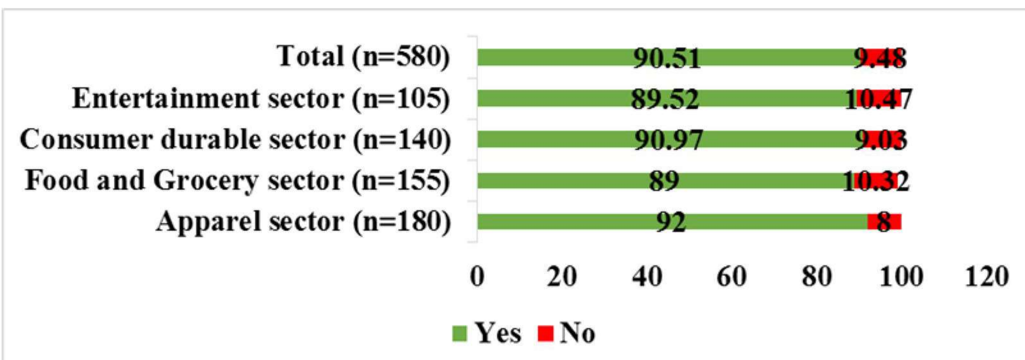
Table 4.2: Trust in Organisation's working on Big Data

Respondent Trust	Apparel sector (n=180)	Food & Grocery sector (n=155)	Consumer durable sector (n=140)	Entertainment sector (n=105)	Total (n=580)
Yes	166 (92.00)	139 (89.67)	126 (90.97)	94 (89.52)	525 (90.51)
No	14 (8.00)	16 (10.32)	14 (9.03)	11 (10.47)	55 (9.48)
Total	180 (100)	155 (100)	140 (100)	105 (100)	580 (100)

Source: primary data

Note: Values given in parenthesis are calculated in percentage of their column totals.

Figure 4.1: Trust in retail organisation's working on big data analytics



4.1.3 Responses to Question "Do you think big data analytics is important for managerial decision making?"

Results shown in Table-4.3 reveal that, overall, 93.6 percent of respondents have viewed big data analytics are important in retail organisations. 95.5 percent of the respondents from food and grocery retailing indicate that big data analytics are important in managerial decision making compared to respondents (95%) and (92%) in apparel and consumer durable retailing respectively. The Chi-square statistic results ($\chi 2$ = 3.74, df, 3, $p > 0.05$) reveal that there is no difference importance of big data analytics among four retail organisations considered in the study. They are independent of each other. The results shown in Figure-4.2 implied that retailers are aware of the importance of big data and analytics in informed managerial decision making. However the importance of big data analytics is differed for variety of reasons.

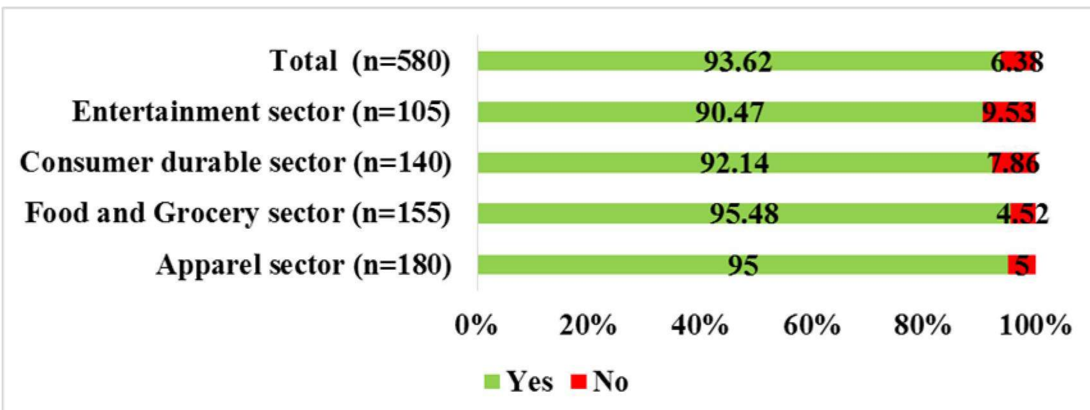
Table 4.3: Importance of Big Data in Retail Organizations

Importance of Big data	Apparel sector (n=180)	Food & Grocery sector (n=155)	Consumer durable sector (n=140)	Entertainment sector (n=105)	Total
Yes	171(95.00)	148 (95.48)	129 (92.14)	95 (90.47)	543 (93.62)
No	9 (5.00)	7 (4.52)	11 (7.86)	10 (9.53)	37 (6.38)
Total	180 (100)	155 (100)	140 (100)	105 (110)	580 (100)

Source: primary data

Note: Values given in parenthesis are calculated in percentage of their column totals.

Figure 4.2: Importance of Big Data analytics in Retail Organizations



4.1.4 Responses to question "Does your firm have a well-defined policy for analysing Data?"

Results shown in Table-4.4 reveal that, overall, 71 percent of the respondents say that retail organisations do not have well defined policy on big data analytics. The analysis further reveals that 75.72 percent of respondents in consumer durable retailing say that there are no well-defined policies in place for analysing big data compared to entertainment (74.29%), apparel (71.11%) and food & grocery retailing (64.52%). The Chi-square statistic results ($\chi 2$ = 2.412, df, 3, $p > 0.05$) reveal that that well defined policies for analysing big data and type of retail organisation are independent. There is no association between type of retail organisation and well defined policy of analysing big data. There is no difference in the distribution of responses to the outcome variable among the comparison groups. That is retail managers' perception or opinion towards well defined policies for analysing data is same. The results shown in Figure 4.3 are implied that retailers are unclear about big data analytics or have devised policies towards big data analytics. Nevertheless, respondents all say their firms are prioritizing data collection, but still only 29 percent of respondents believe that they have a well-defined policy for analysing the most valuable information.

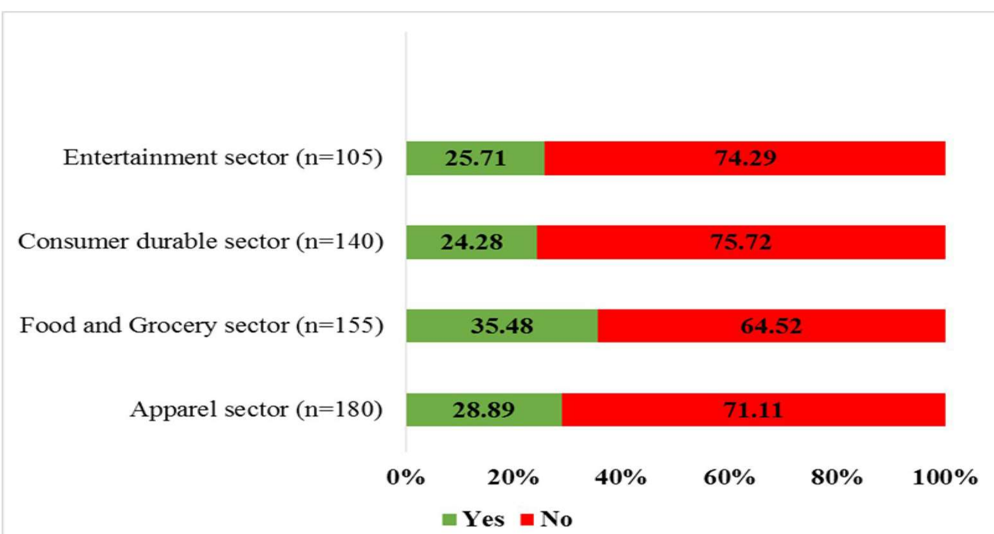
Table 4.4: Well Defined Policy for Analysing Big Data in Retail Organisations

Well defined Policy	Apparel sector (n=180)	Food &Grocery sector (n=155)	Consumer durable sector (n=140)	Entertainment sector (n=105)	Total
Yes	52 (28.89)	55 (35.48)	34 (24.28)	27 (25.71)	168 (28.96)
No	128 (71.11)	100 (64.52)	106 75.72)	78 (74.29)	412 (71.04)
Total	180 (100)	155 (100)	140 (100)	105 (100)	580 (100)

Source: primary data

Note: Values given in parenthesis are calculated in percentage of their column totals.

Figure 4.3: Well Defined Policy for Analysing Big Data in Retail Organisations



4.1.5 Responses to the question "Which of the following big data analytics techniques (s) that your organisation is currently using in managerial decision making?"

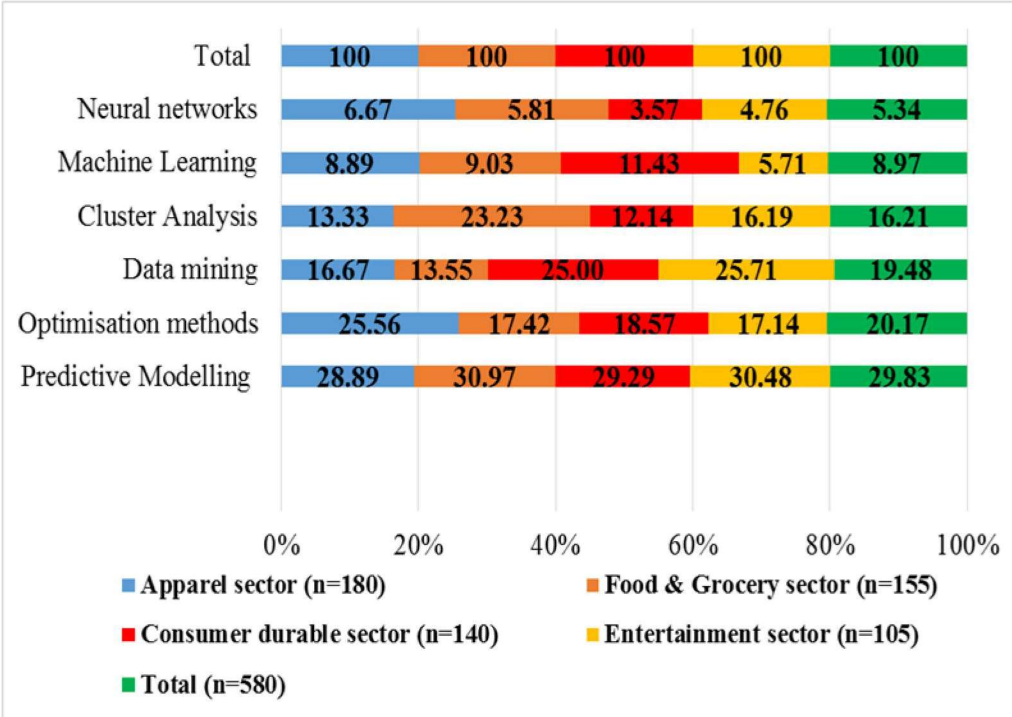
Results shown in Table-4.5 reveal that, overall; about 30 percent of respondents' ranked predictive modelling is the highest techniques of big data retail business analytics currently used in managerial decision making in retail organisations. A number of respondents (20.17 %) indicate that optimisation methods, followed by data mining (19.5%), cluster analysis (16.20%), machine learning (9 %) and neural networks (5.3%) are ranked second, third, fourth, fifth and sixth respectively, as the techniques of big data analytics currently used in retail organisations. The Chi-square statistic results ($\chi2 = 27.42$, df, 15, $p < 0.05$) reveal that there is significant difference in the distribution of responses to the techniques of big data analytics among the comparison groups. The results shown in Figure 4.4 implied that there are significant differences in techniques of big data analytics used among retail organisations.

Table 4.5: Techniques of big data analytics used in retail organisations

Techniques of big data analytics used in Retail Organisations	**Apparel sector (n=180)**	**Food & Grocery sector (n=155)**	**Consumer durable sector (n=140)**	**Entertainment sector (n=105)**	**Total (n=580**
Predictive Modelling	52 (28.89)	48 (30.97)	41 (29.29)	32 (30.48)	173 (29.83)
Optimisation methods	46 (25.26)	27 (17.42)	26 (18.57)	18 (17.14)	117 (20.17)
Data mining	30 (16.67)	21 (13.55)	35 (25.00)	27 (25.71)	113 (19.48)
Cluster Analysis	24 (13.33)	36 (23.23)	17 (12.14)	17 (16.19)	94 (16.21)
Machine Learning	16 (8.89)	14 (9.03)	16 (11.43)	6 (5.71)	52 (8.97)
Neural networks	12 (6.67)	9 (5.81)	5 (3.57)	5 (4.76)	31 (5.34)
Total	180 (100)	155 (100)	140 (100)	105 (100)	580 (100)

Source: primary data.
Note: Values given in parenthesis are calculated in frequencies of their column totals.

Figure 4.4: Techniques of big data analytics used in retail organisations



4.1.6 Responses to question "How important do you think using big data analytics is, if at all, for retailers to stay competitive?"

Results shown in Table-4.6 reveal, overall, 63.3 percent of respondents state that use of big data retail business analytics is extremely important in retailing to stay competitive. Majority of the respondents (71.6%) say that use of big data analytics is extremely important to stay competitive in food and grocery retailing compared to apparel retailing (68.3%) and consumer durable retailing (67.1%). The Chi-square statistic results ($\chi 2$ = 11.34, df, 12, p >0.05) reveal that there is no difference in the distribution of responses to the outcome variable among the comparison groups. The results implied that retail managers among four groups have similar kind of opinion or view towards importance of using data analytics in retailing to stay competitive. The results shown in Figure 4.5 also reveal that a few respondents (less than 12 percent) view that using big data analytics to stay competitive in retailing is unimportant and/or extremely unimportant. The analysis shows that while retailers realize the value of maximizing their use of big data and analytics, many are still unable to utilize the data they are collecting in full.

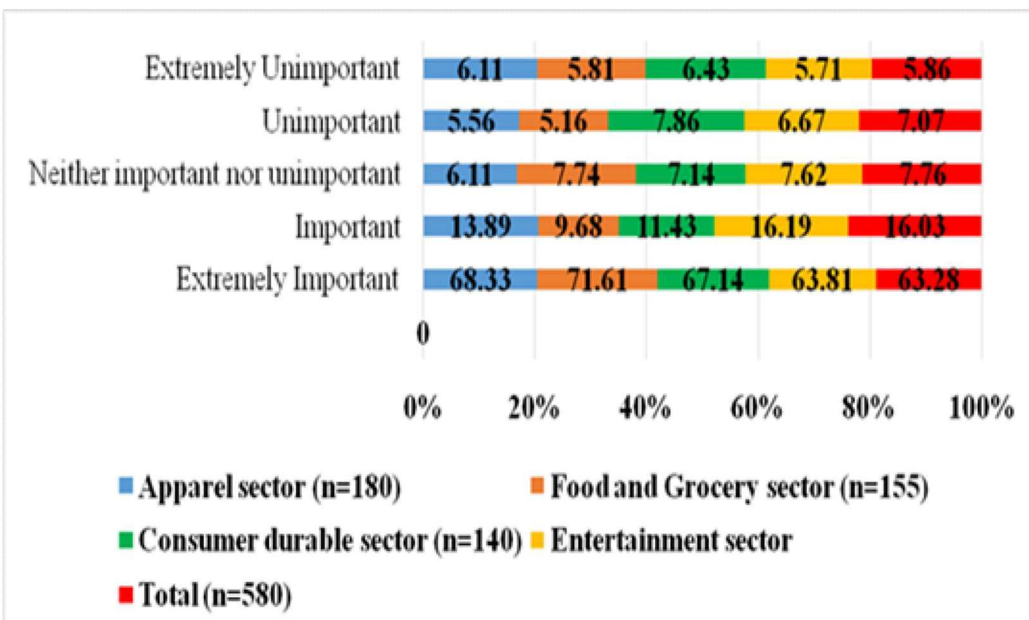
Table 4.6: Using Big Data Analytics in Retail Organisations to Stay Competitive

Using of Big data analytics to stay competitive	Apparel sector (n=180)	Food & Grocery sector (n=155)	Consumer durable sector (n=140)	Entertainment sector (n=105)	Total (n=580)
Extremely Important	123 (68.33)	111 (71.61)	94 (67.13)	67 (63.81)	367 (63.28)
Important	25 (13.88)	15 (9.67)	16 (11.41)	17 (16.19)	93 (16.05)
Neither important nor unimportant	11 (6.12)	12 (7.75)	10 (7.13)	8 (7.62)	45 (7.76)
Unimportant	10 (5.55)	8 (5.16)	11 (7.83)	7 (6.66)	41 (7.05)
Extremely Unimportant	11 (6.12)	9 (5.81)	9 (6.40)	6 (5.72)	34 (5.86)

Source: primary data

Note: Values given in parenthesis are calculated in percentage of their column totals

Figure 4.5: Using Big Data Analytics in Retail Organisations to Stay Competitive



4.1.7 Responses to Question "How would you rate the access to relevant, accurate and timely big data in the retail organizations?"

Results shown in Table-4.7 reveal, overall, 64. 5 percent of respondents state that access to relevant, accurate and timely big data in their retail companies is either inadequate (45%) or minimal (19.5%). A few respondents (25%) say that access to relevant, accurate and timely big data in their retail companies is adequate compared to respondents (10.5 percent) who have viewed the access to relevant, accurate and timely big data in their retail companies is world class. Further analysis reveals that respondents from consumer durables retailing (25.7 %) state that access to relevant, accurate and timely big data is adequate compared to apparel (24.4%), food and grocery (25.2%), and entertainment retailing (24.7%). The Chi-square statistic results ($\chi 2$ = 0.453, df, 9, $p > 0.05$) reveal that there is no difference in the distribution of responses to the outcome variable among the comparison groups. The results implied that retail managers' opinion or perception towards access to relevant, accurate and timely big data in the four retail companies is similar. The results shown in Figure 4.5 implied that there is a need to enhance the access to relevant, accurate and timely big data in retail companies. This is one of the key challenges faced by retailers.

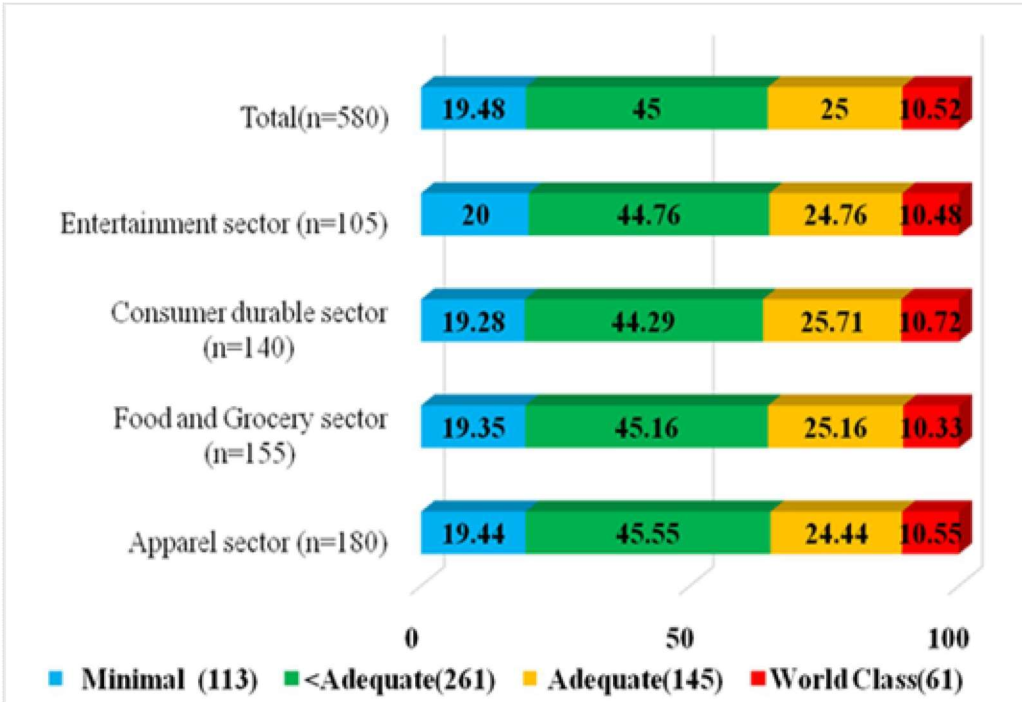
Table 4.7: Access to Relevant, Accurate and Timely Big Data in the Retail Organisations

Access to relevant, accurate and timely big data	**Apparel sector (n=180)**	**Food &Grocery sector (n=155)**	**Consumer durable sector (n=140)**	**Entertainment sector (n=105)**	**Total (n=580)**
Minimal	35 (19.44)	30 (19.36)	27 (19.28)	21 (20.00)	113 (19.48)
<Adequate	82 (45.56)	70 (45.16)	62 (44.28)	47 (44.77)	261(45.00)
Adequate	44 (24.44)	39 (25.16)	36 (25.72)	26 (24.76)	145 (25.00)
World Class	19 (10.56)	16 (10.32)	15 (10.72)	11 (10.47)	61 (10.52)
Total	180 (100)	155 (100)	140 (100)	105 (100)	580 (100)

Source: primary data

Note: Values given in parenthesis are calculated in percentage of their column totals

Figure 4.6: Access to Relevant, Accurate and Timely Big Data in Retail Organisations



4.1.8 Responses to question "How would you rate the business analytics capabilities in retail organizations?"

Results shown in Table-4.8 reveal, overall, 65.8 percent of respondents rate that analytics capabilities in retail complies are less than adequate (39.66%) and/or minimal (26.21). Mere 10.34 percent respondents say that retail companies have world class business analytics capabilities compared to 25.7 percent of respondents who rate retail organisation have adequate business analytics capabilities. Further, the Chi-square statistic results ($\chi 2$ = 17.16, df, 9, $p < .05$) reveal that there is a significant association between type of retail organisation and business analytics capabilities. The results shown in Figure 4.7 are implicit that 10.71 percent respondents from consumer durables retailing say that their business analytics capabilities are world class compared to entertainment (10.48%), food and grocery (10.33 %) and apparel retailing (10%). However, only 40 percent are confident that their organisation's analytical abilities are keeping up with data volumes. This is also one of the biggest barriers in harnessing the effectiveness of big data analytics. The results can also be interpreted that there is a need to increase business analytics capabilities in retailing industry so as to optimise the ever increasing big data in today's context.

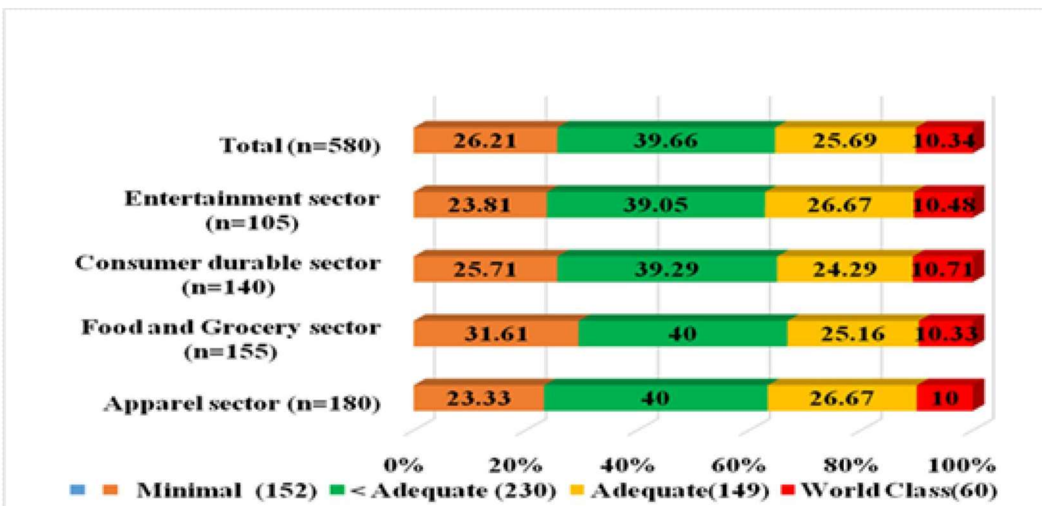
Table 4.8: Business Analytics Capabilities in Retail Organisations

Business Analytics Capabilities	Apparel sector (n=180)	Food and Grocery sector (n=155)	Consumer durable sector (n=140)	Entertainment sector (n=105)	Total (n=580)
Minimal	42 (23.33)	49 (31.61)	36 (25.71)	25 (23.81)	152 (26.21)
< Adequate	72 (40.00)	62 (40.00)	55 (39.29)	41(39.05)	230 (39.66)
Adequate	48 (26.67)	39 (25.16)	34 (24.29)	28 (26.67)	149 (25.69)
World Class	18 (10.00)	16 (10.33)	15 (10.71)	11 (10.47)	60 (10.34)
Total	180 (100)	155 (100)	140 (100)	105 (100)	580 (100)

Source: primary data

Note: Values given in parenthesis are calculated in percentage of their column totals.

