Small Businesses and the Use of a Market Information System: An Experimental Approach

Konrad Jakub Maliszewski

A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy.

University of East Anglia,
Norwich Business School

February 2021

Abstract

The ongoing digital revolution is redefining not only certain industries but also the wider society and economy. One of the major promises of the digital transformation for businesses is the increased capability of evidence-based decision-making, thus increasing the effectiveness of decisions and reducing associated costs. Data is one of the most important business assets, and the ability to incorporate it into decision-making is an essential ingredient for success. However, small businesses are inherently at a disadvantage due to their scarce resources and informal, often intuitive, management style. Not only do they lack strategic management capability and processes that facilitate evidence-based decision making but they also struggle with adopting and using information technology that is a necessary component of this. Nonetheless, they are the backbone of the economy and their survival is key for preserving thousands of jobs and the healthy functioning of the fabric of society.

This study investigates this general problem in the specific context of small food and drink producers supplying a major UK supermarket. The focus is on marketing decision-making and the use of a custom-built market information system. A behavioural lens was applied to the design of a theory-based intervention to increase system use. Environmental restructuring, which involved a change to the data presentation format, was identified as a viable intervention with a scope to make the system more adjusted to the specific context of this study. Two experiments were conducted to test the effectiveness of the intervention. First, a laboratory experiment with 154 students tested the impact of different data presentation formats on decision-making performance. Second, a 9-month long field experiment with 113 small food producers built on the findings from the laboratory experiment and investigated the scope for the change in data presentation format to influence actual system use behaviour.

The results of this study make a number of contributions to theory, method and practice. Broadly, the study demonstrated how behavioural analysis combined with design science and experimental methods can deliver impactful interventions amongst small businesses. Specifically, it revealed the causal effect between the data presentation format and actual system use behaviour. The importance of incorporating contextually relevant variables is also highlighted. Methodologically, the study highlighted the shortcomings in previous studies treating system use as a dichotomous variable and the reliance on reported usage instead of objective measures. Finally, the study resulted in an improved version of the market information system, which is now used by over 120 small food businesses to inform their marketing decisions. In this way this study has improved the usage of invaluable market information, which will help small businesses to become more competitive and better prepared for the digital revolution.

Table of Contents

List of Tables

List of Figures

Acknowledgments

This doctoral project would have never taken place and succeeded without support from a number of organisations and individuals, who were not afraid to do something novel that crossed the traditional boundaries. I would like to thank all of them and express my utmost gratitude for the opportunity to work with them.

Tesco and dunnhumby are the two organisations which constituted a considerable part of this study. I would like to thank the key people for enabling such an unusual partnership between their organisations and the University of East Anglia. Special thanks go to Emma Hutchinson who invested extra effort to secure our partnership.

Invest Northern Ireland is another organisation which was instrumental to this project. Thanks to their generous funding we have been able to offer support to small food and drink producers from all over the country. Their Customer Insights Team is led by Thelma Fitzgerald. Thelma made it her mission to ensure that small food and drink producers have the necessary skills and access to relevant sources of information to be competitive in the 21st century. She and her team are doing tremendous work that has greatly influenced this study. She is also a creative, knowledgeable and kind person. I have been privileged to work with her.

This project was fully focused on learning how small food and drink producers operate, the opportunities and challenges they face. I spent four years working very closely with absolutely brilliant small businesses from across the country producing everything from pork scratchings to amazing soft drinks. Despite the many challenges they face they have always been willing to pick up the phone to chat or even to welcome me in their offices. Many of them have sustained me with never-ending parcels of samples. Thanks to all of you for giving me this opportunity to learn. Keep up the good work!

I would also like to thank my fellow PhD students, especially Artyom Gollosenko and Amin Vafadarnikjoo. Both our causal chats and our thought-provoking discussions during the “very important lunches” were key to keeping me sane during this time. Special thanks to Artie for helping me with conducting the laboratory experiment.

Andrew Fearne and Stefan Penczynski were my supervisors, and I am eternally grateful for all of our stimulating discussions, helpful feedback and any other moments we shared. Stefan introduced me to the arcane world of experiments that became the central method of this research. Thanks for your insightful comments and willingness to engage in multi-disciplinary research.

Andrew has not only been my primary supervisor (since my master's degree) but also a true mentor. Andrew has never spared his time or efforts to support me in my development as a student and as a researcher. He presented me with numerous opportunities to engage widely with both the academic and practitioners' worlds. He has taught me what research truly is about and always treated me like a peer. He convinced me that I should never be afraid to follow a different path and under-value myself. His humour, curiosity, energy and motivation are an inspiration to me every day. All of these lessons were invaluable and will stay with me for the rest of my life. Thank you, Andrew!

Finally, special thanks go to my parents, Marzena and Jacek, for giving me the necessary foundations to accomplish everything I have accomplished so far; for always being there for me and supporting me in every endeavour I undertook. Thanks to my sister Sandra, who is so curious about the world that she was curious enough to ask what my research was about.

And of course, thanks to my wife Hania, for her never-ending patience, support and ability to motivate me regardless of the circumstances. She actually listened to me repeating the argument so many times she learnt nothing new from reading my thesis… This must be love!

Introduction

The purpose of this brief introduction is to explain the unusual structure of this thesis, which reflects the author's learning journey resulting from the adoption of the Design Science Research Methodology (DSRM). DSRM is a rigorous procedure for conducting Design Science (DS) research. DS is a research paradigm with its roots in the pragmatist philosophy that attempts to make novel contributions to knowledge whilst delivering solutions to real-world problems which can be easily used by practitioners. Since this research was deeply rooted within the Who Buys My Food project, a collaborative action research project working with over 100 small food and drink producers, it was deemed to be an appropriate choice.

The thesis is structured in the following way. Chapter 1 is used to define the broad research problem, the importance of using evidence in marketing decision-making and the specific context of small food and drink producers involved in a research project that gave them access to an innovative market information system. Chapter 1 concludes with research aim and objectives. Chapter 2 offers a novel theoretical framing, behavioural lens, through which to study the system use amongst small businesses and justifies the two research questions addressed in the experimental chapters, which are part of the problem solution. Chapter 3 introduces the over-arching methodological approach of Design Science and the Design Science Research Methodology that guided the study. The experimental method is identified as appropriate to implement the design loops. Chapters 4 and 5 describe a laboratory and field experiments, each of them corresponding to one of the research objectives. Each study chapter has its own brief introduction, with a specific and relevant literature review which proposes formal hypotheses to be tested, followed by method description and the reporting of the results. The study is summarised in Chapter 6, which discusses the main contributions to theory and practice. The limitations of the study and recommendations for future work are discussed in the final chapter.

As a result of this structure some strands of the literature are re-visited in different chapters. For example, the concept of cognitive style is identified in Chapter 2 as an important user characteristic with the scope to moderate impacts of data presentation format on the resulting user behaviour. In Chapter 2 only a general comment is made about its role in the design of the intervention. However, in Chapters 4 and 5, specific studies concerned with cognitive styles are re-visited in more detail in order to propose formal hypotheses which are tested in the experiments. The repetitions are kept to minimum, but they do happen as brief summaries of the points made earlier in the document are deemed necessary to inform the reader of the theoretical justification for the two experiments, the objectives of which were linked but not shared.

1. Problem Identification

The aim of this chapter is to introduce the research problem central to this thesis and explain why it is important to solve it. The research problem is defined by the means of reviewing the current state of knowledge pertaining to the problem, with the use of the extant academic and practitioner literatures. The chapter is structured as follows. First, the forces shaping the so-called digital revolution and the impact it is having on businesses is presented. The contrasting responses of large and small businesses are discussed. Second, the extant literature on small businesses is reviewed to help with the understanding of this disparity. The review focuses on the economic importance of small businesses, their common managerial characteristics, their marketing decision making style and their relationship with information technology. Finally, the general discussion is made more tangible with the example of the grocery retail sector and the research project which motivated this study. The chapter ends with a proposition of a different approach which shapes the research objectives of this study.

1.1 The next 'revolution'

In the last few years, the business world has witnessed an unprecedent level of disruption (Makridakis, 2017; Grover *et al.*, 2018). Clearly, the world is never a stable place, and there is always change, but what is different about the current situation is its pace and the extent to which it penetrates all industries and affects all companies. It has been popularised under many names – Big Data (Watson, 2014; Erevelles, Fukawa and Swayne, 2016), Analytics 4.0 (Davenport, 2018) or AI revolution (Makridakis, 2017), to name a few. There are many debates about how those terms differ (see e.g. Power *et al.*, 2018; van Duin and Bakhshi, 2018; Hassan, 2019; Ågerfalk, 2020). However, what is relevant to this research project is what that "revolution" entails and means for businesses in general, and small businesses in particular. I will use terms AI, analytics or big data interchangeably (for stylistic reasons) to denote this wider revolutionary trend.

The AI or analytics revolution has been declared as such, as it is set to fundamentally change not only business management (McAfee and Brynjolfsson, 2012) but the whole economic order (Zuboff, 2019) or even what it means to be human (Plummer *et al.*, 2019). It is a product of a number of trends which have been amplified in the recent years, including the exponential growth of data, especially unstructured data, such as text, photos or videos (Figure 1), increased data storage and computing power capacities coupled with declining costs and the development and refinement of new algorithms and analytical techniques (Watson, 2014; Delen and Zolbanin, 2018; Peters and Duncan, 2020; Ågerfalk, 2020). As a result, technology is embedded into every aspect of our daily lives propelling a trend for the so-called "datafication" or the Internet of Things (IoT) (Lycett, 2013; van Duin and Bakhshi, 2018; Cearley *et al.*, 2020). Every person and every physical object which can be connected to the Internet have become incessant generators of behavioural data which is then mined to enable businesses to improve their offerings (Erevelles, Fukawa and Swayne, 2016; Grover *et al.*, 2018; Cearley *et al.*, 2020). The amount of data and the learning possibilities are so great that algorithms are increasingly said to shape the world and transform the reality as we know it (Lycett, 2013; Hassan, 2019).

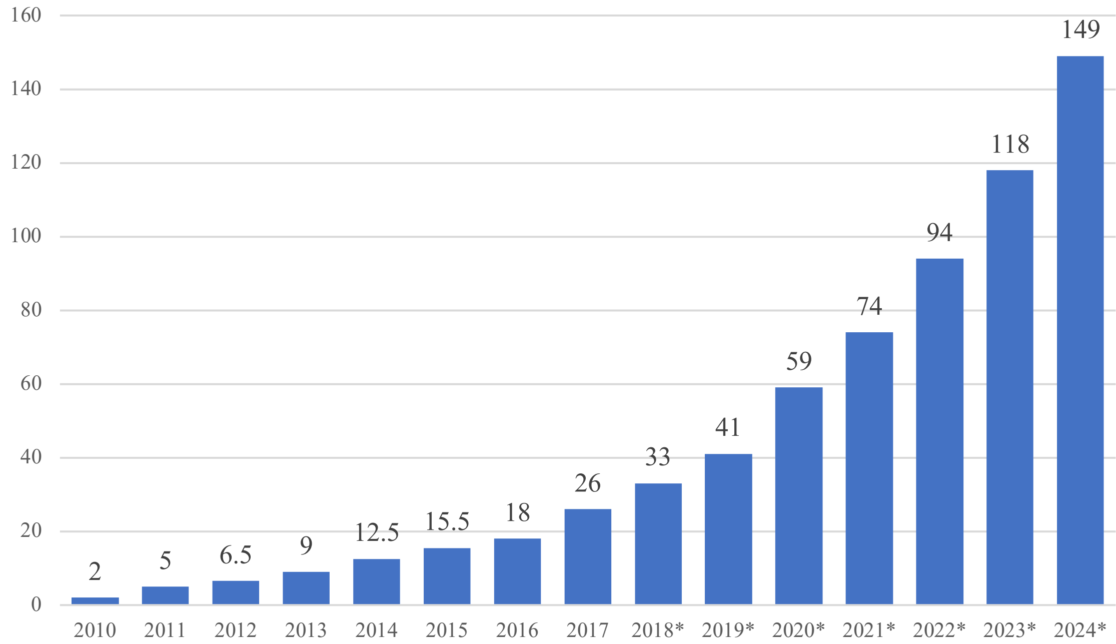


Figure 1 Volume of data/information created worldwide from 2010 to 2024 (in zettabytes[1], 2018-24 shows estimates) (adapted from Reinsel, Gantz and Rydning, 2018; Statista, 2020a).

[1] One zettabyte is equivalent to a trillion gigabytes.

The main promise of big data for managerial practice lies in its propensity to transform decision-making (McAfee and Brynjolfsson, 2012; Watson, 2014; Power *et al.*, 2018). Raw data and information technology (IT) is just infrastructure and will never deliver any value unless it is used by the relevant people in an organisation (Marchand and Peppard, 2013; Watson, 2014). Thanks to analytics "decisions no longer have to be made in the dark or based on gut instinct" (Henke *et al.*, 2016 in 'Preface'), businesses are now operating in an era of comprehensive analysis and experimentation, in which decisions are increasingly based on facts and evidence (Watson, 2014; Rao and Verweij, 2017; Grover *et al.*, 2018). Although intuition is not yet discarded as fully superfluous (Abbasi, Sarker and Chiang, 2016; Rao and Verweij, 2017), there is plenty of evidence of the superiority and competitive advantage delivered by utilising big data. Across all industries, data and analytics are deemed to be critical elements of business strategy (Peters and Duncan, 2020), the biggest commercial opportunity available (Rao and Verweij, 2017) and a primary business asset which is the source of competitive advantage (Abbasi, Sarker and Chiang, 2016; Delen and Zolbanin, 2018; Grover *et al.*, 2018), as they are bound to "lead to previously unimagined breakthrough performance and outcomes" (Manyika, 2017, p. 1) as well as significant improvements in productivity (Makridakis, 2017). What is more, academics and practitioners agree that no industry and no company is unaffected by this trend. Businesses can either develop the analytics themselves or, sooner or later, lose ground as a result of superior capabilities deployed by their competitors (Chen, Chiang and Storey, 2012; Watson, 2014; Henke *et al.*, 2016; Davenport, 2018; McKinsey Analytics, 2018; Cam, Chui and Hall, 2019; Rai, Constantinides and Sarker, 2019; Peters and Duncan, 2020; Ågerfalk, 2020).

However, despite its potential, big data is not yet distributed equally among the sectors and companies, with the disproportionate benefits mainly reaped by a small share of the so-called digital native organisations in a few most digitised and profitable sectors (Manyika, 2017; Cam, Chui and Hall, 2019; Gomes *et al.*, 2019; Rai, Constantinides and Sarker, 2019). Figure 2 presents how AI adoption is distributed among different sectors. Notably, retail and consumer packaged goods sectors (highlighted in green), which are of most interest to the present study, can be seen as late adopters as both current levels of big data adoption and predicted future spending are lagging behind other sectors.

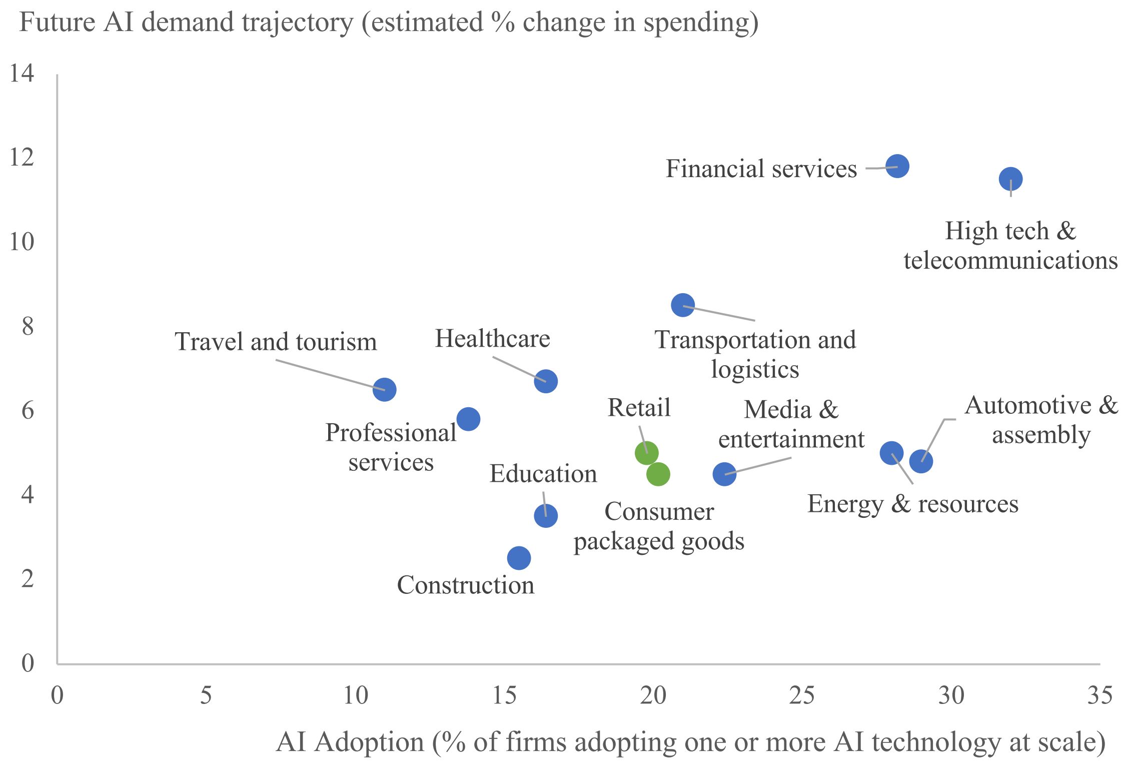


Figure 2 Sectors leading in AI adoption today and their intention to invest (adapted from McKinsey Analytics, 2018).

Digital native organisations, such as Google, Facebook, Amazon, Uber or AirBnb have been shaped by and within the digital world, which is elemental not complimentary to everything they do (Henke *et al.*, 2016). They have also successfully developed new data-driven business models which have disrupted numerous industries, leaving the incumbents playing catch-up ever since to also apply data to improve their operations and decision making (Watson, 2014; Henke *et al.*, 2016; Peters and Duncan, 2020). At first, these companies were confined to their respective industries, but they are quickly spilling over and disrupting numerous others.[2] Outside of the hi-tech sector, many big data initiatives are still in experimental and pilot stages driven primarily by large incumbent companies (McKinsey Global Institute, 2017; McKinsey Analytics, 2018) yet already delivering promising results (Watson, 2014; Cam, Chui and Hall, 2019).

---

[2] For example, Google started as a web search engine barely 20 years ago but, today, its recently formed parent holding company Alphabet includes companies developing autonomous cars, virtual reality, fitness or retail technology, with close to 250 acquisitions completed as of July 2020.
(see https://en.wikipedia.org/wiki/List_of_mergers_and_acquisitions_by_Alphabet)

However, large traditional businesses, e.g. Tesco or Sainsbury's that are relevant to this study, at least have the necessary financial and human resources to try to commence a digital transformation in order to compete with the digital native organisations, e.g. Amazon or Ocado, while small and medium sized enterprises (SMEs) are hardly ever mentioned in both academic and practice discourses despite their economic importance (see sub-section 1.2.2 for more detail). It is acknowledged that to thrive in the current climate every company has to embrace analytics regardless of its size (Davenport, 2018).

SMEs have been reported to be lagging in digital adoption of analytics, despite the fact that they do not have to deal with large-business issues, such as legacy IT systems or the challenges of instilling new corporate culture (McKinsey Analytics, 2018). In the UK, numerous reports from the public and private sectors acknowledge that SMEs face challenges adopting digital technology, which is negatively impacting their productivity and competitiveness (BMG Research and Durham University, 2015; FSB, 2017; BEIS Committee, 2018; Lloyds Bank, 2019). This is not true for all types of technology, as general adoption rates have been on the rise (Roper and Hart, 2018; Lloyds Bank, 2019). Small businesses are reported to be fairly comfortable with digital technologies used for communication (email, social media and websites), transactions (e-commerce, mobile payments, online accounting, etc.) and recognise the importance and challenges of cybersecurity (Lloyds Bank, 2019). However, they still struggle on one important dimension. A comprehensive report by Lloyds Bank on digitalisation of small businesses identified the lowest uptake of digital technology for activities classified as 'Problem Solving' (Lloyds Bank, 2019), with almost half of the businesses reported to not use it all for that purpose. This cluster of activities includes storing and managing digital information, using data for improving products and services, optimising website performance, and in general using digital technology to reduce costs and increase efficiency. Related to this is the use of machine learning and AI, which oscillates around 10%, with half of the small businesses admitting that they do not understand this technology at all (Roper and Hart, 2018; Lloyds Bank, 2019). Figure 3 summarises the detailed results of the survey analysing the understanding of technology by small businesses.

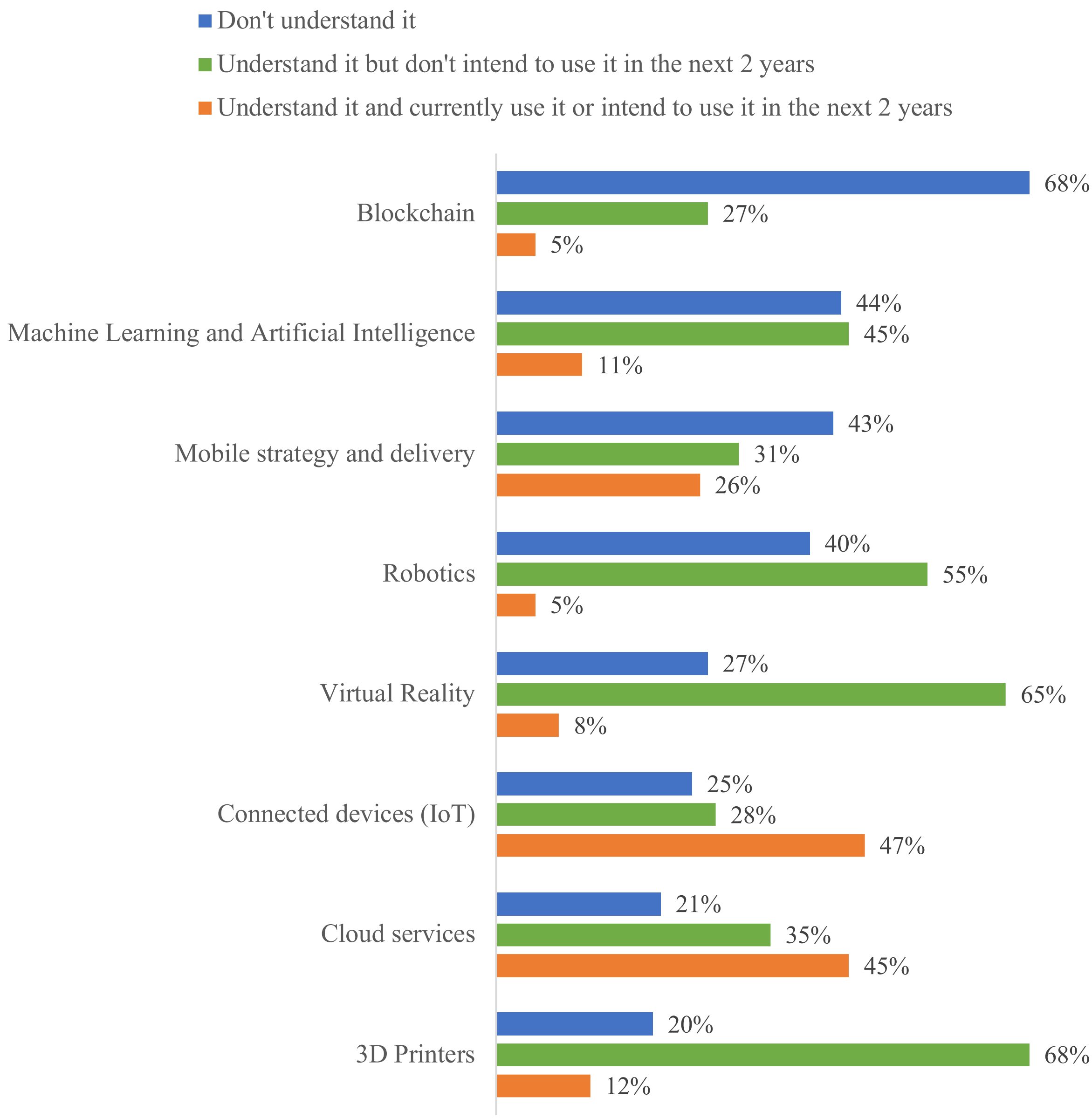


Figure 3 Proportion of small businesses and their understanding and plans with regard to the listed future technologies (adapted from Lloyds Bank, 2019).

Consequently, while the wider world is undergoing an AI revolution trying to make the most of the available data to improve their managerial decision making, almost half of small businesses do not even understand what it is and face the biggest hurdle with the basic use of data for decision making. This is especially relevant as while most of the small business owners recognise the importance of analytics but often lack confidence in their digital skills, a quarter do not deem technology to be important for growing their business and find technology stressful, complicated and "just a lot of hassle" (FSB, 2017; Roper and Hart, 2018, p. 33). This points to a huge divide between what is deemed mainstream in the general business world, and the state of affairs in the small business world.

1.1.1 Summary

It is evident that the business world, but also the wider economy and society, is facing an unprecedent level of change and disruption due to the combination of recent technological innovations. Most researchers agree that no business is safe from it regardless of their sector and size. Companies have to embrace data-driven business models and use data and technology to support their decision making in order to remain competitive. However, while many large incumbent firms only dabble in the latest technologies facing dire challenges from digital native companies, small businesses face even more severe challenges due to their inherent scarce resources and troubles with adopting technology. Not only barely 10 % of small businesses makes any use of machine learning or AI to improve their decision-making, but most of them actually find it difficult to use any structured data to run and develop their business. Why does such a disparity exist? The following sections delve deeper into the world of small business to provide a rationale for a discussion about the challenges and opportunities posed for small businesses by the ongoing analytics revolution.

1.2 SMEs

The previous section broadly characterised current trends that are shaping industries all over the world. The key element of those trends is the growing importance of data and the need for its effective use in decision-making with the use of new technologies. The analysis identified the disparity in the response to those trends between large and small businesses. The aim of the following sections is to examine the current state of knowledge with regard to small businesses to uncover the reasons for such a situation. First, the term small business is defined. Second, the economic importance of small businesses is presented. Third, common characteristics of small businesses are discussed which differentiate them from their larger counterparts. Fourth, the peculiarities of the decision-making style practiced by small businesses are explored. Finally, a detailed account of antecedents and barriers to technology adoption and use is provided.

1.2.1 SMEs defined

Small and medium-sized enterprises (SMEs) are described as the backbone of the European economy (Eurostat, 2020). Since this study is fully focused on the context of UK businesses, the role played by SMEs in the UK economy is described.

Most of the definitions of SMEs use the number of employees, with some organisations also including turnover (Eurostat, 2020). In the UK, an SME is a business that employs fewer than 250 people (Department for Business, Energy & Industrial Strategy, 2019). This can be further broken down into sole-proprietors (0 employees), micro (1-9 employees), small (10-49 employees) and medium businesses (50-250 employees) (Roper and Hart, 2018). Although most of the general statistics and academic research differentiates between large businesses (>250 employees) and SMEs, it is important to acknowledge that SMEs are not a homogenous group. It is easy to imagine that, for example, a micro family business employing a few people to brew and sell beer will be incomparable in terms of the resources, processes, strategy and operations to a brewery employing 200 people. Yet both businesses operate in the same industry, may well serve the same markets and are classified as an SME. Almost all of the businesses that are part of this study employ less than 50 people (more on the research participants in the sub-section 5.2.4), hence the focus is on micro and small businesses (1-49 employees) (referred to as small businesses), and this is what is meant whenever a reference to the study participants is made. However, not all statistics, reports and research studies break down SMEs into their respective segments, and the literature focusing solely on small businesses is very limited. So, mostly the literature with a broader (SME) focus is used, with the differentiation highlighted whenever that detail is available.

1.2.2 Economic importance

Why are SMEs important? Why are they described as the backbone of the economy? According to the latest Business Population Estimates, in the UK, there are close to 6 million businesses, with SMEs accounting for 99.9% of that number (Department for Business, Energy & Industrial Strategy, 2019). Those businesses also account for 60% and 52% of private sector employment and turnover, respectively. However, caution has to be exercised since 76% of those businesses did not employ anyone aside from the owner(s). Small businesses account for 23% of all businesses, 30% of the private sector employment, and generate 29% of the private sector turnover (Department for Business, Energy & Industrial Strategy, 2019). Regardless of their contribution to the economy, as a group, they are a very different breed of companies as compared to their larger counterparts.

1.2.3 Common characteristics

It is widely agreed that SMEs share a number of inherent characteristics which make them considerably different from larger businesses and impact the way in which they operate (McCartan-Quinn and Carson, 2003). One of the main differences is that SMEs face so-called “resource poverty” (Welsh and White, 1981), i.e. limited financial, human, material and informational resources (Shrader, Mulford and Blackburn, 1989; Blankson and Omar, 2002; Didonet, Fearne and Simmons, 2020). What is more, they often have inferior skills and lack the necessary expertise, e.g. in digital or managerial domains (Ates *et al.*, 2013; Roper and Hart, 2018; Wang and Wang, 2020). This often results in a negative approach to long-term planning and a reliance on informal organisational structures. As a result, they face continuous uncertainty and focus their scarce resources on surviving (McCartan-Quinn and Carson, 2003) and reactive tactics to achieve short-term gains (Länsiluoto *et al.*, 2019; Didonet, Fearne and Simmons, 2020). However, limited resources force them to be ingenious with what is available resulting in greater flexibility (Motwani, Jiang and Kumar, 1998; Alpkan, Yilmaz and Kaya, 2007). This often leads to the delivery of creative and innovative solutions (O’Dwyer, Gilmore and Carson, 2009; Didonet *et al.*, 2016). For instance, they are able to operate longer on slimmer margins and respond more quickly to changing customer needs than larger businesses.

Moreover, the success or failure of a business is critical to owner-manager’s personal and professional goals, meaning they are considerably more invested in the affairs of the business (Mazzarol, Reboud and Soutar, 2009). As a result, SMEs are characterised by a dominant presence of the owner-manager, with their own highly personalised management style (McCartan-Quinn and Carson, 2003; Blankson, Motwani and Levenburg, 2006). For example, many key relationships with both suppliers and customers often hinge on the relationships developed by the owner-manager through networking, which is one of the main marketing techniques employed (Gilmore, Carson and Grant, 2001; Donnelly *et al.*, 2012). Being close to the key stakeholders and the market has its pros and cons. One the one hand, it allows for a deeper understanding of customer needs and the development of close and intimate relationships (Pitkänen, Parvinen and Töytäri, 2014). On the other hand, it makes SMEs dependent on a relatively small customer base, threatening the long-term survival of the firm (Jones *et al.*, 2007).