Figure: 4.7: Business Analytics Capabilities in Retail Organisations



4.1.9 Responses to question "How would you define big data analytics?"

Results shown in Table-4.9 reveal that, overall, 60.3 percent of respondents strongly agree with the big data retail business analytics as tool for identifying right customers, followed by a tool for real-time market knowledge about the hottest trends (55.2%), segmenting/targeting (50%), optimizing customer experiences (49.82%), forecasting demand for better inventory management (45.17%), customer satisfaction strategies (44.65%), product profitability (42.41%), customer acquisition and retention(39.1%), and optimising pricing (38.1%). The analysis also reveals 34.12 percent respondents' agreed with big data analytics as a tool used for optimising pricing strategies and/or techniques in retailing. The analysis shown in Figure 4.8 is implied that respondents' perception toward big data analytics in retailing is positive, proactive and encouraging as most decisions are insights-driven retail marketing, insights-driven retail merchandising, and insights-driven retail operations. Although big data analytics play a critical role in retail mangers' decision making, most of the respondents were unclear about big data analytics or devised their own definitions.

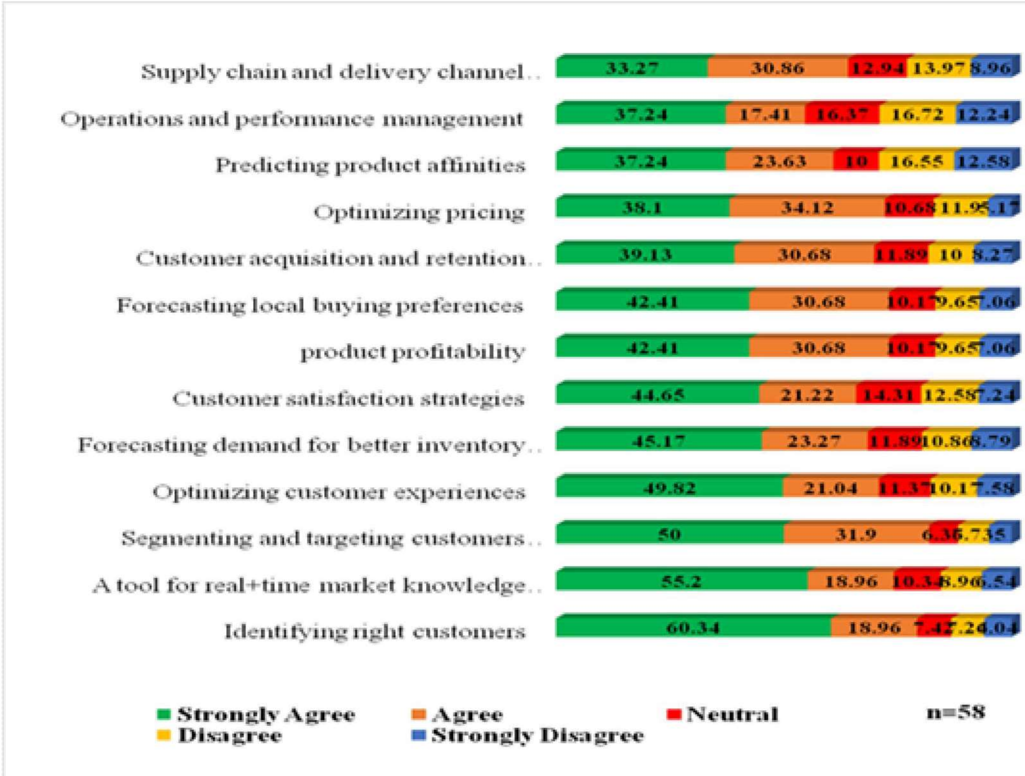
Table 4.9: Perception of Big Data Retail Business Analytics

Definition of Big data analytics	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	Total (n=580)
Identifying right customers	350 (60.34)	110 (18.96)	43 (7.42)	42 (7.24)	35 (6.04)	580 (100)
A tool for real-time market knowledge about the hottest trends	320 (55.20)	110 (18.96)	60 (10.34)	52 (8.96)	38 (6.54)	580 (100)
Segmenting and targeting customers precisely	290 (50.0)	185 (31.90)	37 (6.37)	39 (6.73)	29 (5.0)	580 (100)
Optimizing customer experiences	289 (49.82)	122 (21.04)	66 (11.37)	59 (10.17)	44 (7.58)	580 (100)
Forecasting demand for better inventory management	262 (45.17)	135 (23.27)	69 (11.89)	63 (10.86)	51 (8.79)	580 (100)
Customer satisfaction strategies	259 (44.65)	123 (21.22)	83 (14.31)	73 (12.58)	42 (7.24)	580 (100)
product profitability	246 (42.41)	178 (30.68)	59 (10.17)	56 (9.65)	41 (7.06)	580 (100)
Forecasting local buying preferences	229 (39.48)	144 (24.82)	76 (13.10)	68 (11.72)	63 (10.86)	580 (100)
Customer acquisition and retention strategies	227 (39.13)	178 (30.68)	69 (11.89)	58 (10.0)	48 (8.27)	580 (100)
Optimizing pricing	221 (38.10)	198 (34.12)	62 (10.68)	69 (11.90)	30 (5.17)	580 (100)
Predicting product affinities	216 (37.24)	137 (23.63)	58 (10.0)	96 (16.55)	73 (12.58)	580 (100)
Operations and performance management	216 (37.24)	101 (17.41)	95 (16.37)	97 (16.72)	71 (12.24)	580 (100)
Supply chain and delivery channel strategy	193 (33.27)	179 (30.86)	75 (12.94)	81 (13.97)	52 (8.96)	580 (100)

Source: Primary data

Note: Values given in parenthesis are calculated in percentage of their row totals.

Figure 4.8: Perception of Big Data Retail Business Analytics



4.1.10 Response to question "Which Parameter of big data analytics is the most important as per you?

Results presented in Table-4.10 reveal that, overall, 50.5 percent of respondents' state that veracity (correctness) is an important parameter of big data analytics in retailing. 20.86 percent of respondents say that variety is second important parameter of big data in retailing. Surprisingly, overall, 12.41 percent of respondents state that volume is the least parameter of big data in retailing. The Chi-square statistic results ($\chi2$ = 0.14, df, 9, $p > 0.05$) reveal that there is no difference in the distribution of responses to the outcome variable among the comparison groups. The results implied that there is no difference among retail managers from four retail sectors with respect to the most important parameter of big data analytics in retailing. The results shown in Figure 4.9 are implied that having a lot of data in different volumes coming in at high speed is worthless if that data is incorrect. Incorrect data can cause a lot of problems for retail organisations as well as for consumers. Therefore, retail organisations need to ensure that the data is correct as well as the analyses performed on the data is correct.

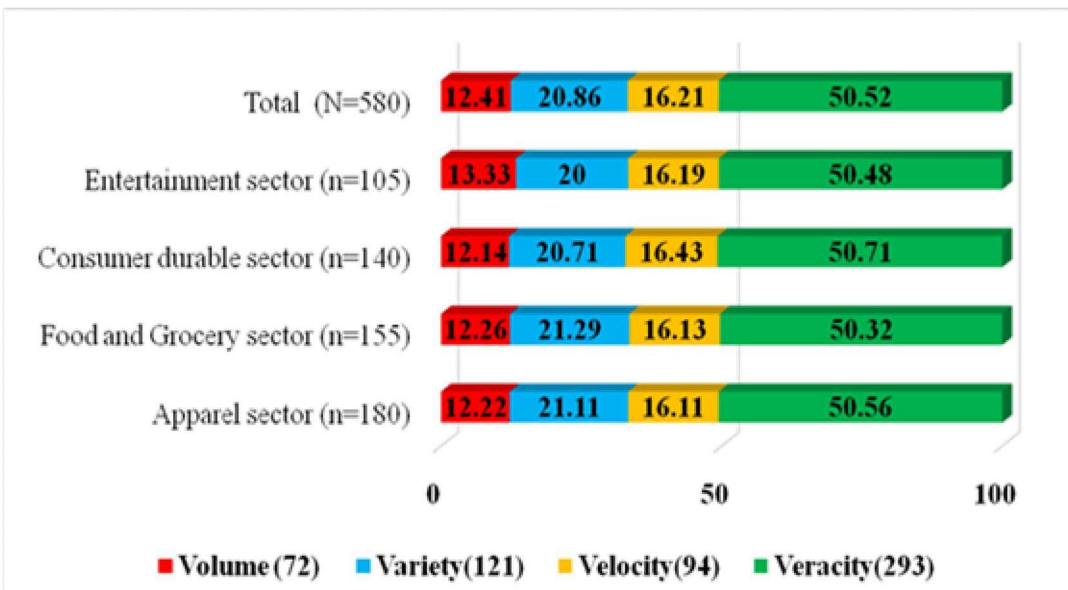
Table 4.10: Most important parameter of big data analytics in retailing

Important Parameter of Big data analytics	Apparel sector (n=180)	Food & Grocery sector (n=155)	Consumer durable sector (n=140)	Entertainment sector (n=105)	Total (n=580)
Volume	22 (12.22)	19 (12.26)	17 (12.14)	14 (13.33)	72 (12.41)
Variety	38 (21.11)	33 (21.29)	29 (20.71)	21 (20.00)	121(20.86)
Velocity	29 (16.11)	25 (16.13)	23 (16.43)	17 (16.19)	94 (16.21)
Veracity	91(50.56)	78 (50.32)	71 (50.71)	53 (50.48)	293 (50.52)
Total	180 (100)	155 (100)	140 (100)	105 (100)	580 (100)

Source: primary data

Note: Values given in parenthesis are calculated in percentage of their column totals.

Figure 4.9: Most Important Parameter of big data analytics in retailing



4.1.11 Responses to question "How seriously is big data analytics taken by retailers in the decision making?"

Results presented in Table-4.11 reveal that, overall, 45.5 percent of respondents' view that retail companies have not taken seriously the usage of big data analytics in managerial decision making while 33.28 percent of respondents have viewed usage of big data analytics little seriously. In contradictory, meagre 5 percent of respondents view usage of big data analytics very seriously in managerial decision making. The Chi-square statistic results ($\chi 2$ = 1.81, df, 9, $p > 0.05$) reveal that there is no difference in the distribution of responses to the outcome variable among the comparison groups. All respondents from four retail sectors have same kind of seriousness in use of big data analytics in retailing. The results shown in Figure 4.10 are implied that while the adoption of big data analytics in the retail sector is happening, the speed is still slow given the volume of data that is generated and can be leveraged to enhance operational excellence as well as to provide customers a more customised shopping experience.

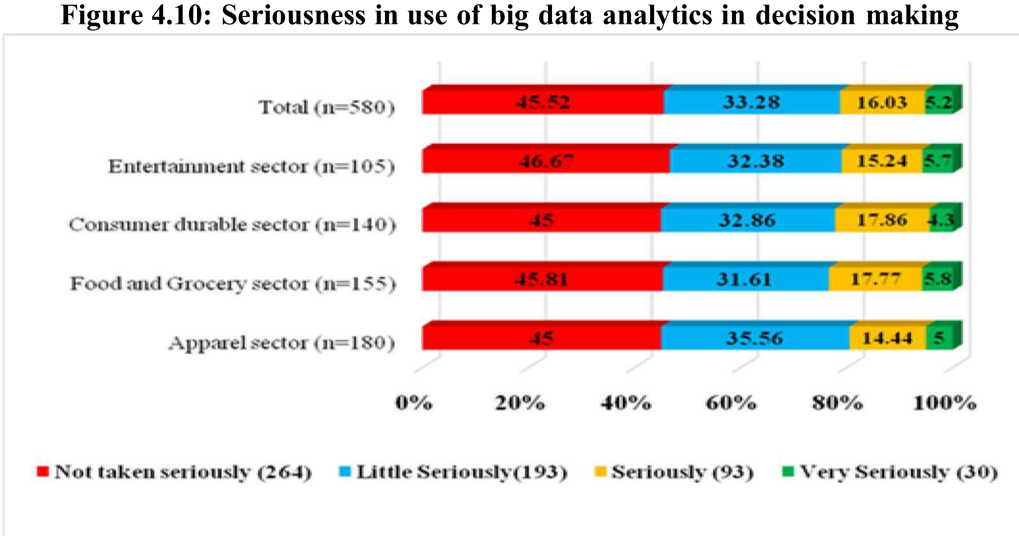
Table 4.11: Seriousness in use of big data analytics in decision making

Seriousness in usage of big data	Apparel sector (n=180)	Food & Grocery sector (n=155)	Consumer durable sector (n=140)	Entertainment sector (n=105)	Total (n=580)
Not taken seriously	81 (45.00)	71 (45.81)	63 (45.00)	49 (46.68)	264 (45.52)
Little Seriously	64 (35.56)	49 (31.61)	46 (32.86)	34 (32.38)	193 (33.28)
Seriously	26 (14.44)	26 (17.77)	25 (17.86)	16 (15.23)	93 (16.03)
Very Seriously	9 (5.00)	9 (5.81)	6 (4.28)	6 (5.71)	30 (5.17)
Total	180 (100)	155 (100)	140 (100)	105 (100)	580 (100)

Source: primary data

Note: Values given in parenthesis are calculated in percentage of their column totals.

Figure 4.10: Seriousness in use of big data analytics in decision making



4.1.12 Responses to question "What, as per you, is the most important element of big data retail business analytics scenario in India?"

Results shown in Table-4.12 reveal that, overall, 42.93 percent of respondents' view that technology is the most important element of big data analytics in retailing. 28.28 percent of respondents view that competent skill set is the most important element in big data analytics in retailing. While 45 percent of respondents from apparel retailing view that technology is the most important element in big data analytics, 43.57 percent of respondents from consumer durable retailing view technology is the most important element compared to 42.58 percent respondents from food and grocery sector. The Chi-square statistic results ($\chi 2 = 3.457$, df, 15, $p > 0.05$) reveal that there is no difference in the distribution of responses to the most important element of big data analytics among the comparison groups. The results shown in Figure 4.11 implied that retailers must equip their IT infrastructures to handle the rapid rate of delivery of extreme volumes of data, with varying data types so as to make the most of big data. Secondly, the results also implied that there is a dearth of talent and skilled IT professionals to deal with advanced analytics for better decision-making which is a fact-based decision-making in retailing.

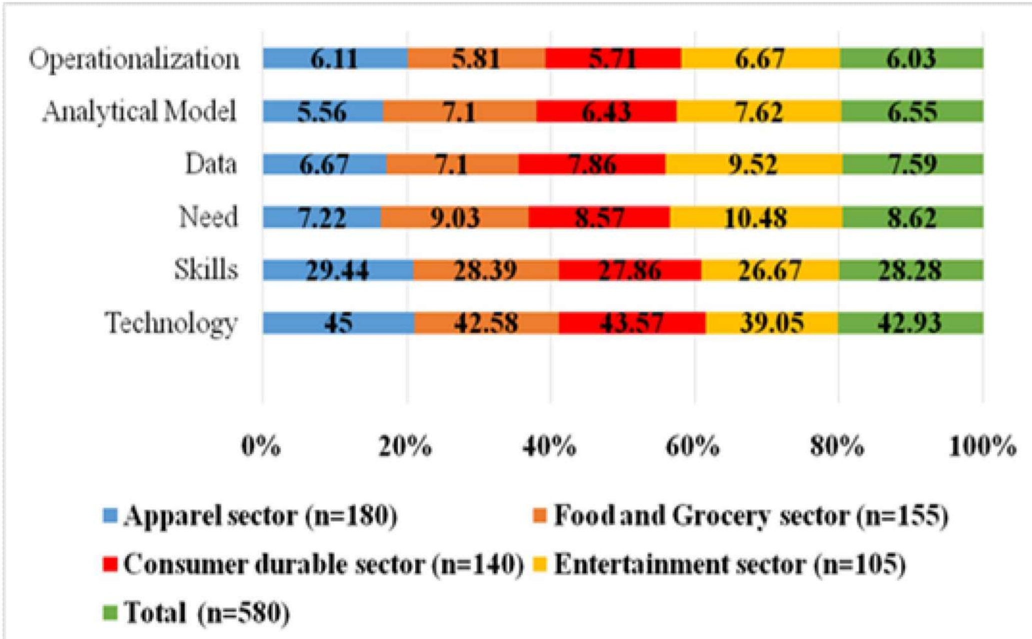
Table 4.12: Most Important Element of Big Data Analytics in Retailing

Important element of big data analytics	**Apparel sector (n=180)**	**Food & Grocery sector (n=155)**	**Consumer durable sector (n=140)**	**Entertainment sector (n=105)**	**Total (n=580)**
Need	13 (7.22)	14 (9.03)	12 (8.57)	11(10.48)	50 (8.62)
Data	12(6.67)	11(7.10)	11(7.86)	10 (9.52)	44 (7.59)
Analytical Model	10 (5.56)	11(7.10)	9 (6.43)	8 (7.62)	38 (6.55)
Technology	81 (45.00)	66 (42.58)	61 (43.57)	41 (39.05)	249 (42.93)
Skills	53 (29.44)	44 (28.39)	39 (27.86)	28 (26.67)	164 (28.28)
Operationalization	11 (6.11)	9 (5.81)	8 (5.71)	7 (6.67)	35 (6.03)
Total	180 (100)	155 (100)	140 (100)	105 (100)	580 (100)

Source: primary data

Note: Values given in parenthesis are calculated in percentage of their column totals.

Figure 4.11: Most Important Element of Big Data Analytics in Retailing



4.1.13 Responses to question "What must be the objective of effective big data retail business analytics?"

Results shown in Table-4.13 reveal that, overall, 43.27 percent of respondents' ranked customer centric outcomes are the highest followed by operational optimisation (24.31%), and financial management (14.13%), risk management (9.48%), and new business model (8.79%) as second, third fourth and fifth respectively. Most respondents have ranked customer centric outcomes is the prime objective of big data analytics in apparel, food and grocery and consumer durables in contrast to the respondents who ranked operational optimisation is the prime objective in entertainment retailing. The Chi-square statistic results ($\chi2$ = 61.38, df 12, $p < 0.001$) reveal that there is significant difference in the distribution of responses to the objectives of big data retail business analytics among the comparison groups. The results shown in Figure 4.12 implied that retailers' primary objective of using big data retail business analytics is to obtain better customer centric outcomes as retailers today face a new breed of empowered customers who are always connected and have more information on products than sometimes even the retailers do. Being customer-centric is the new competitive differentiation for retailers today.

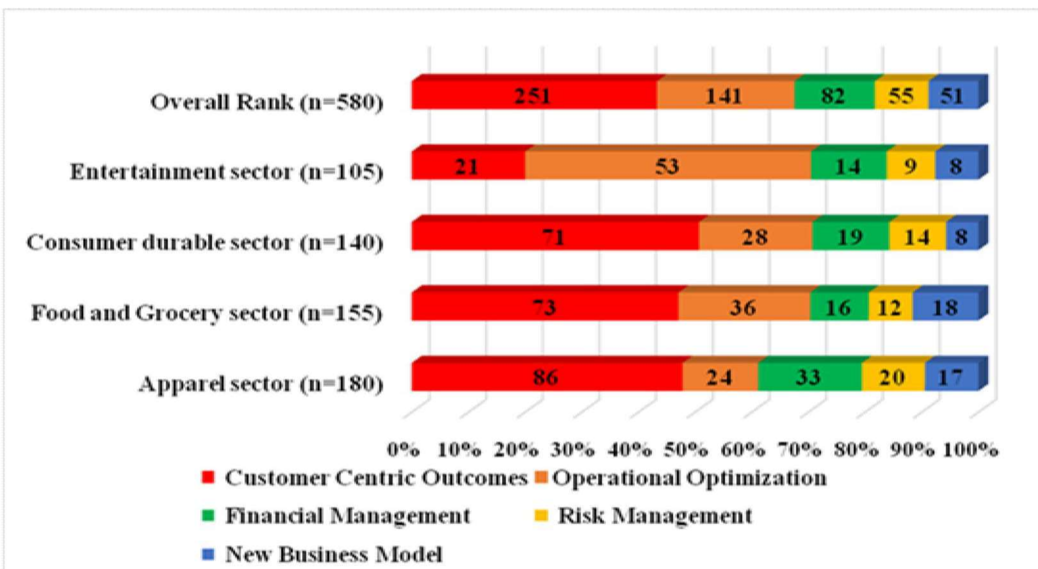
Table 4.13: Objective of Big Data Retail Business Analytics

Objectives of the big data retail business analytics	Apparel sector (n=180)	Food & Grocery sector (n=155)	Consumer durable sector (n=140)	Entertainment sector (n=105)	Overall Rank (n=580)
Customer centric Outcomes	1 (86)	1 (73)	1 (71)	2 (21)	1 (251)
Operational Optimization	3 (24)	2 (36)	2 (28)	1 (53)	2 (141)
Financial Management	2 (33)	4 (16)	3 (19)	3 (14)	3 (82)
Risk Management	4 (20)	5 (12)	4 (14)	4 (9)	4 (55)
New Business Model	5 (17)	3 (18)	5 (8)	5 (8)	5 (51)

Source: primary data

Note: Values given in parenthesis are calculated in frequencies of their column totals.

Figure 4.12: Objectives of Big Data Retail Business Analytics



4.1.14 Responses to question "what are the key challenges in big data and analytics in retailing?"

Results shown in Table-4.14 reveal that, overall, 51.03 percent of respondents' strongly agree that understanding customers by establishing a single view across multiple sources of customer information is the key challenge in big data retail business analytics compared to respondents (49.48%) who strongly agree with improving the accuracy of product data to support cross-channel merchandising programs, discount pricing models and operations management. However, 42.58 percent of respondents agree that predicting the customer buying habits is the key challenge for retailers in using big data retail business analytics compared to Enhancing the reliability of vendor information to support pricing negotiations, contract renewals, score carding and profitability analysis (38.95%).The results shown in Figure 4.13 implied that retailers face key challenge in building and maintaining increasingly complex integrations to deliver a multi-channel experience to the customer. And understanding their customer well — across all channels — is still a major difficulty as retailers have many sources of data from each channel, and typically these are not well integrated.

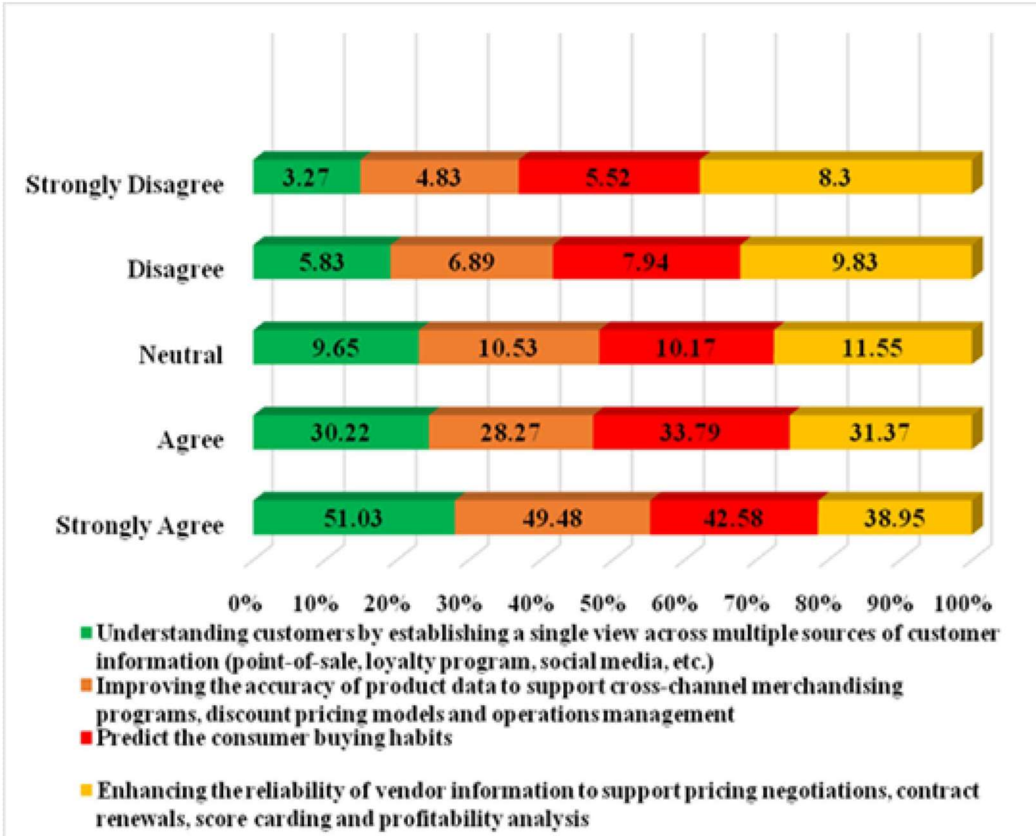
Table 4.14: Key Challenges in Big Data Analytics in Retail Organisations

Key Challenges	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	Total (n=580)
Understanding customers by establishing a single view across multiple sources of customer information (point-of-sale, loyalty program, social media, etc.)	296 (51.03)	175 (30.22)	56 (9.65)	34 (5.83)	19 (3.27)	580 (100)
Improving the accuracy of product data to support cross-channel merchandising programs, discount pricing models and operations management	287 (49.48)	164 (28.27)	61 (10.53)	40 (6.89)	28 (4.83)	580 (100)
Predict the consumer buying habits	247 (42.58)	196 (33.79)	59 (10.17)	46 (7.94)	32 (5.52)	580 (100)
Enhancing the reliability of vendor information to support pricing negotiations, contract renewals, score carding and profitability analysis	226 (38.95)	182 (31.37)	67 (11.55)	57 (9.83)	48 (8.30)	580 (100)

Source: primary data

Note: Values given in parenthesis are calculated in percentage of their row totals.

Figure 4.13: Key Challenges in Big Data Analytics in Retail Organisations



4.1.15 Responses to question "What are the retailers' obstacles in adopting big data analytics in retail organizations?"

Results shown in Table-4.15 reveal that, overall, 62.75 percent of respondents strongly agree that lack of understanding of how to use data analytics to improve the business is one of the major obstacles in adopting big data analytics in retail organisations. 47.75 percent of respondents say that insufficient existing infrastructure is the second major obstacle in implementing big data analytics in retail organisations.

42.75 percent of respondents indicate that lack of right internal skills is the third major obstacle in implementing big data analytics, followed by organisational complexity (41.76%), security or compliance (40.68%), lack of budget resources (39.13), lack of visibility into information and processes (38.96%), difficult to justify from an ROI standpoint (37.06%), risk-averse corporate culture (31.37%) as third, fourth, fifth, sixth, seventh, eighth and ninth obstacles respectively. A number of respondents (12.58%) indicated that we do not know where to begin, followed by right tools are not available (11.89%) in adopting big data retail business analytics.

Table 4.15: Major obstacles in adopting big data analytics in retail organizations

Major obstacles in implementing big data analytics in your retail organization	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	Total (n=580)
Lack of understanding of how to use data analytics to improve the business	364 (62.75)	113 (19.48)	46 (7.93)	33 (5.68)	24 (4.13)	580 (100)
Existing infrastructure is not sufficient	277 (47.75)	178 (30.68)	55 (9.48)	44 (7.58)	26 (4.48)	580 (100)
Lack of right internal skills	248 (42.75)	122 (21.03)	65 (11.20)	67 (11.55)	78 (13.44)	580 (100)
Organizational complexity	242 (41.72)	176 (30.34)	64 (11.03)	55 (9.48)	43 (7.41)	580 (100)
Security or compliance concerns	236 (40.68)	189 (32.58)	71 (12.24)	52 (8.96)	32 (5.51)	580 (100)
Lack of budget or resources	227 (39.13)	174 (30.00)	54 (9.31)	63 (10.86)	62 (10.68)	580 (100)
Lack of visibility into information and processes	226 (38.96)	179 (30.86)	69 (11.89)	71 (12.24)	35 (6.03)	580 (100)
Difficult to justify from an ROI standpoint	215 (37.06)	196 (33.79)	69 (11.89)	58 (10.00)	42 (7.24)	580 (100)
Risk-averse corporate culture	182 (31.37)	221 (38.10)	75 (12.93)	64 (11.03)	38 (6.55)	580 (100)
We do not know where to begin	73 (12.58)	84 (14.48)	48 (8.27)	211 (36.37)	164 (28.27)	580 (100)
Right tools are not available	69 (11.89)	84 (14.48)	59 (10.17)	196 (33.79)	172 (29.65)	580 (100)
There are no major obstacles	37 (6.37)	58 (10.00)	72 (12.41)	178 (30.68)	235 (40.51)	580 (100)

Source: primary data

Note: Values given in parenthesis are calculated in percentage of their row totals.

Figure 4.14: Major Obstacles in adopting Big Data Analytics in Retail Organizations

4.1.16 Responses to question "What are the challenges that prevent retailers from implementing big data analytics more strategically?"

Results shown in Table-4.16 reveal that, overall, 50.86 percent of respondents strongly agree that delivery of insights to the right resource at the right time is one of the prime challenges that prevent retailers from implementing big data analytics more strategically; followed by lack of clearly articulated analytics strategy (47.93%), poor data quality (47.10%), inadequate analytics resources (41.37%), management style restraining data-driven decisions (41.04%), difficulty in measuring analytics ROI (40.51%), outdated software and tools (37.41%), and previous failure in analytics investment (3020%) prevent retailers from implementing analytics more strategically. The results shown in Figure 4.15 implied that right insights to the right resource at the right time are a bigger challenge than the perennial lack of resources.

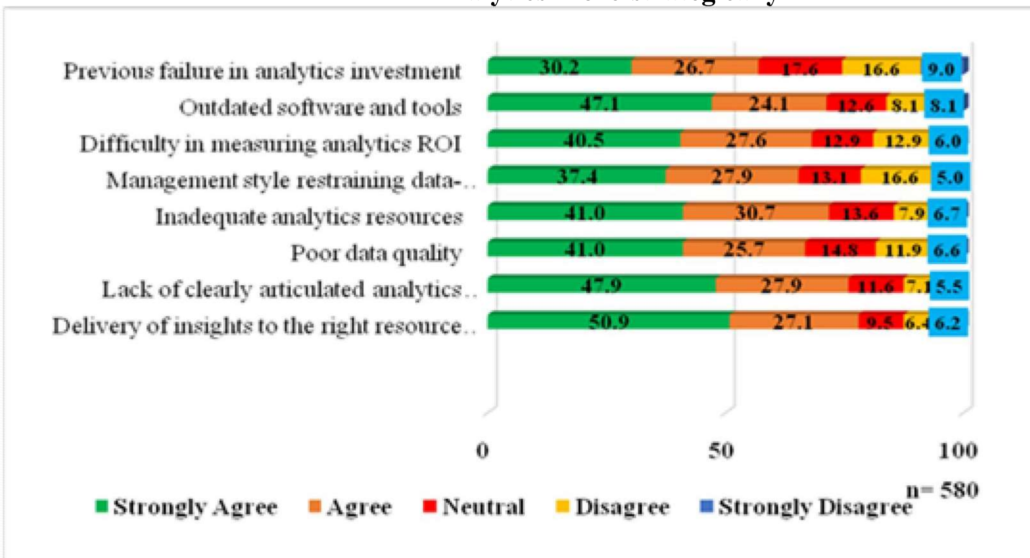
Table 4.16: Challenges that Prevent Retailers from implementing Big Data Analytics More Strategically

Challenges that prevent retailers from implementing analytics more strategically	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	Total (n=580)
Delivery of insights to the right resource at the right time	295 (50.86)	157 (27.06)	55 (9.48)	37 (6.40)	36 (6.20)	580 (100)
Lack of clearly articulated analytics strategy	278 (47.93)	162 (27.94)	67 (11.55)	41 (7.06)	32 (5.52)	580 (100)
Poor data quality	273 (47.10)	140 (24.12)	73 (12.58)	47 (8.10)	47 (8.10)	580 (100)
Inadequate analytics resources	240 (41.37)	178 (30.70)	79 (13.63)	46 (7.92)	39 (6.72)	580 (100)
Management style restraining data-driven decisions	238 (41.04)	149 (25.68)	86 (14.83)	69 (11.89)	38 (6.56)	580 (100)
Difficulty in measuring analytics ROI	235 (40.51)	160 (27.60)	75 (12.93)	75 (12.93)	35 (6.03)	580 (100)
Outdated software and tools	217 (37.41)	162 (27.93)	76 (13.11)	96 (16.55)	29 (5.00)	580 (100)
Previous failure in analytics investment	175 (30.20)	155 (26.71)	102 (17.58)	96 (16.55)	52 (8.96)	580 (100)

Source: primary data

Note: Values given in parenthesis are calculated in percentage of their row totals.

Figure 4.15: Challenges that Prevent Retailers from implementing Big Data Analytics more strategically



4.1.17 Responses to question "what are retailers' biggest obstacles in getting big data retail business analytics in order to make better data driven decisions?"

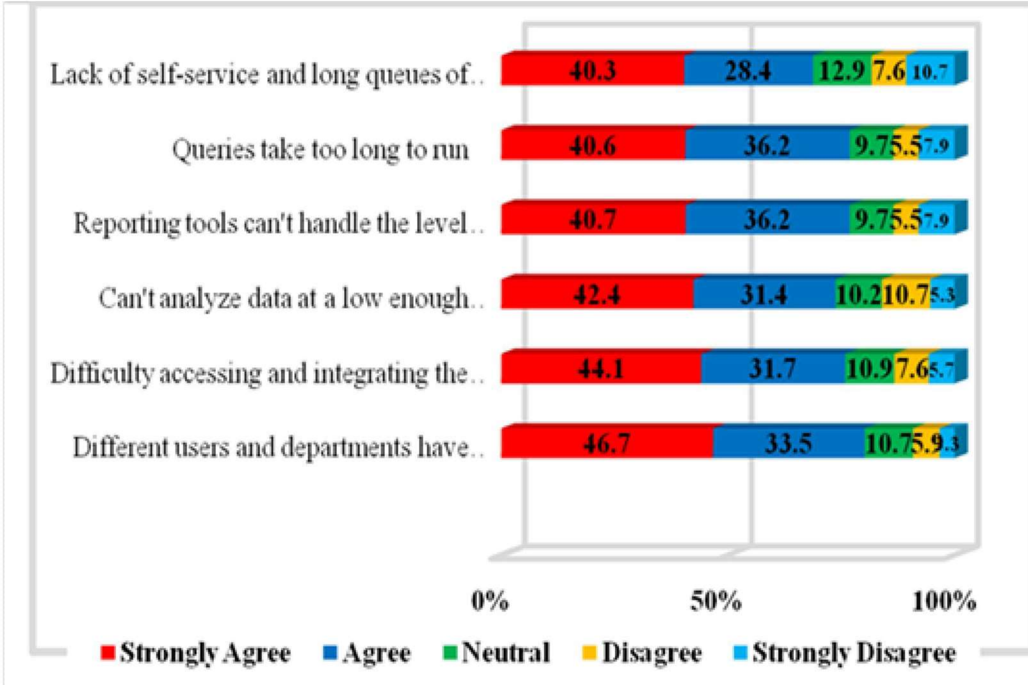
Results shown in Table-4.17 reveal that, overall, 46.73 percent of respondents' strongly agree that different users and different departments have different ways of measuring the business is the biggest obstacle in getting big data analytics in order to make better data-driven business decisions; followed by difficulty in accessing and integrating the enterprise or third party data users need to analyse (44.14%), can't analyse data at a low enough level of detail (e.g. Store / SKU / Day / Transaction / Customer) (42.43%), reporting tools can't handle the level of sophistication of retailers' business questions (40.70%), queries take too long to run (40.68%), lack of self-service and long queues of reporting requests to IT (40.34%) are also the biggest obstacles in big data retail business analytics driven managerial decision making. The results shown in Figure 4.16 implied that the biggest obstacle in getting big data retail business analytics in order to make better data-driven business decision is the need to structure the various data types measured differently from different users in different departments so that information can be understood and analysed. Respondents identified that structuring data in a format in which it can be consumed is a biggest challenge in general.

Table 4.17: Biggest Obstacles in getting Big Data Analytics in order to make Better Data-driven Business Decisions in Retail Organisations

Biggest obstacles in getting big data retail business analytics in business decisions	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	Total (n=580)
Different users and different departments have different ways of measuring the business	271 (46.73)	194 (33.45)	62 (10.68)	34 (5.87)	19 (3.27)	580 (100)
Difficulty in accessing and integrating the enterprise or 3rd party data users need to analyse	256 (44.14)	184 (31.73)	63 (10.86)	44 (7.60)	33 (5.67)	580 (100)
Can't analyse data at a low enough level of detail (e.g. Store/SKU/Day/Transaction/Customer)	246 (42.43)	182 (31.38)	59 (10.17)	62 (10.68)	31 (5.34)	580 (100)
Reporting tools can't handle the level of sophistication of retailers' business questions	236 (40.70)	210 (36.21)	56 (9.65)	32 (5.51)	46 (7.93)	580 (100)
Queries take too long to run	185 (40.68)	226 (36.22)	64 (9.65)	53 (5.52)	52 (7.93)	580 (100)
Lack of self-service and long queues of reporting requests to IT	234 (40.34)	165 (28.44)	75 (12.94)	44 (7.60)	62 (10.68)	580 (100)

Source: primary data
Note: Values given in parenthesis are calculated in percentage of their row totals.

Figure 4.16: Biggest Obstacles in getting Big Data Analytics in order to make Better Data-driven Business Decisions in Retail Organisations



4.1.18 Responses to question "Which are business functions leveraged by big data analytics more strategically in retail organisations?"

Results shown in Table-4.18 reveal that, overall, 31.12 percent of respondents' say that customer insights are the most important business function which is leveraged by big data analytics in retailing; followed by multi-channels (25.69%), merchandising (18.28%), supply chain (16.38%), and marketing (8.45%). Most respondents (36.43%) from consumer durables state that customer insights is the business function leveraged by big data analytics compared to 35.5 percent of respondents from apparel retailing, 27.74 percent of respondents from food and grocery retailing and 21.90 percent from entertainment retailing. The Chi-square statistic results ($\chi 2 = 27.89$, df 9, $p < 0.05$) reveal that there is significant difference in the distribution of responses to the business functions leveraged by big data analytics more strategically among the comparison groups. The results shown in Figure 4.16 implied that retailers using big data analytics as a leveraging tool in customer insights business functions across comparison groups as customer-centric is the new competitive differentiation for retailers today.

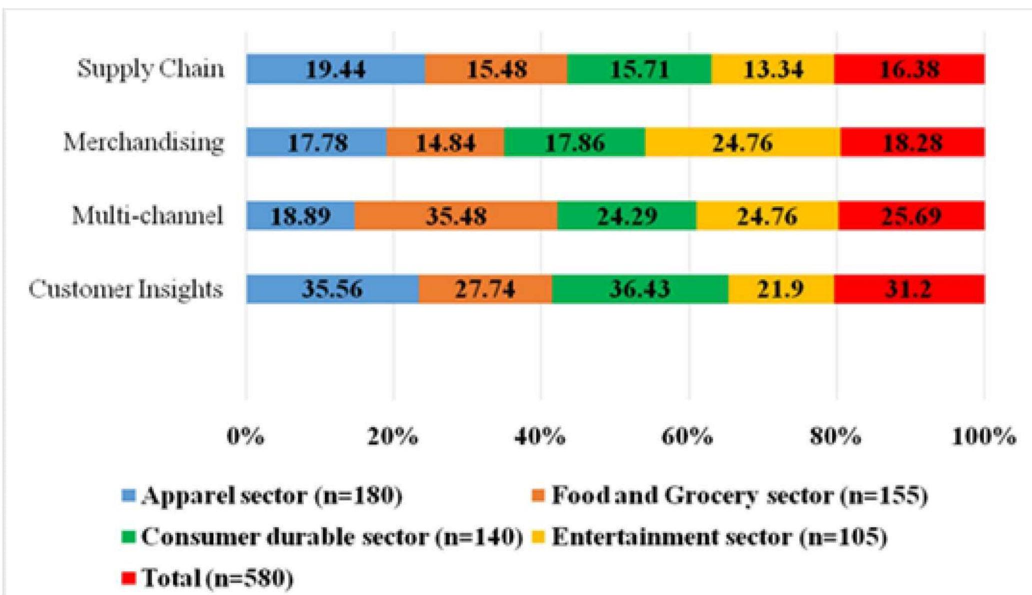
Table 4.18: Opinion on Business Functions leveraged by Big Data Analytics more Strategically in Retail Organisations

Business functions leveraged by big data analytics more strategically	Apparel sector (n=180)	Food & Grocery sector (n=155)	Consumer durable sector (n=140)	Entertainment sector (n=105)	Total (n=580)
Customer Insights	64 (35.56)	43 (27.74)	51 (36.43)	23 (21.90)	181 (31.2)
Multi-channel	34 (18.89)	55 (35.48)	34 (24.29)	26 (24.76)	149 (25.69)
Merchandising	32 (17.78)	23 (14.84)	25 (17.86)	26 (24.76)	106 (18.28)
Supply Chain	35 (19.44)	24 (15.48)	22 (15.71)	14 (13.33)	95 (16.38)
Marketing	15 (8.33)	10 (6.46)	8 (5.71)	16 (15.24)	49 (8.45)

Source: primary data

Note: Values given in parenthesis are calculated in percentage of their column totals.

Figure 4.17: Opinion on Business Functions leveraged by Big Data Analytics more Strategically in Retail Organisations



4.1.19 Responses to the question "Which business functions in the retail organisation stand to make the best use of insights from big data analytics?"

Results shown in Table-4.19 reveal that, overall, 16.72 percent of respondents' ranked customer and market analytics is the highest business function followed by Product development/management (14.48%), store operations (11.37%), direct and digital marketing (10.51%), and supply chain (10.34%) as second, third, fourth and fifth ranks respectively in the retail organisation stand to make the best use of use of insights from big data analytics. Majority of respondents from apparel, food and grocery and entertainment have ranked customer and market analysis is the highest compared to the respondents of consumer durables who ranked Product development/management is the highest ranked business function which makes use of insights from big data analytics in retail organisations. The Chi-square statistic results ($\chi 2$ = 15.84, df 30, $p > 0.05$) reveal that there is no difference in the distribution of responses to the business functions stand to make use of big data analytics among the comparison groups. The results shown in Figure 4.18 implied that retailers' primary business function stand to make use of insights from big data analytics is customer and market analysis as retailers today face a new breed of empowered customers who are always connected and have more information on products than sometimes even the retailers do.

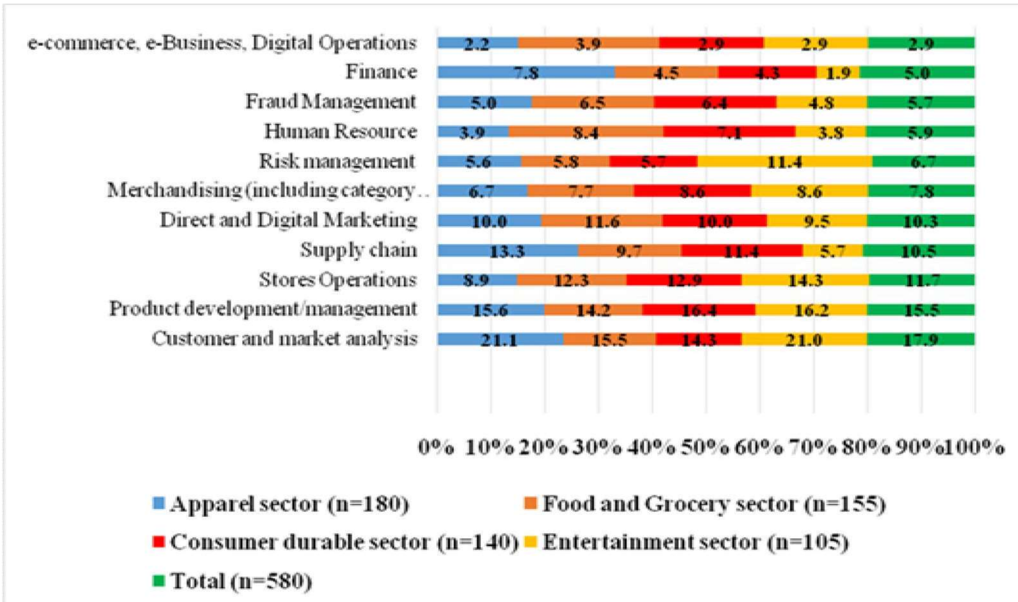
Table 4.19: Business Functions in the retail organisation stand to make the best use of insights from big data analytics

Business functions in the retail organisation stand to make the best use of insights from big data retail business analytics	Apparel sector (n=180)	Food & Grocery sector (n=155)	Consumer durable sector (n=140)	Entertainment sector (n=105)	Total (n=580
Customer and market analysis	1 (38)	1 (24)	2 (20)	1 (15)	1 (97)
Product development/management	2 (26)	2 (22)	1 (22)	2 (14)	2 (84)
Stores Operations	5 (16)	3 (19)	3 (18)	3 (13)	3 (66)
Direct and Digital Marketing	4 (18)	4 (18)	5 (14)	5 (11)	4 (61)
Supply chain	3 (24)	5 (15)	4 (16)	7 (8)	5 (63)
Merchandising (including category management, buying planning, allocation)	7 (12)	7 (12)	6 (12)	6 (10)	6 (46)
Risk management	8 (10)	9 (9)	9 (8)	4 (12)	7 (39)
Human Resource	10 (7)	6 (13)	7 (10)	9 (5)	8 (35)
Fraud Management	9 (9)	8 (10)	8 (9)	8 (7)	9 (35)
Finance	6 (14)	10 (7)	10 (6)	11 (5)	10 (32)
e-commerce, e-Business, Digital Operations	11 (6)	11 (6)	11 (5)	10 (5)	11 (22)

Source: primary data

Note: Values given in parenthesis are frequencies in terms of their column totals.