Small size and the omnipresence of the owner-manager have their implications for the internal and external environment of small firms. Internally, SMEs cherish and celebrate traditional values, especially in family-owned businesses (Aronoff, 2004; Pérez and Duréndez, 2007). Thanks to the close-knit atmosphere, employees are often highly motivated and have meaningful relationships with their line manager and customers (Hernández-Linares, Kellermanns and López-Fernández, 2018). However, a smaller number of employees and the constant need to be resourceful means employees are often required to carry out a wider range of tasks (McCartan-Quinn and Carson, 2003). This results in many employees being generalists rather than specialists which can prove problematic as the company grows (Fuller, 1994; Gilmore, Carson and Grant, 2001). Finally, their limited size means that, individually, small businesses have little impact on the industry in which they operate, leaving them vulnerable to wider business trends, without the ability to influence or shape them (McGaughey, 1998; Motwani, Jiang and Kumar, 1998; Roper and Hart, 2018).

These inherent characteristics, to a large extent, influence all aspects of small businesses operations and shape their business style. Although they indicate that small businesses do not fare well with the adoption of large business management practice, “paradoxically, adoption of good management practices is deemed to be vital to small firms” (McCartan-Quinn and Carson, 2003, p. 203). Special attention is paid to planning and decision-making in the context of marketing, since this is a key set of activities performed by truly market oriented companies (Jaworski and Kohli, 1993) and this is where this study focuses. This is discussed in more detail in the next section.

1.2.4 Decision-making

Small businesses are not smaller versions of large businesses (Welsh and White, 1981), which means that management concepts and techniques developed by large businesses are not readily transferable to the context of small business management (McCartan-Quinn and Carson, 2003). Welsh and White identify the main differentiation point between small businesses and their larger counterparts in “a special condition”, so-called “resource poverty” (Welsh and White, 1981, p. 18) discussed in the previous section. That special condition results in most small businesses sharing inherent characteristics which impact the way in which they operate, especially with respect to marketing planning and decision-making (McCartan-Quinn and Carson, 2003). In general, their marketing decision-making is described as haphazard and informal (Gilmore, Carson and Grant, 2001), with long-term and strategic planning often left neglected (Länsiluoto *et al.*, 2019). Planning is viewed as in stark contrast to "the art of intuition" which is at the heart of small business management (McKiernan and Morris, 1994, p. S32). Owner-managers of small firms prefer to make their decisions based on their past experiences and common sense (McCartan-Quinn and Carson, 2003) or gut feeling (Moriarty *et al.*, 2008), rather than relying on the utilisation of traditional marketing techniques and tactics, which are perceived as stifling their flexibility. As a result, many small businesses "have their own way" of doing business as shaped and delivered by the owner-manager (Spillan and Ziemnowicz, 2003, p. 473).

It becomes obvious from the discussion above that the approach of small businesses to decision-making and planning is inextricably linked with the influence over the business of the owner-manager, just a single person with their own quirks and characteristics (Blankson, Motwani and Levenburg, 2006; Reijonen, 2010). Although it often results in a "distinctive marketing style" (Blankson, Motwani and Levenburg, 2006, p. 572), Shepherd et al. (2015) report that there are certain personality traits and other tendencies that differentiate entrepreneurs from non-entrepreneurs. For example, entrepreneurs tend to be more individualistic and open to change but score lower on traits, such as conformity. Interestingly, they also tend to rely more on nonlinear thinking processes, such as imagination, holistic thinking and intuitive judgment (Shepherd, Williams and Patzelt, 2015). However, research demonstrates that entrepreneurs and their enterprises can benefit from a more versatile thinking style that balances both linear (analytic and rational) and nonlinear (intuitive and creative) types of thinking (Groves, Vance and Choi, 2011). And yet, such a balanced thinking style is associated with greater experience and more years spent in higher education, which implies the importance of different tools in supporting linear thinking in a small business context.

Furthermore, the goals and objectives of the entrepreneurs with regard to their businesses have significant effects on their decision making practices, including the extent to which they employ formal management tools and technological solutions (Marcketti, 2006; Peters, Frehse and Buhalis, 2009; Dominici, Boncinelli and Marone, 2019). Research has shown that a considerable number of small business owners do not adhere to what are deemed typical entrepreneurial attitudes of business growth and profit maximisation (Peters, Frehse and Buhalis, 2009). Such entrepreneurs are often called "lifestyle entrepreneurs" as they have clear non-economic motives that have prompted them to start a business, such as fulfilling a lifelong dream (Lashley and Rowson, 2010), living close to nature in an iconic location (Dominici, Boncinelli and Marone, 2019) or, more generally, improving life quality by taking more control over their everyday life (Marcketti, 2006). As a result, they often enter the business without adequate prior experience and skills and learn by doing as they develop their business (Lashley and Rowson, 2010; Woodfield and Husted, 2017). Non-economic motivations combined with lack of adequate skills and experience mean that such entrepreneurs do not strive to develop formal practices or optimise their operations, which can easily be achieved with the appropriate use of formal tools and data in decision-making (Marcketti, 2006; Peters, Frehse and Buhalis, 2009). Lifestyle entrepreneurs or businesses with a high degree of such characteristics are prevalent in traditional industries such as food and drink production (Karali *et al.*, 2013; Howley *et al.*, 2015; Dominici, Boncinelli and Marone, 2019). According to Karali et al (2013), only 20% of the farmers participating in their study could be classified as truly “business-oriented”, i.e. farmers who treat food production as their primary source of income, develop long-term strategic plans and utilise formal farm management planning tools. In a similar vein, Dominic et al. (2019) distinguish between business and lifestyle oriented winemakers where the latter are far more concerned with expressing their personal style and creativity through the wine they create rather than a product based on a thorough analysis of the market that has the potential to increase the likelihood of a high selling and profitable product.

A related stream of research explores the peculiar small business decision-making practices focusing exclusively on family businesses. Family firms are especially relevant as they constitute most of the firms all over the world, especially among small businesses (Dunn, 1996; Nordqvist and Melin, 2010) and create a unique context due to the convergence of family and business realms (Carrasco-Hernández and Jiménez-Jiménez, 2013). The majority of firms participating in this study are also family businesses.

Family firms are often described as inflexible and resisting change (Eddleston, Kellermanns and Sarathy, 2008) as they are burdened by old traditions and practices set by the firm founder (Carrasco-Hernández and Jiménez-Jiménez, 2013). The firm’s founder is often the central decision maker within the business (Hatak and Roessl, 2015), characterised by the paternalistic and authoritative management style which denies autonomy and input from other employees (Chirico and Nordqvist, 2010). As a result, founders are often central repositories of an in-depth tacit knowledge about the business (Nordqvist and Melin, 2010) and custodians of long-standing personal relationships with customers, suppliers and even competitors (Hatak and Roessl, 2015). What is more, family firms experience special problems with regard to information sharing and decision making due to the double role that family members play – that of a family member and a business employee (Eddleston, Otondo and Kellermanns, 2008). This leads to family firms struggling to embrace formal marketing tools and incorporate data into their decision making (Bruque and Moyano, 2007; Woodfield and Husted, 2017).

However, family businesses display a strong long-term orientation (Hatak *et al.*, 2016) and a considerable concern for firm longevity and a successful transfer of the ownership to future generations (König, Kammerlander and Enders, 2013). The issue of intragenerational succession is a particularly fertile ground for inner family conflicts (Block, 2012; De Massis, Frattini and Lichtenthaler, 2012). It is most often a moment when two divergent viewpoints collide: that of an intuitive founder who has built the business with trial and error and younger generations who are more likely to have received a formal education leading them to propose new technological and rigorous solutions to improve the business, such as formal reporting or experimentation (König, Kammerlander and Enders, 2013; Woodfield and Husted, 2017). The succession process must be managed carefully as previous research has shown that the excessive involvement of the prior generation stifles the modernisation of the business (Eddleston, Otondo and Kellermanns, 2008) and decreases firm's innovativeness (Kellermanns *et al.*, 2012). Nevertheless, successful successions happen and share common characteristics, such as bi-directional learning, where successors spend time with the predecessors to acquire some of that tacit knowledge which underlies their decision making style (Jaskiewicz, Combs and Rau, 2015) and successors carefully manage the introductions of new decision-making solutions without alienating the older generations (Woodfield and Husted, 2017).

The extant research suggests that small businesses approach their marketing in an informal and intuitive manner driven by the ingrained characteristics, goals and motivations of the owner-manager or the firm founder (Bocconcelli *et al.*, 2018). Does that mean that small businesses are inherently unable to use more traditional marketing tools and techniques, especially with respect to the use of data to support their decision-making? Few recent studies suggest that this is not the case (Donnelly *et al.*, 2015; O'Connor and Kelly, 2017; Wang and Wang, 2020), and certain formalised and structured tools, such as "big data" have a potential to complement the informal marketing style of small businesses (Donnelly *et al.*, 2012).

Marketing planning is a complex process which requires collection, analysis and dissemination of data related to customers, competitors and firm performance (Jaworski and Kohli, 1993). It is a vital process enabling a firm to respond promptly to market changes and satisfy customer needs. Marketing intelligence, also dubbed as "big data" is a collective term for the aggregated data sources necessary for successful and effective marketing planning (Donnelly *et al.*, 2015). As it often involves highly formalised and structured data it seems to be to be in stark contrast to the marketing style of small businesses. However, it turns out that small businesses are able to successfully leverage insight provided by the structured marketing intelligence to build upon the intuitive feel for markets (Donnelly *et al.*, 2015; O'Connor and Kelly, 2017). Once exposed to the relevant data they were able to confidently target new customers with new products (O'Connor and Kelly, 2017). What is more, having an objective source of data within a company allowed inclusion of other employees (in addition to the owner-manager) in the decision-making process, in a way, democratising the marketing planning process (Donnelly *et al.*, 2015). Nonetheless, these studies highlight the belief that small businesses in most cases are not able to use off-the-shelf tools for big data analytics designed with big companies in mind (Wang and Wang, 2020). O'Connor and Kelly (2017) reported relevant marketing intelligence reports being delivered in one-to-one sessions by a trained facilitator, and even that resulted in a mixed success. Although this gives an indication of the potential for successful big data use amongst small businesses, it does not offer a sustainable solution.

The review of SMEs characteristics has revealed that they face serious resource constraints, which results, among other things, in a lack of strategic planning and informal and intuitive decision-making. This is exactly what information technology promises to alleviate – enhanced productivity (gaining more from the existing scarce resources) and evidence-based decision making. As early as by the end of the 20th century, researchers envisioned a way for SMEs to be enabled to use marketing tools normally reserved for large businesses thanks to the power of information and communications technology (ICT) (Hsieh and Lin, 1998). Information Technology (IT) in general, and ICT specifically, promise to alleviate resource constraints faced by small businesses and make practices, such as market research or marketing planning more available and accessible (Bocconcelli *et al.*, 2018). However, technology adoption and use come with its own challenges. This is discussed in more detail in the next section.

1.2.5 SMEs and IT

The extant small business literature highlights the resource poverty faced by SMEs, which shapes their business style in general and marketing practice in particular. It seems that the promises of digital technology could alleviate those challenges by enabling better allocation of scarce resources (improved productivity) through automation and evidence-based decision-making, extended reach to customers and suppliers and numerous other ways (BEIS Committee, 2018; Roper and Hart, 2018; Lloyds Bank, 2019). However, while some digital technologies are used quite extensively by small businesses, others are neglected. A report on digitalisation of small businesses in the UK prepared by Lloyds Bank (2019) states that: 92% of small businesses use email to communicate with their customers and suppliers and close to half make use of social media and cloud-based IT systems; around 80% use Internet banking, buy goods online and manage invoices and accounts via cloud-based systems; almost 50% sell online. But, at the same time, only half of the businesses ever use data to improve their operations and decision-making and less than 10% use latest technologies, such as blockchain, machine learning, robotics or virtual reality (Lloyds Bank, 2019). Furthermore, the adoption rates differ between sectors (with Construction, Manufacturing and Agriculture sectors facing the biggest barriers to their digital development) and depend on firm age and size (Roper and Hart, 2018; Lloyds Bank, 2019). Predictably, an important role is played by the owner-manager (Peltier, Zhao and Schibrowsky, 2012; Ghobakhloo and Hong Tang, 2013; Jones *et al.*, 2014). It is key to understand the antecedents of technology adoption among small businesses to shed light on the adoption disparities not only between large and small but also within the world of SMEs. The next section reviews the extant literature on that topic.

1.2.5.1 Definition

Before discussing the antecedents of technology adoption, just a note on definitions and terminology. There seems to be a plethora of inconsistencies and little effort to define information technology (Ghobakhloo *et al.*, 2011) in the SME literature. Studies usually start fairly generally with (information) technology or (information) system,[3] and then specify which particular example of technology they are focusing on (e.g. customer relationship management, supply chain management, social media, etc.) (see e.g. Ortiz de Guinea and Webster, 2013; Sergeeva *et al.*, 2017; Sykes and Venkatesh, 2017). In the SME literature the groups of technologies are mostly described as information and communication technology (ICT) (Díaz-Chao, Sainz-González and Torrent-Sellens, 2015; Morgan-Thomas, 2016), electronic commerce (EC) (Abebe, 2014) or enterprise application

[3] This already implies four different terms used interchangeably.

(EA) (Ramdani, Chevers and Williams, 2013). They have been defined in the following ways:

- ICT – "a collective term of a wide range of software, hardware, telecommunications and information management techniques, applications and devices that are used to create, produce, analyse, process, package, distribute, receive, retrieve, store and transform information" (Barba-Sánchez, Jimenez-Zarco and Martinez-Ruiz, 2007),
- EC – "the use of electronic networks and associated technologies to enable, improve, enhance, transform or invent a business process or business system to create superior value for current or potential customers" (Chaffey, 2009) or "conduct of any type of business via the internet" (Carter, 2001)
- EA – "EA include ERP, CRM, SCM and e-procurement systems"[4] (Ramdani, Chevers and Williams, 2013),

While ICT is probably the broadest umbrella term, there is a considerable overlap between them. In this study, the object of interest is **a range of software/hardware tools which are used to create, produce, analyse, process, package, distribute, receive, store and transform information to enable, improve, enhance, transform or invent a business process or business system to create superior value**, which will subsequently be referred to as technology/information technology (IT) or system/information system (IS). The definition is purposefully kept fairly general. This is to enable a synthesis of findings from the seemingly different strands of literature to understand the current general state of knowledge of information technology in the context of SMEs.

Additionally, it is essential to note the difference between technology "adoption" and "use", terms often used interchangeably in the literature. IT adoption is the decision made by a business to adopt a certain technology, i.e. introduce it to the business (Thong, 1999). Use is what comes after the initial decision to adopt and is a longitudinal event, driven by different factors than a decision to adopt. It is discussed in detail in Chapter 2. In a process sense, adoption is a prerequisite to use, but it is only through actual use that technology can deliver any kind of impact to a business. The following sections review the literature with that differentiation in mind, first focusing on studies on IT adoption and then on IT use.

[4] ERP – Enterprise Resource Planning; CRM – Customer Relationship Management; SCM – Supply Chain Management

1.2.5.2 IT adoption

This section focuses on the research that examines the antecedents and barriers to IT adoption amongst SMEs. In other words, what conditions a small business to decide to introduce a new technology and what hinders this decision? There have been a number of reviews synthesising what we know about IT adoption in the context of SMEs (Barba-Sánchez, Jimenez-Zarco and Martinez-Ruiz, 2007; Nguyen, 2009; Ghobakhloo *et al.*, 2011, 2012). They generally agree that there are three sources of antecedents and barriers: owner-based (personal), organisational and environmental (Peltier, Schibrowsky and Zhao, 2009), also grouped into internal and external factors (Nguyen, 2009; Ghobakhloo *et al.*, 2011). Each of these is now discussed in turn.

Owner-based

Unlike large businesses, most of the SMEs management decisions and daily practices are heavily influenced by just one person, the owner-manager (Nguyen, 2009; Shepherd, Williams and Patzelt, 2015; Bocconcelli *et al.*, 2018). The situation is very much the same in the case of IT adoption. The research has examined the influence of owner-manager's demographics and characteristics, attitudes and perceptions on the decision to adopt (Peltier, Zhao and Schibrowsky, 2012; Ghobakhloo and Hong Tang, 2013; Jones *et al.*, 2014).

It was demonstrated that innovativeness of the SMEs management positively influences the decision to adopt (Ghobakhloo and Hong Tang, 2013; Nguyen and Waring, 2013) as well as their business change and personal risk orientations (Peltier, Schibrowsky and Zhao, 2009; Peltier, Zhao and Schibrowsky, 2012). However, the demographics, such as age, gender and education had no significant influence on the decision to adopt (Peltier, Schibrowsky and Zhao, 2009; Nguyen and Waring, 2013). The work of Peltier et al. (2012) demonstrated significant negative influence of age and positive influence of education on product class knowledge, one of the most important predictors of adoption, thus indicating an indirect effect of age and education on technology adoption.

Product class knowledge, i.e. a perceived level of knowledge about a certain technology, is recognised as one of the most important factors positively influencing the decision to adopt (Peltier, Schibrowsky and Zhao, 2009; Peltier, Zhao and Schibrowsky, 2012). This is also closely linked with the positive perception of the benefits of the technology (Jones *et al.*, 2014; Kim, Jang and Yang, 2017) and the perception of the relative advantage it can bring to the business (Wolcott, Kamal and Qureshi, 2008; Peltier, Schibrowsky and Zhao, 2009). Owner-managers with positive attitudes toward technology understand how it can improve operational efficiency or help with reaching new markets and customers and therefore are more likely to adopt a new technology (Nguyen and Waring, 2013). The degree of benefit perception was actually shown to be one of the best differentiators between adopters and non-adopters (Ghobakhloo and Hong Tang, 2013). This then translates into the level of support and commitment towards IT offered by owner-managers, which increases the likelihood of technology adoption (Nguyen, 2009; Ghobakhloo *et al.*, 2011; Kim, Jang and Yang, 2017).

Based on the research into the personal factors of SMEs owner-managers it seems that the recognition of the need and perception of the benefits that the technology can bring to the business is far more influential than their inherent demographic characteristics.

Organisational

A second important dimension of factors influencing the decision to adopt is the organisational context. Based on the technology-organisation-environment (TOE) framework, Ramdani et al. (2013) demonstrated the organisational context, consisting of dimensions such as organisational readiness, ICT experience and firm size, to have the largest (compared with technological and environmental contexts) positive influence on the adoption of technology.

Further organisational factors often found to be hindering the process of adoption are resource constraints, especially lack of time, scarce financial resources and inadequate IT skills (Wolcott, Kamal and Qureshi, 2008; Durkin, McGowan and McKeown, 2013). Although Durkin et al. (2013) and Wolcott et al. (2008) propose resource constraints as important barriers to adoption, other studies have failed to show the impact of financial resources on the perceived benefits (Kim, Jang and Yang, 2017). However, this might be due to the lack of consideration of firm size as financial and time resources constraints are an especially acute barrier to technology adoption for micro-enterprises (Durkin, McGowan and McKeown, 2013; Jones *et al.*, 2014), which is consistent with the research concluding that firm size plays an important role as a determinant of IT adoption (Jeyaraj, Rottman and Lacity, 2006; Peltier, Zhao and Schibrowsky, 2012).

Another organisational factor with a considerable influence on IT adoption decision are employees. Employees' knowledge and degree of involvement were found to be important for successful IT adoption (Igbaria *et al.*, 1997; Nguyen, Newby and Macaulay, 2015). These in turn are influenced by the knowledge sharing practices within the firm (Zahra, Neubaum and Larrañeta, 2007; Nguyen, 2009) and the availability of relevant training (Igbaria *et al.*, 1997; Wolcott, Kamal and Qureshi, 2008). Employees' behaviour is generally conditioned on the existing organisational culture. If owner-managers or IT leaders instil within the firm the recognition of the need for change, the likelihood of adoption is substantially increased (Bruque and Moyano, 2007).

Finally, a firm's ownership structure and strategic orientation were also found to play a role. Family businesses, which are very common amongst SMEs, might approach the decision to adopt technology in a different way, as the management practice might be guided by factors other than rationality and logic (Bruque and Moyano, 2007; Eggers *et al.*, 2017). Furthermore, varied effects of entrepreneurial and market orientations on the adoption of technology have been observed (Peña, Jamilena and Molina, 2011; Abebe, 2014; Eggers *et al.*, 2017; Länsiluoto *et al.*, 2019). However, none of these studies consider the impact of firm orientations on the actual use of technology.

The finding that firm size is a very important predictor of technology adoption is a very relevant point for a study focusing on small businesses. What is more, it seems the attitudes of employees are somewhat neglected as they exert too weak an influence on the decision to adopt. However, they become more important when the actual use of technology is considered.

Environmental

A final dimension often cited as an important influence on the IT adoption is the external environment (Jeyaraj, Rottman and Lacity, 2006). This includes pressures exerted by customers, competitors and suppliers, who influence the owner's attitude towards technology (Simmons, Armstrong and Durkin, 2008; Jones *et al.*, 2014; Nguyen, Newby and Macaulay, 2015) and ultimately the decision to adopt (Durkin, McGowan and McKeown, 2013). Interestingly, government has not been found to be a significant influence (Kim, Jang and Yang, 2017). According to the TOE framework, environmental context includes industry, market scope, competitive pressure and external ICT support (Ramdani, Chevers and Williams, 2013) and was found to be a positive significant predictor of IT adoption. Moreover, market uncertainty and environmental hostility are also significant predictors of the decision to adopt technology (Peltier, Schibrowsky and Zhao, 2009).

An interesting remark is also made by Durkin et al. (2013), who engaged in action research with eight companies preparing to adopt social media. They discovered that adoption behaviour is very rarely driven by purposeful agenda of creating value for customers (to which research on the personal factors points) but rather by fear and anxiety of not adopting a tool generally perceived as essential. This might indicate that in larger quantitative studies, respondents who have already adopted a technology retrospectively rationalise their choices, when in reality in the process of adoption, different factors come into play, and they do not necessarily include, a rather rational, cost/benefit analysis.

Others

Finally, a few studies also mention technological context, i.e. relative advantage, compatibility, complexity, trialability and observability of the technological solution, to be an important predictor of the decisions to adopt (e.g. Ramdani, Chevers and Williams, 2013). A smaller number of studies examining this dimension is understandable due to the difficulty of objectively evaluating the IT artifact before it is actually implemented and can deliver anything.

It is also important to highlight the operationalisation of the adoption construct. Most of the studies referenced above treat it is as a binary construct (1 or 0, adopted or not adopted), which is probably appropriate for examining factors influencing the decision to adopt. The trouble with this approach is when the adoption is being related to organisational impacts as this treatment suggests that all of the companies which have adopted a certain technology are homogeneous with regard to the use of it. To deal with this problem some studies have looked at the extent of adoption, i.e. which features of the introduced technology are actually being used (Zhou, Chuang and Nakatani, 2009; Nguyen and Waring, 2013). Although they still rely on reported use not actual use, it is an important and informative development.

Having reviewed the research stream into the antecedents of IT adoption, the next section looks more closely on a few recent studies that have attempted to go beyond treating adoption as a binary construct and examined how SMEs are actually using the technologies they had adopted.

1.2.5.3 IT use

Research into the actual post-adoptive use of IT amongst SMEs is rather limited. A few studies that have explored this concept in more detail are mostly qualitative relying on interviews and observations (e.g. Hutchinson *et al.*, 2015). Although they lack the generalisability offered by larger quantitative studies they still provide extremely interesting insights into the actual use of technology and are in line with the recent calls to focus on "technology-in-practice", i.e. how technology is actually being used by organisations (Morgan-Thomas, 2016).

Hutchinson et al. (2015) carried out a three year case study with a medium sized retailer to examine the process of CRM implementation. Through interviews, observations and the analysis of company documentation they investigated what hindered the new technology from being fully utilised. They discovered that although the system was adopted and introduced to the businesses, most of the departments and managers struggled with making use of it, and the data it produced, instead they kept working as they used to do. The researchers discovered that old habits, lack of training and lack of formal decision-making structures, with a very poor example set by the owner-manager who used the system only to confirm his existing beliefs, were the major reasons. This study demonstrated that the mere presence of the system and data it generated did not change anything in the business operations due to the absence of behavioural change amongst employees. It is noteworthy that in the standard IT impact study, such a company would be treated as an adopter and performance impacts would be hypothesised, while a detailed investigation showed that the system was hardly ever used, and hence the impacts were impossible to achieve.

In a study which involved 12 micro enterprises Barnes et al. (2012) carried out semi-structured interviews to explore how they used Web 2.0 ICT to work collaboratively with other small businesses. As a result, they produced a framework with four different types of users. Users were classified depending on the type of technology used (simple vs sophisticated) and the purpose of use (control vs collaboration). Unlike classic adoption studies which ask whether a technology was introduced to a business they examined the purpose of use. They discovered that the tools were used to find external personnel which helped to reduce operational costs; to source suppliers and collaborators, generally to network, which provided the businesses with the capabilities necessary to complete the job, otherwise unavailable in-house; to communicate effectively and at low cost with the relevant stakeholders; and via communication to better understand customer needs resulting in the offering of customised services. The results show how the same suite of tools can be used very differently by different businesses, and yet again that the mere fact of adoption does not always mean the same thing for each business.

Baird et al. (2017) in their four year action research with ten small physician practices went beyond simple investigation of technology use. They argued that small business, unlike larger ones, do not have formal organisational change plans and comprehensive training programs whenever a new system is introduced, and they quickly navigate towards “good enough” or “satisficing” use of the technology. However, to make the most of the IT and for it to have the greatest impact, users have to engage in constant learning and reflection to improve their use of the system capabilities. Through their research they organised bi-monthly joint workshops and individual consultation to facilitate reflection and learning. They discovered that thanks to these interventions the physicians started optimising their workflows and making more use of the system features.

The qualitative studies on the actual use of technology amongst SMEs shed light on this rather neglected concept. They clearly point out the heterogeneity amongst adopters and the dangers that stem from treating them as a homogeneous group. There were few attempts at incorporating actual use to the quantitative studies but they relied purely on reported or even perceived usage rates, with respondent asked to estimate, e.g. on average how much time they used the system daily or the number of reports generated (Ruivo, Oliveira and Neto, 2012; Ruivo *et al.*, 2013). Although an attempt to incorporate the actual use, and the argument for doing so, are very much welcomed, its reliability might be doubted due to the widely recognised inability of people to correctly estimate and a simple failure of human’s memory. In a similar vein, Popovič et al. (2019) attempted to distinguish between routine and innovative use of technology but actually they only looked at perceived routine and innovative use. What is more the questions to measure the constructs are arguably rather difficult to answer, e.g. “We often use more features than the average user of the technology to support our work” as this assumes that each user is well aware of the average use of an average user. This again brings in the obvious issues with the ability to estimate and reflect on the behaviour of other users.

Although there were few attempts to investigate the actual use of technology amongst SMEs, it seems this concept is rather neglected. When studies do actually focus on technology as it is used by small businesses, they examine the practice of using it without really answering what determines the use or non-use of technology after it was adopted by a business.

1.2.6 Summary of SMEs research

All businesses are under the pressure to make more effective use of data and analytics, but a considerable disparity exists between large and small businesses. The aim of this section was to review the current state of knowledge about small businesses to discover the reasons for the divergent response. The literature review points to two main reasons. One is concerned with the characteristics of small businesses, while the other has more to do with how we, as researchers, approach the study of this problem.

SMEs inherently are faced with scarce resources, which impact how they conduct their business. The result is an informal and intuitive management style centred around one key person, the owner-manager. Subsequently, the characteristics, perceptions and behaviour of that one person exert a significant influence on how decisions are made and the extent to which new technology is adopted and used throughout the whole organisation. Often, since there are no formally defined processes and procedures which can be altered as necessary, the problem boils down to the existing habits and continuing with "business as usual". However, there are a few case studies which suggest that there is a scope for small businesses to effectively use data and technology, given the right circumstances. When the right people are targeted with the relevant and contextualised interventions, small businesses embrace data and technology and cherish the value its use delivers.

This points to some of the concerns with certain research studies. First, the exaggerated focus on adoption of technology, without enough attention paid to whether it is ever used. Second, the scarce use of objective behavioural metrics in favour of asking people to report what they do. Finally, interventions designed to operate mainly in the rational plane despite all the evidence suggesting that small businesses tend to be led by their intuition and ingrained habits. This results in a difficulty to assess the real scale of the use of data and analytics by small businesses and explains the failure to make a difference. It also, provides some indication of how to approach the design of different solutions with a higher likelihood of success (more details to follow in Chapter 2).

Having identified the research problem, the following section puts it into the specific context of this study. A tangible example of what was discussed so far is provided using the case of the grocery retail sector and a research project operating in that space.

1.3 Grocery retail and the “Who Buys My Food” research project

Previous sections described the wider trends shaking up the business world and the commonly faced challenges by small businesses in terms using data and technology to facilitate evidence-based marketing decision-making. This section focuses on the grocery retail sector in the UK. This sector is discussed in detail as it is the setting of the research project that motivated this study.

1.3.1 Grocery retail

Retailing is a very expansive and diversified industry with a central role in the economy (Dekimpe, 2020). Grocery retail in the UK is a sector with a value close to £200b in 2019 (Mintel, 2020a; Statista, 2020b) and involves thousands of businesses from multi-national corporations (MNCs) to local micro enterprises. For years the market has been dominated by large scale supermarkets but their market share has been consistently falling in the last decade – from almost 60% in 2013 to barely 50% in 2020 (see Figure 4) (Mintel, 2019; Statista, 2020b). In the recent years the whole industry had to evolve rapidly to accommodate changing customer tastes and behaviours, such as the increasing search for value (the rise of discounters) and the need for convenience (new store formats and the expansion of the omnichannel – the rise of online) (Nielsen, 2018; Mintel, 2019; Edge, 2020).

However, the ongoing digital revolution is said to be a “game changer” (Grewal, Roggeveen and Nordfält, 2017), with a “systemic structural impact” (Reinartz, Wiegand and Imschloss, 2019, p. 353) and the promises of fundamental transformations of all aspects of the retail operations (IGD, 2018; Genpact, 2020). For example, in the shoppers’ path to purchase thousands of data points are generated (Mintel, 2019). Companies which are able to connect all those data points and use them to fuel their marketing decision making will thrive in the near future (IRI, 2017; Genpact, 2020). AI and data analytics is set to take shopper insight to a new level resulting in increased personalisation and product innovations (Edge, 2020). Other potential use cases are envisioned to improve demand forecasting, inventory management, to develop highly-responsive manufacturing and supply chain systems, or to increase store automation, just to name a few (Barclays, 2018; IGD, 2018, 2019; Reinartz, Wiegand and Imschloss, 2019; Dekimpe, 2020; Edge, 2020).