Figure 4.18: Business Functions in the retail organisation stand to make the best use of insights from big data analytics



4.1.20 Responses to the question "On which of these retail business processes do you think big data technology can have the greatest impact?"

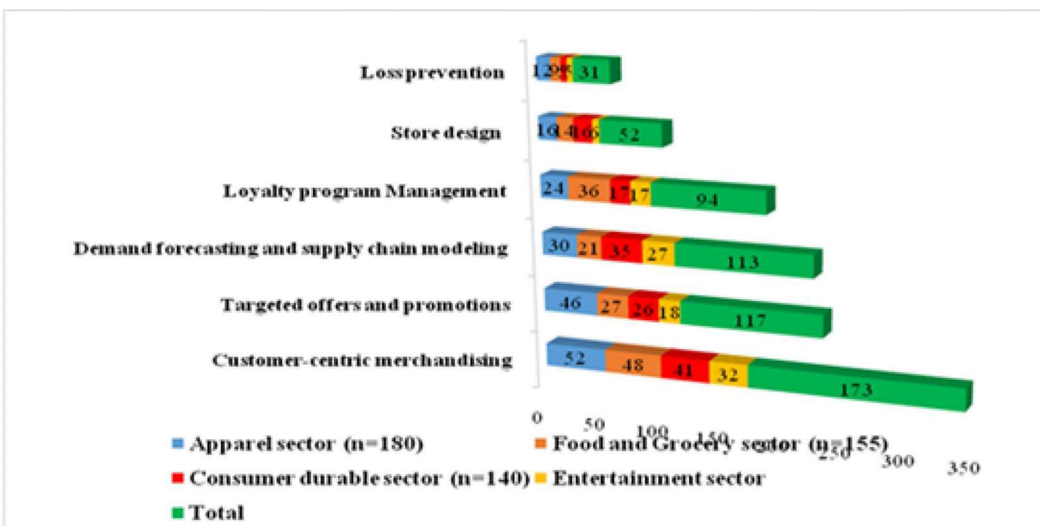
Results shown in Table-4.20 reveal that, overall, 29.82 percent of respondents' ranked customer centric merchandising is the highest business process hugely impacted by big data technology in retail organisations. Respondents felt that big data technology could most impact the design of targeted offers and promotions (20.2%) is the second highest business process followed by demand forecasting and supply chain modelling (19.5 %), loyalty program management (16.20%), store design (9%), loss prevention (5.34%) as third, fourth and fifth ranks respectively. Majority of respondents, that is 30 percent each from apparel, food and grocery, consumer durables, and entertainment have ranked customer and market analysis is the highest compared to the other business processes impacted by big data technology. The Chi-square statistic results ($\chi2 = 25.12$, df 15, $p < 0.05$) reveal that there is significant difference in the distribution of responses to the business processes impacted by big data technology among the comparison groups. The results shown in Figure 4.19 implied that the cumulative effect of big data technologies and practices into the retail organisations results in transformational change across various business functions. In practice, the results show that big data technologies impact central functions from customer-centric merchandising, target offers and promotions, demand forecasting and supply chain management, loyalty program management, store design to loss.

Table 4.20: Retail Business Processes that can benefit Most from Big Data Technology

Business processes that big data technology can have the greatest impact	Apparel sector (n=180)	Food &Grocery sector (n=155)	Consumer durable sector (n=140)	Entertainment sector (n=105)	Total (n=580
Customer-centric merchandising	1 (52)	1 (48)	1 (41)	1 (32)	1 (173)
Targeted offers and promotions	2 (46)	3 (27)	3 (26)	3 (18)	2 (117)
Demand forecasting and supply chain modelling	3 (30)	4 (21)	2 (35)	2 (27)	3 (113)
Loyalty program Management	4 (24)	2 (36)	4 (17)	4 (17)	4 (94)
Store design	5 (16)	5 (14)	5 (16)	5 (6)	5 (52)
Loss prevention	6 (12)	6 (9)	6 (5)	6 (5)	6 (31)

Source: primary data.
Note: Values given in parenthesis are calculated in frequencies of their column totals.

Figure: 4.19: Retail Business Processes that can benefit Most from Big Data Technology



4.1.21 Responses to "Why, if at all, do you think retailers are holding out on using Big Data solutions?"

Results shown in Table-4.21 reveal that majority of the respondents (42.93%) strongly agree with the need for simplified big data solutions that are intuitive to business users is the major potential reason holding back on using big data technologies to leverage large and complex data sets, while retail managers see the potential of big data analytics to make an impact across a range of retail business functions and business processes. 40. 34 percent of respondents strongly agree with cost and complexity of implementing big data solutions needs to come down is second most potential reason for holding back on using big data technologies to leverage large and complex data sets. Survey respondents also indicated that the need big data solutions to better address the needs of retailers (36.72%) is one of the potential reasons holding out at all on leveraging Big Data. A number of respondents (31.89%) indicated that retailers are still challenged with basic business reporting and not ready for big data is also one of the potential reasons for holding back on using big data technologies to leverage large and complex data sets. Less than eight percent of respondents indicated that they don't perceive retailers as holding out at all on leveraging Big Data solutions in retail organisations.

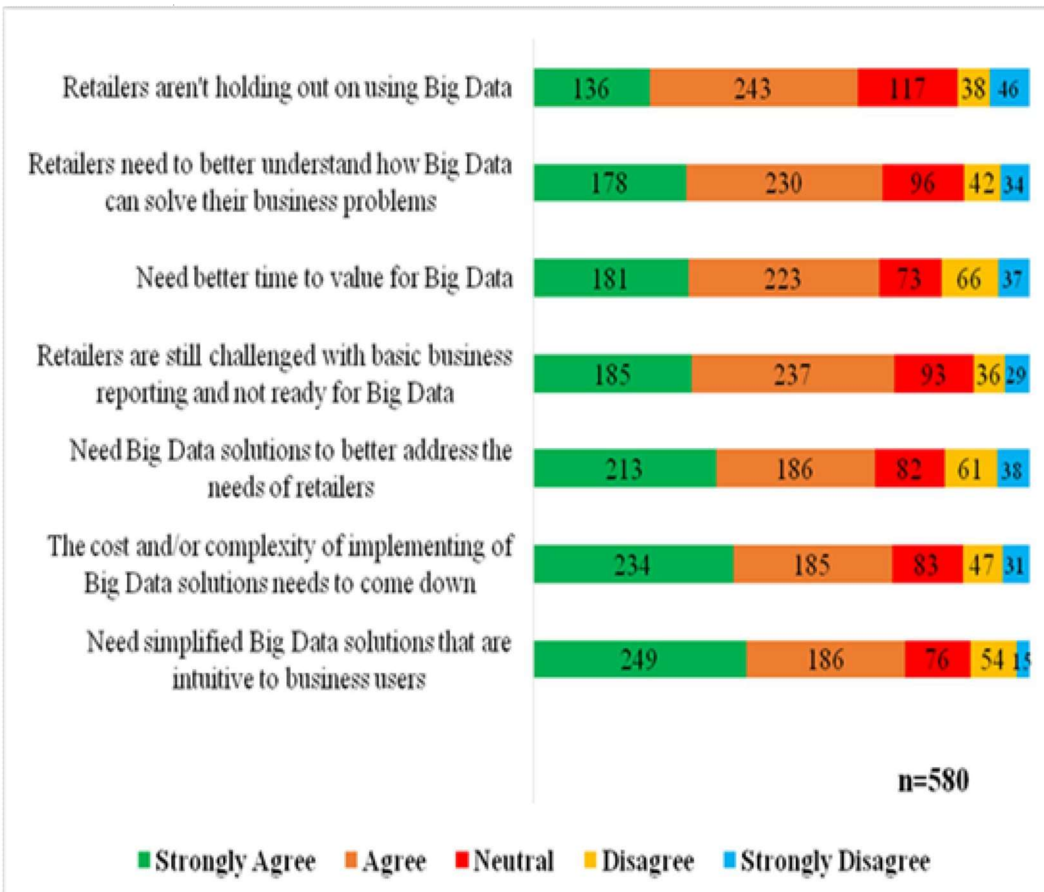
Table 4.21: Obstacles Preventing Retailers from using Big Data

Reasons for retailers holding out on using big data solutions in retail organizations	**Strongly Agree**	**Agree**	**Neutral**	**Disagree**	**Strongly Disagree**	**Total (n=580**
Need simplified Big Data solutions that are intuitive to business users	249 (42.93)	186 (32.06)	76 (13.10)	54 (9.31)	15 (2.58)	580 (100)
Retailers aren't holding out on using Big Data	243 (41.89)	136 (23.34)	117 (20.17)	38 (6.55)	46 (7.93)	580 (100)
The cost and/or complexity of implementing of Big Data solutions needs to come down	234 (40.34)	185 (31.86)	83 (14.31)	47 (8.10)	31 (5.34)	580 (100)
Need better time to value for Big Data	223 (38.44)	181 (31.20)	73 (12.58)	66 (11.37)	37 (6.37)	580 (100)
Need Big Data solutions to better address the needs of retailers	213 (36.72)	186 (32.06)	82 (14.13)	61 (10.51)	38 (6.55)	580 (100)
Retailers are still challenged with basic business reporting and not ready for Big Data	185 (31.89)	237 (40.86)	93 (16.34)	36 (6.20)	29 (5.00)	580 (100)
Retailers need to better understand how Big Data can solve their business problems	178 (30.68)	230 (39.65)	96 (16.55)	42 (7.24)	34 (3.86)	580 (100)

Source: primary data

Note: Values given in parenthesis are calculated in percentages of their row totals.

Figure 4.20: Obstacles Preventing Retailers from using Big Data



4.1.22 Responses to "How can big data help retailers do a better job of managing product availability for consumers?"

Results shown in Table-4.22 reveal that majority of the respondents (42.75%) strongly agree that big data retail business analytics help retailers to predict future demand to inform supply chain decisions, followed by reducing overstocks that negatively impact turns and could lead to margin erosion (40.68%), reducing out-of-stock situations that lead to lost sales and dissatisfied customers (38.27%), ensuring product assortments are finely turned to store and channel-based demand (38.10%), and enabling alternative fulfilment means such as ship-to-store and ship-from-store (35.34%).

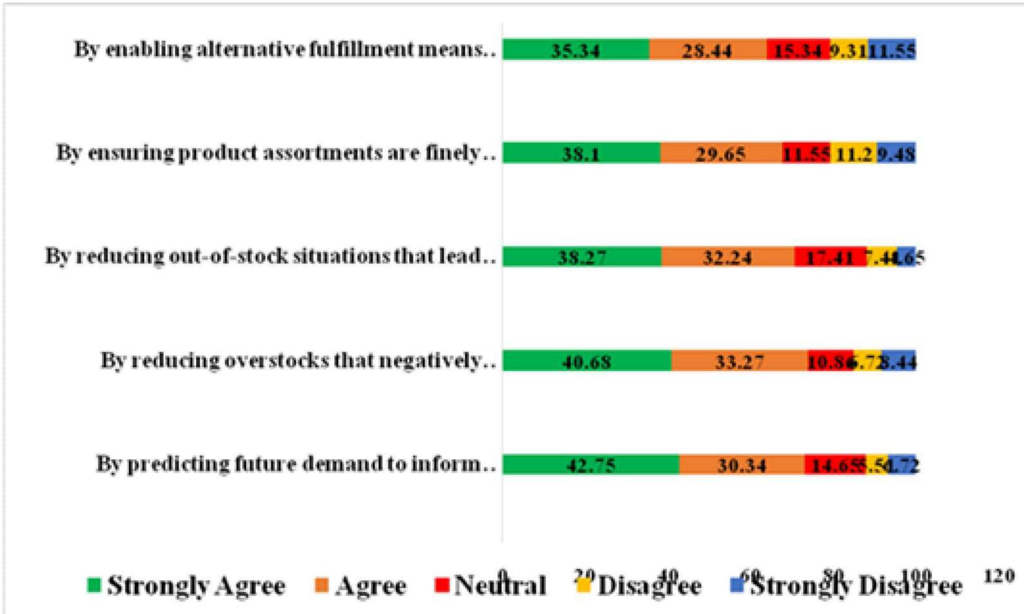
Table 4.22: Big data analytics help retailers do a better job of managing product availability for consumers

Big data retail business analytics help retailers in managing product availability for consumers	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	Total (n=580)
By predicting future demand to inform supply chain decisions	248 (42.75)	176 (30.34)	85 (14.65)	32 (5.51)	39 (6.72)	580 (100)
By reducing overstocks that negatively impact turns and could lead to margin erosion	236 (40.68)	193 (33.27)	63 (10.86)	39 (6.72)	49 (8.44)	580 (100)
By reducing out-of-stock situations that lead to lost sales and dissatisfied customers	222 (38.27)	187 (32.24)	101 (17.41)	43 (7.41)	27 (4.65)	580 (100)
By ensuring product assortments are finely turned to store and channel-based demand	221 (38.10)	172 (29.65)	67 (11.55)	65 (11.20)	55 (9.48)	580 (100)
By enabling alternative fulfilment means such as ship-to-store and ship-from-store	205 (35.34)	165 (28.44)	89 (15.34)	54 (9.31)	67 (11.55)	580 (100)

Source: primary data

Note: Values given in parenthesis are calculated in percentages of their row totals.

Figure 4.21: Respondents view towards big data retail business analytics help retailers do a better job of managing product availability for consumers



4.1.23 Responses to the question "What tangible business value/benefits do you hope to achieve through big data retail business analytics to outperform competition?"

The results shown in Table 4.23 reveal that, overall, 24.65 percent of respondents' indicate that better, fast-based decision making is the biggest tangible benefit big data retail business analytics. A number of survey respondents say that the tangible benefits of big data retail business analytics could be more efficient operations (18.44%), followed by new product innovations (16.20%), improved customer service (14.31), higher quality products and services (14.13%), and increased sales (12.24%). Most respondents (27.85%) from consumer durables indicate that better and fast based decision making is the tangible benefit of big data retail business analytics compared to respondents from apparel retailing (25.5%), food and grocery (24.51%) and entertainment sector (19.04%). The Chi-square statistic results ($\chi 2$ = 5.71, df, 15, p > 0.05) reveal that there is no difference in the distribution of responses to the tangible benefits hoped to achieve through big data retail business analytics among the comparison groups.

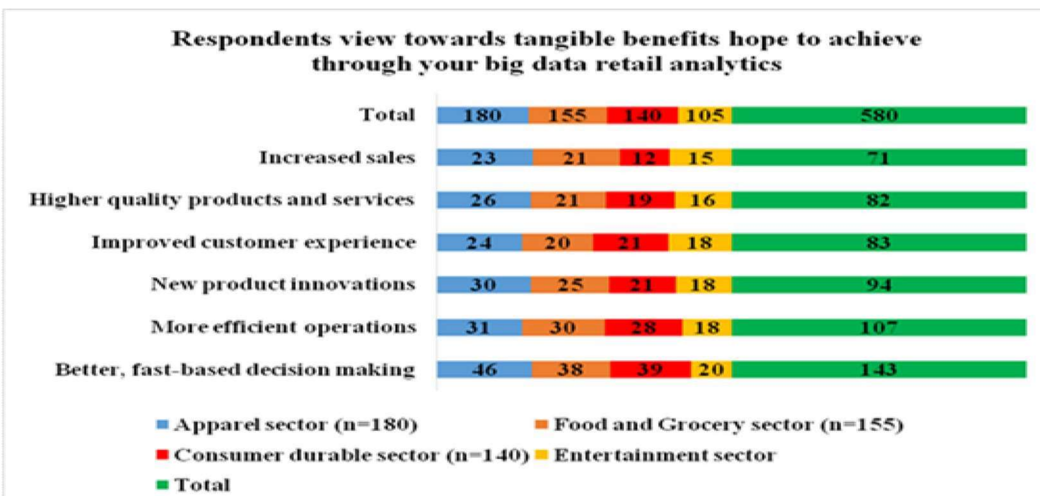
Table 4.23: Tangible Business Value/Benefits of Big Data Retail Business Analytics

Tangible business value/benefits of big data retail business analytics	Apparel sector (n=180)	Food & Grocery sector (n=155)	Consumer durable sector (n=140)	Entertainment sector (n=105)	Total (n=580
Better, fast-based decision making	46 (25.55)	38 (24.51)	39 (27.85)	20 (19.04)	143 (24.65)
More efficient operations	31 (17.22)	30 (19.35)	28 (20.00)	18 (17.14)	107 (18.44)
New product innovations	30 (16.66)	25 (16.12)	21 (15.00)	18 (17.14)	94 (16.20)
Improved customer experience	24 (13.33)	20 (12.90)	21 (15.00)	18 (17.14)	83 (14.31)
Higher quality products and services	26 (14.44)	21 (13.54)	19 (13.57)	16 (15.23)	82 (14.13)
Increased sales	23 (12.77)	21 (13.54)	12 (8.57)	15 (14.28)	71 (12.24)
Total	180(100)	155(100)	140(100)	105(100)	580(100)

Source: primary data

Note: Values given in parenthesis are calculated in percentages of their column totals.

Figure 4.22: Tangible Business Value/Benefits of Big Data Retail Business Analytics



4.1.24 Responses to question "which areas of retail business do you think benefit (or could benefit) the most from IOT-Internet of Things technology?"

The results shown in Table 4.24 reveal that, overall, 19.31 percent of respondents indicate that IOT technology could benefit the retail business areas of customer engagement/customer experience management, followed by digital marketing and sales (17.75%), forecasting future trends (16.37%), operational process

(15.17%), inventory/stock management (14.13%), building customer trust models (9.1%) and staff productivity (8.10%). In contrast, a number of respondents (25.55%) from apparel retailing indicate that the most IOT technological benefits the digital marketing and sales areas in contrast to food and grocery (10.96%), consumer durables (15.71%) and entertainment (17.14%). A number of respondents (22.85%) from entertainment say that IOT technology could benefit the customer engagement/customer experience management business area compared to consumer durables (20 %), food and grocery (18.06%) and apparel retailing (17.77%). The Chi-square statistic results ($\chi 2$ = 21.83, df 18, p > 0.05) reveal that there is no difference in the distribution of responses to the benefits of IOT technology in retail business areas among the comparison groups. The results shown in Figure 4.22 implied that IoT technology offers compelling business benefits and value that retail organizations cannot afford to ignore in the areas of customer experience digital marketing and sales, supply chain logistics and staff productivity. The results implied that organizations can use IoT to drive considerable benefits by improving Inventory/stock management, enhancing process efficiency and boosting productivity.

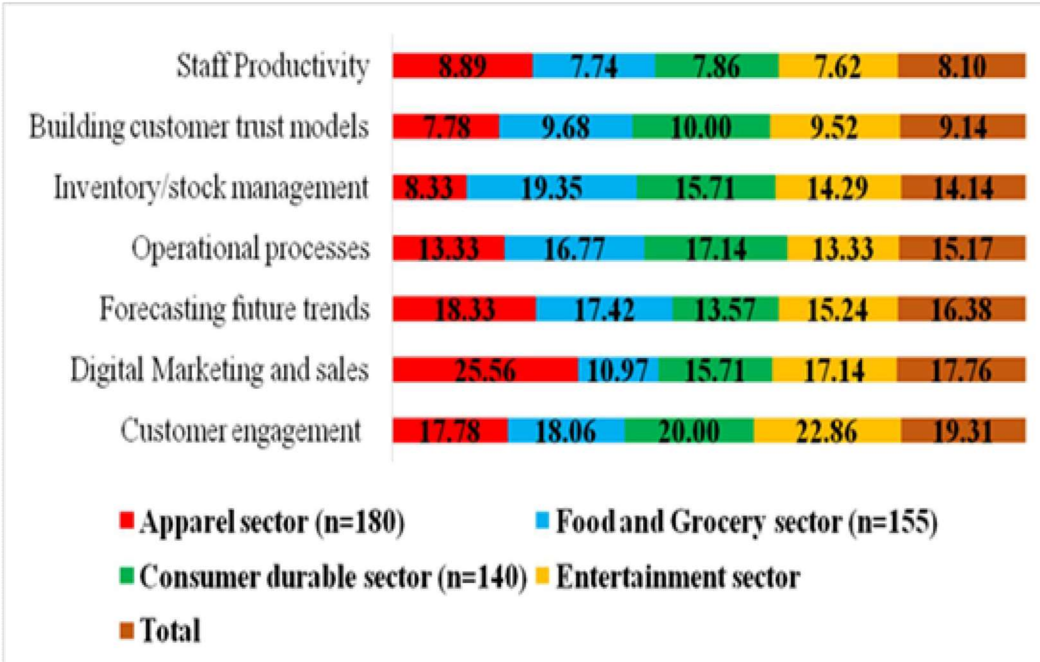
Table 4.24: Retail business areas that benefit (or could benefit) the most from IOT - Internet of Things Technology

Benefits of IOT technology	Apparel sector (n=180)	Food & Grocery sector (n=155)	Consumer durable sector (n=140)	Entertainment sector (n=105)	Total (n=580
Customer engagement / customer experience management	32 (17.77)	28 (18.06)	28 (20.00)	24 (22.85)	112 (19.31)
Digital Marketing and sales	46 (25.55)	17 (10.96)	22 (15.71)	18 (17.14)	103 (17.75)
Forecasting future trends	33 (18.33)	27 (17.41)	19 (13.57)	16 (15.23)	95 (16.37)
Operational processes	24 (13.33)	26 (16.77)	24 (17.14)	14 (13.33)	88 (15.17)
Inventory/stock management	15 (8.33)	30 (19.34)	22 (15.71)	15 (14.28)	82 (14.13)
Building customer trust models	14 (7.77)	15 (9.67)	14 (10.00)	10 (9.52)	53 (9.13)
Staff Productivity	16 (8.88)	12 (7.74)	11 (7.85)	8 (5.71)	47 (8.10)
Total	180 (100)	155 (100)	140 (100)	105 (100)	580 (100)

Source: primary data

Note: Values given in parenthesis are calculated in percentages of their column totals.

Figure 4.23: Retail business areas that benefit (or could benefit) the most from IOT -Internet of Things technology



4.1.25 Responses to question "Which are your thoughts on biggest stumbling blocks to IOT adoption in retail organisation?"

The results shown in Table 4.25 reveal that majority of the respondents (44.84%) indicate that the biggest stumbling block in adopting IOT technology in retail organisation is the technical issues with interoperability between different solutions, followed by fragmented eco-system, not enough successful partnerships being formed (41.56%), data privacy and security (41.37%), initial investment and/cost (40%), lack of legal clarity over standard and regulation (38.62%), low consumer confidence over trust and security (34.48%), and lack of clear business model or business case (27.72%). The results shown in Figure 4.23 implied that notwithstanding IoT's tremendous potential, retail organizations must overcome numerous stumbling blocks and challenges that are inhibiting IoT's growth.

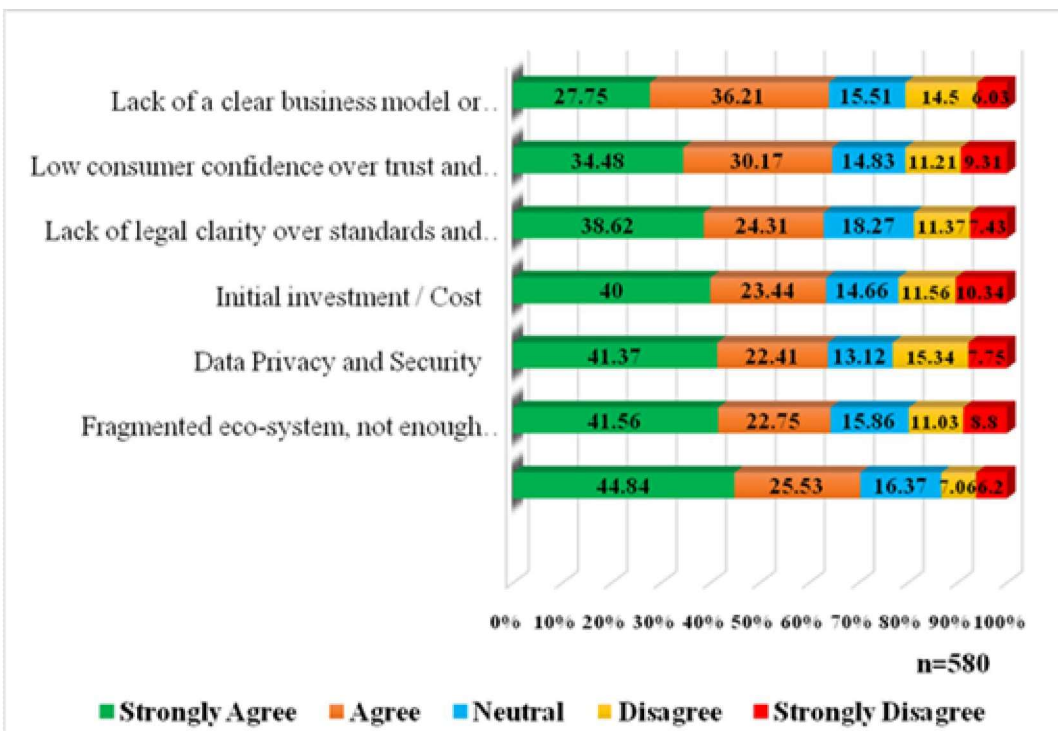
Table 4.25: Biggest stumbling blocks to IOT adoption in retail organisation

The biggest stumbling blocks to IOT adoption in your business?	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	Total (n=580
Technical issues with interoperability between different solutions	260 (44.84)	148 (25.53)	95 (16.37)	41 (7.06)	36 (6.20)	580 (100)
Fragmented eco-system, not enough successful partnerships being formed	241 (41.56)	132 (22.75)	92 (15.86)	64 (11.03)	51 (8.80)	580 (100)
Data Privacy and Security	240 (41.37)	130 (22.41)	76 (13.12)	89 (15.34)	45 (7.75)	580 (100)
Initial investment / Cost	232 (40.00)	136 (23.44)	85 (14.66)	67 (11.56)	60 (10.34)	580 (100)
Lack of legal clarity over standards and regulation	224 (38.62)	141 (24.31)	106 (18.27)	66 (11.37)	43 (7.43)	580 (100)
Low consumer confidence over trust and security	200 (34.48)	175 (30.17)	86 (14.83)	65 (11.21)	54 (9.31)	580 (100)
Lack of a clear business model or business case	210 (27.75)	161 (36.21)	90 (15.51)	84 (14.50)	35 (6.03)	580 (100)

Source: primary data

Note: Values given in parenthesis are calculated in terms of their row totals.

Figure 4.24: Biggest stumbling blocks to IOT adoption in retail business



4.1.26 Responses to question "How would you describe your organisation's use of big data analytics compared to your competitors?"

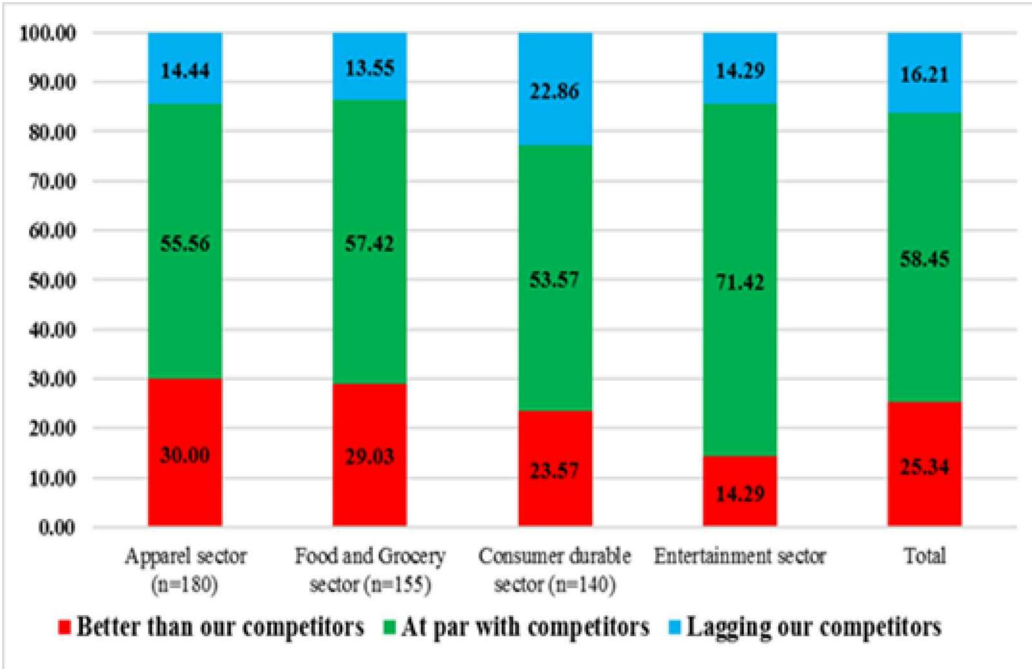
The results shown in Table-4.26 reveal that majority of the respondents (58.44%) indicate that the organisation's use of big data retail business analytics is on par with competitors, followed by better than our competitors (25.34%) and lagging behind others (16.20%). The Chi-square statistic results ($\chi 2$ = 15.44, df 6, p < 0.025) reveal that there are significant differences in the distribution of responses to the organisations' use of big data retail business analytics compared to competitors among the comparison groups. The results shown in Figure 4.25 implied that retailers rate improving customer insight as their most important goal from big data analytics initiatives in the coming five years as consumers are changed, changing and will change.

Table 4.26: Retail Organisation's use of big data analytics compared to competitors

Use of big data retail business analytics compared to your competitors	Apparel sector (n=180)	Food & Grocery sector (n=155)	Consumer durable sector (n=140)	Entertainment sector (n=105)	Total (n=580)
Better than our competitors	54 (30.00)	45 (29.03)	33 (23.57)	15 (14.29)	147 (25.34)
At par with competitors	100 (55.56)	89 (57.42)	75 (53.57)	75 (71.42)	339 (58.45)
Lagging our competitors	26 (14.44)	21 (13.55)	32 (22.86)	15 (14.29)	94 (16.21)

Source: primary data
Note: Values given in parenthesis are calculated in percentage of their column totals.

Figure 4.25: Retail Organisation's use of big data analytics compared to competitors



4.1.27 Responses to question "what are the most important goals from big data retail business analytics in the coming five years?"

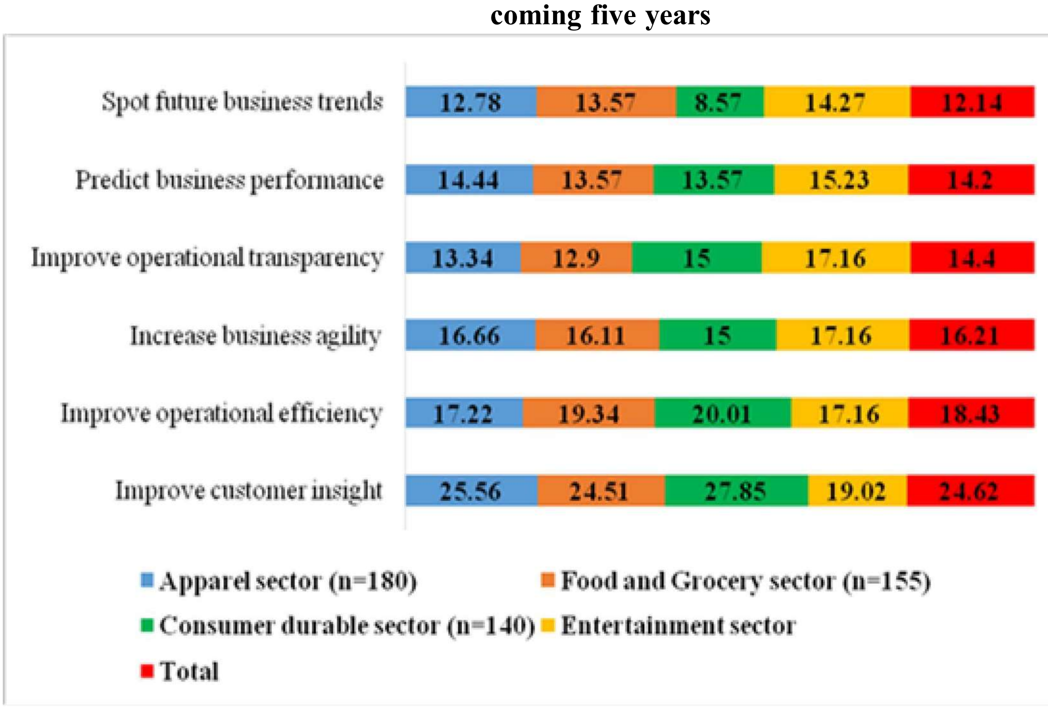
The results shown in Table-4.27 reveal that majority of the respondents (24.65%) indicate that the most important goals from big data retail business analytics in the coming five years is improve the customer insight, followed by improve operational efficiency (18.44%), increase business agility (16.20%), improve operational transparency (14.31%), predict business performance (14.13%), spot future business trends (12.24%). The Chi-square statistic results ($\chi 2 = 6.71$, df 15, $p > 0.05$) reveal that there is no difference in the distribution of responses to the most important goals from big data retail business analytics in the coming five years among the comparison groups. The results shown in Figure 4.26 implied that few retailers rate themselves lagging behind competition in terms of their use of big data retail business analytics. Clearly, those that consider themselves leaders in this space are few and far between.

Table 4.27: The most important goals from big data retail business analytics in the coming five years

Most important goals from big data retail business analytics in the coming five years	Apparel sector (n=180)	Food & Grocery sector (n=155)	Consumer durable sector (n=140)	Entertainment sector (n=105)	Total (n=580
Improve customer insight	46 (25.56)	38 (24.51)	39 (27.85)	20 (19.02)	143 (24.62)
Improve operational efficiency	31 (17.22)	30 (19.34)	28 (20.01)	18 (17.16)	107 (18.43)
Increase business agility	30 (16.66)	25 (16.11)	21 (15.00)	18 (17.16)	94 (16.21)
Improve operational transparency	24 (13.35)	20 (12.90)	21 (15.00)	18 (17.16)	83 (14.40)
Predict business performance	26 (14.44)	21 (13.57)	19 (13.57)	16 (15.23)	82 (14.20)
Spot future business trends	23 (12.77)	21 (13.57)	12 (8.57)	15 (14.27)	71 (12.14)
Total	180	155	140	105	580

Source: primary data
Note: Values given in parenthesis are calculated in percentages of their column totals.

Figure 4.26: Most important goals from big data retail business analytics in the coming five years



4.1.28 Responses to question "what are the big data retail business analytics solutions that you are going to invest and adopt over the next five years?"

The results shown in Table-4.28 reveal that majority of the respondents (19.31%) indicate that the organisation's investment and adoption over the next five years will be in web and social media analytics, followed by digital dashboards (12.58%),master data management (10.68%), big data analytics (9.31%), data visualisation (9.31%), mobile business intelligence (8.27%), enterprise data ware house (8.27%), predictive analytics (7.58%), Olap + basic reporting & querying (7,41) and enterprise big analytics tools (7.24%). The Chi-square statistic results ($\chi 2$ = 15.75, df 27, $p > 0.05$) reveal that there are no differences in the distribution of responses to the investments and adoption of big data retail business analytics solutions over the next five years among the comparison groups. The results shown in Figure 4.27 implied that the investment priorities and adoption of big data retail business analytics in organizations are not directed toward mitigating the challenges faced by retailers among the comparison groups.

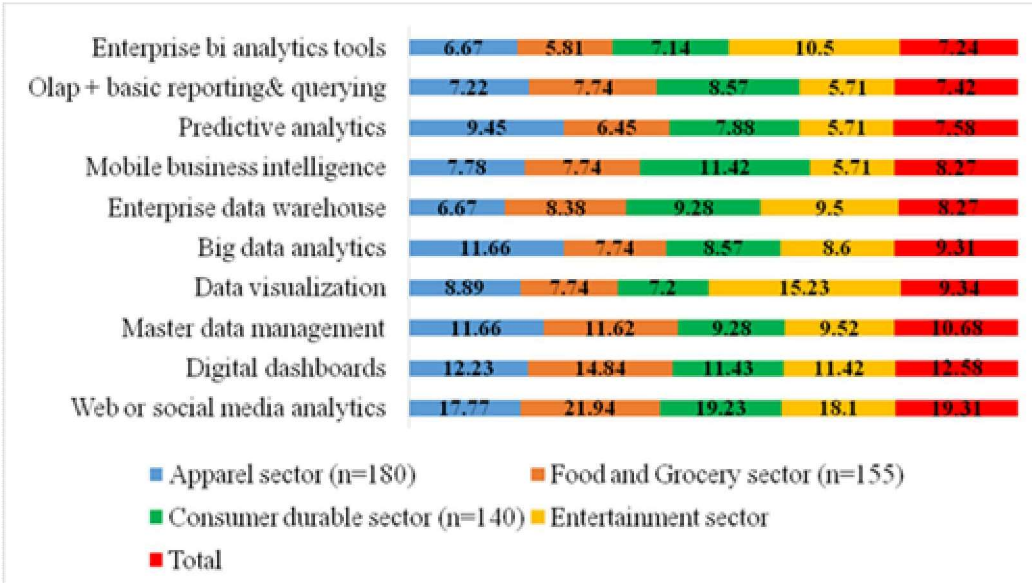
Table 4.28: Investment and Adoption of Big Data Retail Business Analytics Solutions over the Next Five Years

Big data retail business analytics solutions that retailers going to invest and adopt over the next five years	Apparel sector (n=180)	Food & Grocery sector (n=155)	Consumer durable sector (n=140)	Entertainment sector (n=105)	Total (n=580)
Web or social media analytics	32 (17.77)	34 (21.94)	27 (19.22)	19 (18.10)	112 (19.31)
Digital dashboards	22 (12.23)	23 (14.84)	16 (11.43)	12 (11.42)	73 (12.58)
Master data management	21 (11.66)	18 (11.62)	13 (9.28)	10 (9.52)	62 (10.68)
Data visualization	16 (8.89)	12 (7.74)	10 (7.14)	16 (15.23)	54 (9.31)
Big data analytics	21 (11.66)	12 (7.74)	12 (8.57)	9 (8.60)	54 (9.31)
Enterprise data warehouse	12 (6.67)	13 (8.38)	13 (9.28)	10 (9.50)	48 (8.27)
Mobile business intelligence	14 (7.78)	12 (7.74)	16 (11.42)	6 (5.71)	48 (8.27)
Predictive analytics	17 (9.45)	10 (6.45)	11 (7.85)	6 (5.71)	44 (7.58)
Olap + basic reporting& querying	13 (7.22)	12 (7.74)	12 (8.57)	6 (5.71)	43 (7.41)
Enterprise bi analytics tools	12 (6.67)	9 (5.81)	10 (7.14)	11 (10.50)	42 (7.24)

Source: primary data

Note: Values given in parenthesis are calculated in percentages of their column totals.

Figure 4.27: Investments and Adoption of Big Data Retail Business Analytics Solutions over the Next Five Years



4.1.29 Factor Structure of Customer Process and Customer Acquisition

In determining the factor structure of customer process and customer acquisition, exploratory factor analysis was conducted with 20 customer process and customer acquisition statements. Throughout the process, two items were dropped because of a low communality (< 0.60). An additional four items were dropped because of cross-loadings (> 0.50) on several factors. The final factor solution had four factors as follows: customer relationship management, customer knowledge capture, customer acquisition and customer analytics. Factors were moderately correlated (Pearson correlation ranging from 0.32 to 0.51). Table-4.29 presents the list of scale items, their sources, factor loadings, Cronbach's alpha, and item-total correlations for each of the four factors. The four factors combined explain 72.5 % of the total variance. After rotation, each factor explained between 21.8 and 15.8. The KMO of the final factor solution was 0.893, which shows good fit of the data, with item's KMO all above 0.79 and the Chi-Square of Bartlett's test of sphericity was highly significant (p<0.001). All items retained in the final solution have high communalities (>0.60) with an average communality of 0.71. All factors have more than recommended minimum number of items 3. Most factors have several items with high loadings above 0.70. The resulting factor scores were determined by taking the average of the individual scale items.

Table 4.29: List of customer process and customer acquisition Factor Analysis

Factor label	Statements	Factor Loadings	Cronbach 'α'	Variance
Relationship management	CRM is important way to establish a successful relationship with the customers	0.749	0.741	21.8 %
	Customer relation as communication to describe company's objectives	0.724		
	CRM system regularly and automatically updates the data contents	0.7105		
	Company has clear customer relationship management policy	0.697		
Customer knowledge Capture	Focuses on capturing customer knowledge existing within the customers	0.738	0.725	18.6%
	Helps understanding how to capture the knowledge needed	0.711		
	Essential to test the reliability and correctness of customer knowledge for further processing	0.696		
Customer acquisition	Selecting a new customer is considered an important part of attraction	0.725	0.717	16.3 %
	Company uses any basic information about the customers in order to attract them.	0.713		
	Marketing communication tools are used for acquiring new customers	0.693		
Customer analytics	Company adopts certain analytical techniques for acquiring new customers	0.720	0.708	15.8 %
	Company utilizes different analytical tools to attract the customers	0.712		
	The quality of data existing has an impact on the attracted customer	0.703		
	Analysing data requires classification of the composed data	0.684		
	Analysing customer's data can help predicting the behaviour of the customers	0.670		

a. Extraction Method: Principle Components Analysis, Rotation Method: Varimax with Kaiser Normalisation, Total variance explained 72.5 %, p=0.001

4.1.30 Response to question "is your company focused on customer acquisition or retention marketing?"

The results shown in Table-4.30, overall, reveal that majority of the respondents (50%) indicate that company focuses on customer acquisition marketing, followed by customer retention marketing (30.35%) and equal focus on acquisition and retention marketing (19.65%). A number of respondents (67.86%) from consumer durable retailing indicate that customer acquisition is their focal area compared to customer retention (17.86%) and equal focus on acquisition and retention (14.28%). In contrast 49 percent of respondents from food and grocery retailing indicate that customer acquisition is their prime focus area compared to retention marketing (26.45%). The Chi-square statistic results ($\chi 2$ = 34.72, df 6, $p < 0.001$) reveal that there are significant differences in the distribution of responses to customer acquisition/retention marketing among the comparison groups. The results shown in Figure 4.28 implied that customer acquisition is the primary focal area of retailers among the comparison groups.

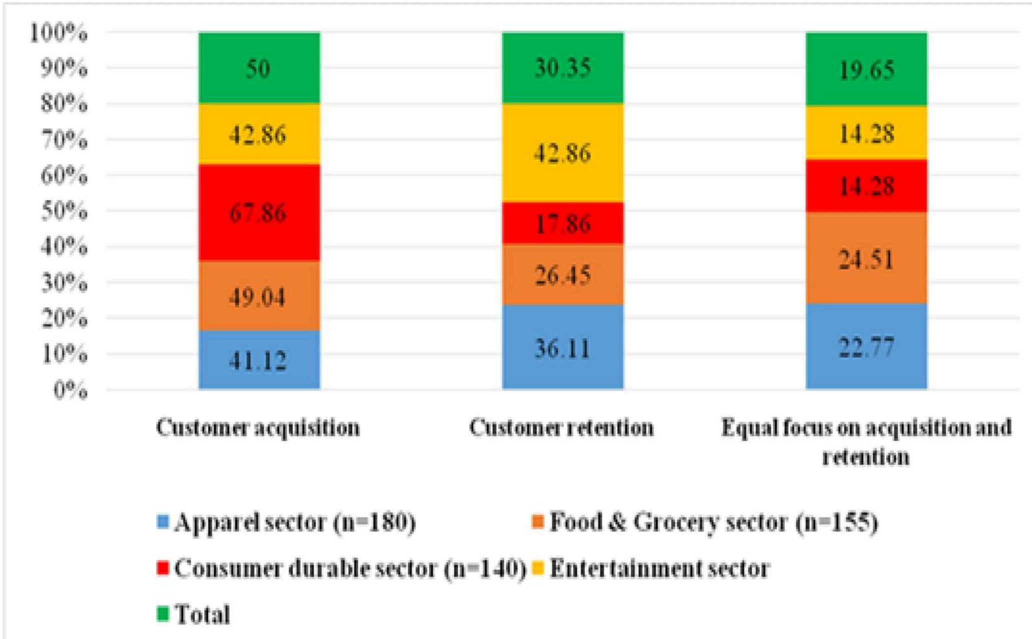
Table 4.30: Company focus on customer acquisition/retention marketing

Company focus	Apparel sector (n=180)	Food &Grocery sector (n=155)	Consumer durable sector (n=140)	Entertainment sector (n=105)	Total (n=580)
Customer acquisition	74 (41.12)	76 (49.04)	95 (67.86)	45 (42.86)	290 (50.00)
Customer retention	65 (36.11)	41 (26.45)	25(17.86)	45 (42.86)	176 (30.35)
Equal focus on acquisition and retention	41 (22.77)	38 (24.51)	20 (14.28)	15 (14.28)	114 (19.65)
Total	180 (100)	155 (100)	140 (100)	105 (100)	580 (100)

Source: primary data

Note: Values given in parenthesis are calculated in percentage of their column totals.

Figure 4.28: Company focus on customer acquisition/retention marketing



4.1.31 Response to customer acquisition strategies by retail organisations

Results shown in Table-4.31 reveal that majority of the respondents (50.86%) strongly agree that price discounts and other benefits are major customer acquisition strategies of retailers' followed by customized services (46.93%), wide-variety of products/services (47.10%), advertisement's reliability (41.56%), nearby locations (41.04%), well-known image (40.51%), partnerships with other firms (38.62%), contact by recommendations (37.41%), and contact by e-mails and SMSs (30.20%). The results shown in Figure 4.29 and further analysis revealed that there is no consistency in adoption of customer acquisition strategies among the comparison groups.