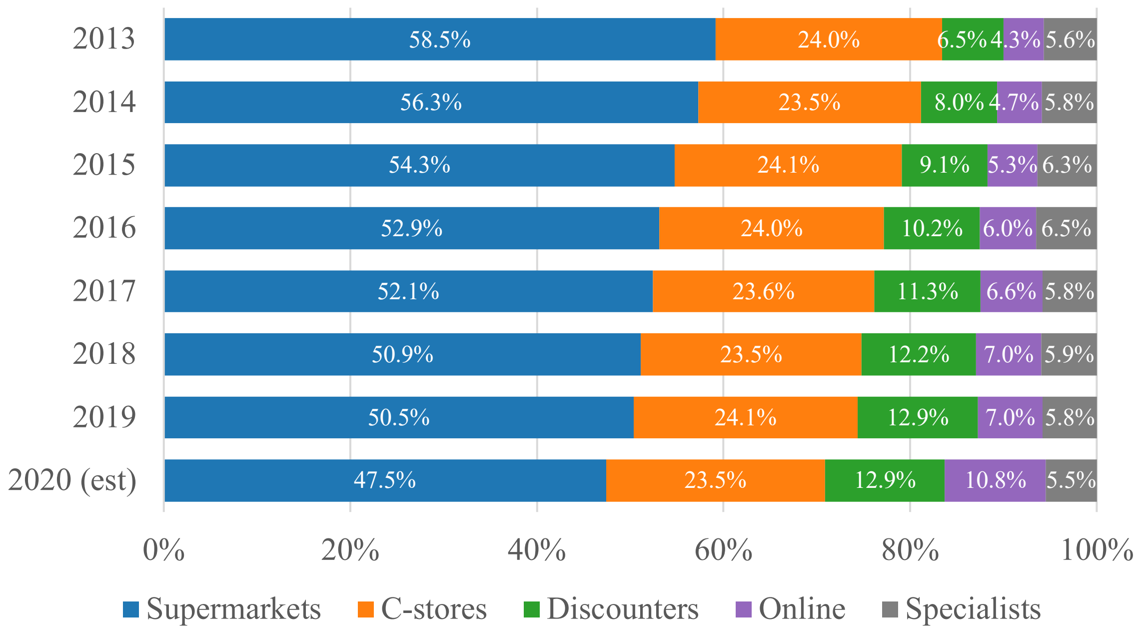


Figure 4 Actual and estimated breakdown of all UK grocery retail sales by channel (Mintel, 2020c).

The abundance of data in the retail sector is nothing new. However, the need to make the most of it is no longer an added value option but an absolute necessity (Grewal, Roggeveen and Nordfält, 2017; McKenzie, Burt and Dukeov, 2018). It is becoming the most vital business asset, its effective use hailed as the determinant of survival or failure in the foreseeable future (IGD, 2018, 2019). There seems to be an agreement that no established retailer can be complacent no matter how successful today (Grewal, Roggeveen and Nordfält, 2017; Fisher and Raman, 2018; IGD, 2019). The effective use of the generated data also serves as the fuel for the emerging business models, mainly e-commerce (Bayfield, 2018; Nielsen, 2018). Although the leading supermarkets have managed to establish their foothold in the online markets the challenge by digital native companies, such as Ocado or Amazon is intensifying (Fisher and Raman, 2018; IGD, 2019). Ocado is experiencing continued double digit growth while Amazon is scoring highest on all brand metrics and is yet to make a serious foray into online sales of food, the impact of which is likely to be considerable (Mintel, 2019, 2020a).

The growing importance of online commerce has also offered numerous opportunities for smaller producers, e.g. by being able to ship directly to the consumer, by-passing the traditional supermarket channel (Nielsen, 2018; Reinartz, Wiegand and Imschloss, 2019). Nonetheless, in 2019 online food sales accounted for only 7% of all grocery sales, and most of them via supermarkets. So the primary focus of most of food and drink producers has been to secure listings in mainstream supermarkets, as this is the most viable way to the mass-market (the Big Four, i.e. Tesco, Sainsbury's, Asda and Morrisons, accounts for two thirds of all retail sales) (Mintel, 2020b). However, the competition is fierce not only because many small producers have to compete for shelf-space with national and international brands but also because of continued range rationalisations at the major supermarkets (Barclays, 2018; The Grocer, 2020).

These trends have been further accelerated by the COVID-19 pandemic and the resulting national lockdowns (see e.g. FSA, 2020; Mintel, 2020c, 2020b; ONS, 2020; Perkins, 2020). Despite the general negative impact on retailing and the considerable initial pressures on food supply chains at the onset of the pandemic, grocery retailing achieved stable growth in 2020 (Mintel, 2020b; BRC, 2021; CRR, 2021). As a result of lockdowns, online sales grew by more than 50% and accounted for more than 10% of all grocery sales (Mintel, 2020b). The economic implications of the lockdowns (Gopinath, 2020) have also strengthened the influence of price on food purchasing behaviour, which is particularly challenging for smaller brands (Mintel, 2020b). Furthermore, in the face of the strains on the food supply chains caused by the unprecedented customer behaviour, 9% of product lines were removed from supermarkets between March and June 2020 exacerbating the competition for shelf-space between the suppliers (Holmes, 2020). Arguably, the pandemic has demonstrated even further how important it is for UK retailers and suppliers to further invest in the digital technologies and analytics (Mason, 2020)

With the growing pressure on retailers to utilise data, the brands which successfully secure the listings with the leading supermarkets are also expected to be data-driven in their marketing decisions regardless of their size or market share (IRI, 2017; IGD, 2018; Edge, 2020). This is particularly challenging for smaller brands, for the reasons discussed in the previous sections. What is more, few retailers make the data available to their suppliers free of charge. Even if basic sales data is made available for free, accessing it through the relevant web portals is rarely a simple task. So much so that specialist intermediary companies have emerged to assist food and drink producers in this task. This is where the Who Buys My Food (WBMF) research project operates.

1.3.2 Who Buys My Food

WBMF is a collaborative action research project involving University of East Anglia, Tesco, Dunnhumby and Invest Northern Ireland (INI).[5] The aim of the project is to help small Tesco suppliers improve their business by increasing their understanding of shopper behaviour, and, more generally, the value of evidence-based marketing decision-making. Via the project, qualifying Tesco suppliers (those with <£1m Tesco turnover) gain access to a customised shopper insight derived from Tesco Clubcard (loyalty card) data free of charge. The project has been running for over 15 years and has assisted over 700 SMEs from all over the UK.

Tesco is the leading UK food retailer, with the largest market share in both traditional supermarket and e-commerce channels. It covers over a quarter of supermarket sales (see Figure 5) (Mintel, 2019) and more than 30% of online food sales (Mintel, 2020a). Tesco's (Clubcard) loyalty programme is reported to reach close to 70% of UK households (Statista, 2017). Dunnhumby is a wholly owned subsidiary of Tesco with responsibility for managing the data derived from the loyalty programme, providing a detailed view of food purchasing behaviour across the Tesco estate of over 3,000 stores. These behavioural insights constitute a solid basis for evidence-based marketing decision-making and the development of a collaborative buyer-seller relationships and sustainable business with the UK's largest grocery retailer.

The data the project makes available can be qualified as customised market information since it involves three key elements: a) suppliers' key performance indicators (KPIs), b) their comparison against the competitors and c) shopper segmentation data. Thus, information is provided about the performance of a supplier, their competitors and their customers. The information can be used for a variety of marketing decisions, such as preparation for buyer review meetings, promotional planning, new product development or packaging re-design.

[5] More information available at www.whobuysmyfood.com.

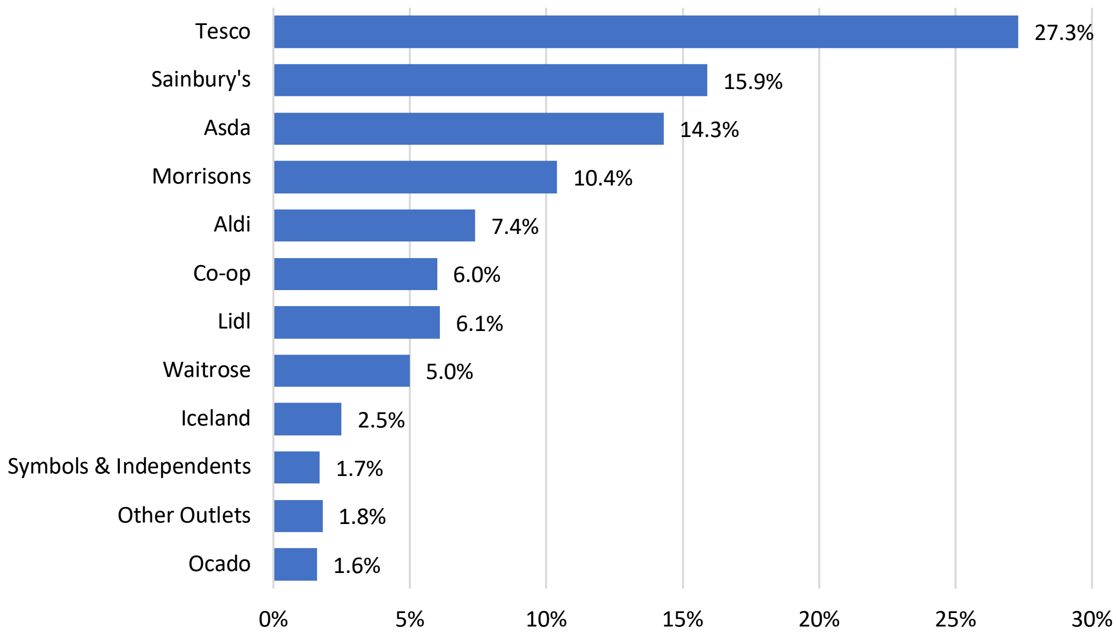


Figure 5 Grocery market share in the UK (Kantar Worldpanel data for 12 weeks ending 27/12/2020).

Historically, shopper insight reports were delivered in the form of PowerPoint presentations. However, from September 2019 a web-based app was developed, providing suppliers with open access to information updated on a weekly basis. In addition, the participating companies are invited to quarterly webinars and are offered one to one consultation with the project team. At the time of writing (July 2020), there are close to 120 food and drink producers enrolled in the project.

It seems that the commonly mentioned barriers to the adoption of technology and its use for evidence-based marketing decision making faced by small businesses are significantly reduced. Data is always accessible and there is no cost associated with it. The companies are regularly educated about the importance of using the data and one to one support is offered. And yet, it is not used to its full extent. In the first six months when the new system was operating, 82% of the enrolled companies accessed the reports on average once a month, with 33% of the companies accessing their market information reports only once or twice. It is noteworthy that each of them had to face at least two quarterly buyer review meetings in that time period. That does not mean to say that there are no heavy users – 10% of companies have accessed their information at the rate of 10 logins per month.

This brief overview of usage rates provided further evidence of the problem characterised in this chapter and some of the issues with the traditional research process on technology adoption and use. All companies from the WBMF project would be traditionally treated as “adopters” of the market information system that was made available to them. After all, they all had enrolled to the programme, created their accounts and had logged in at least once. However, only the investigation of the actual behavioural data (generated from the system logs) demonstrated the considerable heterogeneity in the actual use of the system and information therein. And only through use of the information can the system make a difference business performance.

This final section provided a real-world example of the research problem discussed – low usage rates of data for marketing decision-making among small business. It takes place even when the commonly mentioned barriers to the adoption and use are removed. This would indicate that other solutions have to be sought to design successful interventions which can enable small businesses to compete with their much larger competitors.

1.4 Summary of Chapter 1

In this chapter the research problem of this study was presented, and its importance highlighted. The main premise is built around the ongoing digital revolution that is affecting all industries and companies regardless of their location or size. The revolution has its threats but, at the same time, offers opportunities for improvement. Its key promise lies in the exponential growth of data and the development of tools to store, transform and analyse it, resulting in improved (more evidence-based) marketing decision-making.

However, despite the ubiquitous need for the evidence-based decision-making, great disparities in the use of big data exist, particularly, in the case of smaller businesses. What is deemed to be mainstream in the business world is unimaginable to almost half of small businesses. Small businesses are lagging behind their larger counterparts despite the mounting pressure to use data and technology for decision-making in order to remain competitive.

The current state of the academic research was reviewed to investigate the potential reasons for such a divide. There is a wide agreement that smaller businesses are nothing like their larger counterparts in terms of their management practice. The main reason being the resource gap they face. But also, the significant influence of just one person, the owner-manager, whose perceptions, characteristics and behaviours shape the business as a whole. This results in an informal, intuitive and habitual approach to management, marketing and decision-making, often with scant regard to the role of technology therein.

The review has also highlighted the shortcomings of previous research in this area. Technology adoption is viewed as a binary construct with little effort given to the study of actual use of technology, which is a necessary prerequisite for the delivery of business impacts. The use of actual objective usage data is scarce, with perceptions assumed to reflect the everyday reality of small businesses. Even less attention is paid to the IT artifact itself, with previous studies over-generalising the similarity of the available tools. Interventions aimed at increasing the adoption rates mainly operate in the rational plane – educating users about the benefits or improving their IT skills. Yet most of the research agrees that small businesses are informal and intuitive in the way they respond and act. This critique is not meant to discard the advances of the previous research, merely to suggest that other factors can and should be taken into consideration to improve the progress in this important domain.

Finally, the broad research problem was exemplified with the context of this study, namely the need for evidence-based marketing decision-making by small businesses within the grocery retail sector. In order to remain competitive small businesses supplying major supermarkets need to make their marketing decisions based on solid evidence to effectively allocate their scarce resources but also to satisfy the requirements of their customers. However, as it was shown with the example of the Who Buys My Food research project, even if the richest of customised market information, is made available digitally, free of charge, many small businesses make little use of it. Is it then that small businesses are inherently unable to use more structured and advanced tools (the market information systems and the data feeding them)? What else could we do to influence their behaviour to assist them in their digital transformations so they can remain competitive in the 21st century?

"Behaviour" and "tool" are the key words used to advance this argument in the following chapters. A proposition is made that to assist small businesses in using market information systems and the underlying data to effectively make marketing decisions based on evidence (when appropriate) rather than intuition, two things could be done. First, we technology use should be viewed as a behavioural act that is performed by individuals within the company. In other words, the research needs to focus on individuals interacting with technology rather than viewing them as a collective whole. This means the findings from the wider and richer information systems research on the actual post-adoptive use of technology of individuals can be used to better understand the use (or rather lack of it) of technology among small businesses. Using the behavioural lens also provides tried frameworks to design targeted interventions, which can be tested experimentally to establish causal links. Second, more attention should be paid to the IT artifact itself. There is great scope for interventions and improvements derived from modifying the information system itself, so it becomes better suited for the small business context. Much like it was assumed that small businesses can use managerial principles developed for larger businesses (which proved to be grossly wrong), it seems that today many IT tools are marketed to all companies equally, without a proper regard to the context of small businesses. These two aspects constitute the crux of the research objectives of this study.

1.5 Research Aim and Objectives

In summary, the aim of this research project is to help small food producers be more competitive and ready for the technological revolution of the 21st century. Specifically, the focus is on the use of high-quality structured market information in marketing decision-making by small food and drink producers. The aim is realised by focusing on the use of market information via actual continued market information system use. System use is a prerequisite to any evidence-based marketing decision-making of small food and drink producers. To enable more use, a focus is placed on the characteristics of a market information system, specifically their possible modifications. And then a behavioural analysis is conducted to enable a development of a targeted intervention to increase the system use. Therefore, this research has the following two objectives:

1. Design, test and evaluate system modifications, which have the scope to influence the market information system use.
2. Design, test and evaluate a behavioural change intervention to facilitate the market information system use.

The following Chapter introduces in detail the behavioural lens, which is used to study the problem and, ultimately, which leads to the design of a targeted behavioural change intervention.

2. Theoretical Framing

The aim of this chapter is to present the behavioural lens used to study the problem identified in the first chapter. Behavioural Change Wheel (BCW) is introduced as a guiding framework. Its main component, the Capability-Opportunity-Motivation-Behaviour (COM-B) model serves as a way to review the extant information systems literature on continued individual system use. By contextualising the reviewed literature, a targeted behavioural change intervention is proposed as a way to address the research problem.

2.1 Introduction

In the previous chapter a research problem was identified and justified. The real-world problem identified is an insufficient use of evidence-based marketing decision-making by small food and drink producers, leaving them vulnerable in an increasingly competitive grocery market. Small food and drink producers struggle with the use of formalised data due to their inherent characteristics. However, the extant research does not suggest they are unable to make decisions based on evidence, rather that they need specific conditions to do so. The aim of this chapter is to provide a theoretical framing to address the identified problem. The starting point is to view the decision-making of small companies as a set of behaviours performed by individuals. Such a view allows us to draw from the expansive literature on designing interventions that aim to change the behaviour of people, not merely describe it. This offers a more systematic way to design a theory-based intervention which is most suited to the context of small businesses. Second, more attention has to be paid to the technological artifact itself in its relevant context, to ensure its compatibility with the people who are using it. This moves us from the organisational literature on technology adoption by small businesses into the research on individual continued technology use, allowing a more nuanced and fine-grained analysis.

This chapter is structured as follows. First, behavioural change research is briefly introduced with the Behaviour Change Wheel (BCW) used as an organising framework. In the rest of this chapter, the steps suggested by the BCW are followed to design a targeted intervention with the potential to influence the behaviour of small businesses. Second, in order to develop a thorough understanding of the target behaviour, the extant information systems literature on individual system use is reviewed. The review is summarised within the Capability-Opportunity-Motivation-Behaviour (COM-B) model, which details the possible mechanisms for behavioural change interventions. Third, the resulting COM-B model analysis is enhanced with the context of the current study – the sustained use of a market information system. Finally, a number of possible behavioural change interventions are identified, with the environmental restructuring proposed as the most suitable in this context.

2.2 Behavioural Change

Behavioural change research is most developed with respect to health, with scientists addressing many topical human behaviours in order to reduce the risk of death and improve human wellbeing (Davis *et al.*, 2015). Most commonly the research involves the dissemination of safe sex practices, assistance in smoking cessation or with increasing the levels of physical activity (Davis *et al.*, 2015). The field has produced tens of theories modelling behaviour (Michie, van Stralen and West, 2011). However, most of the theories focus on characterising and explaining the behaviour offering little guidance in developing theory-driven interventions to influence the behaviour (Michie *et al.*, 2008; Michie and Johnston, 2012; Michie, Atkins and West, 2014). One notable exception is the Behavioural Change Wheel (BCW), with the Capability-Opportunity-Motivation-Behaviour (COM-B) model of behaviour at its centre (Michie, van Stralen and West, 2011; Michie, Atkins and West, 2014). It is based on an extensive analysis and synthesis of other behavioural theories and frameworks. It has become a standard in the field with over 4,000 citations in less than 10 years since its publication. The framework suggests a number of steps to be followed to ensure that interventions are theory-based in order to maximise the effectiveness of the intervention. It has been applied in numerous behavioural change studies (e.g. Barker, Atkins and de Lusignan, 2016; Gallagher, Ashley and Needleman, 2020) including in the IS domain (e.g. Alshaikh *et al.*, 2019). The following section describes the framework in more detail and applies its steps to the specific context of this study.

2.2.1 Behavioural Change Wheel

Behavioural Change Wheel (BCW) is a comprehensive tool for a detailed behavioural analysis and behavioural change interventions design. In this study it is used as a guiding framework to address the research problem. Such an approach was chosen since the problem identified is not a technical problem per se; it is a managerial problem which is treated with a technical solution. Therefore, it requires a “human” behavioural organising framework not merely technical one.

BCW was proposed by Michie et al. (2011) to systematise the process of designing theory-based behavioural change interventions. The framework consists of three layers, with the COM-B model of behaviour at its centre (more details to follow in the next section), surrounded by 9 intervention functions and 7 policy categories. Interventions are the activities aimed at changing the behaviour while the policies are the actual actions taken by the person implementing the intervention (Michie, van Stralen and West, 2011). The method of applying BCW for intervention design consists of three main steps: a) understand the behaviour, b) identify intervention options and c) identify content and implementation details (Atkins and Michie, 2015), following the "wheel" layers from the inside to the outside (see Figure 6).

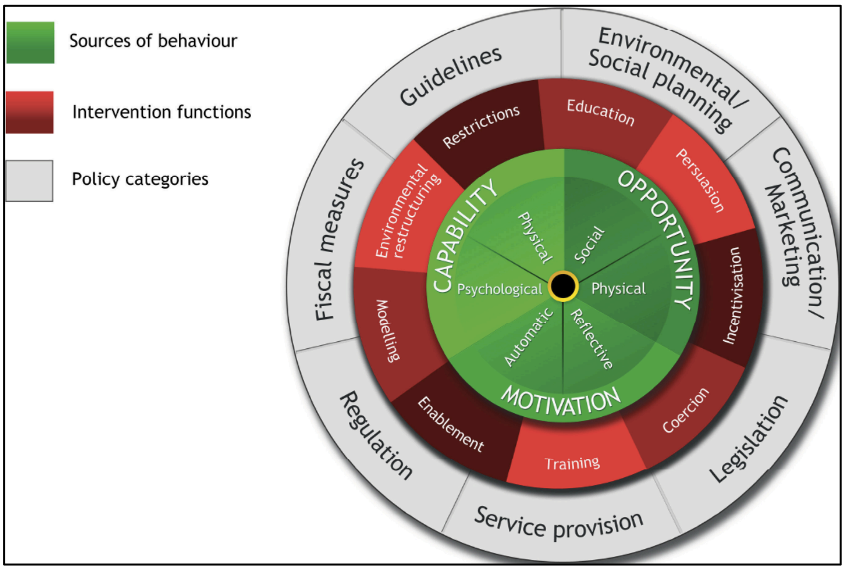


Figure 6 Behavioural Change Wheel framework (adapted from Michie, van Stralen and West, 2011).

The starting point of the first stage of "understanding the behaviour" is to define the problem in behavioural terms, i.e. to explain who is performing what behaviour. It is important to define the broad system and context of the target behaviour as it never occurs in a vacuum (Michie, Atkins and West, 2014).

In this study the focus is on small food producers (who?) making marketing decisions based on structured evidence derived from behavioural shopper data (what?). The "evidence" includes information on the company itself, its customers, the market in which it operates and company's competitors. The information is gathered formally (e.g. analysis of sales data) and informally (e.g. in discussion with colleagues, intermediaries and customers). It is then used to inform specific decisions on new product development, pricing, packaging, promotions, etc. This creates a broader behavioural system within which the WBMF market information system sits and is designed to support marketing decision-making.

The one particular behaviour targeted in this study is the formal process of consulting the relevant market information (data on the company, its customers and competitors). The use of the system is assumed to be a proxy for using evidence for decision-making. Although it is an assumption, we can be fairly confident that, at the very least, it is the first and necessary stage of this process. If the system is the only source of such data and it is not being accessed, then we can be confident that it is not being used for decision making.

Once the target behaviour is identified, the next step is to identify what needs to change in order to influence that behaviour. This is detailed by the COM-B model.

2.2.2 COM-B

Capability-Opportunity-Motivation-Behaviour (COM-B) model is a model of behaviour, which enables a detailed analysis of the target behaviour (Michie, van Stralen and West, 2011; Michie, Atkins and West, 2014). It proposes that every behaviour (B) is generated by the interaction of the remaining three elements (COM), which are also influenced by the behaviour. The elements are defined in the following way. Capability has two dimensions, psychological and physical, and represents individual's capacity to engage in an activity. Capability might include e.g. skills and knowledge. Motivation is concerned with all of the psychological, "brain" processes which drive behaviour. Following the two-system view of the human mind (see e.g. Sloman, 2002; Epstein, 2003), it also has two dimensions, reflective and automatic. Motivation might include e.g. goals and habits. Opportunity defines all the environmental factors that lie outside an individual but also exert control over or enable a behaviour. It consists of two broad dimensions of physical and social environments. Opportunity might include e.g. financial resources and cultural norms. See Figure 7 for a visual representation of the model.

The model places no priority on either of the components assuming that all elements have an equal possibility of influencing the behaviour. Importantly, it acknowledges and places equal value on both automatic and reflective psychological processes, unlike early theories which treated behaviour as fully intentional (e.g. Ajzen, 1985). Following the analysis of the target behaviour guided by the COM-B model, interventions are designed in such a way as to effect one or more components of the behavioural system.

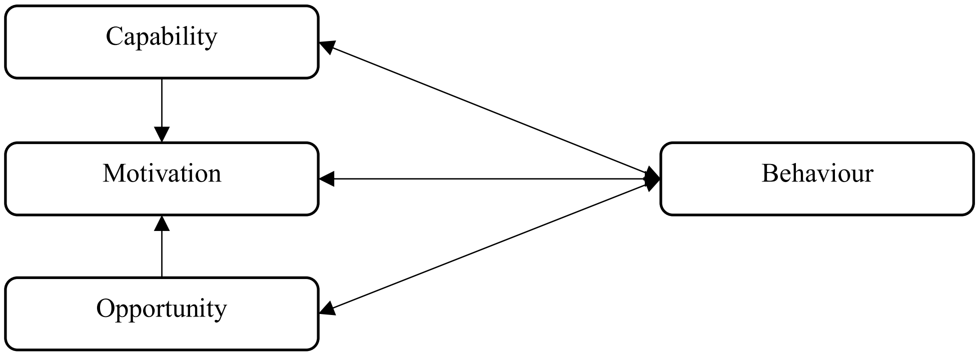


Figure 7 The COM-B model (adapted from Michie, van Stralen and West, 2011).

In this study the behaviour we are trying to influence is the use of an information system displaying market information. In order to design a behavioural change intervention, we need to understand the mechanisms driving this behaviour with the use of the COM-B model (see Figure 8). The following sub-section reviews information systems literature on system use by individuals (as opposed to the previously reviewed literature on adoption/use of technology by small businesses) to summarise the current state of knowledge and identify opportunities for a behavioural change intervention.

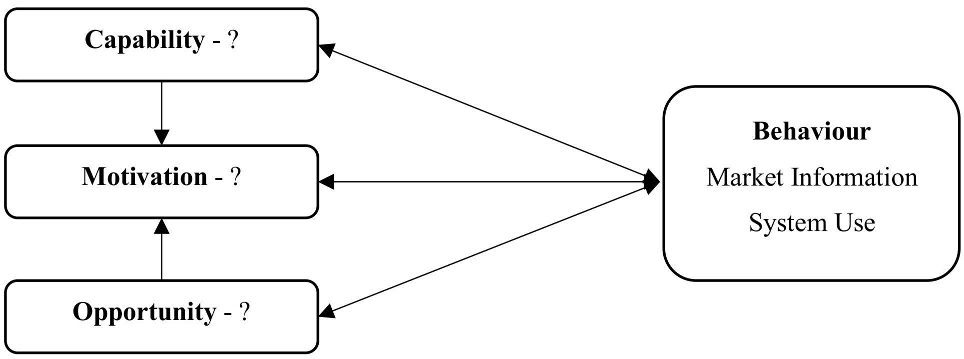


Figure 8 The COM-B model applied to the research problem of this study (before literature review)

2.2.3 IS Use Behaviour Analysis

This section focuses on the review of the Information Systems research into the use of technology by individuals. The IS field has a long tradition of investigating the reasons determining the use of technology.[6] At the beginning this literature was dominated by the Technology Acceptance Model (TAM) (Davis, Bagozzi and Warshaw, 1989), which equated technology adoption (or acceptance) with its subsequent use. It is now accepted that these two behaviours are driven by substantially different factors. However, since the acceptance literature began this line of inquiry and laid the necessary groundwork for the use research, a brief review is included.

2.2.3.1 IT adoption

The research on technology adoption is dominated by studies which use the Technology Acceptance Model (TAM) (van Oorschot, Hofman and Halman, 2018). The TAM model was first proposed in the 1980s by Fred Davis (Davis, Bagozzi and Warshaw, 1989). It combines and modifies two earlier and broader behavioural theories, namely the Theory of Reasoned Action (TRA) (Fishbein, 1979) and the Theory of Planned Behaviour (TPB) (Ajzen, 1985), for the specific context of technology adoption.

The underlying assumption incorporated from TRA and TPB to TAM was the rational and careful planning of the behaviour resulting in Behavioural Intention (BI) preceding the behaviour itself. BI is considered the main predictor of behaviour, in this case technology acceptance or use (Davis, Bagozzi and Warshaw, 1989). In turn, as the original TAM model suggested, BI was explained by three factors: Perceived Ease of Use (PEOU), Perceived Usefulness (PU) and Attitude Toward Using the technology in question (Davis, Bagozzi and Warshaw, 1989). More recent research proposes the removal of the attitude construct finding its explanatory power limited compared with PU and PEOU (Venkatesh *et al.*, 2003). In short, the model posits that a person will evaluate the usefulness and ease of use of an artifact and the more useful and easier to use they find it the more likely they are to form an intention to use it, which is assumed to translate into actual (repeated) use.

Despite criticisms about the subjectivity of and difficulty to judge and measure the PU and PEOU constructs (Benbasat and Barki, 2007), TAM gained more and more

[6] A note on terminology – following the definition from the sub-section 1.2.5.1, the following terms technology, IT, system, IS will be used interchangeably for stylistic purposes.

popularity and the model was further refined into TAM2 by including the introduction of external variables, such as job relevance, experience, voluntariness, output quality, result demonstrability or subjective norm grouped broadly into social influences and cognitive instrumental processes (Venkatesh and Davis, 2000). Over the years, the model has been validated in a number of studies confirming its predictive power in the context of individual technology acceptance (Lee, Kozar and Larsen, 2003).

The next development saw a comparison of TAM with some earlier or competing theories, such as Diffusion of Innovation Theory (DIT) (Rogers, 2003) resulting in the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh *et al.*, 2003). UTAUT combines a number of constructs into performance expectancy, effort expectancy, social influence, facilitating conditions acting as predictors of the BI, and includes moderators such as gender, age, experience and voluntariness. However, despite successful validation most researchers have returned to using PU and PEOU (Marangunić and Granić, 2015).

PU and PEOU are modelled as the two main predictors of the BI. As a result, considerable research effort went into investigating the antecedents of these two constructs, summarised by Venkatesh and Bala (2008) in what they termed as TAM3. Broadly, they identify three sources of antecedents of PU and PEOU, namely individual differences, system characteristics and external environment (social influence and facilitating conditions). Together they include eleven constructs, with all but one representing beliefs of the system users. Computer self-efficacy, perceptions of external control, computer anxiety and computer playfulness are confirmed to be significant predictors of perceived ease of use. Subjective norm, image and result demonstrability are found to be significant predictors of perceived usefulness. All the results are in line with previous research (e.g. Venkatesh and Davis, 2000). As a result, although it is acknowledged that the system being used and the environment in which the users function play a role, these constructs, measured objectively, have yet to be incorporated into the model.