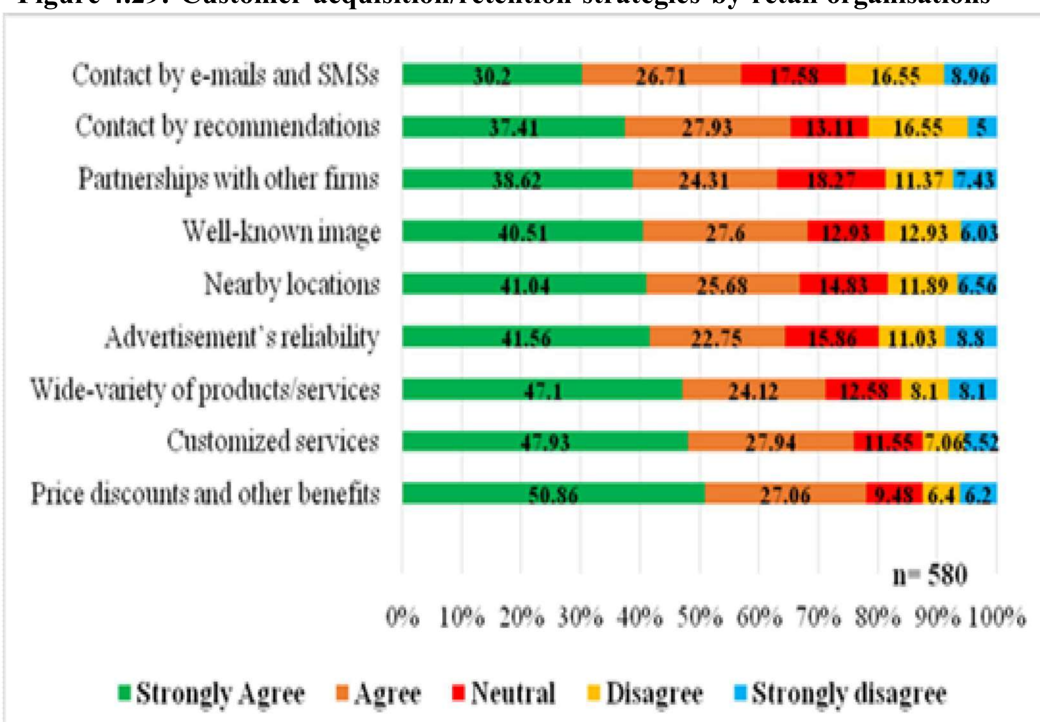
Table 4.31: Customer acquisition strategies by retail organisations

Customer acquisition efforts	Strongly Agree	Agree	Neutral	Disagree	Strongly disagree	Total (n=580
Price discounts and other benefits	295 (50.86)	157 (27.06)	55 (9.48)	37 (6.40)	36 (6.20)	580 (100)
Customized services	278 (47.93)	162 (27.94)	67 (11.55)	41 (7.06)	32 (5.52)	580 (100)
Wide-variety of merchandise	273 (47.10)	140 (24.12)	73 (12.58)	47 (8.10)	47 (8.10)	580 (100)
Advertisement's reliability	241 (41.56)	132 (22.75)	92 (15.86)	64 (11.03)	51 (8.80)	580 (100)
Nearby locations	238 (41.04)	149 (25.68)	86 (14.83)	69 (11.89)	38 (6.56)	580 (100)
Well-known image	235 (40.51)	160 (27.60)	75 (12.93)	75 (12.93)	35 (6.03)	580 (100)
Partnerships with other firms	224 (38.62)	141 (24.31)	106 (18.27)	66 (11.37)	43 (7.43)	580 (100)
Contact by recommendations	217 (37.41)	162 (27.93)	76 (13.11)	96 (16.55)	29 (5.00)	580 (100)
Contact by e-mails and SMSs	175 (30.20)	155 (26.71)	102 (17.58)	96 (16.55)	52 (8.96)	580 (100)

Source: primary data

Note: Values given in parenthesis are calculated in percentage of their column totals

Figure 4.29: Customer acquisition/retention strategies by retail organisations



4.1.32 Response to big data analytics versus customer acquisition in retail organisations

Results shown in Table-4.32 reveal that majority of the respondents (62.75%) strongly agree that customer acquisition strategies impacted by the application of big data retail business analytics as it enables understand customer information like demographics, behaviour or usage information and the average lifetime value, followed by enabling retailers gather customer information in real time over all distribution channels (47.75%), enabling retailers define framework of customer acquisition (42.75%), enabling retailers improve customer acquisition (41.72%), enabling retailers increase understanding of unique consumer needs (40.68%), enables improvement in terms of regaining lost customers (39.13%), enables obtain 360º customers view to gain a deeper understanding of customer sentiment from both internal and external sources (38.96%), enable decide launch new, targeted products as an acquisition strategy (38.10%), enables deliver valuable, personalized customer messages (37.06%), enables gain buying pattern insights (36.37%), enables improvement in the terms of the expansion of customer relationships (33. 97%). The results shown in Figure 4.30 also reveal that customer acquisition strategies are being driven by big data analytics in retailing.

Table 4.32: Big data analytics versus customer acquisition in retail organisations

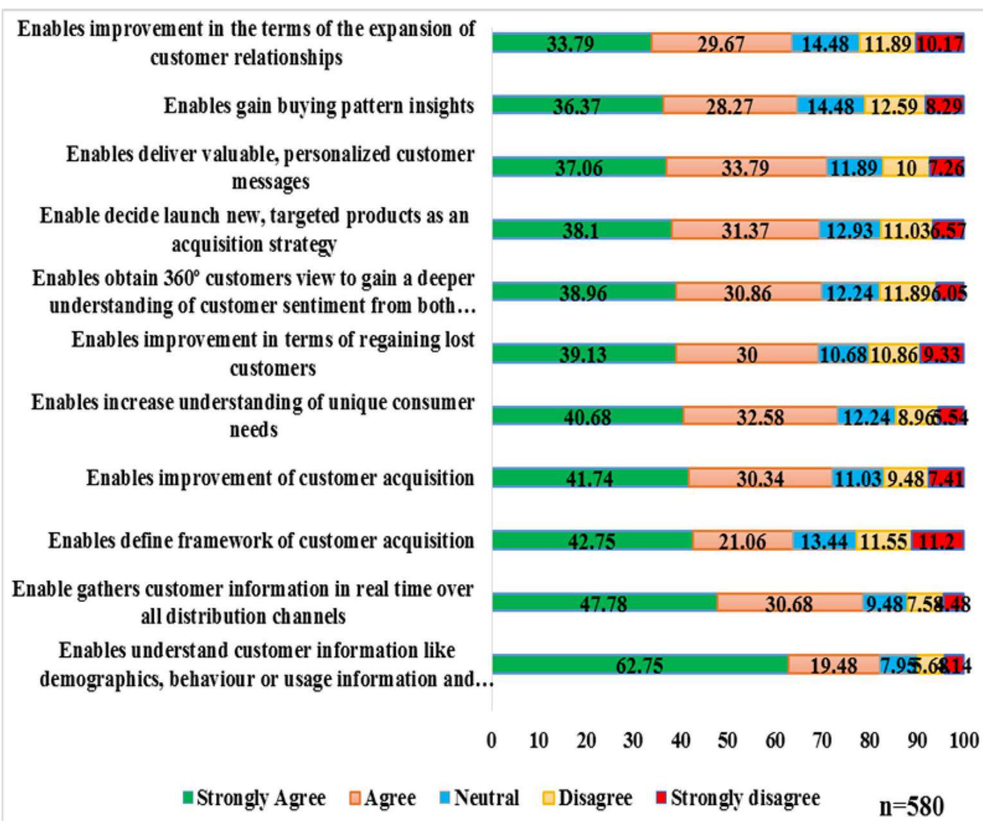
Customer acquisition efforts	Strongly Agree	Agree	Neutral	Disagree	Strongly disagree	Total (n=580
Enables understand customer information like demographics, behaviour or usage information and the average lifetime value.	364 (62.75)	113 (19.48)	46 (7.93)	33 (5.68)	24 (4.13)	580 (100)
Enable gathers customer information in real time over all distribution channels	277 (47.75)	178 (30.68)	55 (9.48)	44 (7.58)	26 (4.48)	580 (100)
Enables define framework of customer acquisition	248 (42.75)	122 (21.03)	78 (13.44)	67 (11.55)	65 (11.20)	580 (100)
Enables improvement of customer acquisition	242 (41.72)	176 (30.34)	64 (11.03)	55 (9.48)	43 (7.41)	580 (100)
Enables increase understanding of unique consumer needs	236 (40.68)	189 (32.58)	71 (12.24)	52 (8.96)	32 (5.51)	580 (100)
Enables improvement in terms of regaining lost customers	227 (39.13)	174 (30.00)	62 (10.68)	63 (10.86)	54 (9.31)	580 (100)

Enables obtain 360º customers view to gain a deeper understanding of customer sentiment from both internal and external sources	226 (38.96)	179 (30.86)	71 (12.24)	69 (11.89)	35 (6.03)	580 (100)
Enable decide launch new, targeted products as an acquisition strategy	221 (38.10)	182 (31.37)	75 (12.93)	64 (11.03)	38 (6.55)	580 (100)
Enables deliver valuable, personalized customer messages	215 (37.06)	196 (33.79)	69 (11.89)	58 (10.00)	42 (7.24)	580 (100)
Enables gain buying pattern insights	211 (36.37)	164 (28.27)	84 (14.48)	73 (12.58)	48 (8.27)	580 (100)
Enables improvement in the terms of the expansion of customer relationships	196 (33.79)	172 (29.65)	84 (14.48)	69 (11.89)	59 (10.17)	580 (100)

Source: Primary data

Note: Values given in parenthesis are calculated in percentage of their column totals

Figure 4.30: big data analytics versus customer acquisition in retail organisations



4.1.33 Responses to the question "What's the most effective practice for customer acquisition?"

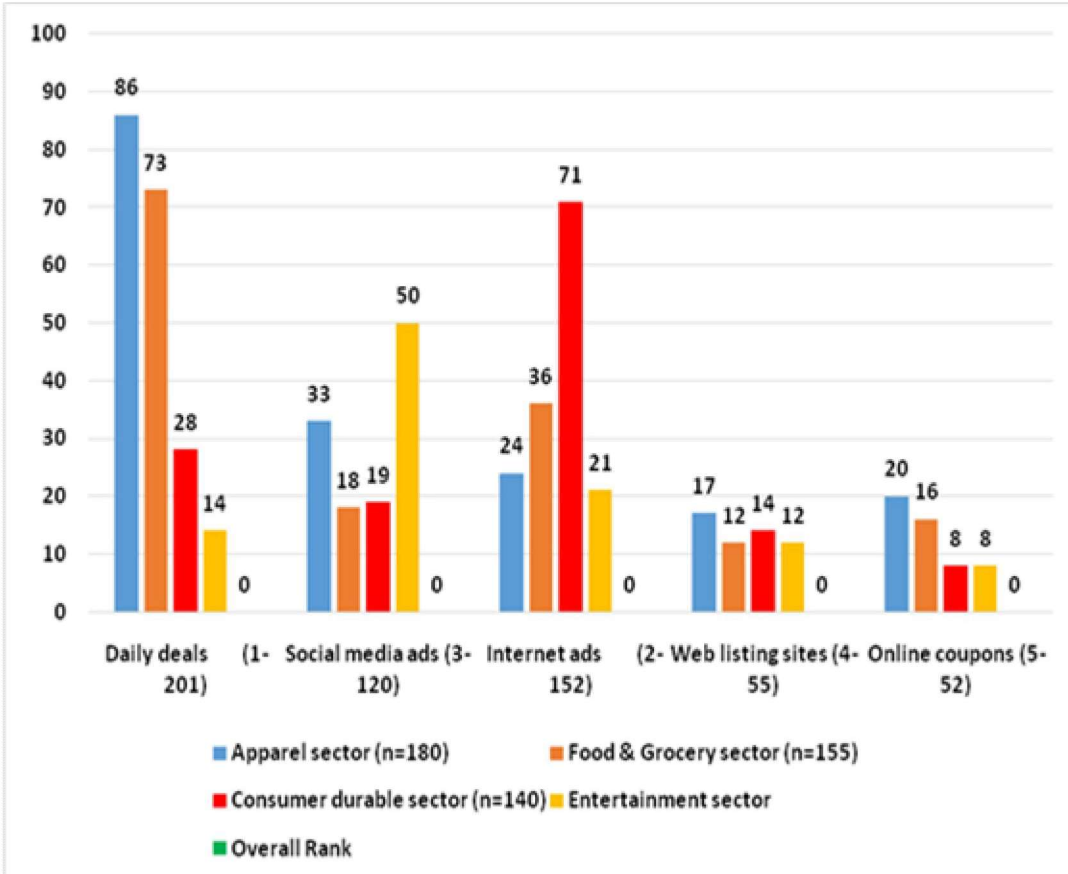
Results shown in Table-4.33 reveal that, overall, majority of the respondents (34.65%) ranked daily deals is the highest effective tool for customer acquisition, followed by internet ads (26.20%), social media ads (20.68%), web listing sites (9.48%), and online coupons (8.96%). Sector wise analysis reveal that 47.77 percent respondents from apparel felt that daily deals is the most effective for customer acquisition compared to internet ads (50.74%) in consumer durable sector and social media ads (47.6%) in entertainment sector. The Chi-square statistic results ($\chi 2$ = 134.80, df 12, $p < 0.001$) reveal that there is significant difference in the distribution of responses to the most effective for customer acquisition among the comparison groups in retailing. The results shown in Figure 4.31 also implied that retailers mostly resorting to daily deals as the effective tool for customer acquisition.

Table 4.33: The most effective practice for customer acquisition

Effective tool for customer acquisition	Apparel sector (n=180)	Food & Grocery sector (n=155)	Consumer durable sector (n=140)	Entertainment sector (n=105)	Overall Rank (n=580)
Daily deals	1 (86)	1 (73)	2 (28)	3 (14)	1 (201)
Internet ads	3 (24)	2 (36)	1 (71)	2 (21)	2 (152)
Social media ads	2 (33)	3 (18)	3 (19)	1 (50)	3 (120)
Web listing sites	5 (17)	5 (12)	4 (14)	4 (12)	4 (55)
Online coupons	4 (20)	4 (16)	5 (8)	5 (8)	5 (52)

Source: primary data
Note: Values given in parenthesis are calculated in frequencies of their column totals.

Figure 4.31: The most effective practice for customer acquisition



4.1.34 Responses to the question "What's the most effective tool for engaging existing customers (loyalty)?"

Results shown in Table-4.34 reveal that, overall, 39.48 percent of respondents' ranked CRM systems is the first one used for engaging existing customers, followed by digital loyalty/frequent shopper tracking systems (24.48%), online survey tools (15.86%), e-mail marketing (13.79%), and contact management (8.0%). The Chi-square statistic results ($\chi2$ = 24.40, df 12, $p < 0.05$) reveal that there is significant difference in the distribution of responses to the most effective for engaging existing customers among the comparison groups. The results shown in Figure 4.31 revealed that the CRM systems is the most preferred techniques used to engage existing customers in retailing industry.

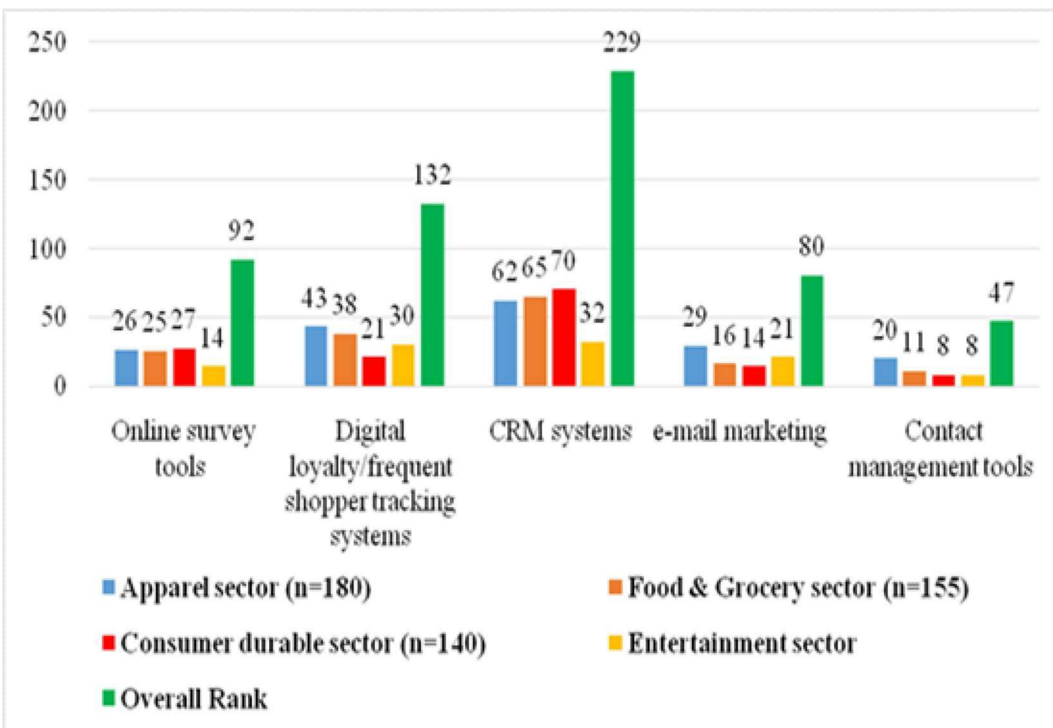
Table 4.34: The most effective tool for engaging existing customers

Effective for engaging existing customers	Apparel sector (n=180)	Food & Grocery sector (n=155)	Consumer durable sector (n=140)	Entertainment sector (n=105)	Overall Rank (n=580)
CRM systems	1 (62)	1 (65)	1 (70)	1 (32)	1 (229)
Digital loyalty/frequent shopper tracking systems	2 (43)	2 (38)	3 (21)	2 (30)	2 (132)
Online survey tools	4 (26)	3 (25)	2 (27)	4 (14)	3 (92)
e-mail marketing	3 (29)	4 (16)	4 (14)	3 (21)	4 (80)
Contact management tools	5 (20)	5 (11)	5 (8)	5 (8)	5 (47)

Source: primary data

Note: Values given in parenthesis are calculated in frequencies of their column totals.

Figure 4.32: The most effective practice for engaging existing customers



4.1.35 Responses to the question "Which tools are effective at both attracting an engaging customer?"

Results shown in Table-4.35 reveal that, overall, 29.66 percent of respondents' ranked websites is the highest effective tool at both attracting and engaging customers in retail organisations. A number of respondents (23.62%) felt that social media is the second highest effective tool, followed by video sites (15.86%), blogs (14.31%), e-mail marketing (8.27%) and event management (6.55%). Respondents felt that big data technology could most impact the design of targeted offers and promotions (20.2%) is the second highest business process followed by demand forecasting and supply chain modelling (19.5 %), loyalty program management (16.20%), store design (9%),loss prevention (5.34%) as third, fourth and fifth ranks respectively. A number of respondents (32.9%) from food and grocery sector indicate that social media is the effective tool at both attracting and engaging customers compared to other tools. The Chi-square statistic results ($\chi 2$ = 56.09, df 15, $p < 0.001$) reveal that there is significant difference in the distribution of responses to the most effective tool at attracting and engaging customers among the comparison groups.

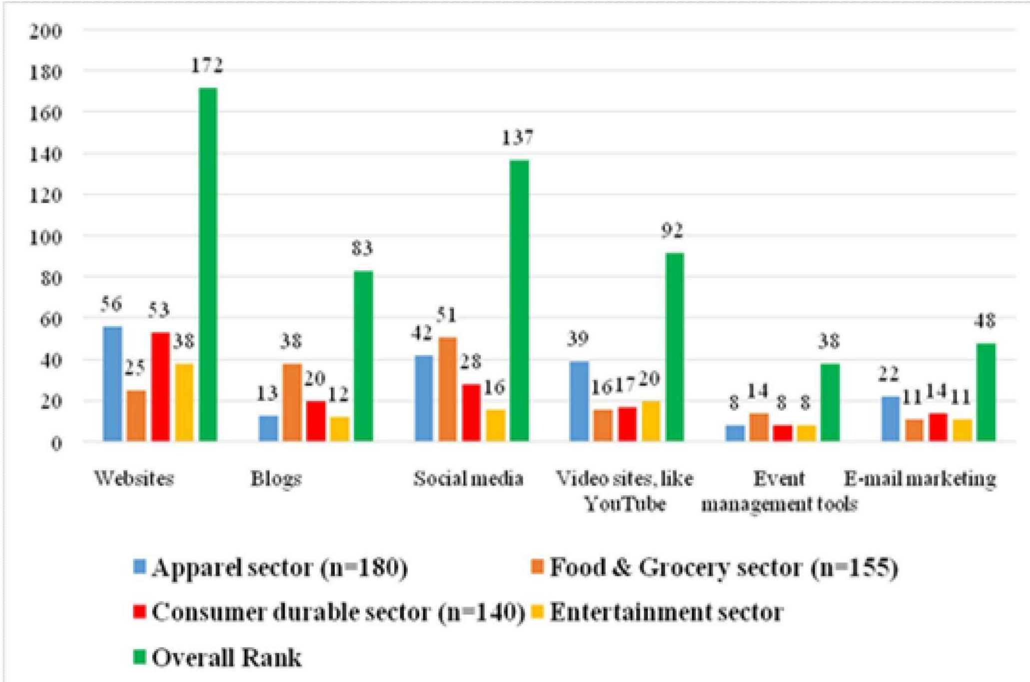
Table 4.35: Effective tools at both attracting and engaging customers

Effective for engaging existing customers	Apparel sector (n=180)	Food & Grocery sector (n=155)	Consumer durable sector (n=140)	Entertainment sector (n=105)	Overall Rank (n=580)
Websites	1 (56)	3 (25)	1 (53)	1(38)	1 (172)
Social media	2 (42)	1 (51)	2 (28)	3 (16)	2 (137)
Video sites, like YouTube	3 (39)	4 (16)	4 (17)	2 (20)	3 (92)
Blogs	5 (13)	2 (38)	3 (20)	4 (12)	4 (83)
E-mail marketing	4 (22)	6 (11)	5 (14)	5 (11)	5 (48)
Event management tools	6 (8)	5 (14)	6 (8)	6 (8)	6 (38)

Source: primary data

Note: Values given in parenthesis are calculated in frequencies of their column totals

Figure 4.33: Effective tools at both attracting and engaging customers



4.1.36 Factor Structure of Customer retention efforts and practices

In determining the factor structure of customer retention efforts and process, exploratory factor analysis was conducted with 23statements. Throughout the process, two items were dropped because of a low communality (< 0.60). An additional one item was dropped because of cross-loadings (> 0.50) on several factors. The final factor solution had four factors as follows: customer service, merchandise related, promotions and offers, and location and facilities. Factors were moderately correlated (Pearson correlation ranging from 0.35 to 0.48). Table-4.36 presents the list of scale items, their sources, factor loadings, Cronbach's alpha, and item-total correlations for each of the four factors. The three factors combined explain 89.8 % of the total variance. After rotation, each factor explained between 27.6 and 16.2. The KMO of the final factor solution was 0.932, which shows good fit of the data, with item's KMO all above 0.852 and the Chi-Square of Bartlett's test of sphericity was highly significant (p<0.001). All items retained in the final solution have high communalities (>0.60) with an average communality of 0.75. All factors have more than recommended minimum number of items 3. Most factors have several items with high loadings above 0.75. The resulting factor scores were determined by taking the average of the individual scale items.

Table 4.36: Customer retention efforts and processes

Factor label	Statements	Factor Loadings	Cronbach 'α'	Variance
Customer service	Caring attitude	0.824	0.788	27.6 %
	Skilled and experienced employees	0.782		
	Familiarity with service staff	0.771		
	Consistent quality	0.763		
	Problem solving	0.722		
	Always provided satisfactory customer service along with incentives to buy again	0.705		
Merchandise	Good quality merchandise	0.754	0.714	24.2 %
	Product/service prices are competitive	0.724		
	Additional product/service categories	0.711		
	Recommend product /service to family and friends	0.689		
Promotions & offers	Advertisements as Reminder	0.771	0.712	21.8%
	Rational advertisement	0.720		
	Loyalty card programmes			
	Surety of promotional offers	0.685		
	Reminder by emails and SMSs	0.649		
Location and facilities	Convenient location	0.734	0.710	16.2%
	Ease of parking facility	0.714		
	Familiarity with service surroundings	0.684		
	Recognition as regular and special consumer	0.640		
	Switching costs	0.634		

a. Extraction Method: Principle Components Analysis, Rotation Method: Varimax with Kaiser Normalisation, Total variance explained 89.8 %, p=0.001

4.1.37 Response to big data analytics versus customer retention

Results shown in Table-4.37 reveal that majority of the respondents (65.87%) strongly agree that big data retail business analytics influence customers retention by predicting which consumers may be experiencing issues with a product or service, followed by big data analysis offers companies a way to identify those shoppers who are the most valuable as returning customers (47.76%), reduction of customer migration (46.22%), make customized offers so that you can keep the customer satisfied and make a sale (41.72%), it creates successful customer loyalty and retention programs and personalize consumer interactions in meaningful ways (40.68%), it prevents customer churn and detect up selling opportunities (39.13%), and improve customer experience through real-time data (38.27%). The results shown in Figure 4.34 indicate that big data analytics influence customer retention in different ways in retail business.