Despite the widespread use and the predictive power, TAM and related models are not without their critics. TAM focuses on the acceptance decision and initial use, ignoring the temporal perspective of technology use beyond its introduction (Bhattacherjee, 2001). Orlikowski (2000, p. 425) points out that it is people's interaction with, "not mere presence of the technology" that can have any consequences on productivity or performance – the main reasons for investing and introducing any kind of IT (Goodhue and Thompson, 1995). What is more, the so-called intention-behaviour linkage was pronounced to be "probably the most uncritically accepted assumption in social science research in general and IS research in particular" (Bagozzi, 2007, p. 245). These realisations and criticisms prompted research into what is referred to as IT continuance, continued behaviour or IS/IT/system use/usage. In other, words the behaviour after the initial introduction of the technology, and its unique antecedents. This stream of research is discussed in the following section.

2.2.3.2 IT use

Distinguishing system use from adoption or initial use meant that different theoretical lenses were required to explain the decision to continue the use of IT. The most popular ones include Expectation-Confirmation Model (ECM) (Bhattacherjee, 2001), addition of habit (Jasperson, Carter and Zmud, 2005; Limayem, Hirt and Cheung, 2007) and emotions (Kim, Chan and Chan, 2007) resulting in UTAUT2 and its synthesised version (Venkatesh, Thong and Xu, 2012, 2016) and the unified model of IT continuance (Bhattacherjee and Lin, 2015). What is more, a stream of research has focused on approaching technology use through the social network perspective (e.g. Sykes, Venkatesh and Gosain, 2009). The findings from these strands of research are synthesised in the next sections.

Expectation-Confirmation Model (ECM)

A decade after the introduction of TAM Bhattacherjee (2001) proposed an alternative model, ECM based on the Expectation-Confirmation theory (Oliver, 1980), a theory widely used in consumer behaviour literature to study consumer satisfaction and re-purchase intention. ECM suggests that technology continuance intention is predicted by three factors: perceived usefulness (from TAM), confirmation of the expected benefits and satisfaction with prior use. The original ECM was further modified by Bhattacherjee and Premkumar (2004) to include beliefs and attitudes as predictors of the continuance intention, and the changes of the constructs were examined over time. Interestingly, the examination over time revealed that the model explained significantly more variance for initial use than for later use. This would suggest that with time new mechanisms guiding system use emerge and go beyond mere intention. In the direct comparison of ECM with TAM for the context of intention to use Halilovic and Cicic (2013) demonstrated that ECM was able to explain almost twice as much variance as TAM. ECM was embraced by the community and has been a leading model applied by researchers investigating technology continuance intention (Hossain and Quaddus, 2012). It has been applied in a variety of contexts and a recent meta-analysis confirmed its robustness and predictive power (Ambalov, 2018). It also suggested the presence of moderators based on the individual's characteristics, such as age, gender, privacy concerns or trust.

However, as ECM was establishing its foothold in continuance research, new perspectives were proposed. Venkatesh et al. (2008) urged for the system use research to break out and go beyond the "intentionality framework". They proposed a construct of behavioural expectation which was believed to address most of the limitations of BI, such as capturing external factors or accounting for uncertainty and lack of information. However, it was still closely related to previous research which assumed technology use to be "fundamentally intentional behaviour – driven by conscious decisions to act" (de Guinea and Markus, 2009, p. 433). A more radical extension of ECM was to add the construct of habit (Limayem, Hirt and Cheung, 2007), which was the first step, beyond the rational and conscious BI, towards the recognition of the role of automatic behaviours. Habit was not envisioned as a replacement for BI but another construct which could build on the cumulated knowledge to enrich "our understanding of individual post-adoptive behaviours" (Jasperson, Carter and Zmud, 2005, p. 527).

Habit and emotion

The main advantage of introducing the habit construct to models examining individual system use is the ability to account for automatic behaviours (Limayem, Hirt and Cheung, 2007), which have been demonstrated to be a considerable part of all human behaviours (Evans and Stanovich, 2013). Although habit was studied across many disciplines and therefore had many definitions, Limayem et al. (2007, p. 709) proposed the IS habit definition as "the extent to which people tend to perform behaviours (use IS) automatically because of learning". As the antecedents of habit, they suggested frequency of past behaviours, comprehensiveness of usage and satisfaction with the technology. In the validation of their proposition, they designed a research model based on ECM and incorporated habit and its antecedents. They found that habit exerts both significant direct effect on IS continuance usage and significant moderating effect on the relationships between IS Continuance Intention and Usage.

Ortiz de Guinea and Markus (2009) called for empirical research to compare the traditional models with those stemming from unplanned and unreasoned action to discover the differing implications. In this vein, Kim (2009) examined temporal effects of habit and reason-oriented constructs, finding that reason-oriented constructs effect proximal use but not distal use, a finding later replicated by Lee (2014). It was also suggested that the event that triggers use will impact the type of response, with expected events triggering the automatic mode and discrepant events triggering the adjusting use pattern (Ortiz de Guinea and Webster, 2013). What is more Kroenung et al. (2017) used habit strength as a basis for classifying individuals to discover the heterogeneous clusters amongst users in order to suggest different persuasion strategies. These findings yield even more support for propositions that both conscious and unconscious mechanisms are important for technology use behaviours, but their importance will differ depending on the experience and type of the users, and the purpose/situation of use of the system in question.

A linked stream of research looked at the negative impact of habits. Polites and Karahanna (2012) proposed habit to be an inhibitor of use. In their modelling based on status quo bias theory, they included habit as an antecedent to inertia, which leads to the decreased intention and use behaviour. It was one of the first studies to look at the negative impacts of habit. More recent studies looked at the negative effects of habit as part of the research examining the "dark side" of technology (e.g. Turel and Serenko, 2012; Soror *et al.*, 2015; Turel, 2015; Yang, Wang and Lu, 2016; Clements and Boyle, 2018; Polites *et al.*, 2018). Habit was modelled as an antecedent of compulsive technology use (Clements and Boyle, 2018) or even of addiction to social networking sites (Turel and Serenko, 2012) or mobile phone use (Soror *et al.*, 2015). Since habit is guided by automatic mechanisms it is viewed as a threat to self-regulation behaviours (Polites *et al.*, 2018), yet it was noted that habits are not inherently bad but can become such when they lead to undesired behaviours (Soror *et al.*, 2015).

In addition to habit, Kim et al. (2007) put forward their balanced thinking-feelings model, which took account of feelings and emotions. They proposed that feelings, such as pleasure or arousal, are also important significant predictors of both the attitude to the intention and the IS continuance intention. However, this remained mostly relevant in the voluntary and hedonistic contexts rather than the workplace.

These developments, summarised in a very critical article by de Guinea and Markus (2009), led to the incorporation of these mechanisms to more established models by previously conservative researchers. Venkatesh et al. (2012) extended their Unified Theory of Acceptance and Use of Technology (UTAUT) to UTAUT2 by incorporating hedonic motivation and habit constructs. This resulted in a significant improvement in the explained variance in both the BI and technology use constructs. Similarly, a unified model of information technology (IT) continuance was proposed which integrated three perspectives: reasoned action, experiential and habitual responses (Bhattacherjee and Lin, 2015). Like UTAUT2 it also resulted in enhanced robustness and predictive power of the model.

Additionally, alongside the most popular research within the intentionality framework, which later incorporated habit and emotions, technology use was also studied with the help of other theoretical lenses, such as social network theory.

Social network

Social network theory postulates that the position people have in their social networks influences both how they behave and the performance outcomes they achieve (Borgatti and Foster, 2003). The reasons for that are grounded in social capital and include information, influence, social credentials and reinforcement. The research suggests that individuals more embedded in social networks, measured by network centrality, i.e. how well connected they are, are more likely to perform certain target behaviours (Lin, 2017). This perspective was used to explain individuals' use of technology and the impacts their behaviours have.

Social network ties were found to be important for deep structure use (the degree to which an employee is using the appropriate features for various tasks) of the new ERP system and deep structure use was found to be important in explaining job performance (Sykes and Venkatesh, 2017). Along these lines, a Model of Acceptance with Peer Support (MAPS) was proposed which investigated the importance of the social network (density and centrality) combined with the behavioural intention and facilitating condition. As hypothesised the impact of peers was significant in explaining the intention to use the system (Sykes, Venkatesh and Gosain, 2009).

Venkatesh et al. (2011) explored how network centrality influences the use of the electronic healthcare system among doctors, paraprofessionals and hospital administrative personnel, and what impact the use has on quality of care and patient satisfaction. They found that greater network centrality is negatively associated with the use of the system among doctors but not among other hospital workers, and that greater use is associated with improved patient satisfaction mediated by quality care variables. This study indicated how crucial certain well-connected individuals within a social network can be in deterring from or encouraging others to use the system. It also provided evidence that increased system use can lead to the increased organisational performance outcomes, such as patient satisfaction.

Another study pointed out the importance of social influence in predicting use (Wang, Meister and Gray, 2013). The authors used prior Knowledge Management System (KMS) use among superiors, peers, subordinates and professional population and prior KMS use as predictors of current KMS use and found strong support for the effect of prior use, and prior use by subordinates and peers (Wang, Meister and Gray, 2013). Yet again, demonstrating the influences people around the individuals exert on their technology use.

The research within this area demonstrates the influence certain social ties have on the system use among individuals. The so-called influencers can sway the use both positively and negatively depending on their initial stance. It would also suggest that for any intervention aiming at improving the use in an organisation to succeed, the relevant individuals have to be identified and convinced due to their influence over their peers.

Other factors

Apart from the three main streams of research that examined how technology is used, a number of additional perspectives and antecedents have been proposed. Within the realm of social influences it was discovered that the so-called, onlookers, i.e. people who look or are around people using technology but themselves do not use technology, were found to be an important factor in determining technology use (Sergeeva *et al.*, 2017). The position of the onlookers especially influences the desire of individuals to use or not use the technology.

Another study extended ECM to include subjective norms, i.e. social pressures to perform or not perform a behaviour, to predict continuance intention of social networking sites (Mouakket, 2015). Although they have found subjective norms to be a significant predictor, a meta-analysis by Wu and Lederer (2009) discovered the related construct of voluntariness to be an insignificant moderator of the relationships between PU and PEOU and usage and BI. These findings would suggest that social pressure of the peers would exert stronger influence on the use than the official recommendations within an organisation.

Further perspectives aiming at explaining technology use amongst individuals include: IT mindfulness (Thatcher *et al.*, 2018), Big Five personality (Devaraj, Easley and Crant, 2008), IT provider support (Retana *et al.*, 2018) and previous IT knowledge (Aggarwal *et al.*, 2015).

IT mindfulness is treated as a predictor of continuance intention and deep structure usage and found to be an insignificant predictor of the former (Thatcher *et al.*, 2018), strengthening the argument in favour of perspectives postulating automatic behaviours as the driver of continued system use. Big Five personality traits have been used as predictors of perceptions of usefulness, subjective norms and as a result the intention to use, revealing they are indeed important significant drivers (Devaraj, Easley and Crant, 2008), thus suggesting greater personalisation in the way system use is taught. Retana et al. (2018) hypothesised the quality of an IT provider's IT support as a predictor of technology use, and used system logs to examine the volume and efficiency of system usage. They discovered IT support services to be an important predictor of more, and crucially, better system use. What is more, the effect was carried over even after the users stopped their IT support package indicating long-lasting learning effects and reiterating the importance of support in the initial stages of new technology use. The impact of IT knowledge on system adoption is not straightforward (Aggarwal *et al.*, 2015). Actual IT knowledge makes an individual more likely to adopt, and less likely to discontinue, yet low actual but high self-perceived knowledge makes you likely to adopt and then likely to discontinue. This again provides some evidence for the importance of training and support in the initial stages of use.

Lastly, a recent study proposed a new framework to explain technology use combining Theory of Affordances (Gibson, 1979) with theories of human motivation including Self-Determination Theory (SDT) (Ryan and Deci, 2000). Karahanna et al. (2018) put forward Needs-Affordances-Features (NAF) framework as one of the very few studies using human motivation perspective to explain technology use. They argued that the needs-based and motivational theories (Li, Hsieh and Rai, 2013) are a powerful lens to explain technology use, especially in the voluntary and personal context. Having said that, these theories might also be able to shed some light on the low levels of usage of existing applications, arguing that current systems do not cater to psychological needs, thus reducing motivation to use them.

2.2.4 Summary of IT Use Research and Contextualisation

This section reviewed the extant literature on individual technology adoption and use. The decision to use technology (assumed to be equal to the behaviour itself) is explained by a host of factors, with perceived usefulness (PU) and perceived ease of use (PEOU) being the two most important ones. A big shift in the research was to break from the so-called "intentionality framework" and recognise that sub-conscious, automatic processes, such as habits and emotions, also play a role in technology use, especially in the continued post-adoptive settings. In addition, the environmental factors, especially originating in the social plane, are found to play an important role. The similarity of the findings from the extant IS literature on individual technology use to the COM-B model are stark. However, subtle differences are revealed following more detailed scrutiny.

First, most of the extant IS research aims to explain behavioural intention (BI), which is equated with the performance of the behaviour itself. This is a limitation, with the existence of the intention-behaviour gap widely acknowledged (Sheeran, 2002; Sheeran and Webb, 2016). Second, the post-hoc explanation of the behaviour is the focus of most of the studies, with very few interventions establishing causal relationships being implemented (Venkatesh and Bala, 2008; Hong *et al.*, 2014; Venkatesh, Thong and Xu, 2016). The aim of this study is to design an intervention that successfully changes the behaviour of individuals, which means that apart from the measurement considerations (actual rather than reported behaviour – more detail to follow in Chapter 5), we need to identify the drivers of the actual behaviour that can be modified. However, one of the most common criticism of the leading models revolves around the lack of actionable guidance that would be implementable either by researchers or practitioners (Venkatesh and Bala, 2008). Undoubtedly, the models provide crucial starting points highlighting the most important antecedents and the relationships between them but in order to design an effective behavioural change intervention we need to adapt the general model to the specific context of the intervention, and its unique characteristics (March and Smith, 1995; Hong *et al.*, 2014; Burton-Jones and Volkoff, 2017).

In the IS research on individual technology use, the context refers to the specific characteristics and usage contexts of the technology artifact (Orlikowski and Iacono, 2001), and the characteristics of the users (Hevner, March and Park, 2004). For example, usefulness and ease of use mean very different things for a business intelligence system and a social media platform (Hong *et al.*, 2014), hence an intervention changing the system would have to target very different elements. In order to contextualise the general model, much like in the BCW process, we need to understand the nature of the studied IT artifact and identify the relevant users and their characteristics (Burton-Jones and Volkoff, 2017). Once the mechanism is identified theoretically, we can implement an intervention to examine its impact on the user perceptions and use patterns (Venkatesh, Thong and Xu, 2016), thus validating the theoretical underpinnings and establishing the effectiveness of the intervention.

This has already been introduced in Chapter 1 and reinforced in at the beginning of Chapter 2. This study focuses on small food producers in mainstream supermarket distribution using a market information system to support their marketing decisions. The market information system is effectively an information system that gathers and presents data related to the company itself, their customers and competitors. Hence, the most important component of that system is the data feeding it. However, from the use point of view, the data presentation format can be assumed to be one of the major building components determining the perceptions of usefulness and ease of use. Data (the most important part of the system), presented in an unintelligible way would impact the evaluation of the system as a whole, deemed difficult to use and not very useful, as a result, decreasing the overall use. Moreover, we know from the research on information presentation format which user characteristics play an important role (Frias-Martinez, Chen and Liu, 2009; Liu *et al.*, 2014; Luo, 2019). In the context of a data-focused system, one of the most important user characteristics is how they process the information they see. This individual characteristic is captured by the concept of cognitive style. Each person has their own cognitive style, which determines how they interpret information, and which information presentation format they prefer (more details in the sub-section 2.2.5.2).

Table 1 presents the synthesis of constructs most relevant for the understanding of the market information system use based on the review of the extant IS literature and the specific context of this study. On the Capability dimension, psychological capabilities of previous experience and cognitive style are included. The Motivation dimension includes the reflective concepts of PU, PEOU, the emotive construct of Satisfaction, and the automatic concept of Habit. The Opportunity dimension includes the constructs from the social environment important for individuals, such as subjective norms and facilitating conditions. For contextual purposes, variables are included from the SME literature, such as the degree of market orientation, Tesco dependency, and firm size (more details on the inclusion of these variables in Chapter 5). Finally, the physical environment includes artifact characteristics, namely the information presentation format. Since, we are dealing with a system that has already been deployed, satisfaction and habit, which have been confirmed as more important for continued post-adoptive use as opposed to initial system adoption are also included. Figure 9 visualises the same constructs within the boundaries of the COM-B model.

Having carried out a detailed analysis of behaviour, the next step in the BCW framework is to identify behavioural change intervention opportunities.

COM-B dimension	COM-B sub-dimension	Construct	Definition
Capability	Psychological	Market information use experience	Individuals' number of years of experience working with data (Venkatesh and Bala, 2008)
	Psychological	Cognitive Style	Individual differences to which people rely on the experiential and rational modes of information processing (Epstein *et al.*, 1996, p. 391)
Motivation	Reflective	Perceived Usefulness	The degree to which a person believes that using a particular system would enhance his or her job performance (Davis, 1989, p. 320)
	Reflective	Perceived Ease of Use	The degree to which a person believes that using a particular system would be free of efforts (Davis, 1989, p. 320)
	Reflective	Satisfaction	Users' affect with (feelings about) prior system use (Bhattacherjee, 2001, p. 359)
	Automatic	Habit	The extent to which people tend to perform behaviours (use IS) automatically because of learning (Limayem, Hirt and Cheung, 2007, p. 709)
Opportunity	Social	Subjective Norm	The degree to which an individual believes that people who are important to her/him think she/he should perform the behaviour in question (Venkatesh and Morris, 2000, p. 119)
	Social	Facilitating Conditions	The degree to which an individual believes that an organisational and technical infrastructure exists to support use of the system (Venkatesh *et al.*, 2003, p. 453)
	Social[7]	Market Orientation	The degree of organisation-wide generation, dissemination and responsiveness to market intelligence (Narver and Slater, 1990)
	Social	Tesco dependency	Importance of Tesco as a customer (Duffy *et al.*, 2013; Malagueño, Gölgeci and Fearne, 2019)
	Social	Firm Size	Number of employees (Department for Business, Energy & Industrial Strategy, 2019)
	Physical	Information Presentation Format	Symbolic or spatial data representations (Vessey, 1991, p. 225)

Table 1 Constructs important in understanding market intelligence IS use - COM-B analysis.

[7] The greyed-out constructs based on the SME literature are important because of the specific context in which the research operates despite not being directly derived from the literature on the individual system use. They are discussed in more detail in the Chapter 5 where field experiment is reported.

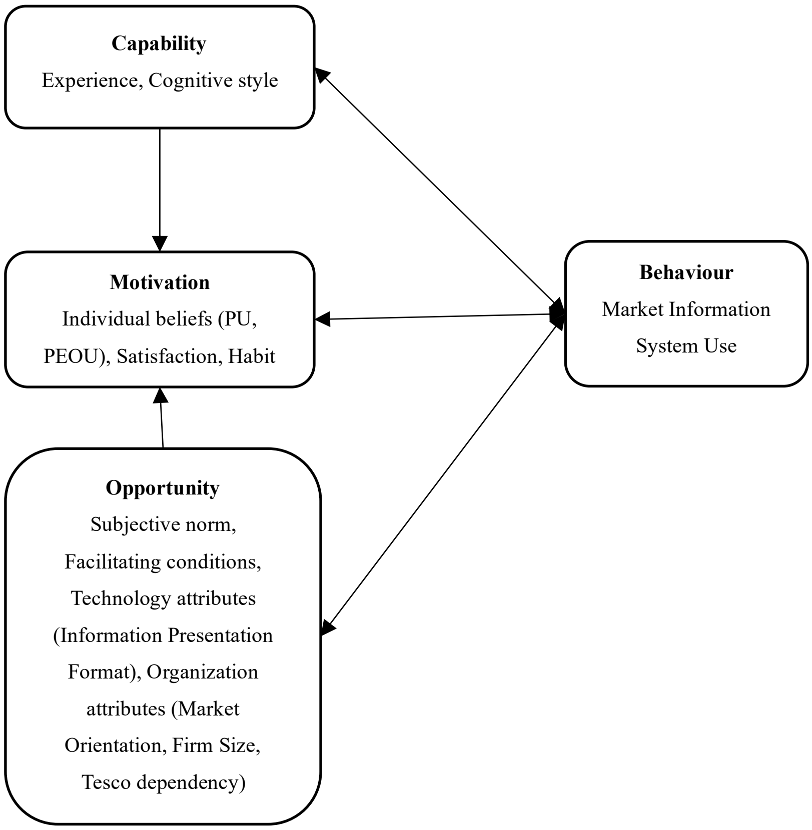


Figure 9 The COM-B model applied to the investigated research problem - the use of an information system (after literature review).

2.2.5 Intervention opportunities

Detailed analysis of the target behaviour revealed that, broadly speaking, there are three key components giving raise to individual IS use: the user, the technological artifact and the environment. According to the extant research, user perceptions and beliefs have the largest influence on the target future behaviour. In addition, there is a role played by sub-conscious and emotive processes, becoming increasingly more important as we move from the adoption to the continued use of the system. This implies that to design an effective behavioural change intervention that increases the system use, we need to find a mechanism which affects the individual beliefs, ideally through the sub-conscious processes (such as habits and emotions). This is strengthened by the previous synthesis of the research on small businesses, which suggests their business style to be highly informal and intuitive. The COM-B model provides guidance in this respect, as a) we could target Motivation directly or b) the Motivation component could be influenced by the Capability and Opportunity components.

Numerous behavioural change techniques (or intervention types) have been identified and used in previous research (see e.g. Michie *et al.*, 2013 for a detailed taxonomy). Rather than listing every possible intervention, the next paragraphs identify four alternative interventions which could be successful in the context of continued market information system use by small businesses, concluding with the justification for selecting one of them. The focus is on the theoretical mechanism underlying the intervention rather than the methodological implementation considerations which follow in Chapter 3.

First, an intervention could target the Motivation component directly in order to influence the target behaviour. However, to be fully relevant in the context of continued system use it must cater not only for the rational decision-making mechanism but also the more intuitive sub-conscious one. A recent framework put forward by Liu et al. (2017) proposed how gamified information systems can lead to meaningful engagement and increased motivation (Karahanna, Xin Xu, *et al.*, 2018). Gamification is commonly defined as “the use of game design elements in non-game contexts” (Deterding *et al.*, 2011 p. 2). It basically means incorporating game design elements, such as leader boards, rankings, tasks (quests) or self-created avatars (Blohm and Leimeister, 2013) to contexts outside of gaming, such as sustainability, teaching (Seaborn and Fels, 2015) or consumer research (Adamou, 2018). The main rationale behind its implementation is to facilitate behavioural change (Seaborn and Fels, 2015) by boosting employee motivation and engagement through the enhancement of relatively mundane and routine tasks (Robson *et al.*, 2016). As a result, the use of such systems delivers meaningful engagement, i.e. experiential and instrumental outcomes (Liu *et al.*, 2017). The instrumental outcomes are what is traditionally deemed as the goal of using work-related IS – the completion of work tasks (e.g. Barki, Titah and Boffo, 2007). The experiential outcomes is the added value generated by the gamification of the system, and can include e.g. enjoyment, joy or cognitive absorption (Liu *et al.*, 2017). Undoubtedly, gamification is a very promising research avenue with the potential to improve the frequency of use of workplace technology through the increased motivation and the delivery of hedonic benefits. However, it still remains unclear whether or not it facilitates effective use (Khan, 2020), by allowing faster and more accurate information extraction, a key consideration for a market information system. Therefore, it seems inadequate on its own in our specific context. Gamification is not dismissed but perhaps it should be a part of a larger, more complex project.

Another type of intervention would target the Capability component. An example could be a training intervention that increases users’ skills and knowledge. Experience with the system is an important moderator of the individual beliefs and intentions (Venkatesh and Bala, 2008; Venkatesh, Thong and Xu, 2016). What is more, the extant IS literature has established IT training to be an important activity, especially when system modifications are impossible to implement (Santhanam *et al.*, 2013; Hwang, 2014). However, the majority of studies used students samples in the lab-based experiments, and only a handful of studies looked at the actual continued system use impacts of the training sessions (Santhanam *et al.*, 2013). Most crucially, the mechanism through which training is said to influence the use of the system is considered to be heavily dependent on "conscious cognitive processing of information" since sub-conscious intuitive response are not necessarily created by digesting organised information in a few training sessions (Santhanam *et al.*, 2013, p. 136). As a result, any intervention focused on training would be inadequate on its own as it does not reach the user through the sub-conscious mechanisms.

The final choice is based around the Opportunity component, i.e. the social and physical environments. We have established that the social environment is an important enabler to system use therefore social environmental restructuring offers a valid route for increasing the target behaviour. However, the context of this study must be taken into account. Social environmental restructuring is always a challenging task, but it might be achievable in a single organisation with appropriate support from the senior management. However, a modification of social environments of numerous small companies is far less feasible and feasibility of an intervention is an important aspect that has to be taken into consideration during the design (Michie, van Stralen and West, 2011). Furthermore, such an intervention would invariably depend on the self-selection of the companies to participate in the programme undoubtedly greatly reducing the potential impact of the intervention and the final sample size.

This leaves us with the modification of the physical environment, which in this case relates primarily to the technological artifact. Clearly, usefulness and ease of use will be influenced by what the system can do and how it works. Also, there is an established feedback loop with satisfaction with the system swaying the perceptions and the target behaviour (Bhattacherjee and Lin, 2015). As explained in the previous section, the information presentation format is a key component of the market information system. What is more, the technological artifact is a component of the physical environment to which we as researchers have full access and the ability to modify in equal manner for all of the research participants. As a result, we increase the degree of control that we can exercise in the very complex field environment and ensure that we reach all of the companies participating in the research. Therefore, an intervention is proposed that will result in a restructuring of the environment, where the technological artifact characteristics are modified to influence user perceptions and habits, and as a result the target behaviour of continued system use. The proposed modification relates to the data presentation format, which will be modified to make the system more useful, easier to use and to take advantage of the more ingrained and natural way of human information processing mechanisms. The rationale for the environmental restructuring intervention is described in the next section.

2.2.5.1 Information visualisation

Regardless of how much data is collected and how advanced the algorithms are developed, the only way for these efforts to translate into business impacts is through actual use of the IT systems of which they are a part (Grover *et al.*, 2018). The mere presence of higher quality or increased amount of data does not equate to better decisions and improved insights (Marchand and Peppard, 2013). Marchand and Peppard (2013) note that data makes most people uncomfortable, even managers. A way to deal with the complexity and aid the sense-making efforts of the system users is through the visualisations (Lycett, 2013; Abbasi, Sarker and Chiang, 2016; Henke *et al.*, 2016). Visualisations, often through the use of interactive dashboards (Abbasi, Sarker and Chiang, 2016; McKinsey Analytics, 2018), avoid statistical jargon and unnecessary complexities by bringing information to life and making it more understandable and digestible for decision-makers (Henke *et al.*, 2016; Hassan, 2019).

Visualisations are graphical representations of data or concepts (Ware, 2012), or in a broader sense, they are external artifacts that support (or constrain) cognitive tasks, such as reasoning or decision-making (Zhang, 1997; Tufte, 2001). The effectiveness of visualisations stems from their use of sensory representations instead of arbitrary codes (Ware, 2012). Our visual system is a product perfected by millions of years of evolution, and now consists of approximately 20 billion neurons (Ware, 2012; Hoffman, Singh and Prakash, 2015). As a result, the intake of information through vision is greater than through all of the other senses combined. This has several advantages. First, people are able to perceive meaning from sensory representations (shapes, colours, pictures) without additional training (Hochberg and Brooks, 1962; Deregowski, 1968). Second, in most cases, the meaning is perceived universally across languages and cultures (Tufte, 2001). Finally, this system is fast and able to digest considerable amount of information thanks to the parallel processing (Tory and Moller, 2004). This is in stark contrast to the arbitrary codes, such as number systems, which are socially constructed. They have only evolved in the past few thousand years, or even in the last few centuries (Ware, 2012). Such representations are difficult to learn, easy to forget and are embedded in a given culture or even a single application (Ware, 2012). For example, regardless of the place of birth every child develops an ability to distinguish a larger object from a smaller one. However, the ability to read or count requires hundreds of hours of training, and a complex infrastructure built around it (programmes, schools, teachers, etc.). And even then, it is only useful in a community of people who went through similar training. In that sense, sensory representations play a more "primitive" and "natural" role in our brains.

Visualisations derive their strength from those characteristics of our visual processing systems. They enable us to effectively perceive information of great complexity (Tufte, 2001). They reveal, otherwise imperceptible, patterns and facilitate quick hypothesis formation (Ware, 2012). A well-constructed visualisation is simple yet very powerful as compared with a table of numbers (Tufte, 2001). As a result, artifacts with visualisations play a significant role in the process of knowledge discovery (Pike *et al.*, 2009).

Considerable research effort has examined how visualisations support or constrain users' understanding and the resulting decision-making (Lurie and Mason, 2007; Kelton, Pennington and Tuttle, 2010). It is widely agreed that the effectiveness of the visualisation depends on the user characteristics and the nature of the task it is supposed to support. A detailed review of the research on task influence is provided in Chapter 4. The aim of this section was to provide broad rationale for using visualisations as an IS modification that has a scope for changing users' behaviour. Therefore, an important dimension is user characteristics and in particular their cognitive style.

2.2.5.2 Cognitive Style

Cognitive styles describe consistent differences among individuals with respect to how they perceive, think and make decisions (Armstrong, Cools and Sadler-Smith, 2012). They have also been described as heuristics that individuals employ to process information about their environment (Kozhevnikov, 2007). Their conceptualisation is based on the dual-processing theory, which posits the existence of two information-processing systems, automatic and intentional (e.g. Sloman, 2002; Kahneman, 2012). Cognitive styles are employed to measure the tendencies of individuals to employ the two thinking processes (Phillips *et al.*, 2016), with the empirical evidence suggesting that individuals differ in these tendencies and develop default and preferred approaches which are trait-like and stable across time (Pacini and Epstein, 1999; Betsch and Kunz, 2008). Cognitive styles have been previously used in IS research, to evaluate the success of personalising a digital library (Frias-Martinez, Chen and Liu, 2009), to measure preferences for working in virtual teams (Luse *et al.*, 2013) and to examine their impact on information visualisation preferences (e.g. Luo, 2019).

A number of conceptualisations of cognitive styles exist but it seems the most suitable for the context of this study is the Rational-Experiential Inventory (REI) (Epstein *et al.*, 1996). REI is based on the Cognitive-Experiential Self-Theory (CEST), a comprehensive dual-processing theory of personality (Epstein, 2003). According to CEST, human behaviour is a joint function of the two thinking processes. Hence, cognitive styles are not bipolar constructs but rather two unipolar dimensions (cf. Hodgkinson *et al.*, 2009). REI measures the tendencies of individuals to employ the two systems for their everyday operations, with the rational component measuring the tendency to employ the effortful, intentional mode of thinking and the experiential component tackling the preference for automatic, sub-conscious behaviours (Pacini and Epstein, 1999).

Knowledge of the preferred cognitive style of an individual can inform the way of presenting information and communication in general to influence behaviour, with the appeals to emotions or personal experience more effective for experientially inclined individuals and facts and logical arguments more likely to appeal to the rationally-inclined individuals (Epstein *et al.*, 1996). Hence, a cognitive style measure could be a useful contribution to the discussion on the impact of information visualisation format on the system use. Cognitive style can also explain why individuals, despite their perceived positive intentions, do not perform that behaviour. Their behaviour is most likely determined by their default mode of operation, with experientially-inclined individuals demonstrated to be more naïve and holding more unrealistic beliefs than others (Epstein *et al.*, 1996). Although such individuals can momentarily hold a positive intention towards using a new system, later on their default mode of behaviour over-rides the intention and they fall back to automatic performance of previously established habits.

Due to the role played by cognitive style in information processing, and in preferences for information presentation format, it is included as a moderator of the impact of visualisations.

2.3 Research Questions

Environmental restructuring involving modification of information presentation format has been identified as a valid behavioural change intervention, and the potential role of cognitive styles as a moderating variable. However the details of the intervention and associated hypotheses require further exploration of the literature (Chapters 4 and 5). As a result, two broad research questions are proposed, which guide the detailed designs of the experiments. They are:

Study RQ1. What role does information presentation format play in the actual use of a market information system by small businesses?

Study RQ2. What behavioural and attitudinal differences exist between people with different cognitive styles towards the use of a market information system?

2.4 Summary of Chapter 2

The aim of this chapter was to provide a detailed account of the behavioural lens used to study the lack of evidence-based marketing decision-making by small businesses identified in the first chapter. The Behavioural Change Wheel (BCW) was introduced as a guiding framework for designing theory-based behavioural change interventions. The broad behaviour of evidence-based marketing decision-making is narrowed down to using a market information system, the necessary first step in the process. This allowed the use of individual system use literature to guide a detailed analysis of the behaviour, within the Capability-Opportunity-Motivation-Behaviour (COM-B) model.

The analysis revealed that the main predictors of the continued system use include individual beliefs (perceived usefulness and perceived ease of use), emotions, habits, the social environment and the characteristics of the system itself. The scope for an effective behavioural change intervention was identified within the Opportunity component of the model, by the means of modifying the physical environment, namely the technological artifact characteristics. With data being the most important component of the market intelligence system, its presentation format offers opportunities for influencing the behaviour of the users. Not only can it directly change the perceptions of usefulness and ease of use, but it can also reach the user through more “primitive” and “deep” brain processes. It also connects with the previously reviewed literature on small businesses, which highlighted the informal and intuitive way of doing business. Moreover, the cognitive style of users is deemed to play an important role in the whole process.

The following chapter introduces the methodological approach employed in this study to realise the research objectives and gather evidence for the research questions set out in Chapters 1 and 2.

3. Methodology

The purpose of this chapter is to explain the over-arching methodological approach applied in this study. First, basic philosophical assumptions guiding the methodological choices are discussed. Second, the paradigm of design science is introduced. Third, the design science research methodology (DSRM) is discussed. Fourth, an experimental approach is established as a valid method for implementing DSRM. The strengths and weaknesses of various types of experimental methods are discussed and the choice of two is justified for this study. Finally, the distinct situation in which the market information system was investigated, which forms the focal point of the experimental design, is described in detail.

3.1 Introduction

The need for companies to be data-driven in order to remain competitive was established in Chapter 1, in which the discussion focused on the specific circumstances of small businesses and how they use (or, more often than not, do not use) data and technology for their marketing decision-making. It was noted that previous research examining the use of technology among small businesses has paid little attention to the IT artifact itself. What is more, the research is mostly explanatory in nature, rarely taking a more active stance. There have been a number of action research studies but very few have attempted to modify the IT artifact. The second chapter introduced the need for a theory-driven targeted behavioural change intervention in order to facilitate continued market information system use, in which environmental restructuring was justified. In this study, this involves making changes to the IT artifact.

In general, the importance of the so-called “last research mile”, delivering impact for real people and real organisations in the real-world is becoming acknowledged as more and more important (Nunamaker *et al.*, 2015). In addition to the impact, such an approach also offers opportunities for novel and unique contributions, to academic knowledge and industry practice. For example, a field based experimental approach with real small businesses has the scope to establish causal links between the constructs (thus strengthening the theory) and offer rigorously and systematically tested guidelines for practitioners. The way to incorporate such an approach into a research study is through the paradigm of design science. However, before it is discussed in more detail, first basic philosophical assumptions guiding the methodological choices are briefly considered.

3.2 Philosophical foundations

All decisions made during the course of a research endeavour are influenced by the underlying philosophical position accepted by the researcher. This is especially relevant in the domain of social sciences, where multiple paradigms of ontology and epistemology are widely accepted and applied unlike in natural sciences where virtually all research is done according to one paradigm (Neuman, 2014). As a result, before describing the details of the methodological choices made, first the ontological and epistemological assumptions made in this study are briefly clarified.

Ontology is the study of the nature of beings. It is concerned with the fundamental nature of reality (Lewis-Beck, Bryman and Futing Liao, 2004). There are two main ontological positions, realism and nominalism (Neuman, 2014). Realism assumes that the world exists independently of people and their interpretations. It exists "out there", grouped into categories, and people are able to discover and objectively describe it (Benton, 2014). A related position of Critical Realism, which has been gaining popularity in the area of information systems (Mingers, Mutch and Willcocks, 2013), modifies this assumption by stressing that researchers' interpretations and inquiries are distorted by their subjective experiences and special safeguards are needed when conducting research to account for those. On the other end of the spectrum, the nominalist position argues that people never experience the world directly but rather always view it via their own specific lens of personal experiences, cultural backgrounds and subjective interpretations (Neuman, 2014). As a result, the world can never be described objectively, it can only be interpreted via individual lenses.

In this study, as the discussion from the first two chapters suggests, mostly an ontological lens of realism is embraced. In this study, it is assumed that observable human interaction with an information system can be objectively quantified and described. The observation of that behaviour and the external forces acting upon it are enough to successfully learn about it. The inner and subjective experiences of the system users are assumed to distort the picture, even to relay a false account of what happened.

Epistemology is the study of how knowledge is created – what can be deemed true and meaningful (Lewis-Beck, Bryman and Futing Liao, 2004). There are three leading epistemological positions, positivism, interpretivism and a critical approach (Neuman, 2014). Positivism is, broadly, an approach that is closest to natural sciences. It makes an extensive use of logical arguments to deduce hypothesis, which are then tested against the empirically gathered data. The goal is to predict and establish probabilistic causal mechanisms (Benton, 2014). Experiments are used extensively by positivistic researchers in pursuit of rigour, exact objective measurements and causal effects of different forces on human behaviour (Neuman, 2014). Interpretivism focuses on the analysis of the meaning and interpretations that people attach to their actions. It involves the incorporation of subjective inner experiences and perceptions (Lewis-Beck, Bryman and Futing Liao, 2004). Interpretivists make an extensive use of observational field research to gain an in-depth understanding of the context in which study participants exist. The critical approach stands in between positivism and interpretivism and focuses on stimulating action in the real world (Neuman, 2014).

As was already indicated by the character of the argument in the first two chapters a positivist lens is used in this study. The logical analysis of previous research, the research problem and the specific context is used to seek causal mechanisms influencing human behaviour as it pertains to the use of information systems. Especially, the approach adopted in this study links closely to a branch of positivism called behaviourism. Behaviourism assumes that human behaviour is causally influenced by external factors, which when controlled or changed yield a corresponding change in human behaviour (Skinner, 1953; Watson, 1957). Such an assumption allows for the departure from the intentionality framework towards automatic mechanisms displayed by technology users, such as habits. Internal, unseen and subjective motivations are discarded as superfluous and are not considered in the research investigation. Finally, this study adheres to the principles of methodological individualism (Arrow, 1994), since the use of technology by small businesses is not studied on the organisational level. Rather, it is assumed that the business behaviour is best explained by understanding the behaviour of individuals, who make up the companies and whose behaviour gives rise to what is usually seen as "company behaviour". Having presented key philosophical assumptions underlying this study, the paradigm used to apply them to the research problem is introduced in the next section.

3.3 Design Science

Design is "the act of creating an explicitly applicable solution to a problem" (Peffers *et al.*, 2007, p. 47). Design science (DS) is a research paradigm accepted in a number of applied disciplines, such as engineering and computer science, but with considerably less presence in information systems (IS) or wider management research (Peffers *et al.*, 2007). This section describes DS, its assumptions and purposes, and the role it can play in increasing the relevance and impact of research. Detailed arguments for its role and theoretical grounding were elaborated by a number of leading authors (Nunamaker, Chen and Purdin, 1990; Widmeyer, 1992; March and Smith, 1995; Hevner, March and Park, 2004; Nunamaker *et al.*, 2015).

Research is a knowledge discovery practice. The traditional research approach applied to the social sciences has its roots in the natural sciences. The purpose of natural science research is to create theories that explain phenomena (Widmeyer, 1992). It broadly consists of two activities, discovery (proposing scientific claims) and justification (testing the validity of the proposed claims) (March and Smith, 1995). In the social sphere it is concerned with explaining and predicting the phenomena concerned with people and organisations, most often their behaviour (Hevner, March and Park, 2004). Improved predictions and more nuanced explanations are then the ultimate goal of such science (March and Smith, 1995; Hevner, March and Park, 2004).

Design science is "a fundamentally problem-solving paradigm" (Hevner, March and Park, 2004, p. 76) that "attempts to create things that serve human purposes" (March and Smith, 1995, p. 253). The purpose of such science is not achieved when an explanation is provided but rather when the discovery supports the achievement of specific human or organisational goals (Widmeyer, 1992). It has its roots in the pragmatist philosophy that argues the research should be evaluated in terms of its practical implications (Rorty, 1982). Much like natural science, design science also has two corresponding basic activities, build (propose how a problem can be solved) and evaluate (test the validity of the proposition) (Widmeyer, 1992; March and Smith, 1995). Since "design" is both a noun and a verb, it implies the two-fold nature of design science – the design process and the resulting design artifact (Hevner, March and Park, 2004). Obviously, the two are intertwined since the ultimate goal of the process is to yield the artifact (Widmeyer, 1992).

Both of the research paradigms have yielded enormous value. However, Hevner et al. (2004) argue that the value is considerably greater if we view the two approaches as complementary, two parts of the whole, especially in disciplines such as management or information systems. They explain that the knowledge base (theories, constructs, research methodologies), which is the product of the behavioural science using natural science methods, is necessary to ensure the rigour in DS. On the other hand, the results of design science efforts not only yield relevant research findings (to people, organisations, society) but also create artifacts which can themselves be studied, thus contributing to the knowledge base. Hence, neither of the approaches should be viewed as inferior or inadequate.

Common arguments against DS are that a) it has to trade off rigour for relevance and b) that it is indistinguishable from regular human practice or consulting (March and Smith, 1995; Hevner, March and Park, 2004). However, what distinguishes design research from common practice is that it addresses important unsolved problems thus having a clearly defined novel and innovative research contribution (Widmeyer, 1992; Hevner, March and Park, 2004). Furthermore, in order not to trade off rigour for relevance, a systematic way of conducting DS research has evolved. Peffers et al. (2007) proposed a Design Science Research Methodology (DSRM) which is a common methodological framework for research which incorporates the design component. It ensures the rigour and systematicity of the scientific enquiry while maintaining the relevance to the outside world. It also provides a way to disseminate the findings and enables other researchers to fully appreciate DS research. DSRM is discussed in more detail in the next section.

3.4 Design Science Research Methodology

The previous section summarised the principles and practice rules for the DS paradigm in IS, and highlighted its importance (Nunamaker, Chen and Purdin, 1990; Widmeyer, 1992; March and Smith, 1995; Hevner, March and Park, 2004; Nunamaker *et al.*, 2015). Peffers et al. (2007) proposed DSRM to offer a procedure for conducting and reporting design science research in a systematic and rigorous way. Their resulting DSRM process model is based on an extensive analysis and synthesis of previous research. The proposed process model consists of six activities which are to be carried out in a nominal sequence. See Figure 10 for an overview of the DSRM process model.

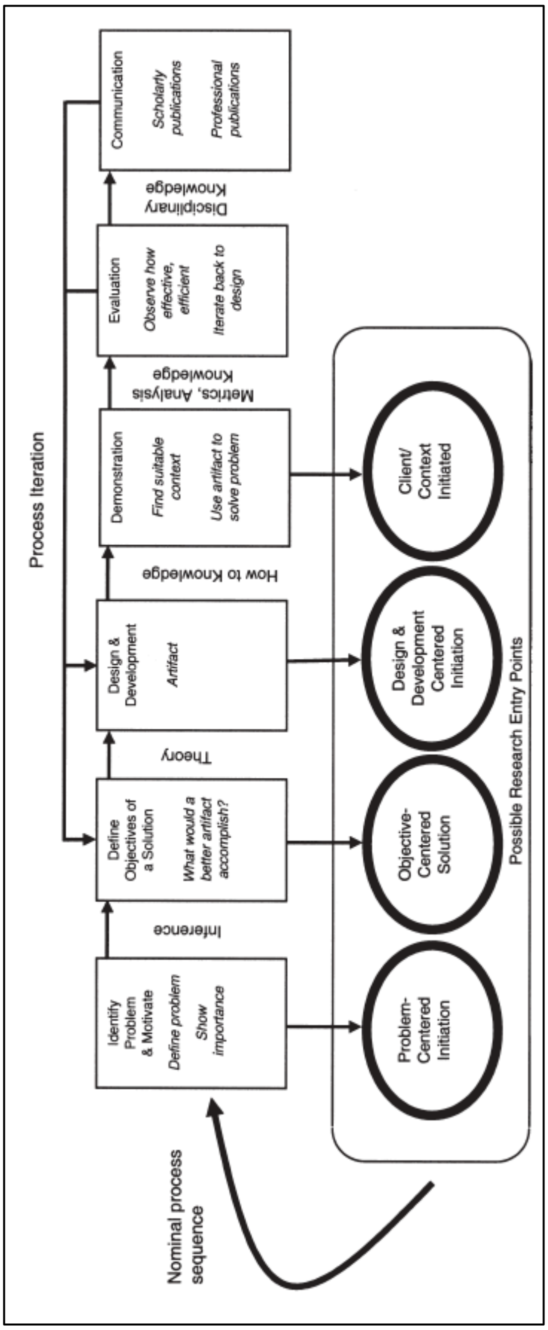


Figure 10 Design Science Research Methodology process model (adapted from Peffers et al.*, 2007)*

The process consists of the following six activities:

1. **Identify and motivate a problem** – the aim of the first stage is to identify the existing research problem and to explain why it is important to solve it. Deep understanding of the problem has to be developed, mostly by reviewing the current state of knowledge about the problem. Highlighting the importance of solving the problem offers additional rationale for conducting the research and ensures the engagement of the researcher and the audience.

2. **Define the objectives for a solution** – in the second stage a way to address the problem is proposed. The solution has to be rationally inferred from the problem identification. It has to be based on the knowledge of what is possible and feasible. The objectives can be either quantitative or qualitative but should describe how the proposed solution addresses the problem.
3. **Design and develop** – the third stage commences a traditional design loop: an artifact is designed and developed. A design artifact "can be any designed object in which a research contribution is embedded in the design" (Peffers *et al.*, 2007, p. 55). This includes constructs, models, methods or specific applications and systems (so-called instantiations). The design must be supported by theory and must include specification of functionalities and architecture.
4. **Demonstrate** – in this stage, the artifact is applied to the problem and its effectiveness is tested. This can be achieved using observational, experimental or simulation methods.
5. **Evaluate** – the stage where the application from the demonstration activity is observed and evaluated. The main criterium is how well it solves the identified problem. Appropriate metrics and evaluation techniques must be used, such that they fit with the nature of the problem and the developed artifact. At this stage, a decision is taken whether to iterate back to stage 3 or to move on to the final stage.
6. **Communicate** – in the final stage, the results of the whole research project are communicated. This involves the discussion of the problem, its importance, the details of the solution and steps taken to evaluate its effectiveness. This can take multiple forms, including a journal article or a doctoral thesis.

Peffers et al. (2007) recommend using the above stages for structuring scholarly publications. However, they stress that it is not necessary to follow it to the letter. Furthermore, they acknowledge that depending on the nature of the research project, researchers may choose to enter the nominal model at different stages. This is clearly visualised in Figure 10.

Since its publication in 2007 DSRM has garnered thousands of citations and has been successfully applied in numerous research studies, from the design of an interface which adapts to the cultural background of the user (Reinecke and Bernstein, 2013) to the improvement of knowledge sharing process in the humanitarian organisation Doctors Without Borders (Holzer *et al.*, 2020).

Chapter 1 and Chapter 2 correspond to the first two steps of the DSRM methodology. In Chapter 1, an important real-world problem was identified and the importance of solving it was explained. Then, in Chapter 2, an approach to solve the problem was elaborated. The following section describes the method used to apply the remaining steps of the DSRM framework.

3.4 Experimental method

This research project adheres to the design science paradigm, with its main objective to design and implement a modification to a market information system in order to facilitate a behavioural change intervention. An experimental approach is the appropriate method for research that seeks to change the behaviour of people (March and Smith, 1995; Hevner, March and Park, 2004).

Experimental research is the default research method of natural scientists; brought to social sciences by psychologists in the early 20th century (Neuman, 2014); it later became a key method for the field of behavioural economics (Croson, 2005). It is not a leading method for management research mainly due to the practical difficulties of implementing such an approach, but it is used sparingly in the information systems domain, especially with the rise of online systems presenting opportunities for large-scale online experiments (Karahanna, Benbasat, *et al.*, 2018).

Experimental research comprises three key elements: a) a deliberate manipulation of a variable (also called treatment), b) a control group and c) random assignment of research participants (or subjects) to either the treatment or control groups (Harrison and List, 2004; Giannoccaro, 2013). The main advantage of experiments is that they offer high internal validity, i.e. "the strongest tests of causal relationships" between the constructs proposed by a theory (Neuman, 2014, p. 282). Due to the high degree of control, the experimenter is able to distil the precise effects of the treatments in a controlled and rigorous manner. However, experiments come with a set of practical and ethical limitations (mainly impacting their external validity), contingent on their implementation details. Experiments can generally take a form of either a laboratory experiment, a randomised field trial or a natural experiment (Harrison and List, 2004; Giannoccaro, 2013; Karahanna, Benbasat, *et al.*, 2018). Each type of experiment affords different levels of control, generalisability and realism, usually trading off one for another (Karahanna, Benbasat, *et al.*, 2018). Each of these is briefly summarised below.

Laboratory (or lab) experiments are studies conducted in an artificial setting (both the study environment and the experimental tasks are tightly controlled) created by the research team in order to investigate a particular research question (Karahanna, Benbasat, *et al.*, 2018). This type of experimental research affords the highest level of control and therefore is hailed as the most effective in investigating causal relationships between variables (Giannoccaro, 2013). The researcher controls the application of the treatment, the surroundings and any other possible, known, confounding variables (Harrison and List, 2004). However, the control comes at a cost. Lab experiments most often use student samples readily available on campus, and simplified experimental tasks adjusted to the student level (Greenberg and Tomlinson, 2004). As a result, the generalisability of findings from lab experiments to the general population or to specialist populations is often doubted, as is the realism of such studies (Harrison and List, 2004; Karahanna, Benbasat, *et al.*, 2018).

Randomised field trials (or simply field experiments) offer an opportunity to deal with the low generalisability and realism of the lab experiments. There are debates about what actually constitutes a field experiment (Harrison and List, 2004) but most often it is an experimental study set in "subjects' naturally occurring environment" (Karahanna, Benbasat, *et al.*, 2018, p. vi), such as within an organisation. Researchers still impose a treatment, randomly assign subjects to treatment and control groups but everything is happening outside the laboratory, in "natural" settings. It is noteworthy, that a field experiment is not conducted to determine what is actually happening in the field (like an exploratory field research) but to test a specific hypothesis in specific natural conditions by deliberately introducing the treatment (Greenberg and Tomlinson, 2004). By being set in the natural settings, the field experiments afford high realism of the study, and depending on the sample size, high generalisability of findings (Karahanna, Benbasat, *et al.*, 2018). However, being in the outside world presents its own challenges. Researchers may be limited in the degree of control they may exercise in different settings, e.g. when experimenting with employees of an organisation, the implementation is always contingent on the approval of the executive team (Greenberg and Tomlinson, 2004). Furthermore, it is considerably more difficult to account for the confounding variables and careful planning is required in order to avoid contamination between the research participants (Giannoccaro, 2013; Neuman, 2014). There are also important ethical issues, as by the virtue of the experiment research subjects must not know they are part of the experiment, which violates their right to informed consent (see Harrison and List, 2004 for a summary and additional references). Some of these limitations are partly resolved by natural experiments.

Natural experiments are a type of a field trial. They take place in natural settings, research participants are randomly assigned to control or treatment groups but the main difference is that a researcher does not impose the treatment but only observes as it naturally unfolds (Harrison and List, 2004). The treatments can either emerge spontaneously or are implemented by other agents without the researchers' intervention, e.g. a social policy introduced by a local government (Karahanna, Benbasat, *et al.*, 2018). Such an approach offers high realism and generalisability (when done on a sufficient scale), it shifts the weight of ethical concerns from the researcher, but it may not be as rigorous in testing theoretical propositions as lab or field experiments due to the reduced level of control.

Each experimental approach has its strengths and limitations, with an ability to answer a variety of research questions. Since the aim of this research project is to find a solution to the problem which exists in the real world, a field experiment seems most suiting in order to preserve the realism and ensure applicability to the companies involved. At the same time, we want the behavioural change intervention to be theory-based and developed in a rigorous and systematic manner. To achieve higher rigour and systematicity, prior to the field test, the elements of the intervention can be tested in a lab-based experiment. This is in line with Harrison and List (2004, p. 1009) who point out that the "beauty of lab experiments within broader context permit sharper and more convincing inference when they are combined with field data". The rationale for adopting such an approach for this study and how it corresponds to the DSRM framework are discussed in the next section.

3.5 Design-test-evaluate loop

At its heart, DSRM includes a traditional design process in order to successfully develop an artifact to solve the previously identified real-world problem (Peffers *et al.*, 2007). Chapter 1 and 2 reviewed the relevant practitioner and academic literature in order to identify and justify the problem, and then propose a broad solution to solve it. It has been established that small businesses do not make adequate use of evidence in their marketing decision-making. This was exemplified with a group of small food producers who supply a major UK retailer, within an established action research project (Who Buys My Food). It is necessary for them to use high quality market information regularly to inform their marketing decisions. Not only is it necessary to make the most of their scarce resources, but it is also an expectation of their retail customer that their marketing proposals are informed by the information. As a solution, it was proposed to design and implement a behavioural change intervention which revolves around developing enhanced data visualisations in the market information system.

In order to test the effectiveness of the behavioural change intervention, a randomised field trial was conducted with a group of small food producers who are part of the Who Buys My Food project. However, in order to develop the visualisations in a rigorous and systematic way, a lab experiment was carried out, with students from the University of East Anglia (UEA). In this way the design-test-evaluate loop in the DSRM was completed twice,[8] visualised below in Figure 11.

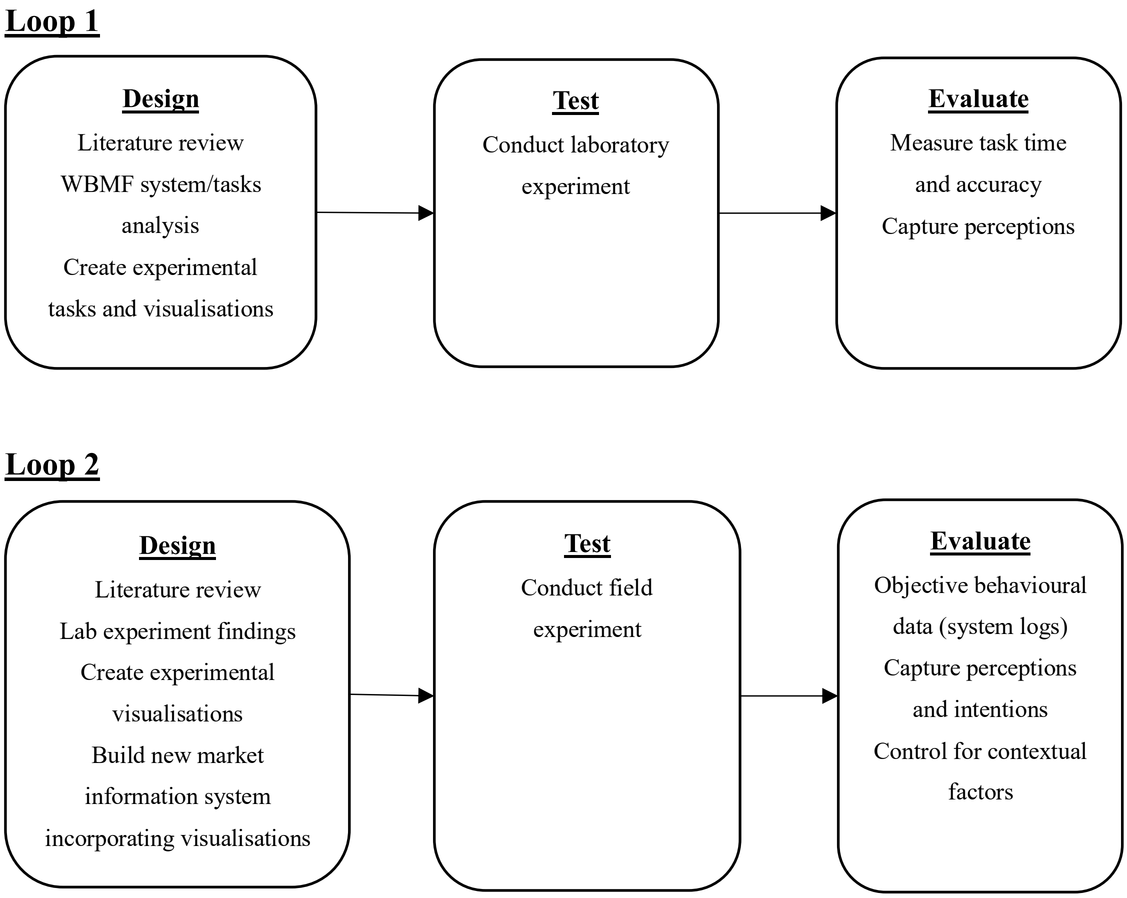


Figure 11 Two design loops iterated over in this research project.

In this study there are two experiments each corresponding to a design loop iteration shown in Figure 11: a lab experiment and a field experiment. Each loop is briefly discussed in turn.

In order to design the lab experiment, the relevant literature on the impact of information presentation format on decision making was reviewed (see Chapter 4). The

[8] Each loop iteration corresponds to a separate chapter in this thesis, which discusses the whole process in detail. This section offers only a high-level overview of the employed research process.

review offered numerous insights but at the same time it revealed a number of limitations, the main one being the use of simplified tasks, thus reducing the realism of the studies. The lab experiment for this study was contextualised by examining the visualisations currently deployed in the market information system and investigating the tasks they were supporting. These two activities were used to create experimental tasks, with new visualisations to be compared with the old information presentation format. The lab experiment was conducted in the Laboratory for Economic and Decision Research (LEDR) at UEA. The objective of the lab experiment was to validate previous research findings with real-world tasks and data visualisations relevant to the small companies, which are the subjects of this research. The lab experiment also served as a testbed for the proposed changes before the new system was released to users (small food producers participating in the Who Buys My Food project) in the real-world.

The findings validated by the lab experiment were then used to inform the design of the field experiment. A replica of the original market information system was created (details to follow in Chapter 5). The underlying data sources and all of the functionalities remained the same, with data presentation format changed as part of the behavioural change intervention. The baseline data was collected for four months followed by a four-month long treatment period. The main source of data for evaluating the field experiment were objective system logs, but self-reported survey data was also collected.

3.6 Field trial context

An inherent part of every field trial is the unpredictability and uncertainty pervasive in natural settings. Since the research participants were small food producers supplying a major UK supermarket, and the experiment was longitudinal in nature, the research sample had to be viewed as “fluid”. Over the course of 8 months, when the field trial was conducted, a number of suppliers lost/gained some or all of their business with Tesco for which the market information system was relevant. In addition, some of the users left the companies they worked for. These changes were diligently recorded and are reported with the results in Chapter 5.

Furthermore, during the course of the field trial a global pandemic of COVID-19 struck. In the UK, a set of nation-wide restrictions (or a ‘national lockdown’) were introduced between March and June 2020.[9] The pandemic and the resulting lockdown led to unprecedented customer behaviour (e.g. considerable stockpiling) leading to supply chain disruptions that lasted for several months and substantially affected all food distribution channels (see e.g. FSA, 2020; Mintel, 2020c; ONS, 2020; Perkins, 2020). In addition, a vast proportion of food sales moved to online channels introducing even further disruptions (see e.g. Mintel, 2020c). Obviously, these circumstances had a major impact on the research participants – small food producers; and, as a result, the field trial. However, we decided to continue with the experiment for the following reasons. First, every research participant faced disruptions caused by the pandemic and the national lockdown. There is no reason to suspect that either control or the treatment group might be disproportionately affected as they were randomly assigned. Second, we ensured that the baseline and treatment data collection periods contain an equal part of the lockdown (see Figure 12 for a detailed project timeline).