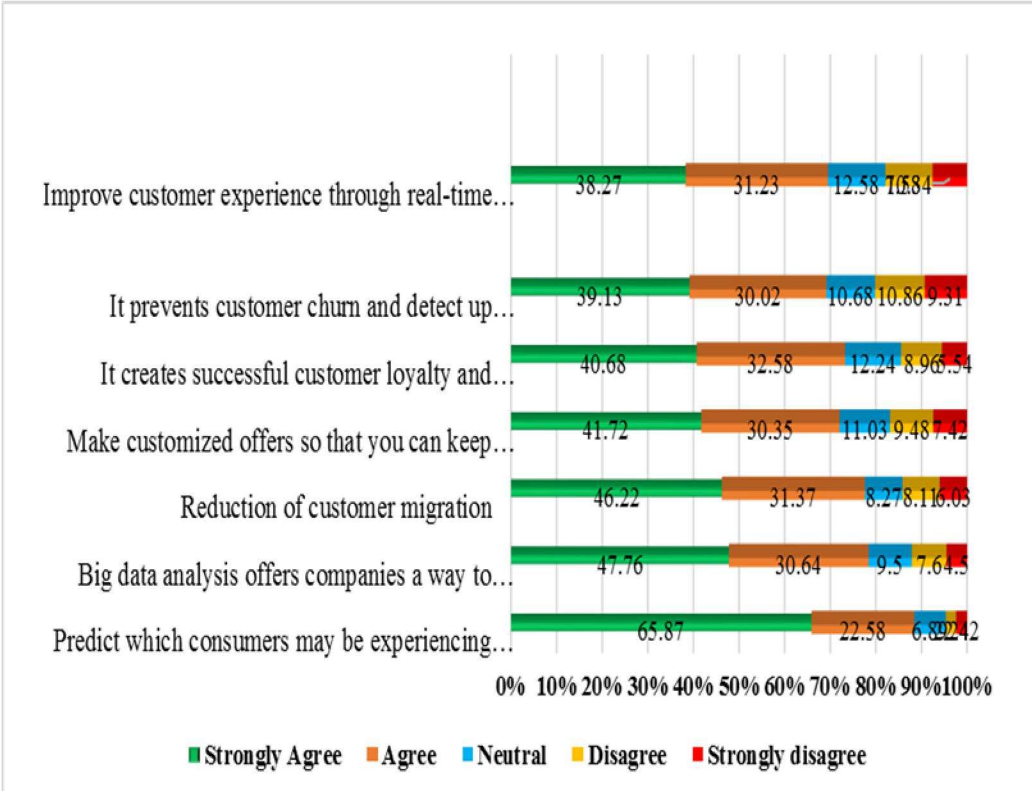
Table 4.37: Big data analytics versus customer retention in retail organisations

Big data analytics versus customer retention	**Strongly Agree**	**Agree**	**Neutral**	**Disagree**	**Strongly disagree**	**Total (n=580**
Predict which consumers may be experiencing issues with a product or service	382 (65.87)	131 (22.58)	40 (6.89)	13 (2.24)	14 (2.42)	580 (100)
Offers companies a way to identify those shoppers who are the most valuable as returning customers.	297 (47.76)	178 (30.68)	55 (9.5)	44 (7.6)	26 (4.5)	580 (100)
Reduction of customer migration	268 (46.22)	182 (31. 37)	48 (8.27)	47 (8.11)	35 (6.03)	580 (100)
Make customized offers so that you can keep the customer satisfied and make a sale.	242 (41.72)	176 (30.35)	64 (11.03)	55 (9.48)	43 (7.42)	580 (100)
It creates successful customer loyalty and retention programs, and personalize consumer interactions in meaningful ways	236 (40.68)	189 (32.58)	71 (12.24)	52 (8.96)	32 (5.54)	580 (100)
It prevents customer churn and detect up selling opportunities	227 (39.13)	174 (30.02)	62 (10.68)	63 (10.86)	54 (9.31)	580 (100)
Improve customer experience through real-time data	222 (38.27)	181 (31.23)	73 (12.58)	60 (10.34)	44 (7.58)	580 (100)

Source: Primary data

Note: Values given in parenthesis are calculated in percentage of their column totals

Figure 4.34: Big data analytics versus Customer retention in retail organisations



4.1.38 Response to question 'pick the following customer retention strategies that you have adopted?"

Results shown in Table-4.38 reveal that, overall, 18.44 percent of respondents' indicated that CRM systems is the most preferred tool for retaining customers followed by loyalty programs (17.06%), regular reviews (11.20%), social media (8.44%), blogs (7.75%), premiums & gifts (7.58), questionnaires and surveys (7.06%), personal touches (6.20%), and magic moments (6.03%). The Chi-square statistic results ($\chi2$ = 7.81, df 27, $p > 0.05$) reveal that there is no difference in the distribution of responses to different strategies for customer retention among the comparison groups.

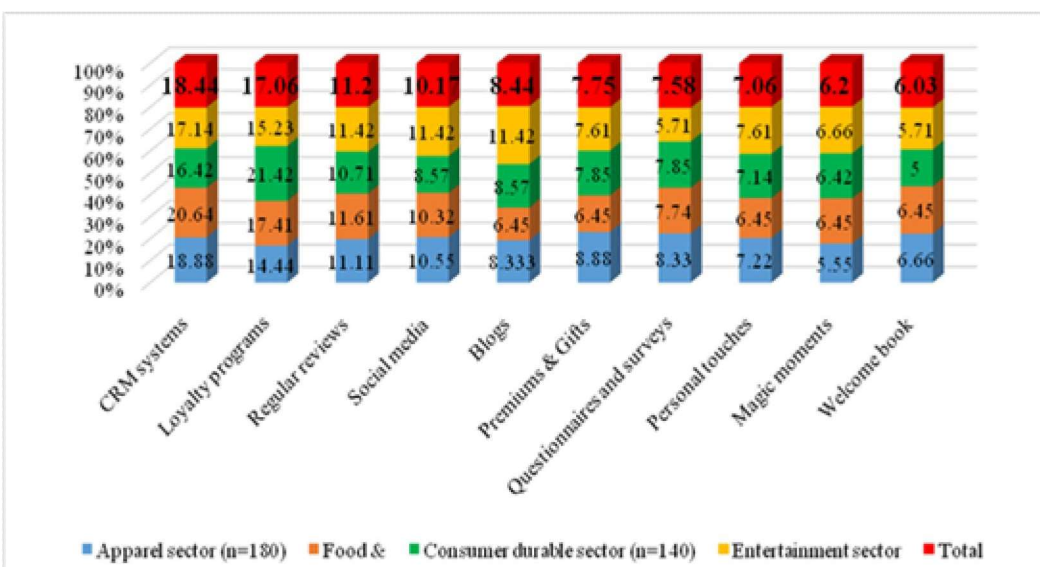
Table 4.38: Adoption of customer retention strategies

Retention strategies	Apparel sector (n=180)	Food & Grocery sector (n=155)	Consumer durable sector (n=140)	Entertainment sector (n=105)	Total (n=580
CRM systems	34 (18.88)	32 (20.63)	23 (16.42)	18 (17.14)	107 (18.44)
Loyalty programs	26 (14.45)	27 (17.41)	30 (21.42)	16 (15.23)	99 (17.06)
Regular reviews	20 (11.12)	18 (11.60)	15 (10.71)	12 (11.42)	65 (11.20)
Social media	19 (10.55)	16 (10.32)	12 (8.57)	12 (11.42)	59 (10.17)
Blogs	15 (8.34)	10 (6.46)	12 (8.57)	12 (11.42)	49 (8.44)
Premiums & Gifts	16 (8.88)	10 (6.46)	11 (7.86)	8 (7.61)	45 (7.75)
Questionnaires and surveys	15 (8.33)	12 (7.74)	11 (7.86)	6 (5.71)	44 (7.58)
Personal touches	13 (7.23)	10 (6.46)	10 (7.14)	8 (7.62)	41 (7.06)
Magic moments	10 (5.56)	10 (6.46)	9 (6.43)	7 (6.66)	36 (6.20)
Welcome book	12 (6.66)	10 (6.46)	7 (5.0)	6 (5.71)	35 (6.10)

Source: Primary data

Note: Values given in parenthesis are calculated in percentage of their column totals

Figure 4.35: Adoption of customer retention strategies



4.2 Inferential statistics

The previously described descriptive statistics and factor analysis results were used to test the formulated hypotheses and further analyse the role of big data retail business analytics in customer acquisition and retention strategies. The results were described in the following paragraphs and tables.

$H1_0$: There is no mean difference among retail organisations in defining big data retail business analytics

$H1_a$: There is significant mean difference among retail organisations in defining big data retail business analytics

To test the above hypothesis, On-way MANOVA is used. The overall test of the One-way multivariate analysis of variance relationship shown in Table 4.39 was rejected at the 0.05 significance level (Pillai's Trace= 0.500, F [39, 1698] = 4352.218, p= 0.001; [Wilk's Lambda = 0.573, F [39, 1670.872] =8.868, p=0.001; Hotelling's Trace= 0.625, F [39, 1688] =9.012, p=0.001). The results indicated that all three tests were significant. The decision was made that there are mean differences in defining big data retail business analytics among retail organisations, and further testing was needed.

Table 4.39: One-way Multivariate analysis of variance between retail organizations and Perceptions of big data retail business analytics

Effect		Value	F	Hypothesis df	Error df	Sig. (p-Value)
Intercept	Pillai's Trace	0.990	4352.218 b	13.000	564.000	0.000
	Wilks' Lambda	0.010	4352.218 b	13.000	564.000	0.000
	Hotelling's Trace	100.317	4352.218 b	13.000	564.000	0.000
Type of retail Organization	Pillai's Trace	0.500	8.703	39.000	1698.000	0.000
	Wilks' Lambda	0.573	8.868	39.000	1670.872	0.000
	Hotelling's Trace	0.625	9.012	39.000	1688.000	0.000
a. Design: Intercept + Type of Retail Organization						
b. Exact statistic						
c. The statistic is an upper bound on F that yields a lower bound on the significance level.						

Source; Primary data

To determine how the dependent variables, differ for the independent variable, the Univariate ANOVA tests were conducted for each dependent variable. The results shown in ***Appendix-B*** (tests of between-subjects effects) revealed that there was significant effect ($P<0.005$) of retail organisation groups on perceptions of big data retail business analytics except one perception such as segmenting and targeting customers precisely and optimising customer experiences ($p > 0.053$).

Further Tukey's HSD post-hoc tests were conducted to follow up the significant ANOVAs identified in tests of between-subjects effects. By and large, the multiple comparisons table (shown in ***Appendix-C***) reveals that mean difference among retail groups for each perception of big data retail business analytics was statistically significant ($p<0.05$) except in some cases where p-value is greater than 0.05. The mixed results implied that there are some similarities and differences among retail groups with respect to perceptions of big data retail business analytics.

Results: It was proved that there were significant mean differences in defining big data retail business analytics among four retail organisations. Further, the error variance of the dependent variables was also proved equal across groups among all perceptions of big data retail business analytics. Hence, null hypothesis was failed to be accepted and alternative hypothesis ($H1_a$) was proved to be accepted for all perceptions of big data retail business analytics.

$H2_0$: Retail organizations and important parameters big data analytics are statistically independent.

$H2_a$: Retail organizations and important parameters big data analytics are statistically dependent

To test the above hypothesis, Chi-square statistic is used for testing difference /independence /association of two variables. The Chi-square statistic results (χ^2=0.14, df9, $p>0.05$) shown in Table 4.10 reveals that there is no difference in the distribution of responses to the outcome variable (i.e., important parameter of big data analytics) among the comparison groups (i.e., type of retail organisation). Thus, null hypothesis ($H2_0$) is proved to be accepted.

Results: The results implied that given the parameters of big data retail business analytics were independent on type of retail organisation. Importance of parameters of big data retail business analytics were differentiated by comparison groups in retailing. The distribution of the observed number of important parameter of big data retail business analytics does not differ significantly among retail organisations.

***$H3_0$*: Retail organisations are not serious towards use of big data retail business analytics in managerial decision making.**

***$H3_a$*: Retail organisations are significantly serious towards use of big data retail business analytics in managerial decision making.**

To test the above hypothesis, Chi-square statistic is used for testing difference between type of retail organisation and seriousness of big data analytics in decision making. The Chi-square statistic results (χ^2=1.81, df 9, p>0.05) shown in Table 4.11 reveals that there is no difference in the distribution of responses to the seriousness of big data analytics in decision making among the comparison groups (i.e., type of retail organisation). Hence null hypothesis ($H3_0$) is proved to be accepted.

Results: The results implied that retail organisations' seriousness towards use of big data analytics in retailing is not different. There is no association between retail organisations and seriousness of using big data retail business analytics in managerial decision making. The two variables are independent.

***$H4_0$*: There is no difference in objectives of big data analytics among retail organisations.**

***$H4_a$*: There is significant difference in objectives of big data analytics among retail organisations.**

To test the above hypothesis, Chi-square statistic is used. The Chi-square statistic results (χ^2=61.38, df12, p<0.001) shown in Table 4.13 reveals that there is significant difference in the distribution of responses to the objectives of big data analytics among the comparison groups (i.e., type of retail organisation). Thus, null hypothesis ($H3_0$) is failed to be accepted. Hence alternative hypothesis ($H4_a$) is proved to be accepted.

Results: The results implied that retail organisations and objectives of big data retail business analytics are statistically dependent. Objectives of big data retail business analytics were differentiated by comparison groups in retailing. The distribution of the observed number of objectives of big data retail business analytics differed significantly among retail organisations.

H5$_0$: There is no mean difference of opinion among retail organisations on major obstacles in adopting big data retail business analytics.

H5$_a$: There is significant mean difference of opinion among retail organisations on major obstacles in adopting big data retail business analytics.

To test the above hypothesis, On-way MANOVA is used. The overall test of the One-way multivariate analysis of variance relationship shown in Table 4.40 was rejected at the 0.05 significance level (Pillai's Trace= 0.440, F [33, 1704] = 8.868, p= 0.001; [Wilk's Lambda = 0.608, F [33, 1668.244] =9.311, p=0.001; Hotelling's Trace= 0.570, F [33, 1694] =9.756, p=0.001). The results indicated that all three tests were significant. The decision was made that the differences did exist among retail organisations on major obstacles in adopting big data retail business analytics, and further testing was needed.

Table 4.40: One-way Multivariate analysis of variance between retail organization and major obstacles in adopting big data retail business analytics

Effect		Value	F	Hypothesis df	Error df	Sig. (p-value)
Intercept	Pillai's Trace	0.990	4889.323^b	11.000	566.000	0.000
	Wilks' Lambda	0.010	4889.323^b	11.000	566.000	0.000
	Hotelling's Trace	95.02	4889.323^b	11.000	566.000	0.000
	Roy's Largest Root	95.02	4889.323^b	11.000	566.000	0.000
Type of retail organization	Pillai's Trace	0.440	8.868	33.000	1704.000	0.000
	Wilks' Lambda	0.608	9.311	33.000	1668.244	0.000
	Hotelling's Trace	0.570	9.756	33.000	1694.000	0.000
	Roy's Largest Root	0.407	21.037^c	11.000	568.000	0.000
a. Design: Intercept + Type of retail organization						
b. Exact statistic						
c. The statistic is an upper bound on F that yields a lower bound on the significance level.						
d. Computed using alpha = .05						

Source: Primary data

To determine how the dependent variables, differ for the independent variable, the Univariate ANOVA tests were conducted for each dependent variable. The results shown in ***Appendix-D*** (tests of between-subjects effects**)** revealed that there was significant effect (P<0.005) of retail organisation groups on major obstacles except insufficient infrastructure and lack of internal skills ($p > 0.053$) in adopting big data retail business analytics.

Further Tukey's HSD post-hoc tests were conducted to follow up the significant ANOVAs identified in tests of between- subjects effects. By and large, the multiple comparisons table (shown in ***Appendix-E***) reveals that mean difference among retail groups for major obstacle in adopting big data retail business analytics was statistically significant ($p<0.05$) except in some cases where p-value is more than 0.04. The mixed results implied that there are some similarities and differences among retail groups with respect to perceptions of big data retail business analytics.

Results: It was proved that there was significant difference exist among four retail organisations towards major obstacles in adopting big data analytics. Further, the error variance of the dependent variable was also proved equal across groups among all major obstacles of big data analytics. Hence, null hypothesis ($H5_0$) is failed to be accepted and alternative hypothesis ($H5_a$) is proved to be accepted for major obstacles in adopting big data retail business analytics. The results implied that there is an association between retail organisation and major obstacles in adopting big data retail business analytics.

***$H6_0$*: There is no mean difference of opinion among retail organisations on challenges in implementing big data retail business analytics**

***$H6_a$*: There is significant mean difference of opinion among retail organisations on challenges in implementing big data retail business analytics**

To test the above hypothesis, On-way MANOVA is used. The overall test of the One-way multivariate analysis of variance relationship shown in Table 4.41 was rejected at the 0.05 significance level (Pillai's Trace= 0.318, $F [24, 1713] = 8.455$, p= 0.001; [Wilk's Lambda = 0.707, $F [24, 1650.874] =8.7238$, p=0.001; Hotelling's Trace= 0.379, $F [24, 1703]=8.964$, p=0.001). The results indicated that all three tests were significant. The decision was made that the differences did exist among retail organisations toward challenges faced by retail organisations in implementing big data retail business analytics, and further testing was needed.

Table 4.41: One- way Multivariate analysis of variance between retail organization and major challenges in implementing big data retail business analytics

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	.968	2169.12[b]	8.000	569.00	.000
	Wilks' Lambda	.032	2169.12[b]	8.000	569.00	.000
	Hotelling's Trace	30.497	2169.12[b]	8.000	569.00	.000
	Roy's Largest Root	30.497	2169.12[b]	8.000	569.00	.000
Retail organization	Pillai's Trace	.318	8.45	24.000	1713.00	.000
	Wilks' Lambda	.707	8.72	24.000	1650.87	.000
	Hotelling's Trace	.379	8.96	24.000	1703.00	.000
	Roy's Largest Root	.254	18.14[c]	8.000	571.00	.000
a. Design: Intercept + Retail organization						
b. Exact statistic						
c. The statistic is an upper bound on F that yields a lower bound on the significance level.						
d. Computed using alpha = .05						

Source: Primary data

To determine how the dependent variable differs for the independent variables, the Univariate ANOVA tests were conducted for each dependent variable. The results shown in ***Appendix-F*** (tests of between-subjects effects) revealed that there was significant effect ($P<0.005$) of retail organisation groups on major challenges except inadequate analytics resources, poor data quality and outdated software and tools ($p > .053$) in implementing big data retail business analytics.

Further Tukey's HSD post-hoc tests were conducted to follow up the significant ANOVAs identified in ttests of between-subjects effects. By and large, the multiple comparisons table (shown in ***Appendix-G***) reveals that mean difference among retail groups for major obstacle in adopting big data retail business analytics was statistically significant ($p<0.05$) except in some cases where p-value is > 0.05. The mixed results implied that there are some similarities and differences among retail groups with respect to perceptions of big data retail business analytics.

Results: It was proved that there was significant difference exist among four retail organisations towards major challenges in implementing big data analytics. Further, the error variance of the dependent variable was also proved equal across groups among all major obstacles of big data analytics. Hence, null hypothesis ($H6_0$) is failed to be accepted and alternative hypothesis ($H6_a$) is proved to be accepted for all major challenges in implementing big data retail business analytics. The results implied that there is an association between type retail organisation and major challenges in implementing big data retail business analytics.

***$H7_0$*: There is no difference in deployment of insights from big data analytics in business functions among retail organisations.**

***$H7_a$*: There is significant difference in deployment of insights from big data analytics in business functions among retail organisations.**

To test the above hypothesis, Chi-square statistic is used for testing difference/ association between deployment of insights from big data analytics in business functions and type of retail organisation. The Chi-square statistic results (χ^2=15.84, df,30, p>0.05) shown in Table 4.19 reveals that there is no difference in the distribution of responses to making best use of insights from big data analytics in business functions among the comparison groups (i.e., four types of retail organisations). Thus, null hypothesis ($H7_0$) is proved to be accepted.

Results: The results implied that business areas in retail organisations are independent of best use of insights from big data analytics. It means that there is no association between the two variables. In contrast to chi-square results, the descriptive statistics shown in table-4.19 reveals that customer and market analysis area is the highest ranked business function that stands to make use of insights from big data analytics used in retail organisations. The Ch-square results high light that business functional areas in retail organisations and use of big data analytics are mutually exclusive.

***$H8_0$*: There is no difference in impact of big data analytics technology on business processes among retail organisations.**

***$H8_a$*: There is significant difference in impact of big data analytics technology on business processes among retail organisations.**

To test the above hypothesis, Chi-square statistic is used for testing difference/ association between big data technology and business processes of retail organisations. The Chi-square statistic results (χ^2=25.12, df 15, p<0.05) shown in Table 4.20 reveals that there is significant difference in the distribution of responses to impact of big data analytics technology on business processes among the comparison groups (i.e., four types of retail organisations). Thus, null hypothesis ($H8_0$) is failed to be accepted. It means alternative hypothesis ($H8_a$) is accepted.

<u>*Results*</u>: The results implied that business processes in retail organisations are highly impacted by big data analytics technology. It means that there is significant association between the two variables. The statistically significant difference proves a causal relationship between two variables.

$H9_0$: There are no differences of opinion exists among retail organisations towards holding out of using big data analytics solutions.

$H9_a$: There are significant differences of opinion exist among retail organisations towards holding out of using big data analytics solutions.

To test the above hypothesis, On-way MANOVA is used. The overall test of the One-way multivariate analysis of variance relationship shown in Table 4.42 was rejected at the 0.05 significance level (Pillai's Trace= 0.722, F [21, 1716] = 25.896, p= 0.001; [Wilk's Lambda = 0.417, F [21, 1637.282] =27.764, p=0.001; Hotelling's Trace= 1.076, F [21, 1706] =43. 461, p=0.001). The results indicated that all three tests were significant. The decision was made that the differences did exist among retail organisations towards challenges faced by retail organisations in implementing big data retail business analytics, and further testing was needed.

Table 4.42: One- way Multivariate analysis of variance between type of retail organization and holding out on using big data analytics solutions

Effect		Value	F	Hypothesis df	Error df	Sig. (p-value)
Intercept	Pillai's Trace	0.980	4073.399^b	7.000	570.000	0.000
	Wilks' Lambda	0.020	4073.399^b	7.000	570.000	0.000
	Hotelling's Trace	50.024	4073.399^b	7.000	570.000	0.000
	Roy's Largest Root	50.024	4073.399^b	7.000	570.000	0.000
Retail organization	Pillai's Trace	0.722	25.896	21.000	1716.000	0.000
	Wilks' Lambda	0.417	27.764	21.000	1637.282	0.000
	Hotelling's Trace	1.076	29.144	21.000	1706.000	0.000
	Roy's Largest Root	0.532	43.461^c	7.000	572.000	0.000
a. Design: Intercept + retail organization						
b. Exact statistic						
c. The statistic is an upper bound on F that yields a lower bound on the significance level.						