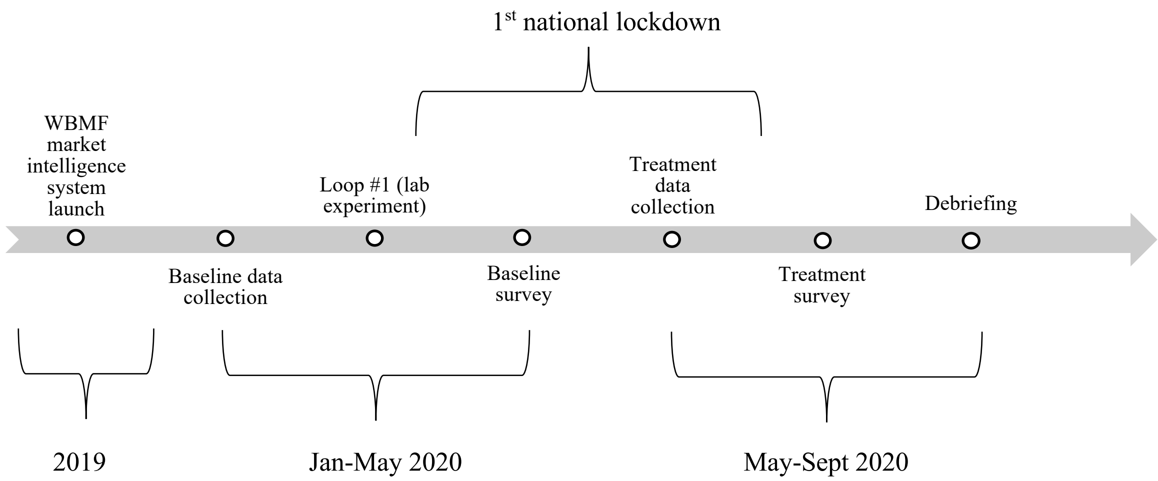


Figure 12 Detailed data collection timeline.

What is more, it could be argued that the post-lockdown period should not be considered "extraordinary circumstances", as this is the "new normal" to which everyone is having to adapt. Third, we included additional questions in a survey administered to all the businesses involved in the project to understand the impact the pandemic and lockdown had on their business. This enabled testing for differences between the groups and to control for any

[9] This was the period that saw the strictest restrictions being introduced in England (see e.g. UK Government, 2020b, and 2020c), specifically they lasted from 16th March 2020 until 23rd June 2020.

unexpected impacts. For example, we asked a question about employees being furloughed[10] as somebody who was furloughed for the time of the experiment was, expectedly, unable to use the system at all. The impact of COVID-19 was not part of the planned research and is not treated as such. However, it was too important an event to be ignored so it was included in the post-hoc analysis.

3.7 Summary of Chapter 3

This chapter provided a high-level overview of the methodological approach used in this research project. First, Design Science paradigm was introduced as a way to approach the design and implementation of a behavioural change intervention. It was followed by a description of the application of DSRM in the context of this study. Second, the three main forms of experiments (laboratory, field, natural) were discussed as possible tools to complete the design loops from the DSRM. Strengths and weaknesses of each method were discussed. Third, the rationale behind conducting first a laboratory-based experiment which informed a randomised field trial was justified. Each study was detailed as a design-test-evaluate loop – a central part of the DSRM framework. Finally, some of the important challenges of conducting field trials were presented, including the fluidity of the research sample and the disruptions caused by the COVID-19 pandemic and the national lockdown that the UK faced.

The following chapter details the laboratory-based experiment (the first design-test-evaluate loop). By the means of reviewing and validating previous research findings in the context relevant to this research project, it aims to answer the following question: How to design intuitive visualisations, in a rigorous and systematic way, with the scope to make the market information system used to a greater extent? As a result, its findings informed the design of the randomised field trial. It has the structure of a typical study, with the literature review and hypothesis generation at the beginning, followed by a methodology section the presentation of results.

[10] Furlough scheme was introduced by the UK government to reduce the impact of the pandemic and national lockdown on British employees. The government paid salaries of employees who otherwise would have to be laid off (see e.g. UK Government, 2020a).

4. Laboratory Experiment

This chapter presents the results of the laboratory experiment, designed to address the first research objective by testing the visual modifications of the market information system. The findings from this experiment also informed the behavioural change intervention developed and implemented in the field experiment (Chapter 5). The chapter begins with a review of the research on the impact of information presentation format on decision-making, which highlights the importance of cognitive fit theory and provides a theoretical rationale for the hypotheses tested. The experimental design is then described, including the development of intuitive data visualisations. Finally, the results of the experiment are reported.

4.1 Introduction (Design)

The motivation for this experiment was the design and evaluation of intuitive data visualisations in a rigorous and systematic way. The visualisations were designed with the aim of making the market information system used more frequently by the target users (small food producers involved in the Who Busy My Food research project). The general argument for using data visualisation was presented in the sub-section 2.2.5.1. In short, the rationale is that some ways of presenting data facilitate effective judgment and decision-making better than others (Lurie and Mason, 2007).

The research on data presentation formats and information visualisation has a long tradition (see e.g. Morton and Stephens, 1968; Dickson, Senn and Chervany, 1977 for some of the first studies) and is typically viewed from the perspectives of two disciplines, computer science and information systems. In computer science, information visualisation is a substantial research area, with hundreds of studies published every year. However, its main focus is on the modelling of the data, improvements to the visualisation algorithms and the development of new visualisation techniques (Lam *et al.*, 2012; Isenberg *et al.*, 2013; Liu *et al.*, 2014). Therefore, it is not directly relevant to this research project. The information systems perspective aligns considerably better with the objectives of this study as it pays more attention to the end user, as well as the managerial and business contexts (Lurie and Mason, 2007; Kelton, Pennington and Tuttle, 2010; Bačić and Fadlalla, 2016).

The organising framework for viewing the research question tackled by the lab experiment is that there are decision-making tasks of different types, as well as different data presentation formats (Lurie and Mason, 2007). They both influence the resulting decision-making outcomes and are moderated by the characteristics of the individuals engaged in solving the tasks (Kelton, Pennington and Tuttle, 2010). The main theoretical base is cognitive fit theory (CFT) (Vessey, 1991; Vessey and Galletta, 1991) and its modifications (Shaft and Vessey, 2006). The initial research focused on the interactions of task types and presentation formats, and their effects on decision outcomes (Kelton, Pennington and Tuttle, 2010). Further research has focused on the role played by the individuals (Bačić and Fadlalla, 2016), the emerging debates about the role of new tools and interactivity (Dilla, Janvrin and Raschke, 2010), cognitive processes of sense making (Baker, Jones and Burkman, 2009), and the growing importance of storytelling (Segel and Heer, 2010; Ma *et al.*, 2012; Kosara and Mackinlay, 2013).

Despite the volume of studies in this area there remain many unresolved issues. For example, how to best solve complex tasks or the use of more complex data presentation formats (e.g. Speier, 2006; Kopp, Riekert and Utz, 2018), which, arguably, are most relevant and impactful for the real-world contexts. What is more, the main criticism, even of the established findings, is that most of our knowledge in this field comes from studies that use over-simplified decision-making tasks and data presentation formats, hence they provide little insight for what might be actually happening in the field (Lurie and Mason, 2007). The lab experiment was designed to address these challenges, with the aims of validating previous research findings and answering the research questions in the specific (real-world) context of marketing decisions by small food producers informed by supermarket loyalty card data, thus contributing to the theoretical debates but also generating actionable insights for practitioners.

The following sub-sections comprise a review of previous research findings and summarise the main unresolved debates, thereby providing a theoretical rationale for hypotheses being tested by the lab experiment. First, cognitive fit theory and its main assumptions and findings are reviewed. Second, the impact of cognitive style (a characteristic of individuals) on decision performance and format preferences is discussed. Finally, the question of complex tasks and complex data presentation formats is presented.

4.1.1 Cognitive Fit Theory

Cognitive fit theory (CFT) was developed by Vessey (1991) to resolve the inconsistent findings from previous research on the impact of information presentation format on decision-making outcomes (Benbasat and Dexter, 1986). It is based on premise that a problem is solved according to the mental representation of the problem in human working memory. In turn, the mental representation is created from the problem representation and the problem-solving task. The theory then postulates that if the type of information emphasised by the problem representation and the problem-solving task match, a cognitive fit occurs and the problem solving is facilitated. If the information emphasised by the problem representation and the task is different, then a mismatch occurs and as a result problem-solving is obstructed, decreasing the problem-solving performance (speed and accuracy).

The general problem-solving model was then adapted to the so-called “tables and charts” research (Vessey, 1991; Vessey and Galletta, 1991). Based on that model, tables or charts (information presentation formats) are two main problem representations, while the nature of the decision task is the problem-solving task. Vessey classifies both problem representations and problem-solving tasks as either spatial or symbolic. Graphs can be viewed as spatial problem representations since they present spatially related information, which emphasises the relationships in the data. Accordingly, spatial tasks are those which enquire about relationships in the data (e.g. were sales in July larger than in June?). Tables are viewed as symbolic problem representations since they facilitate extraction of specific data values. In this vein, symbolic tasks are those which enquire about specific values (e.g. what sales were achieved in July 2019?).

CFT predictions were validated empirically (Vessey and Galletta, 1991), and are still used as the theoretical basis for research on the impacts of data presentation format on decision-making outcomes (Saket, Endert and Demiralp, 2018). CFT has been used in many different contexts, to model uncertainty in Bayesian reasoning (Reani *et al.*, 2018; Reani, Peek and Jay, 2019), compare advanced plots with tables (Gettinger *et al.*, 2013); investigate the impact of visual aids in negotiations (Gettinger, Koeszegi and Schoop, 2012) and explore the effective use of quality assurance data (Teets, Tegarden and Russell, 2010). Therefore, based on the CFT and previous studies, we formulate the following hypothesis to replicate and validate previous research findings in the specific context of this study:

H1a: *Symbolic problem representations (tables) result in better decisions for symbolic tasks than spatial problem representations (charts).*

H1b: *Spatial problem representations (charts) result in better decisions for spatial tasks than symbolic problem representations (tables).*

4.1.2 Cognitive style, decision performance and format preferences

Early research into the impact of data presentation format on decision performance received substantial criticism for not paying enough attention to the characteristics of the individuals involved in the process (Kelton, Pennington and Tuttle, 2010; Liu *et al.*, 2014). Arguably, one of the most relevant characteristics of the individuals for this research problem is how they process information (Bačić and Fadlalla, 2016) often described by the concept of cognitive styles.

Cognitive styles describe consistent differences among individuals with respect to how they perceive information, think and take decisions (Armstrong, Cools and Sadler-Smith, 2012). The conceptualisation of these trait-like characteristics is based on the dual-processing theories of the human mind, which propose that there are two information-processing systems, automatic and intentional (Pacini and Epstein, 1999; Sloman, 2002; Betsch and Kunz, 2008). The instruments which measure cognitive styles, explore the tendencies of individuals to employ either of the systems.

Cognitive styles were included in the recent research into the impact of information presentation format on decision making performance as part of the research stream investigating the role played by decision-makers characteristics (Engin and Vetschera, 2017; Luo, 2019). There were two main hypotheses tested in these studies, which are important for improving the efficacy of real-world market information systems.

The first was concerned with the impact of cognitive style match with the problem representation on the decision performance. The results from the study by Engin and Vetschera (2017) indicate that if the problem representation (data presentation format) matches an individual's cognitive style then the decision performance is improved. The matching condition is said to exist between the increased use of the conscious or intentional system and symbolic representations, and between the increased use of the automatic or intuitive system and spatial representations. However, Luo (2019) failed to find support for the existence of that effect. The two contrasting findings call for more research into that problem. A major difference between the two studies was the measure of cognitive style employed. Engin and Vetschera (2017) used a more business-oriented Cognitive Style Index (CSI) (Allinson and Hayes, 1996, 2011) while Luo (2019) used a visualiser-verbaliser scale used mainly in learning contexts (Kirby, Moore and Schofield, 1988). As explained in the sub-section 2.2.5.2, the Rational-Experiential Inventory (REI) scale was adopted for the lab experiment, which is based on the cognitive-experiential self-theory (CEST), a comprehensive dual-processing theory of personality (Epstein, 2003).

This conceptualisation allows us to investigate general tendencies of individuals to employ effortful or intuitive systems. As explained in the sub-section 2.2.5.1 the intuitive system is what underlies the power of visualisations and hence the more general measure of cognitive style fits better in this context. In line with previous research (Engin and Vetschera, 2017; Luo, 2019), we put forward the following hypotheses:

H2a: *Users with a dominating rational cognitive style make better decisions with symbolic problem representations (tables) than spatial problem representations (charts).*

H2b: *Users with a dominating experiential cognitive style make better decisions with spatial problem representations (charts) than symbolic problem representations (tables).*

The second hypothesis dealt with decision-makers' preference for different data presentation formats. Luo (2019) found that, given a choice, subjects are more likely to choose a problem representation that fits their cognitive style. Again, the fit is conceptualised in the same vein as the matching condition. A behavioural measure was used to evaluate the fit, but it is interesting to investigate satisfaction and subjective preference for the data presentation format they chose. Since subjective evaluations are said to be the key predictors for continued system use (Bhattacherjee and Lin, 2015). Such findings, if validated, would indicate that users should be given a choice of how to see the data if it results in their more positive attitudes and as a result more use. Therefore, we formulate the following hypotheses:

H3a: *Users with a dominating rational cognitive style prefer symbolic problem representations (tables) rather than spatial problem representations (charts).*

H3b: *Users with a dominating experiential cognitive style prefer spatial problem representations (charts) rather than symbolic problem representations (tables).*

4.1.3 Complex tasks and complex visualisations

The previous two sub-sections discussed standard problem representations, such as charts and tables, simple symbolic and spatial tasks and the role played by the cognitive style of the system user. However, in the real-world context few tasks are of a simple nature and most of the data visualisations tend to be more complex than those used in previous studies (Kopp, Riekert and Utz, 2018). This is of most relevance to this study, the aim of which is to inform the field experiment as well as validate previous research findings. Complexity of tasks is a research field in its own right (Wood, 1986; Campbell, 1988), but following previous studies we define complex tasks as those that require comparing more than two values in order to provide an answer (Speier, 2006; Kopp, Riekert and Utz, 2018). As a result, a task such as "Are sales for product A greater than for product B?" is an example of a simple task, while "Which product has above average sales but below average number of customers?" is an example of a complex task. Since previous research findings were either inconclusive (Speier, 2006) or did not address the difference in performance of different data presentation formats and task complexity despite differentiating between simple and complex tasks (Kopp, Riekert and Utz, 2018), we propose the following research question to be investigated in this study:

RQ1: *Which information presentation format results in the best decision performance for complex tasks?*

Furthermore, an interesting recent study looked at the impact of seemingly redundant chart elements and their impact on decision performance (Kopp, Riekert and Utz, 2018). Kopp et al. (2018) found that a spatial problem representation (chart) enhanced with data labels increases decision performance for both spatial and symbolic tasks as compared with basic charts. Therefore, we propose to test the following hypotheses:

H4a: *Charts with labels result in better decision performance for symbolic tasks than charts.*

H4b: *Charts with labels result in better decision performance for spatial tasks than charts.*

A related but unexplored question relates to the comparison of decision performance for symbolic and spatial tasks achieved with charts with labels and tables. Basically, can a chart with labels not only improve the usefulness of charts but match that of tables? Finally, the question of preference, already mentioned in the previous sub-section, remains. Kopp et al. (2018) indicated that people preferred charts with labels to charts (but only as an additional post-hoc analysis), but gave no indication as to how the preference compares to tables. Furthermore, there could be differences in the preferences for the three data presentation formats influenced by cognitive style. Answers to these questions would not only contribute to previous research debates but also provide valuable information for the modification of the market information system. As a result, the following research questions are posed:

RQ2: *How does the decision performance achieved from charts with labels compare against tables for symbolic and spatial tasks?*

RQ3: *How does the preference for charts with labels compare with tables and charts?*

RQ4: *How does the preference for charts with labels of people with different cognitive styles compare with tables and charts?*

4.1.4 Summary of Introduction

The model in Figure 13 summarises the hypotheses and research questions tested in the laboratory experiment. The top part of the model relates to Hypotheses 1 and 4 and Research Questions 1 and 2. It examines how different combinations of information presentation formats (tables, charts and charts with labels) and task types (simple: symbolic or spatial, and complex) affect decision performance. The lower part relates to Hypotheses 2 and 3 and Research Questions 3 and 4. It investigates how different information presentation formats (tables, charts and charts with labels) affect decision performance and the resulting format preferences for people with different cognitive styles. The following section presents in detail the design of the laboratory experiment.

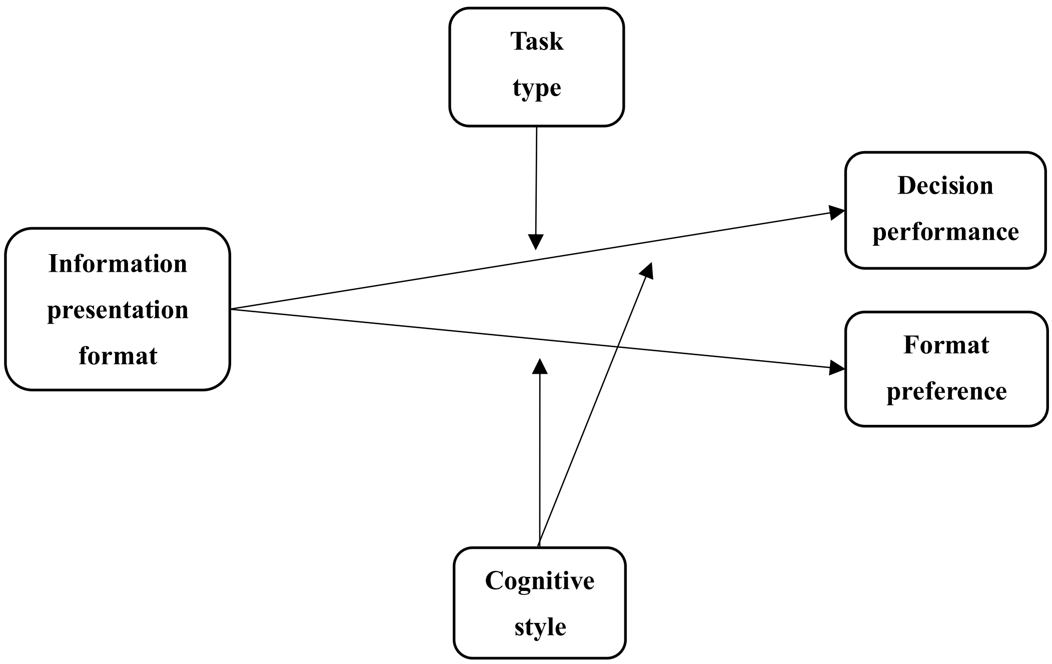


Figure 13 Conceptual research model tested in the laboratory experiment.

4.2 Method (Test)

This section explains the types of tasks used in the experiment, the way in which specific data visualisations were designed and presented, and the outcome measurements and information on the participant sample.

4.2.1 Tasks

A between-subject experiment was designed, comprising a set of 18 information extraction tasks, commonly performed in practice (see Table 2 for the list of tasks used). The tasks were extracted from the report template used in the Who Buys My Food project. The template allows the user to extract information covering three key areas – product performance (KPIs), shopper segmentation and store performance – which can be used to inform a range of marketing decisions. For the purpose of the lab experiment six tasks were set for each of the areas. The tasks were both simple (symbolic and spatial) and complex in nature to reflect the variety of scenarios faced by practitioners using this system.

Task type	Report part	Task number	Task	Additional comments / explanations
Symbolic	KPIs	1	What is the penetration for Wine D?	-
		2	What is the repeat purchase rate for Wine D?	-
	Segmentation	3	What is the index value for Mid-Market shopper segment for Wine D?	-
		4	What is the index value for Older Families shopper segment for Wine D?	-
	Store performance	5	What is the total rate of sales?	-
		6	In how many Upmarket stores is this product sold?	-
Spatial	KPIs	7	Is the growth in sales value for Wine D higher than the growth in sales value for the total product group?	-
		8	Is the number of stores selling for Wine D higher than the average number of stores selling for all SKUs in the product group?	-
	Segmentation	9	To which shopper segment does Wine D appeal most?	The product appeal is determined by the index value. The higher

		10	To which shopper segment does Wine D appeal least?	the index the higher the appal and vice versa.
	Store performance	11	In which store format are sales for this product highest?	-
		12	In which store region is rate of sale for this product highest?	-
Complex	KPIs	13	Which product is at the greatest risk of being delisted?	A product is at the risk of being delisted when both penetration and repeat purchase rate are below the average for all SKUs in the product group.
		14	Which product is most likely to have their number of stores selling increased?	Number of stores selling is increased if a product has penetration above the average for all SKUs in the product group and the number of stores selling below the average for all SKUs in the product group.
	Segmentation	15	How many product(s) are meeting a distinct need?	A product is said to meet a distinct need if, for any particular shopper segment, index value for the total product group is below 100, while product's index value is above 100.
		16	Which product(s) over-index for more than one shopper segment (if appropriate, you can choose more than one)	The value of 100 is the benchmark, anything above is said to over-index.
	Store performance	17	Which three regions have run most successful promotions as measured by sales?	A new promotion was piloted in 8 randomly selected stores in 5 different regions.
		18	How many Extra stores have above average rate of sale?	-

Table 2 List of tasks used in the laboratory experiment.

4.2.2 Visualisations

The visualisations ('charts' condition), were based on the template tables extracted from the deployed market information system ('tables' condition), further enhanced with data labels ('charts with labels' condition). For the purpose of the experiment, all three types of data presentation were prepared with the use of Tableau software.

The design of the graphical visualisations of the existing tables was informed not only by academic experts but also by senior visual analysts from Atheon Analytics, a company specialising in visual analytics for the grocery retail sector. The visualisations have an inherent complexity as they are communicating considerable amounts of relevant and important data yet must be easy to interpret by the target audience (small food producers) most of which are known to struggle with the digestion of highly formalised and structured information (see section 1.2). Therefore, the visualisations were limited to simple bar charts and scatterplots as constituent parts, but, where necessary, where then assembled to form more complex visualisations. Each part of the report, its corresponding data and newly created visualisations are now discussed in turn.

Please note that low quality examples of the visualisations used are placed in the following section to help the reader gain a basic understanding of what the visualisations looked like. Higher resolution screenshots of the same visualisations are available in Appendix A. Original Tableau workbooks are available from the author upon request.

4.2.2.1 Key Performance Indicators

Key Performance Indicators (KPIs) inform suppliers about the performance of their products in a given time period, and how that performance compares against their direct competitors. The latest values of four KPIs are communicated along their year-on-year change. The KPIs mentioned here are the most important metrics that Tesco buyers use to evaluate the performance of individual products (based on the internal dunnhumby documentation, conversations with Tesco buyers and suppliers and consulted with an academic expert). They include:

- customer penetration – share of customers who bought a product at least once in a given time period,
- repeat purchase rate – share of customers who bought a product at least twice in a given time period,
- sales value – total amount of sales generated by a product in a given time period, and
- the number of stores selling – total number of stores that sold at least one unit of a product in a given time period.

The table presenting this information has individual products as rows and KPIs and their respective change as columns. “Average for all Stock Keeping Units (SKUs) in the product group” as well as the values for the “Total Product Group” are also included as rows. An example of such a table is illustrated in Figure 14 – a screenshot from the visualisation as presented in the lab experiment.

KPIs Summary

Product Name	Growth in Sales Value (%)	Penetration (%)	Growth in Penetration (%)	No. of Stores Selling	Growth in No. of Stores Selling (%)	Repeat Purchase Rate (%)	Growth in Repeat Rate (%)
Wine E	-35.29%	0.13%	-38.57%	320	-10.64%	6.75%	57.71%
Wine D	8.72%	0.04%	8.53%	308	12.41%	6.42%	33.00%
Wine C	3.99%	0.52%	10.56%	1,104	36.63%	8.65%	-11.83%
Wine B	-19.06%	1.28%	-17.33%	1,659	5.40%	8.02%	-12.71%
Wine A	7.54%	0.71%	13.68%	862	2.01%	12.22%	-4.53%
Total Product Group	1.04%	10.98%	-0.15%	2,543	-1.05%	27.15%	-0.98%
Average for all SKUs in the product group		0.12%		357		7.92%	

Figure 14 KPIs summary in tables condition.

To communicate the same information in a more visual way, a chart consisting of a number of bar charts was created. The relevant pieces of information are grouped together, and the chart can be navigated both horizontally and vertically. In the horizontal orientation, each of the four KPIs becomes a mini chart (like a row of the bigger chart) consisting of two bar charts. Vertically, the bar charts on the left show values of individual products for each KPI and are compared with average for all SKUs in the product group, while the bar charts on the right show changes in the KPIs for each product and are compared with the change experienced by the product group as a whole (indicated by the vertical dotted line). An exemplary charts representation of the KPIs is presented in Figure 15. The charts with labels condition had additional data labels at the end of each bar.

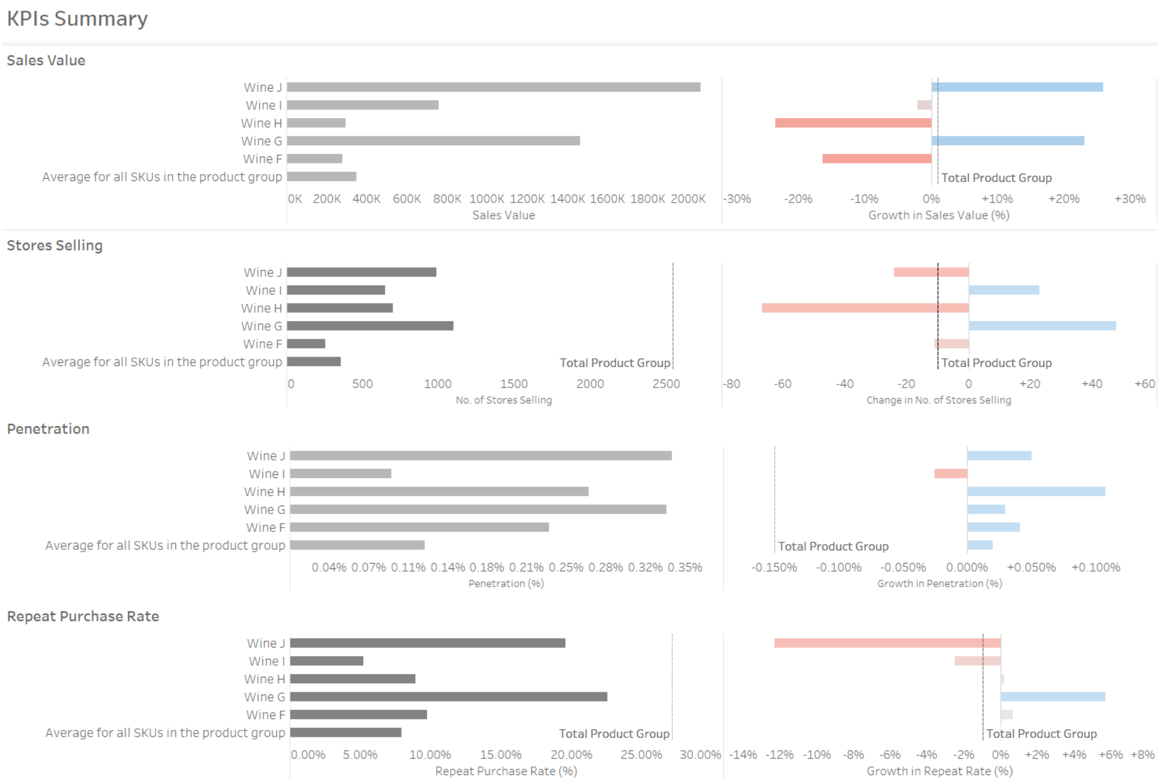


Figure 15 KPIs summary in charts condition.

4.2.2.2 Shopper segmentation

The shopper segmentation part of the report provides crucial information about the type of people who purchase a product, which has implications for branding, pricing and packaging, amongst other things. What is more, individual products are compared against the customer mix for the category in which the product is ranged. This information is presented in an index form (with 100 being the average for all shoppers), so an index greater than 100 means that a shopper segment is more likely to purchase the product and an index below 100 means they are less likely. The index is created at source, by dunnhumby, and is used by the retailer to inform a variety of retailer-led decisions, such as ranging and merchandising. Suppliers are expected to use the indices to inform their own marketing plans. Many ways to segment shoppers exist. In the Who Buys My Food project, suppliers are offered four types of segmentation to allow them to categorise their customers in a variety of ways. The four segmentations are lifestage, lifestyle, five families and cameo (see Appendix B for further details). In the experiment two commonly used segmentations, lifestage and lifestyle, were presented.

In the tables condition, each product is a row of the table and different shopper segments are the columns. The values for the total product group are included as the final row of the table (see Figure 16).

Lifestage Summary

Product Name	Young Adults	Young Families	Older Families	Older Adults	Pensioners
Wine E	73	80	145	128	69
Wine D	59	50	145	136	87
Wine C	84	105	150	119	53
Wine B	77	104	134	109	85
Wine A	60	90	153	119	82
Total Product Group	70	74	119	117	106

Figure 16 Shopper segmentation summary in tables condition.

In order to transform the shopper segmentation table into a chart, a scatterplot was used. Index values are placed on the x-axis while customer segments make up the y-axis. Values for each product are represented as points coloured for each product. The values for the total product group are represented as vertical dotted lines, while the 100 benchmark is represented as the solid vertical line. The chart allows the viewer not only to compare each product against the total product group but also get a quick overview of the more general trends of all of its products (see Figure 17). The charts with labels condition had additional data labels attached to each circle and line.

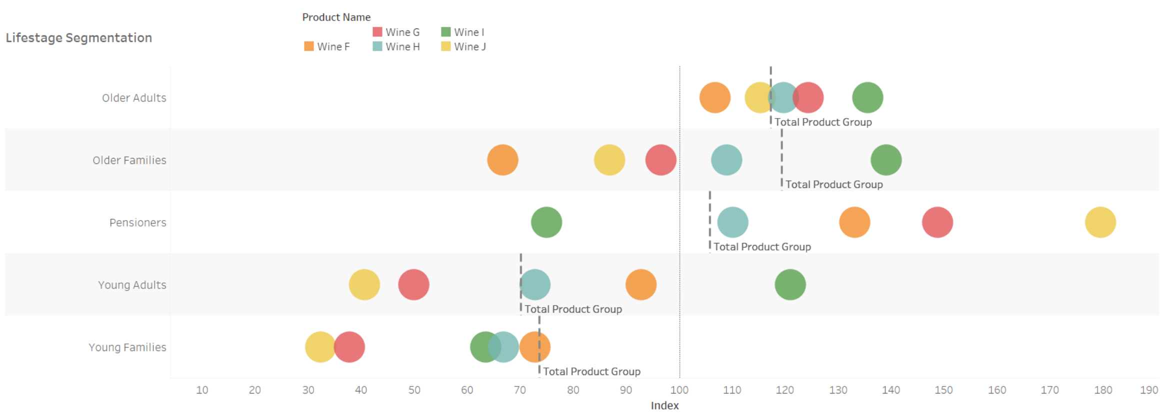


Figure 17 Shopper segmentation summary in charts condition.

4.2.2.3 Store performance

Store performance data is key for understanding the extent to which demand arises across the stores in which a product is listed. This data is very complex as there are several store formats and a number of performance measures, which invariably differ considerably between stores for niche brands, such as those produced by the small producers involved in the Who Buys My Food research project. Moreover, the level of distribution varies considerably, with some products listed in a handful of stores and others listed in hundreds of stores, meaning that data on store performance can be presented in a variety of ways and at many levels of aggregation.

In the experiment, to reflect the complexity of the data and the types of decisions that it can inform, participants were presented with three tables (in separate screens with separate tasks) and three different types of corresponding visualisations. First, a table summarising the number of stores selling, sales value and rate of sale for all stores (total), and stores broken down by their format, affluence or region was created (see Figure 18). The three variables were used as columns and different store types as rows. Second, a table showing a sample of 40 stores and their rate of sales and total sales was created (see Figure 19). Each store was a row, with a final row showing the average values. Finally, a table presenting a sample of 40 stores, their geographic location and sales value was created (see Figure 19). Each store was a separate row of this table.

Total

	Number of Stores	Total Sales	Rate of Sales
Total	801	£688,530	£23.37

Format

Dotcom	6	£6,704	£23.05
Express	176	£30,569	£6.77
Extra	255	£319,494	£29.49
Metro	19	£10,937	£17.47
Superstore	344	£320,825	£25.83

Affluence

Midmarket	315	£332,269	£28.59
No Affluence Stores	142	£29,916	£8.10
Price Sensitive	130	£74,985	£17.69
Super Upmarket Stores	49	£69,258	£28.57
Unclassified	73	£40,762	£17.29
Upmarket	86	£139,666	£33.40

Region

Borders	11	£3,314	£19.17
Central Scotland	45	£15,670	£12.59
East Anglia	96	£198,504	£62.01
London	203	£133,127	£17.57
Midlands	89	£82,992	£23.83
North East	20	£17,504	£20.81
North Scotland	26	£14,093	£18.58
North West	85	£49,599	£16.01
Northern Ireland	29	£10,982	£10.78
South East	67	£62,361	£22.40
South West	26	£22,211	£23.84
Wales	52	£37,340	£20.55
Yorkshire	49	£39,247	£21.27

Figure 18 Store level performance at the highest level of aggregation in tables condition.

Extra stores

Store ID	Rate of Sales	Total Sales
2039	£23.00	£1,196
2073	£29.40	£1,529
2128	£19.87	£1,033
2136	£38.12	£1,982
2141	£19.15	£996
2164	£26.77	£1,392
2361	£7.15	£372
2371	£30.44	£1,583
2436	£56.73	£2,950
2569	£9.92	£516
2587	£4.85	£252
2638	£17.17	£893
2804	£16.42	£854
2819	£17.92	£932
2846	£23.67	£1,231
2898	£27.12	£1,410
3008	£15.63	£813
3107	£24.42	£1,270
3177	£53.75	£2,795
3290	£29.60	£1,539
3345	£16.88	£878
3377	£14.83	£771
5031	£11.81	£614
5249	£2.52	£131
5447	£6.83	£355
5528	£14.69	£764
5652	£24.52	£1,275
5745	£1.69	£88
5851	£17.65	£918
5852	£25.56	£1,329
5904	£13.83	£719
5992	£33.92	£1,764
6025	£9.50	£494
6161	£4.42	£230
6193	£10.83	£563
6419	£17.17	£893
6476	£13.46	£700
6504	£19.63	£1,021
6785	£6.08	£316
6810	£20.69	£1,076
Average	£19.44	£1,011

Stores from 5 regions

Store ID	Region	Sales
2105	Borders	£2,050
2166	Borders	£3,797
2172	Borders	£2,822
2877	Borders	£15,847
3145	Borders	£3,719
4351	Borders	£574
5275	Borders	£111
6179	Borders	£242
2265	South East	£964
2445	South East	£1,735
2718	South East	£332
2722	South East	£244
2757	South East	£116
5222	South East	£100
6077	South East	£205
6554	South East	£100
2142	North West	£1,199
2701	North West	£274
2943	North West	£330
2992	North West	£575
5148	North West	£460
6025	North West	£494
6232	North West	£22
6797	North West	£306
2676	Wales	£428
2880	Wales	£2,314
2913	Wales	£563
5249	Wales	£131
5438	Wales	£1,038
5652	Wales	£1,275
6331	Wales	£619
6475	Wales	£220
2168	Yorkshire	£274
2204	Yorkshire	£1,654
2286	Yorkshire	£1,906
2392	Yorkshire	£854
2693	Yorkshire	£507
2814	Yorkshire	£225
4362	Yorkshire	£1,884
6130	Yorkshire	£263

Figure 19 Store level performance at the lowest level of aggregation in tables condition.

Each table was then transformed into a separate chart. They are shown in separate pages below to ensure their visibility. The rationale for each of them is explained below it, on the same page. The charts with labels condition had additional data labels attached to each circle and at the end of each bar.

The table summarising the number of stores selling, total sales and rate of sales was transformed into a series of grouped bar charts. Vertically the chart is divided into three sections, each corresponding to one of the variables. Horizontally, each row represents a grouping of stores of a specific type and their corresponding values denoted by the length of the bar, spaced out to denote different levels of groupings: the total, by format, by affluence and by region. The x-axis at the bottom of each part of the bar chart show the scales at which the bars are compared with each other.

Figure 20 Store level performance at the highest level of aggregation in charts condition.

The table showing rate of sales and total sales for a sample of 40 individual stores was transformed into a chart consisting of two bar charts placed one below another. Y-axes denote the scales of the values, while the x-axes list the specific stores. The average values are denoted with horizontal solid lines. The line allows for prompt identification of stores with above and below average sales and rate of sales.

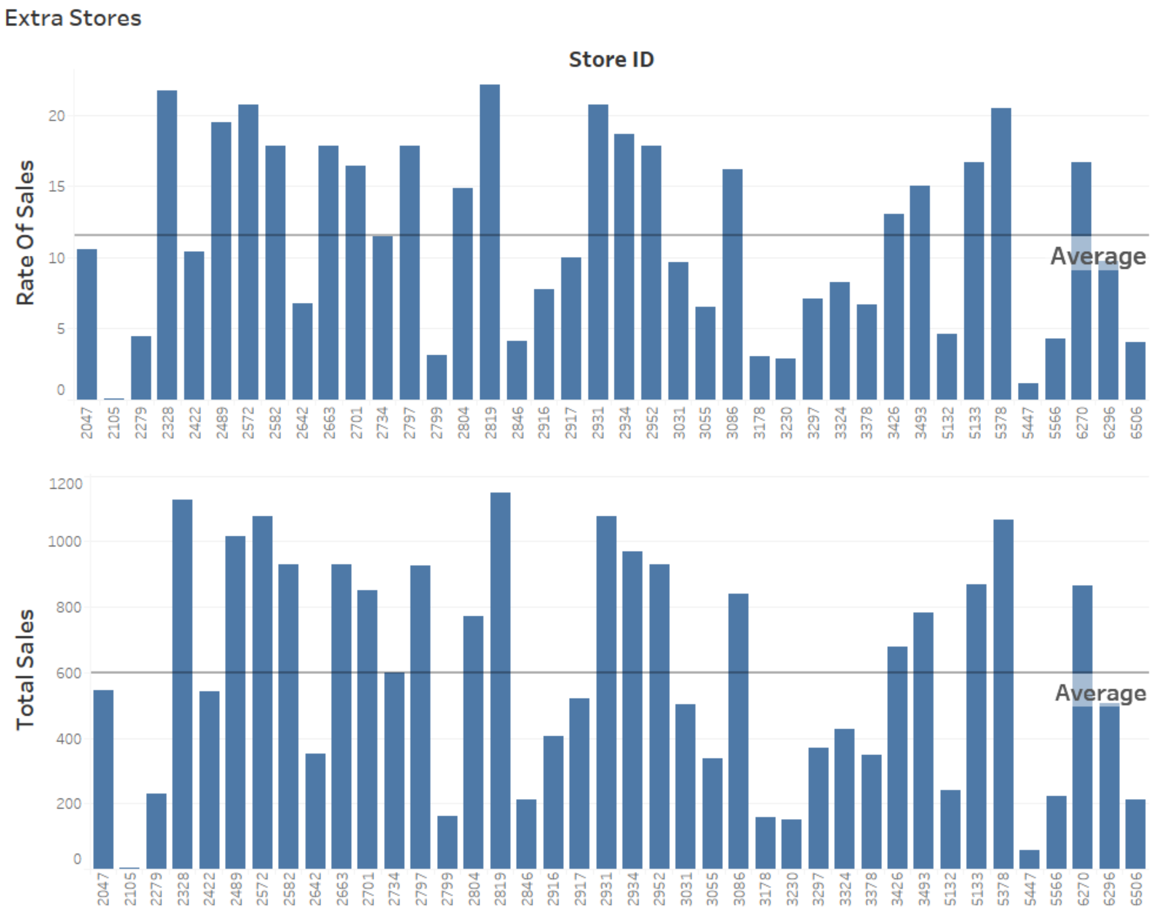


Figure 21 Store level performance at the lowest level of aggregation in charts condition (average comparison).

A commonly used type of chart to visualise geographic data is a map. Hence, the third table detailing a sample of 40 stores, their sales and geographic locations was transformed into a map. Each store is denoted with a point on a map, coloured by the region and its size scaled by the sales value. The map allows for a quick extraction of geographical trends.

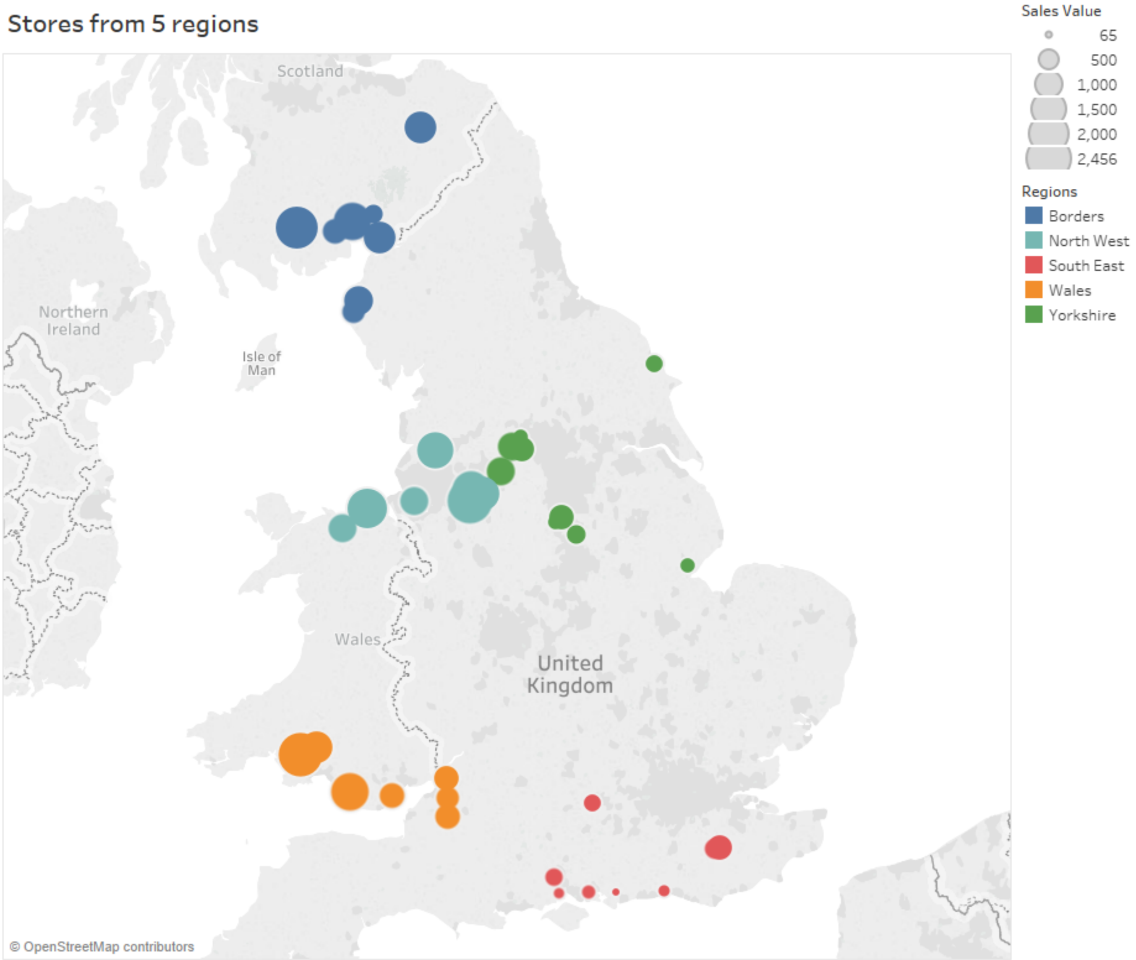


Figure 22 Store level performance at the lowest level of aggregation in charts condition (geographical comparison).

4.2.3 Study procedure

Three task types and three types of data presentation formats (treatments) resulted in a 3x3 (Information Presentation: tables, charts, charts with labels x Task Type: symbolic, spatial, complex) between-subject design. The experiment was implemented using Qualtrics Software. Each subject began the experiment by being randomly allocated to one of the information presentations treatment (tables, charts or charts with labels) and was then instructed to perform 18 information extraction tasks of spatial, symbolic and complex nature. Each task and visualisation were presented as separate screens. Participants had to click the ‘Next’ button to submit their answer and move on to the next task. Even if a number of tasks related to the same visualisations, they were still presented as separate screens to accurately capture the time taken. Within each group, the order of experimental sequences was randomised, so the subjects began either with symbolic or spatial tasks to evenly distribute any ‘familiarisation effects’, i.e. additional time spent on the very first task in each section to orient themselves. After completing the tasks, each participant was asked a number of questions related to their cognitive styles, preferences for the visualisations and their demographics. The experimental design and procedure were first pilot tested in the lab setting and further refined with the feedback from 10 experienced experimentalists from the UEA School of Economics. The experiment was approved by the ethics committees in the Norwich Business School and the School of Economics.

4.2.4 Measurement

The decision performance variable was operationalised in line with previous research (e.g. Engin and Vetschera, 2017; Kopp, Riekert and Utz, 2018), using two dimensions: the time taken to submit an answer; and the share of correct responses. The response times were extracted from the online system logs. In addition to the objective decision performance measures, we also used a number of subjective perceptual measurements to gauge participants’ preference and evaluations for different data presentation formats. Preferences for a data presentation format were evaluated using IS continuance constructs, which answered the call for linking information presentation literature with the extant IS literature (Bačić and Fadlalla, 2016). They included: Perceived Usefulness, Perceived Ease of Use and Satisfaction – the most commonly used predictors for system acceptance and continuance. The items were measured with 7-point scales adapted from the original scales for the purpose of this experiment (Davis, 1989; Venkatesh and Morris, 2000; Bhattacherjee, 2001). Cognitive style was measured using items from the Reflective-Experiential Index (REI) (Epstein *et al.*, 1996; Pacini and Epstein, 1999). The item scales are included in Appendix C.

4.2.5 Participants

The subjects were recruited from the pool of students participating in experiments in the Laboratory for Economic and Decision Research (LEDR) at the University of East Anglia, using a standard laboratory invitation template. 86 female [56%] (age: $\mu = 22.7$, $\sigma = 5.0$) and 66 male [43%] (age: $\mu = 21.2$, $\sigma = 2.1$) students took part in the experiment ($N = 154$; two students decided not to disclose their gender). No demographic screening was applied to the participants in order to get as representative a sample as possible. Participants were students from 15 different schools at UEA, with the three most represented being: the business school (29%), the school of economics (12%) and the medical school (9%). Participants were enrolled on the following degree courses: 101 undergraduates (66%), 47 masters (31%), 6 others (3%). The whole experiment lasted for approximately 20 minutes (questionnaire duration: $\mu = 721.7s$, $\sigma = 186.8s$) and participants were rewarded with £5 for their participation. See Table 3 for the distribution of participants across the experimental treatments.

Treatment	N
Tables	52
Charts	49
Charts with labels	53

Table 3 The number of participants in each treatment group.

4.3 Results (Evaluate)

Table 4 summarises the hypotheses and research questions alongside the main findings from the analyses employed to test them. The rest of this section contains four sub-sections. The first three correspond to the three sub-sections 4.1.1-4.1.3 from the introduction and their corresponding hypotheses. The last sub-section details the results of additional post-hoc analyses that were not formally formulated but nevertheless are important for the design of the field experiment. All calculations within this section were carried out using R statistical software.

Number	Hypothesis / Research Question	Support	Findings
H1a	Symbolic problem representations (tables) result in better decisions for symbolic tasks than spatial problem representations (charts).	Supported	For symbolic tasks tables resulted in statistically significantly faster and more accurate decisions than charts.
H1b	Spatial problem representations (charts) result in better decisions for spatial tasks than symbolic problem representations (tables).	Not supported	The opposite effect was found. For spatial tasks tables also resulted in statistically significantly faster and more accurate decisions than charts.
H2a	Users with a dominating rational cognitive style make better decisions with symbolic problem representations (tables) than spatial problem representations (charts).	Supported	Participants with a dominating rational cognitive style made statistically significantly faster and more accurate decisions using tables than charts.
H2b	Users with a dominating experiential cognitive style make better decisions with spatial problem representations (charts) than with symbolic problem representations (tables).	Not supported	The opposite effect was found. Participants with a dominating experiential cognitive style made statistically significantly faster and more accurate decisions using tables than charts.
H3a	Users with a dominating rational cognitive style prefer symbolic problem representations (tables) rather than spatial problem representations (charts).	Not supported	The preferences of participants with a dominating rational cognitive style for tables were higher than charts but the difference was not statistically significant.
H3b	Users with a dominating experiential cognitive style prefer spatial problem representations (charts) rather than symbolic problem representations (tables).	Not supported	The opposite effect was found. The preferences of participants with a dominating experiential cognitive style for tables were higher than for charts but the difference was not statistically significant.
H4a	Charts with labels result in better decision performance for symbolic tasks than charts.	Supported	Charts with labels resulted in statistically significantly faster and more accurate decisions for symbolic tasks.
H4b	Charts with labels result in better decision performance for spatial tasks than charts.	Partially supported	Charts with labels resulted in statistically significantly more accurate decisions than charts for spatial tasks. However, there was no statistically significant difference in decision speed.
RQ1	Which information presentation format results in best decision performance for complex tasks?	-	For complex tasks, charts resulted in statistically significantly faster decisions than either tables or charts with labels. However, tables resulted in most accurate decisions and charts in least accurate. Charts with labels came in between the two in accuracy.
RQ2	How does the decision performance achieved with charts with labels compare against tables for symbolic and spatial tasks?	-	For both symbolic and spatial tasks tables resulted in faster and more accurate decisions than charts with labels. The difference in accuracy for spatial tasks was not statistically significant. Other differences were statistically significant.

RQ3	How does the preference for charts with labels compare with tables and charts?	-	None of the differences was found to be statistically significantly different. However, participants seem to have expressed greater preference for charts with labels than either for tables or charts.
RQ4	How does the preference for charts with labels of people with different cognitive styles compare with tables and charts?	-	None of the differences was found to be statistically significantly different. However, charts with labels seemed to have been preferred to either tables or charts by rational individuals. Experiential individuals seem to have preferred tables to charts with labels and expressed similar preference for charts.

Table 4 Summary of study hypotheses, research questions and their respective findings.

4.3.1 Data presentation format, task type and decision performance

To test the first two hypotheses concerned with the impact of data presentation format on decision performance across different task types, a series of one-way ANOVA tests were conducted. In the first series of tests, the time to decision was used as the dependent variable, while in the second the share of correct answers was used as the dependent variable (see Figure 23 for the visualisation of results). As shown in Table 5, Hypothesis 1a was fully supported – tables facilitated faster and more accurate decisions than charts for symbolic tasks. However, Hypothesis 1b was not supported. What is more, the opposite effect was found to the one predicted by the Cognitive Fit Theory. Tables, unlike the expected charts, facilitated both significantly faster and significantly more accurate decisions for spatial tasks. The differences between the two treatments were much smaller than for the first hypothesis but they were statistically significant at p-value < 0.01.

Condition	Time (s)			Accuracy (% of correct answers)		
	Tables	**Charts**	**Diff**	**Tables**	**Charts**	**Diff**
Symbolic	17.2	29.2	-12.00***	0.95	0.25	-0.70***
Spatial	23.5	27.9	-4.36***	0.91	0.77	-0.14***

*** *p.value < 0.01;* ** *p.value < 0.05;* * *p.value < 0.1*

Table 5 Statistical tests of differences between tables and charts – decision performance.

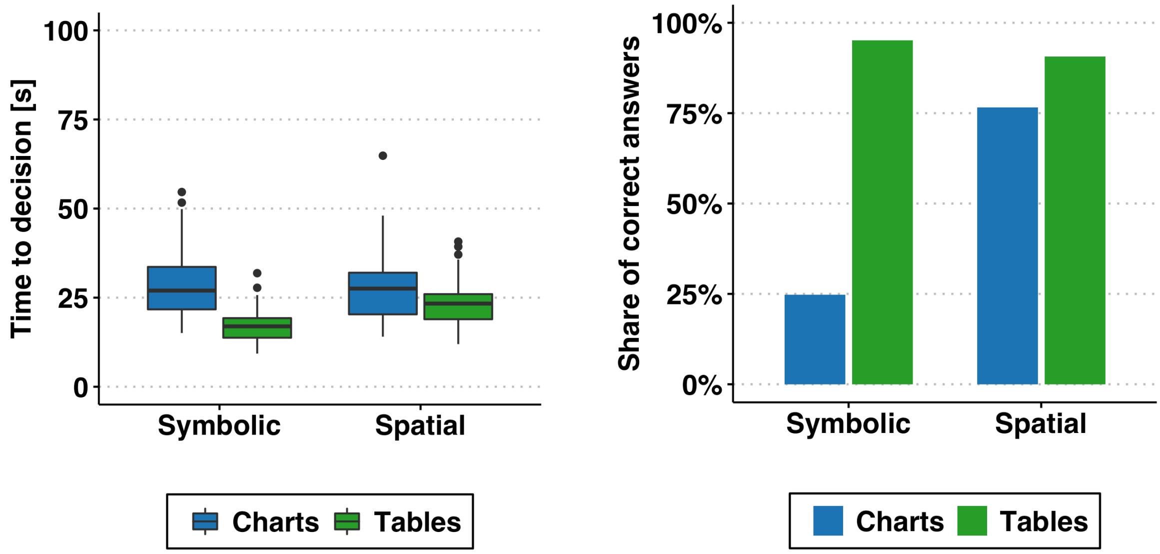


Figure 23 Decision performance across task types (symbolic and spatial) and presentation formats (tables and charts).

4.3.2 Cognitive style, decision performance and data presentation preference

Hypotheses 2 and 3 were concerned with the impact of cognitive style on decision performance and data presentation format preference. Before testing for differences between the groups, we first established the psychometric properties of the measurement scales used to capture participants' cognitive style and data presentation preferences. Scale reliabilities were measured using Cronbach's alpha (α) and reported in Table 6 along with the descriptive statistics and correlations of the constructs. The Cronbach's alpha for all the preference constructs had a very reliable level greater than 0.90. Cronbach's alpha for the cognitive style constructs varied, with the scale of the rational cognitive style resulting in a satisfactory level of reliability of above 0.70. The experiential scale had a lower yet still acceptable reliability of 0.57 (e.g. Bastian and Haslam, 2010). The participants' cognitive style was assigned using a processing style influence (PSI) score which classifies individuals as either rationally inclined (rational) or experientially inclined (experiential) (Pacini and Epstein, 1999; Gunnell and Ceci, 2010). It indicates the extent to which one cognitive style trumps another as a function of the distance of each from the median (see Gunnell and Ceci, 2010 for detailed explanations). See Table 7 for the distribution of individuals with specific dominating cognitive style across treatments. Finally, since this set of hypotheses was based on the findings from previous research that focused on tables and charts as data presentation formats, complex tasks and charts with labels were excluded from these calculations.

Construct	Number of items	α	Mean	Sd	1	2	3	4	5
1. Rational CS	7	0.72	3.65	0.63	-				
2. Experiential CS	5	0.57	3.14	0.63	-0.12	-			
3. Ease of use	4	0.90	5.19	1.31	0.39	-0.02	-		
4. Usefulness	4	0.93	5.61	1.23	0.36	-0.07	0.62	-	
5. Satisfaction	3	0.93	5.30	1.31	0.38	0.06	0.60	0.74	-

Table 6 Descriptive statistics, scale reliabilities and correlations of the cognitive style and preference constructs.

Treatment	Cognitive Style	N	Match
Charts	Experiential	27	Yes
	Rational	22	No
Tables	Experiential	26	No
	Rational	26	Yes

Table 7 Distribution of cognitive styles across treatments.

Hypotheses 2 and 3 were tested with a series of one-way ANOVA tests. Following the procedure in the previous sub-section, to examine Hypothesis 2, time to decision and share of correct answers were used as dependent variables (see Figure 24 for the visualisation of the results). As shown in Table 8, we found support for H2a. People with a dominating rational cognitive style made statistically significantly faster and more accurate decisions with tables rather than charts. However, we failed to find support for H2b. Actually, the opposite effect was found. For experiential individuals for whom we expected charts to facilitate faster and more accurate decisions, tables resulted in significantly better decisions. What is more, the effects magnitude for experiential individuals were slightly larger than for rational ones.

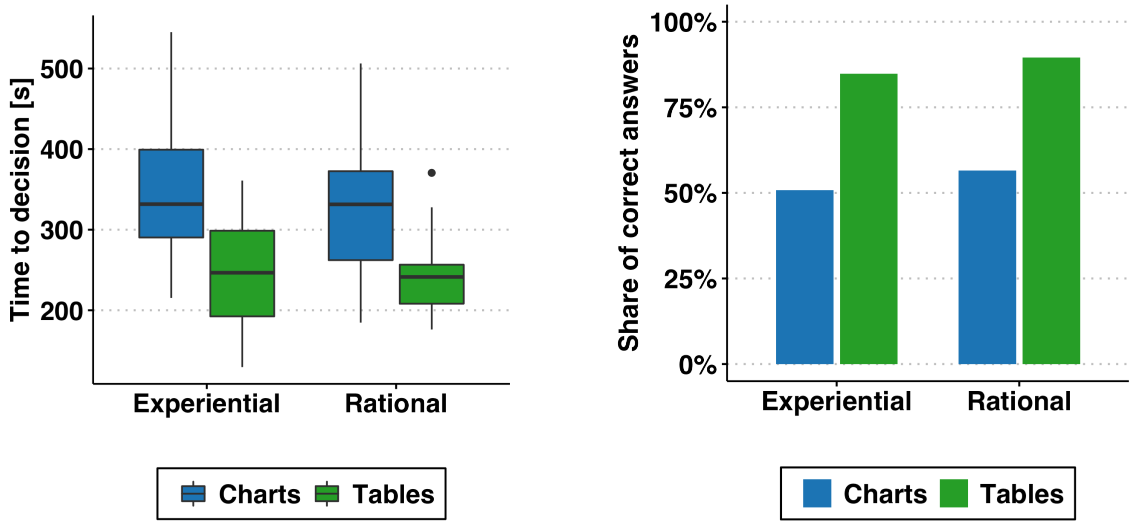


Figure 24 Cognitive style, data presentation format and decision performance.

Condition	Time (s)			Accuracy (% of correct answers)		
	Charts	Tables	Diff	Charts	Tables	Diff
Experiential	351	249	102***	0.51	0.85	-0.34***
Rational	332	240	92***	0.57	0.90	-0.33***

*** *p.value < 0.01;* ** *p.value < 0.05;* * *p.value < 0.1*

Table 8 Statistical tests of differences between the treatment groups in decision performance and by cognitive style.

To test Hypothesis 3, we used the three IS preference constructs, sequentially as dependent variables, as well as a composite preference measure based on the three preference constructs. Figure 25 visualises the collected data.

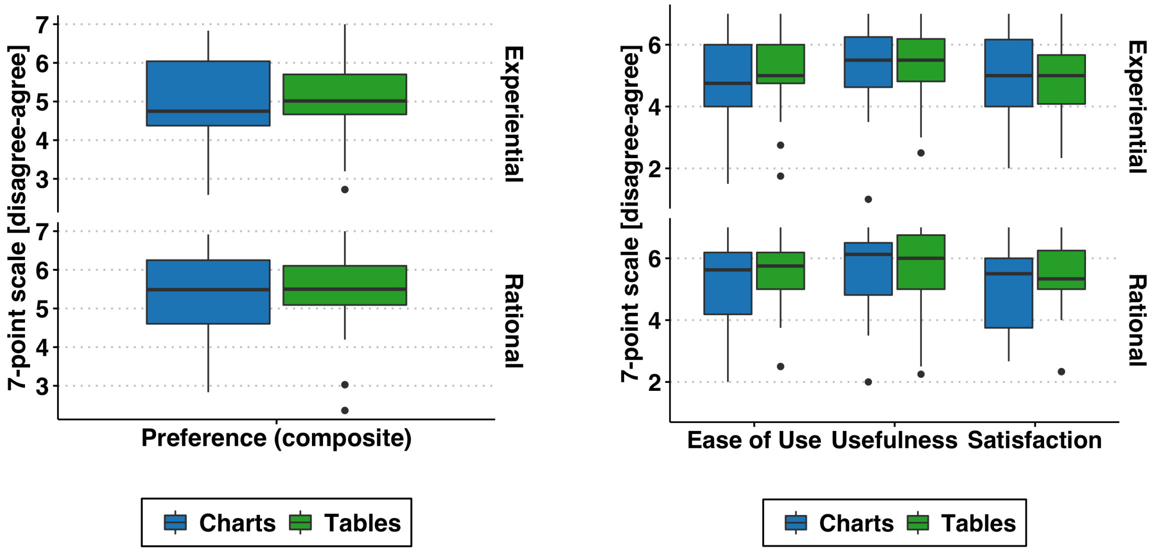


Figure 25 Data presentation format preferences and cognitive styles.

As shown in Table 9, none of the group differences hypothesised based on the previous findings was found to be statistically significant. However, rational individuals scored tables higher than charts in three out of four evaluations. Interestingly, for experiential individuals the effect was the opposite to what was expected – they actually rated tables higher than charts. This is consistent with the reversed effect found for experiential individuals with decision performance. Although no statistical support for the hypothesis was found, there is a consistent finding that rationally inclined individuals score both types of formats higher than experientially inclined individuals. What is more, out of eight comparisons charts were evaluated higher than tables (E-satisfaction and R-usefulness) on just two occasions. This is further explored in the post-hoc analysis in the section 4.3.4.