Source: Primary data

To determine how the dependent variable differs for the independent variables, the Univariate ANOVA tests were conducted for each dependent variable. The results shown in ***Appendix-H*** (tests of between-subjects effects) revealed that there was significant effect ($P<0.001$) of retail organisation groups on holding out on using big data analytics solutions. Further Tukey's HSD post-hoc tests were conducted to follow up the significant ANOVAs identified in ttests of between-subjects effects. By and large, the multiple comparisons table (shown in ***Appendix-J***) reveals that mean difference among retail groups for holding out on using big data analytics solutions was statistically significant ($p<0.05$).

<u>*Results*</u>: It was proved that there was significant difference exist among four retail organisations towards holding out on using big data analytics solutions. Further, the error variance of the dependent variable was also proved equal across groups among all major obstacles of big data analytics. Hence, null hypothesis ($H9_0$) is failed to be accepted and alternative hypothesis ($H9_a$) is proved to be accepted for holding out on using big data retail business analytics solutions. The results implied that there is an association between type retail organisation and holding out on using big data retail business analytics solutions.

$H10_0$: There is no difference of opinion among retail organisations on tangible business value of deployment of big data analytics to outperform competition.

$H10_a$: There is no difference of opinion among retail organisations on tangible business value of deployment of big data analytics to outperform competition.

To test the above hypothesis, Chi-square statistic is used for testing difference/ association between deployment of big data analytics and business value creation in retail organisations. The Chi-square statistic results ($\chi^2=5.71$, df 15, $p>0.05$) shown in Table 4.23 reveals that there is no association between big data analytics in the distribution of responses to business value creation among the comparison groups (i.e., four types of retail organisations). Thus, null hypothesis ($H10_0$) is proved to be accepted.

Results: The results implied that business value creation in retail organisations' is independent of deployment of big data analytics. It means that there is no association between the two variables.

$H11_0$: There is no difference in benefits of IOT technology in business functions among retail organisations.

$H11_a$: There is significant difference in benefits of IOT technology in business functions among retail organisations

To test the above hypothesis, Chi-square statistic is used for testing difference/ association between benefits of IOT technology in business functions and retail organisations. The Chi-square statistic results (χ^2=21.83, df18, p>0.05) shown in Table 4.24 reveals that there is no association between benefits of IOT technology in business functions among the comparison groups (i.e., four types of retail organisations). Thus, null hypothesis ($H11_0$) is proved to be accepted.

Results: The results implied that benefits of IOT technology in business functions are independent of retail organisations.

$H12_0$: Deployment of big data analytics will not mediate the relationship between customer process and customer acquisition in retail organisations

$H12_a$: Deployment of big data analytics will not mediate the relationship between customer process and customer acquisition in retail organisations

To test the above hypothesis, simple linear regression analysis is used to estimate the mediating effect of deployment of big data analytics on the relationship between customer process and customer acquisition. The resulting regressing models for customer acquisition with customer process mediated by big data analytics is statistically significant [F (2,577) =5.809, p=0.003]. The results shown in ANOVA Table 4.43 indicate that independent variable such as customer process and mediating variable big data analytics are related to dependent variable (i.e., customer acquisition). The modal summary of regression model for customer acquisition shown in Table 4.44 contributed meagrely and predicted 1.6 percent variation by customer process and mediating variable big data analytics.

Table 4.43: ANOVA statistics for customer process, moderating variable (big data analytics) and customer acquisition

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	28.276	2	14.138	5.809	.003[b]
	Residual	1404.240	577	2.434		
	Total	1432.516	579			
a. Dependent Variable: customer acquisition						
b. Predictors: (Constant), Mediator (big data analytics), customer process						

Source: Primary data

Table 4.44: Model summary for regression model

Model Summary									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.140[a]	.020	.016	1.560	.020	5.809	2	577	.003
a. Predictors: (Constant), Mediator (big data analytics), Customer service									

Source: Primary data

The coefficient summary for evolved regression models shown in Table 4.45 revealed that customer process (β=0.207, t=3.085, p=0.005) and mediating variable big data analytics (β=0.190, t=2.113, p=0.05) were the significant predictors for customer acquisition in retailing organisations. Thus alternative hypothesis ($H12_a$) is accepted.

Table 4.45: Coefficient summary for regression model

Model		Unstandardized Coefficients		Standardized Coefficients	t-value	Sig. (p-value)
		B	Std. Error	Beta		
1	(Constant)	2.349	0.286		8.213	0.000
	Customer process	0.207	0.067	0.133	3.085	0.05
	Mediator (Big data analytics)	0.190	0.058	0.086	2.113	0.05
a. Dependent Variable: customer acquisition						

Source: Primary data

Results: Although the regression modal was significant, the mediating role of big data analytics between customer process and customer acquisition is significant but not strong. Overall, the results indicate that null hypothesis ($H12_0$) is failed to be accepted and alternative hypothesis ($H12_a$) is proved to be accepted. It indicates that there is a need to improve the effective use of big data analytics in customer acquisition process.

$H13_0$: Retailers' customer acquisition will not increase as their big data retail business analytics deployment increase.

$H13_a$: Retailers' customer acquisition will increase significantly as their big data retail business analytics deployment increase.

To test the above hypothesis, simple linear regression analysis is used to estimate the influence of big data retail business analytics on customer acquisition. The resulting regressing model for customer acquisition with big data analytics is statistically significant (F (1,578) =83.650, p=0.001). The regression modal summary results shown in Table 4.46 indicate that independent variables are related to dependent variable, and predicted by 12.6 percent variation by big data analytics in customer acquisition.

Table 4.46: Regression modal summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	0.356[a]	0.126	0.125	1.127	0.126	83.650	1	578	0.000
a. Predictors: (Constant), big data analytics									

Source: Primary data

The coefficient summary for evolved regression models shown in Table 4.47 revealed that big data analytics (β=0.320, t=9.146, p=0.005) had significant influence on customer acquisition in retailing organisations. Thus alternative hypothesis ($H13_a$) is accepted.

Table 4.47: Coefficient summary for regression model

Model		Unstandardized Coefficients		Standardized Coefficients	t-value	Sig. (p-value)
		B	Std. Error	Beta		
1	(Constant)	2.230	0.107		20.826	0.000
	Big data analytics	0.320	0.035	0.356	9.146	0.000
a. Dependent Variable: customer Acquisition						

Source: Primary data

<u>Results</u>: The results disproved the null hypothesis ($H13_0$) and accepted alternative hypothesis ($H13_a$) that the increase of deployment of big data analytics significantly increase the customer acquisition in retailing.

***$H14_0$*: Retailers' customer retention will not increase as their big data retail business analytics deployment increase.**

***$H14_a$*: Retailers' customer retention will increase significantly as their big data retail business analytics deployment increase.**

To test the above hypothesis, simple linear regression analysis is used to estimate the influence of big data retail business analytics on customer retention. The resulting regressing model for customer retention with big data analytics is statistically significant (F (1,578) =158.608, p=0.001). The regression modal summary results shown in Table 4.48 indicate that independent variables are related to dependent variable, and predicted by 21.3 percent variation by big data analytics in customer retention strategies.

Table 4.48: Regression modal summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.464[a]	.215	.214	.399	.215	158.608	1	578	.000
a. Predictors: (Constant), big data retail business analytics									

Source: Primary data

The coefficient summary for evolved regression models shown in Table 4.49 revealed that big data retail business analytics (β=0.169, t=12.594, p=0.0015) had significant influence on customer retention in retailing organisations.

Table 4.49: Coefficient summary for regression model

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig. (p-value)
		B	Std. Error	Beta		
1	(Constant)	1.352	0.051		26.547	0.000
	Big data analytics	0.169	0.013	0.464	12.594	0.000
a. Dependent Variable: Customer Retention						

Source: Primary data

<u>Results</u>: The results failed to accept null hypothesis ($H14_0$). The alternative hypothesis ($H14_a$) is proved to be accepted that the increase of deployment of big data analytics significantly increase customer retention in retailing.

CHAPTER-6 SUMMARY OF FINDINGS AND KEY SUGGESTIONS

This chapter endeavours to serve the following: a) describing the finding and conclusions of the study; b) offering suggestions to retail organisations to tap the potential benefits of big data retail business analytics to gain competitive advantage; c) mentioning constraints of the study; and finally, ending with the directions for future research in this area and related areas of this study.

The main objectives for this study were:

1. To explore and identify the important parameters and perceptions of big data business analytics in Indian retailing functional areas,
2. To explore and examine the seriousness and holding out of using big data retail business analytics solutions in managerial decision making,
3. To identify and investigate the major obstacles and challenges in adopting and implementing big data retail business analytics infrastructure and tangible business value/benefits of using it in selected retail organizations to outperform competition Indian retailing industry,
4. To identify and examine the stumbling blocks and benefits/impact for the usage of IOT technology in selected retail organization of India,
5. To elicit the views and perceptions of retail managers and IT professionals regarding to the impact of the retail business analytics to achieve the business goals at present and future,
6. To investigate the mediating role of big data analytics in determining relationship between customer process and customer acquisition and also to examine the impact on customer acquisition and retention strategies in retail organisations,
7. To offer suggestions for the stakeholders of the retail industry for the sake of future retail business intelligence excellence.

FINDINGS OF THE STUDY

The main findings of this study were as follows:

- From the analysis it found that, there is a lack of consistent and clear perception of big data and big data analytics and this is shown by the multitude of perceptions used by retail managers, IT professionals although they are well versed the concept of big data analysts. Big data analysts are viewed in many ways hence significant differences.

- From the exploratory analysis it found that, veracity, variety, velocity, and volume as ranked first, second, third and fourth important parameters of big data retail analytics. There was no difference in the perceptions of important parameters of big data analytics among retail managers across four groups.
- Form the descriptive analysis it was observed that, survey respondents from four retail organizations viewed the use of big data analytics with equal seriousness. The results also implied that deployment of big data retail analytics in retail organisations is little and therefore were not serious of using big data retail analytics.
- The analysis revealed that, retailers have yet to find significant business value in deployment of big data analytics although big data analytics is in its infant stage in India. The results also suggest that the lack of seriousness among retailers towards big data analytics is the barriers, challenges and stumbling blocks impeding the adoption and implementation of big data analytics in retailing organisations.
- The analysis made key note that, majority of survey respondents' view that technology is the most important element of big data analytics, followed by skill set required to use big data analytics in retail organisations. Thus lack of adequate technology and competent employees to deal with big data analytics might lead the retailers to be non-serious towards use of big data analytics.
- From the analysis it found that, significant differences were found among survey respondents with respect to the objectives of big data analytics in retail organisations. As the primary goal of big data analytics is to help retailers make more informed strategic and operational decisions, the objectives of big data analytics are mutually exclusive and unique among four retail organisations.
- It is also observed that, the priorities of retail organisations are different hence the goals and objectives of big data analytics are different from retail organisation to organisation. The results suggest that some of the objectives of big data analytics are for creating competitive advantage for their organisations.
- The analysis revels the effects of respondents' perceptions/views/opinions from four retail organisations on major obstacles in adopting big data retail analytics indicated that moderate differences exists among four groups of retail

organisations. The obstacles in adopting big data analytics are dependent on type of retail organisation.

- From the analysis it found that, there is no difference in deployment of insights from big data analytics and type of retail organisation.
- The analysis also states that, the applied uses of big data analytics to real-world decision making are numerous, and retail managers from industry are achieving value with innovative new approaches. Key retail business areas such as customer-centric merchandising, targeted offers and promotions, demand forecasting and supply chain modelling, loyalty program management, store design and loss prevention are significantly impacted by big data retail analytics across four retail organisations.
- The exploratory analysis indicated that, better, fast-based decision making, more efficient operations, new product innovations, improved customer experience, higher quality products and services, and increased sales are the tangible values or benefits of deployment of big data analytics in retail organisations. The tangible business value of use of big data analytics and type of retail organisation are independent.
- Form the analysis it found that, customer engagement/experience management, digital marketing and sales, forecast future trends, operational processes, inventory/stock management, building customer trust models, and staff productivity are the tangible benefits of use of IOT technology in retail organisations. The perceived benefits of use of IOT technology in business functions among four types of retail organisations are same.
- From the analysis it was observed that, the big data analytics moderately mediated the relationship between customer process and customer acquisition in retail organisations. The results imply that big data retail analytics mediate the relationship between customer process and customer acquisition.
- From the multiple regression models indicated that, the influence of big data retail analytics had moderate influence on customer acquisition and customer retention. The analysis revels that, the data retail analytics such as predictive analytics play critical role in acquiring new customers by enabling retailers identify the prospects who are more likely to respond to specific campaigns and promotional offers, or purchase certain products or services when targeted.
- Form the analysis it observed that, a scalable customer acquisition strategy driven

by insights around high-value prospects, offers, channels, and times (e.g. weekends, working hours, or specific events) could be developed. The analysis also implied that with predictive analytics, retail organizations can successfully identify customers who are likely to churn, when and why.

KEY SUGGESTIONS

The statistically significant findings of this study hold specific general suggestions for retailing in India.

- It is suggested that retailers need to formulate well defined policies for analysing data gathered from various sources using big data retail business analytics although about 95 percent of retail managers sated that they have trust in their organisation's working on big data analytics considering its important role in informed decision making.
- There is a need to increase the access to relevant, accurate and timely big data across the business functions and processes to gain competitive advantage. The results also suggest enhancing the business analytics capabilities to create desired deeper insights of customers, markets and operations of retailing as most respondents viewed technology is the important element of big data analytics in apparel retailing. Findings also suggest need to improve the understanding of how to use advanced tools and techniques of big data analytics among the people who are involved and/or used big data analytics.
- The results suggest the importance of the veracity (reliability and quality data) of big data as half of the respondents said that it is the most important parameter of big data.
- Given the objectives of big data retail business analytics, retailers need to focus on understanding customers by establishing a single across multiple sources of customer information as customer centric outcomes is the uppermost objective of big data analytics.
- Results suggest that there is a need to create a unique technology platform to deliver actionable insights to the right resource at the right time seamlessly among
    - different users and different departments as they have different ways of measuring the business outcomes.
- With a growing amount of diverse and unstructured data, there is an urgent need for advanced analytic techniques, such as deep machine learning algorithm that allows

computers to detect items of interest in large quantities of unstructured data, and to deduce relationships without needing specific models or programming instructions.

- Retailers need to simplify the big data solutions that are intuitive to business users in order to decrease the cost and complexity of implanting big data solutions across business functions and processes in retail organisations.
- Results also highlighted the use of predictive analytics to predict future demand for products and services to optimise the performance of supply chain management.
- Need to adopt internet of things (IOT) technology at faster pace to obtain deeper insights from customer engagement/customer experience management practices by ironing out technical issues with interoperability between different solutions.
- Retail organisations typically need new enterprise IT architectures to work with vast volumes of data at speed. Thinking about data as an asset requires organizations to change their mind-sets, becoming more data-focused, and assembling and acquiring the skills needed to manage data at speed and at scale.
- The results found that not only do retailers seem to benefit from deploying big data analytics but that the benefits they can obtain are greater than what firms in other industries can obtain. These results might come as a surprise to some retailers, who neither seem to perceive this potential benefit nor seem to be willing to invest at a level that is in line with that benefit. It is hoped this research encourages retailers to change their beliefs about big data analytics, and that it also encourages academics to further explore the antecedents and impact of customer analytics in the retail sector.
- Need to allocate substantial budget and resources for adopting, implementing and deployment of big data analytics across business functions and processes.
- Results highlighted the influence of big data analytics in customer acquisition and retention strategies. It underlines the importance of predictive analytics and its use
    - in customer process and customer relationship management as predictive analytics seek to uncover patterns and capture relationships in data.

6.2 Limitations of the Study

Because the present research is a starting point for a new direction in studying the big data retail business analytics and its influence on customer acquisition and retention in retail environment, it has encountered a few limitations. The following limitations of the study are as follows:

1. First, the main measures in the study are perceptual, not objective.
2. This study is limited to apparel, food & grocery, consumer durables and entertainment retail organisations spread across four cities – Hyderabad, Secunderabad, Vijayawada, and Visakhapatnam only.
3. Accuracy of the data collection process is contingent on whether or not research team who administered the questionnaire followed the guidelines presented by the researcher.
4. This study has a cross-sectional rather than longitudinal design. That is the data for both independent variables and dependent variables are collected from the same individuals in the same measurement context at one point in time.
5. Although sample size is scientifically determined and found acceptable yet it is to be increased for generalisation of findings to the whole population of the study.
6. More importantly, Available resources (time and money) placed constraints on the size, depth and time frame of the study.

Care was taken throughout the research process to eliminate or at least minimise the stated and unforeseen limitations of the study.

CONCLUSIONS OF THE STUDY

There is no doubt that big data analytics in India is still in the initial stage of development. While big data analytics has been touted as a new research paradigm in many disciplines, it has been observed that very few empirical studies focused in the context of Indian retailing that fully explore and examine its capabilities. The uniqueness of this study lies in the use of big data from four distinct and prominent retail sectors in Indian retail environment. Although this study is a preliminary effort in big data analytics, this study has provided substantial insights into some of the nuances of different aspects and features of big data analytics by thoroughly assessing the current state of big data analytics in Indian retailing. As such, it is hoped that this study sets an example for the development of big data analytics in retail marketing and management. The following succinct conclusions are drawn from the results presented in chapter-4 and discussions held in chapter-5.

The present findings contribute to the better understanding of big data analytics in retailing in India, an area that has received scant attention within the academic literature. From the findings, it is evident that retailers in India are not using big data analytics, due to the lack of an obvious use case to justify the implementation costs. Furthermore, the study has shown a debate around the definition of big data analytics, as well as a multitude of conflicting perceptions on the concept. The findings showed that retail organisations are not very serious toward using big data analytics because there is a focus on exploiting existing structured data completely before tapping into unstructured and semi structured data. Some retailers are, however, leveraging the enhanced processing speeds of big data analytic products to improve on traditional analytics. Thus, this research encourages retailers to change their beliefs about big data retail business analytics, and it also encourages academics to further explore the antecedents and impact of big data analytics in the retailing industry.

The overall results of this study show that there is no difference among four retail organizations in relation to important parameters, important elements of big data analytics. However, 'veracity of the big data' and 'technology of big data analytics' are emerged as the most important parameter and element of big data retail business analytics respectively.

The results underline the extreme importance of big data retail business analytics across four retail organizations albeit they are not very serious of using big data analytics as lee than adequate access to relevant, accurate and timely big data as well as availability of big data analytics capabilities in retail organizations.

The statistical results also highlighted customer centric outcomes and operational optimizations are the most sought after objectives of big data retail business analytics across four retail organizations. It is understood that desired outcomes of big data retail business analytics are customer engagement/experience management and optimizing retail operations.

The statistically significant findings emphasized that understanding customers by establishing a single view across multiple sources of customer information (point-of-sale, loyalty program, social media, etc.) is the key challenges, apart from other three challenges, needs to be addressed across four retail organizations. The study also identified twelve major obstacles in adopting big data retail business analytics in retail organizations. Out of which, 'lack of understanding of how to use data analytics to improve the business' is the major obstacle in adopting the big data retail business analytics. It is understood that big data analytics has not been integrated with the organisational vision and mission as seriousness toward the use of big data analytics is minimal.

Supporting the aforesaid findings, the findings emphasise delivery of insights to the right resource at the right time is the key challenge that prevent retailers from implementing big data analytics across four retail organisations. This is due to lack of clearly articulated analytics strategy in retail organisations as it is identified as second challenge in implementation of big data analytics. Furthermore, the results identified and examined that different users and different departments have different ways of measuring the business is the biggest obstacles in getting big data analytics in order to make better data-driven business decisions in retail organisations besides five other biggest obstacles. The statistical findings also underlined the cost and/or complexity of implementing of big data solutions is the obstacle preventing retail organisations from using big data.

The findings underline customer and market analysis, followed by product development and management are two major business functions in the retail organisations stand to make the best use of insights from big data retail business analytics. In alignment with earlier findings, customer centric merchandising, targeted offers and promotions are the chief business processes immensely benefited from the big data analytics in retail organisations. The study identified six kinds of business values of using big data analytics. Out of which, better, fast-based decision making is the ultimate tangible value derived from using big data analytics across four retail organisations.

The study identified seven tangible benefits of using IOT technology in retail organisations. Out of which, customer engagement/customer experience management is the business area benefited most from the use of IOT technology in retail organisations. The study also identified seven stumbling blocks which prevent retail organisations from adopting IOT technology. Out of which, technical issues with interoperability between different solutions, followed by fragmented eco-system not enough successful partnerships being formed, data privacy and security are the first, second and third important stumbling blocks to IOT adoption in retail organisations.

The study identified six most important goals of big data retail business analytics across the four retail organisations in the coming five years are improving customer insight, improving operational efficiency, increasing business agility, improving operational transparency, predicting business performance, and spotting future business trends. The research also identified ten investment and adoption areas such as web or social media analytics, digital dashboards, master data management, data visualization, big data analytics, enterprise data warehouse, mobile business intelligence, predictive analytics, Olap + basic reporting & querying, and enterprise bi analytics tools are the big data retail business analytics solutions over the next five years. Out of which, web or social media analytics is the highest priority area in which retail organisations invest and adopt big data retail business analytics solutions over the coming five years.

The statistically significant findings underscored the influence of big data retail business analytics in customer acquisition and retention strategies in retailing. The findings also revealed the mediating role of big data retail business analytics in the relationship between customer process and customer acquisition in retailing.

DIRECTIONS FOR FURTHER RESEARCH

Some of these limitations may be used as directions for future research in this area and related areas of the present study are as follows:

a) First of all, the study was based in a limited amount of interviews with retail managers during exploratory study and sample size in main survey is not big that sounds big data and although they were with the most knowledgeable on the matter, they might not represent the whole picture of the retail organization, which can be better captured in further studies. In addition, the perceptions and

views/opinions of respondents are subjective rather objective. Moreover, investigating the perceived organizational effects of a phenomenon which is very recent, and therefore companies engaging in big data analytics are still in the beginning of that process.

b) The findings also show that there are many avenues for exploring and conceptualizing the multifaceted nature of big data analytics. It is important to have an acceptable conceptual framework for capturing the business value in a systematic manner in this research stream. Therefore, future research can focus on developing explanatory and predictive theories that encompasses all cross functional facets for better understanding and growth of knowledge in this domain. Specifically, future research can explore topics, such as, leadership, talent management, technology and tools, information eco-systems, company culture, data privacy, business value and decision making process, which have an enormous impact on 'big data analytics' implementation.

c) In addition, the definitional perspectives and findings can be used as a research agenda for future in this nascent area. We emphasize the importance of 'big data' orientations and related managerial and operations issues as an area in which further research is urgently needed. Future organizational performance is inextricably interlinked with these orientations, which can ensure hard to replicate competitive advantage and business results.

d) Future research using a longitudinal approach would be useful to focus on how changes in the deployment of customer analytics affect (subsequent) firm performance.

e) Future research based on larger samples from multiple cities may yield different findings.

f) The present study focused on the most abstract business processes such as operations, marketing, etc.. In the future there is a need to explore business processes in detail (e.g. process of customer relationship management or sales) and to evaluate the best implementation points for big data analytics. That helps to improve business processes (e.g. reduce process time and process costs, improve process quality) in detail.

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