Condition	**Preference (composite)**			**Ease of Use**			**Usefulness**			**Satisfaction**		
	C	**T**	**Diff**	**C**	**T**	**Diff**	**C**	**T**	**Diff**	**C**	**T**	**Diff**
Experiential	5.03	5.13	-0.10	4.71	5.09	-0.38	5.31	5.38	-0.07	5.06	4.94	0.12
Rational	5.34	5.49	-0.15	5.16	5.44	-0.28	5.72	5.64	0.08	5.15	5.38	-0.23

**** p.value < 0.01; ** p.value < 0.05; * p.value < 0.1*

Legend: C = Charts, T = Tables, Diff = Difference

Table 9 Statistical tests of differences between the treatment groups in format preference and by cognitive style.

4.3.3 Complex tasks and visualisations

Hypothesis 4 and the four research questions were concerned with complex tasks and complex data presentation formats. A series of one-way ANOVA tests were used here, as previously, with time to decision and share of correct answers were sequentially used as dependent variables. The tests were carried out in two ways. First, values for tables and charts were compared with charts with labels. Then, the differences between all three formats were examined to identify the best performing format for complex tasks. The results are visualised in Figure 26 below.

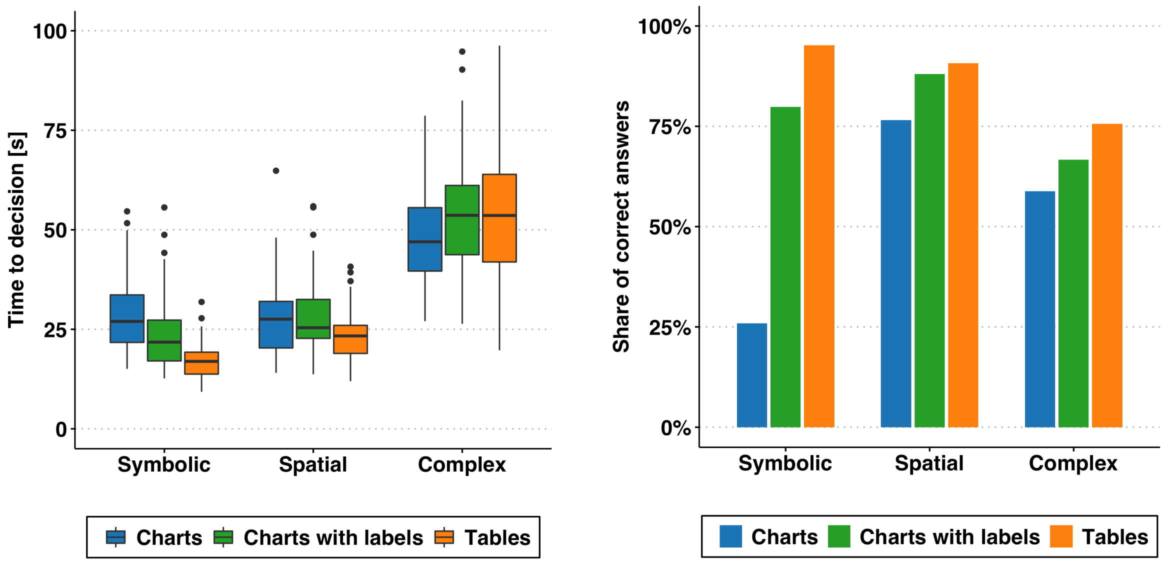


Figure 26 Comparison of decision performance achieved with charts with labels with charts and tables for symbolic, spatial and complex tasks.

The results of the tests indicate support for H4a and partial support for H4b as shown in Table 10. As predicted, charts with labels resulted in statistically significantly faster and more accurate decisions for symbolic tasks than charts. However, for spatial tasks, charts with labels resulted in more accurate decisions but no statistically significant difference in speed.

Condition	Treatment	Time (s)			Accuracy (% of correct answers)		
		Treatment value	Charts with labels	Diff	Treatment value	Charts with labels	Diff
Symbolic	Tables	17.2	23.9	-6.7***	0.95	0.80	0.15***
	Charts	29.2	23.9	5.3**	0.25	0.80	-0.55***
Spatial	Tables	23.5	28.7	-5.2**	0.91	0.88	0.03
	Charts	27.9	28.7	-0.8	0.77	0.88	-0.11**

*** *p.value < 0.01;* ** *p.value < 0.05;* * *p.value < 0.1*

Table 10 Statistical tests of differences in decision performance for symbolic and spatial tasks between tables and charts, and charts with labels.

The previously unexplored question of how decision performance of charts with labels compares against tables was also tested. According to the tests reported in Table 11, charts with labels resulted in significantly slower and less accurate decisions for symbolic tasks than tables, which corresponds to the predictions of CFT and findings from H1a. With regard to spatial tasks, charts with labels resulted in significantly slower performance than tables but yielded roughly the same accuracy. This finding offers a counterbalance for the opposite effect discovered in H1b. All of this indicates that charts with labels preserve performance achieved by charts for spatial tasks at the same time much improving performance for symbolic tasks, almost equalling that of tables. This offers charts with labels as an interesting alternative to regular charts.

Condition1	Condition2	Time (s)			Accuracy (% of correct answers)		
		Value1	Value2	Diff	Value1	Value2	Diff
Charts	Tables	47.9	52.8	-4.9**	0.59	0.76	-0.17***
Charts	Charts with labels	47.9	56.3	-8.4***	0.59	0.67	-0.08
Tables	Charts with labels	52.8	56.3	-3.5	0.76	0.67	0.09

*** *p.value < 0.01;* ** *p.value < 0.05;* * *p.value < 0.1*

Table 11 Statistical tests of differences in decision performance for complex tasks between tables, charts, and charts with labels.

RQ1 investigated which data presentation format facilitates best decision performance for complex tasks. On the time dimension the results suggest that charts were faster than tables by 4.9 seconds at the significance level of p-value <0.05; and faster than charts with labels by 8.4 seconds at p-value <0.01. Therefore, charts appear to facilitate fastest decisions for complex tasks. On the dimension of accuracy, we found the best accuracy was achieved with tables, then with charts with labels and lastly with charts. However, a statistically significant difference was only found between tables and charts. This indicates that charts with labels and tables seem to offer similar decision performance for complex tasks.

To investigate RQs 3 and 4, we first looked at the general preferences for the three data presentations formats, and then at how it changed with the influence of the cognitive style (see Figure 27 for the visualisation of the results). Once again, a series of one-way ANOVA tests were conducted with the three preference constructs and the composite preference measure used sequentially as dependent variables. As shown in Table 12, consistently, charts with labels are evaluated most favourably, with the largest differences in the composite preference measure and satisfaction measure. However, none of the averages were found to be statistically significantly different from each other.

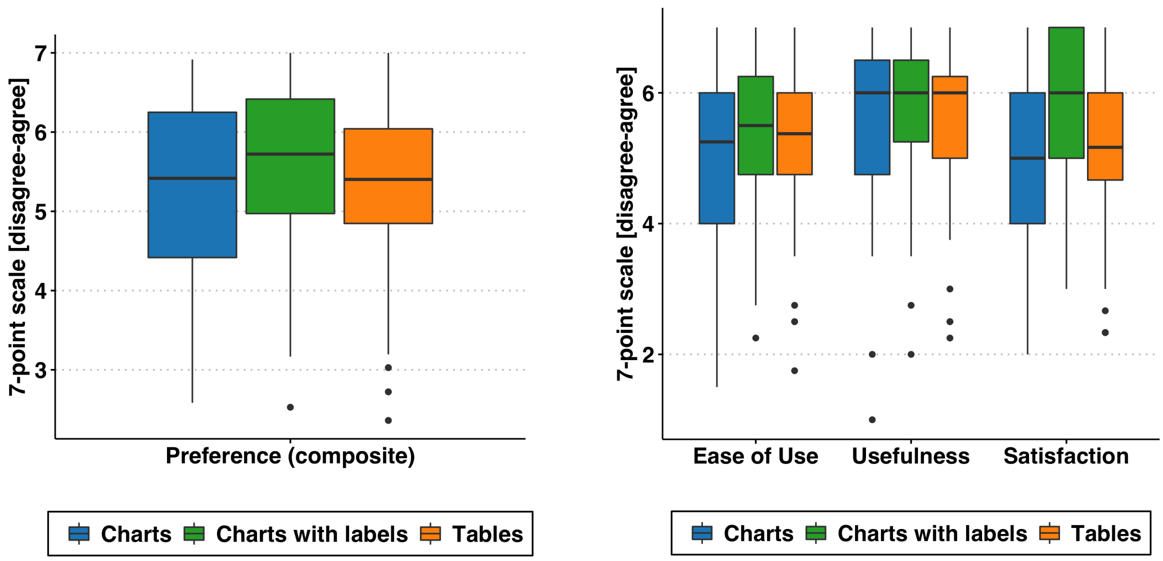


Figure 27 Preferences for the three data presentation formats.

C1	C2	Preference (composite)			Ease of use			Usefulness			Satisfaction		
		V1	V2	Diff	V1	V2	Diff	V1	V2	Diff	V1	V2	Diff
Charts	CWL	5.17	5.61	-0.44	4.91	5.37	-0.46	5.49	5.83	-0.33	5.10	5.62	-0.52
Tables	CWL	5.31	5.61	-0.30	5.26	5.37	-0.11	5.51	5.83	-0.32	5.16	5.62	-0.46

**** p.value < 0.01; ** p.value < 0.05; * p.value < 0.1*

Legend: C1 = Condition 1, C2 = Condition 2, CWL = Charts with labels, V1 = Condition 1 Value, V2 = Condition 2 Value, Diff = Difference

Table 12 Comparison of preferences for the three data presentation formats.

The attempt to answer research question 4 is visualised in Figure 28 and statistical tests reported in Table 13. It seems there are differences in how people with a different dominating cognitive style evaluated charts with labels versus either tables or charts. For experientially inclined individuals charts with labels were neither preferred to charts or tables, resulting in mostly similar scores. However, rationally inclined individuals scored charts with labels higher than either charts or tables across all four measures. Unfortunately, only one difference in the scores was found to be statistically significant. This was the difference in satisfaction between charts and charts with labels for rationally inclined individuals.

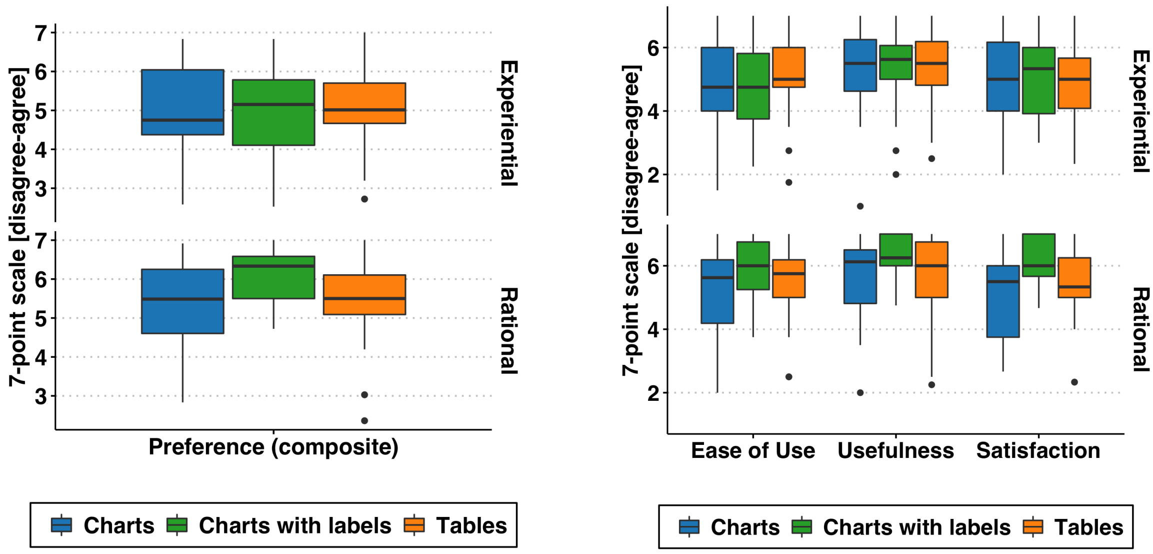


Figure 28 Preferences for the three data presentation formats by cognitive style.

CS	T	Preference (composite)			Ease of Use			Usefulness			Satisfaction		
		TV	CWL	Diff	TV	CWL	Diff	TV	CWL	Diff	TV	CWL	Diff
E	C	5.03	5.04	-0.01	4.71	4.77	-0.06	5.31	5.34	-0.03	5.06	5.01	0.05
	Tb	5.13	5.04	0.09	5.09	4.77	0.32	5.38	5.34	0.04	4.94	5.01	-0.07
R	C	5.34	6.07	-0.73	5.16	5.86	-0.70	5.72	6.22	-0.50	5.15	6.13	-0.98*
	Tb	5.49	6.07	-0.58	5.44	5.86	-0.42	5.64	6.22	-0.58	5.38	6.13	-0.75

**** p.value < 0.01; ** p.value < 0.05; * p.value < 0.1*

Legend: CS = cognitive style, E = Experiential, R = Rational, T = Treatment, C = Charts, Tb = Tables, TV = Treatment Value, CWL = Charts with labels, Diff = Difference

Table 13 Comparison of preferences for the three data presentation formats by cognitive style.

4.3.4 Post-hoc analysis

This sub-section reports two more sets of post-hoc exploratory analyses that were not formally formulated at the onset of this experiment. First, while testing the hypotheses it emerged that there seemed to be additional decision performance and preference differences between individuals with different cognitive styles. What is more, with one of the objectives of the laboratory experiment being to inform the field experiment, the opportunity was taken to explore decision performance facilitated by different data presentation formats across the different parts of the shopper insight report.

4.3.4.1 Performance and preferences by cognitive styles

Based on the theoretical assumptions and previous research findings different data presentation formats were expected to result in better or worse decision performance for individuals with different dominating cognitive styles. Although many of the hypothesised effects for cognitive style did not materialise, there is one quite interesting theme that emerged. Namely, it seems that rational individuals tended to achieve better decision performance than experiential individuals regardless of the data presentation format (see Figure 29 and Figure 30).

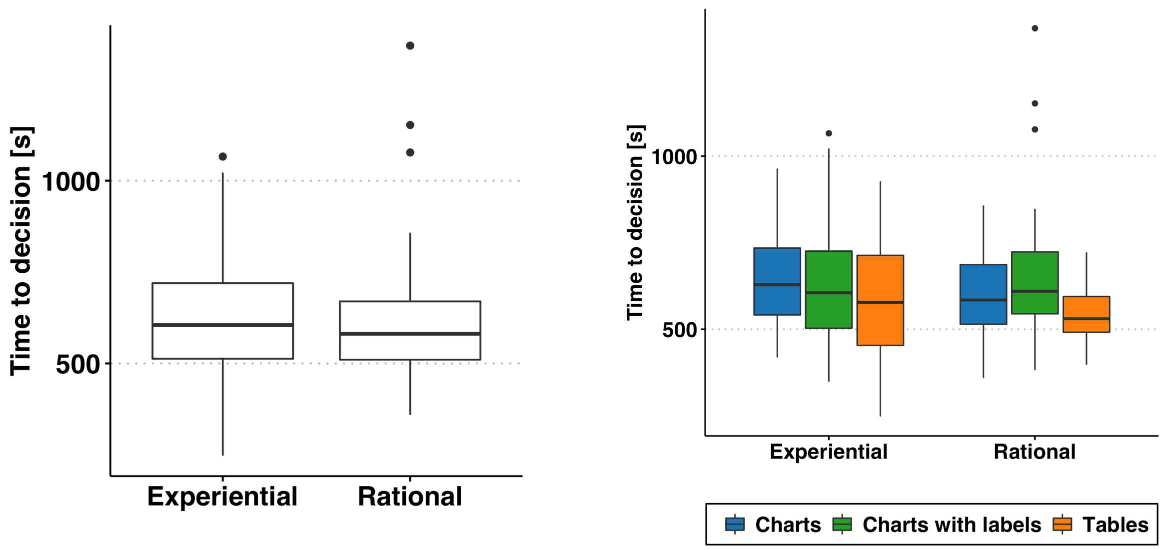


Figure 29 Time to decision by cognitive style, and by data presentation format and cognitive style.

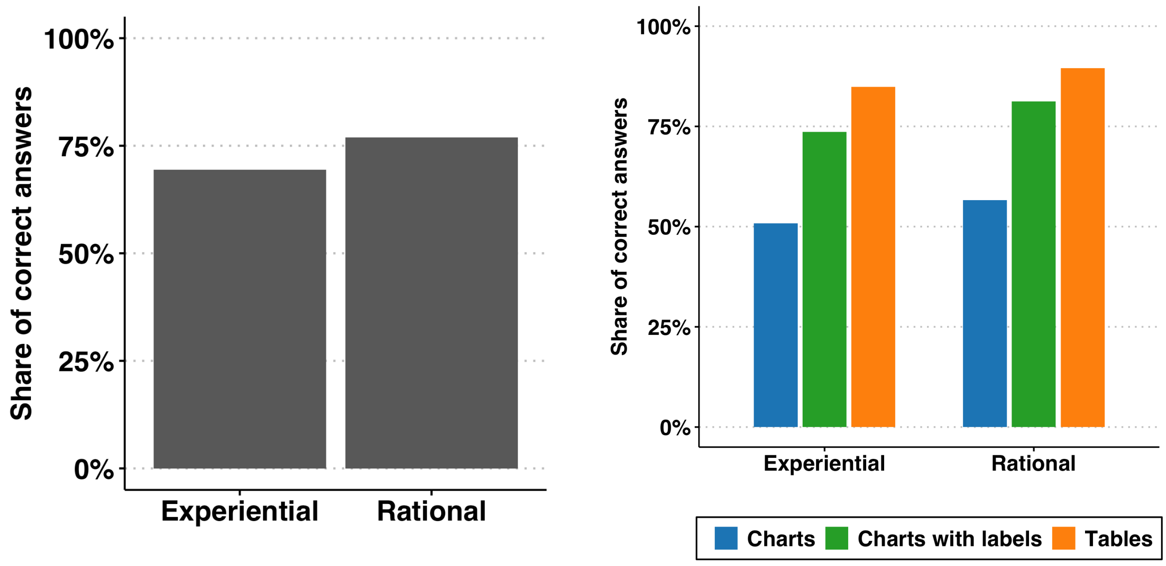


Figure 30 Share of correct answers by cognitive style, and by data presentation format and cognitive style.

The differences between the groups were tested with a series of one-way ANOVA tests, with time to decision and share of correct answers as the dependent variables. When general performance is taken into consideration (as shown in Table 14), rational individuals made faster and more accurate decisions than experiential individuals. The difference in accuracy was statistically significant at the level of p.value < 0.01. The same effect was found across the three data presentation formats (with the exception of time difference for charts with labels). However, none of the detailed differences was found to be statistically significantly different.

Condition	Time (s)			Accuracy (% of correct answers)		
	Experiential	Rational	Diff	Experiential	Rational	Diff
Total	623	607	16	0.69	0.77	-0.08***
Charts	651	603	48	0.51	0.57	-0.06
Charts with labels	636	668	-32	0.74	0.81	-0.07
Tables	581	542	41	0.85	0.90	-0.05

**** p.value < 0.01; ** p.value < 0.05; * p.value < 0.1*

Table 14 Tests of statistical differences of decision performance achieved by individuals with the two dominating cognitive styles.

In addition to the difference in performance, the extent to which stated preferences for the three data presentation formats varied by cognitive styles was also explored. As before, the differences were tested with a series of one-way ANOVA tests, with preference measures used as dependent variables. As can be seen in Figure 31 and Table 15, rationally inclined individuals gave higher scores than experiential individuals to all three types of information visualisations. It seems that rational people deal better with data, and more has to be done to satisfy experiential individuals than mere change in format. Although the differences existed across all data presentation formats, only the difference in preference for charts with labels was found to be statistically significant.

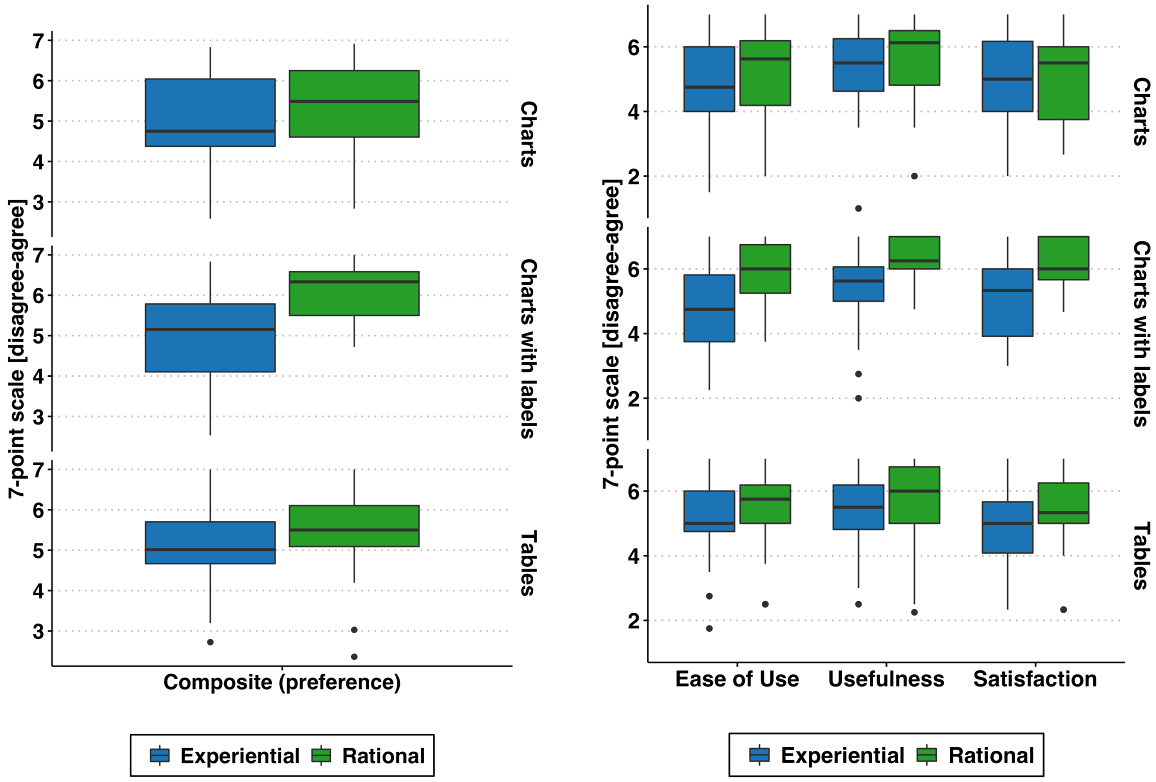


Figure 31 Preferences for the three data presentation formats by cognitive styles.

Condition1	Preference (composite)			Ease of use			Usefulness			Satisfaction		
	E	R	Diff	E	R	Diff	E	R	Diff	E	R	Diff
Charts	5.03	5.34	-0.31	4.71	5.16	-0.45	5.31	5.72	-0.41	5.06	5.15	-0.09
Charts with labels	5.04	6.07	-1.03***	4.77	5.86	-1.09**	5.34	6.22	-0.88*	5.01	6.13	-1.12**
Tables	5.13	5.49	-0.36	5.09	5.44	-0.35	5.38	5.64	-0.26	4.94	5.38	-0.44

**** p.value < 0.01; ** p.value < 0.05; * p.value < 0.1*

Legend: E = Experiential, R = Rational, Diff = Difference

Table 15 Statistical tests of differences in preferences for the three data presentation formats by cognitive styles.

4.3.4.2 Performance by report parts

Although not included in the formal hypotheses, an integral part of the lab experiment was the exploration of how different data presentation formats facilitate decision performance across different elements of the shopper insight report. For this analysis only the share of correct answers was used as a performance outcome, as this is the most important consideration for practitioners. As shown in Figure 32, tables were associated with considerably more correct answers for the KPIs than either charts or charts with labels. Charts with labels and tables were associated with similar shares of correct answers for segmentation and stores performance. Consistently, charts alone resulted in the smallest share of accurate decisions.

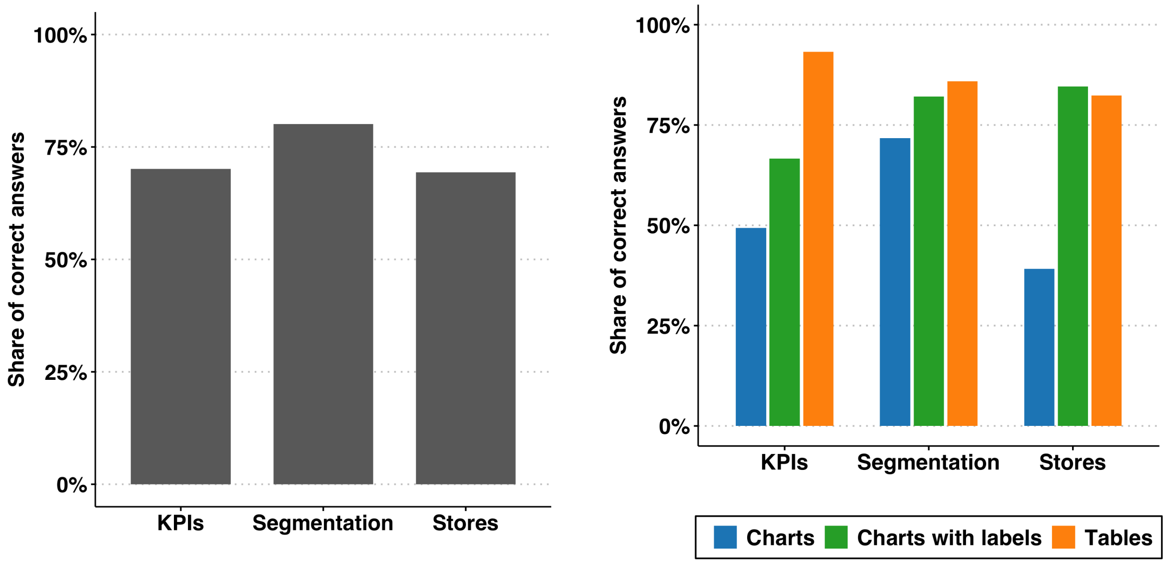


Figure 32 Share of correct answers by report part and data presentation format.

The findings discussed above correspond to a more granular analysis. As shown in Figure 33, when task types are considered charts with labels and tables still outperformed regular charts in the share of correct answers. Tables consistently resulted in the best decisions for tasks involving KPIs. The situation is less clear for the remaining two parts of the report, where either tables or charts with labels were equally associated with decision accuracy.

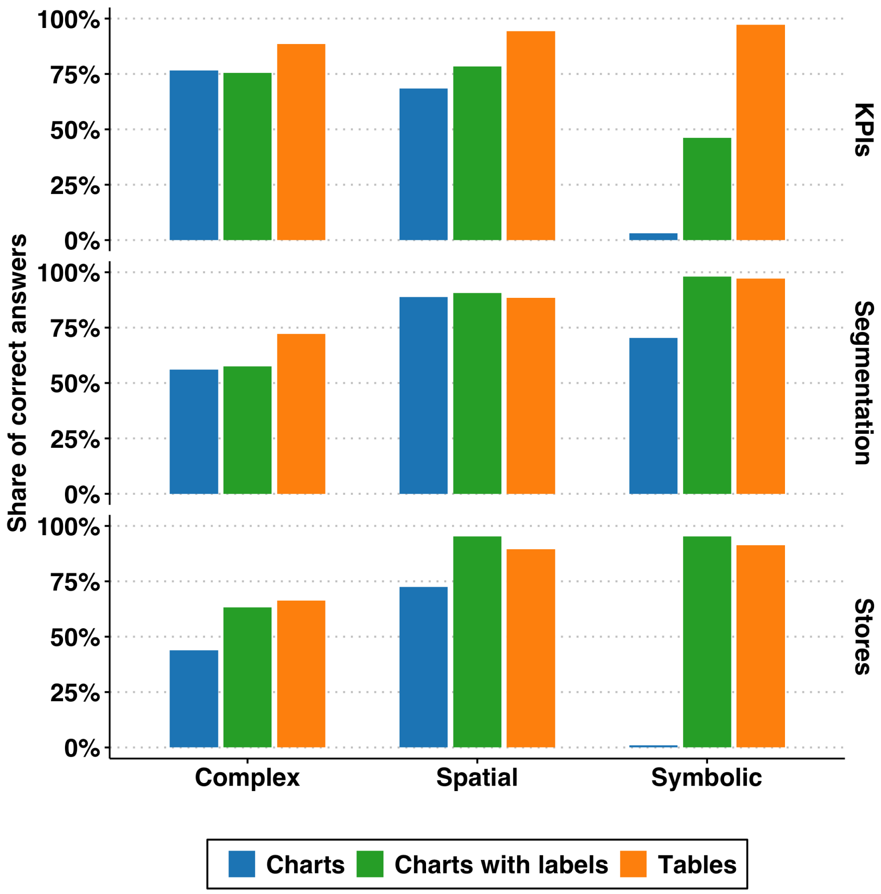


Figure 33 Share of correct answers by task type and data presentation format faceted by report part.

4.4 Summary of Chapter 4

This section comprises a brief summary of the findings from the lab experiment, which are discussed further in Chapter 5 (since the findings from the lab experiment were used to inform the field experiment) and Chapter 6, which discusses the overall findings from the study as a whole.

The objectives of the lab experiment were to a) attempt to replicate and validate previous research findings in a real-world context of marketing decision-making using real-world data, and b) inform the design of the field experiment by first conducting a rigorous lab experiment. A sample of university students was recruited for the experiment, which consisted of 18 information extraction tasks of various types, and were randomly assigned to one of three treatments, i.e. different data presentation formats. The tasks were either symbolic, spatial or complex in nature. The data presentation formats included tables, charts and charts with labels. In addition, participants' cognitive style and preferences for the formats were captured, alongside their demographic characteristics.

The study resulted in a number of interesting and relevant findings. First, it seems that not all theoretical predictions and previous research findings hold when real-world decision tasks are used with complex real-world data. Specifically, with regard to the predictions of the CFT on decision performance for spatial problem representations, where the opposite effect was found since tables allowed significantly better decision performance than charts. Furthermore, the findings related to format preferences can be described as unclear at best. Second, there is an indication about the unexpected role played by cognitive styles. We failed to find evidence of the previously suggested “fits” and “matches” between cognitive styles and data presentation formats. However, our findings revealed that rational individual achieved better decision performance and scored all types of data visualisations higher then experiential individuals. This suggests that there might be inherent differences between individuals, which are rather difficult to offset with data presentation formats. Finally, across the board, the performance of and preferences for charts alone were considerably worse than for the other two formats. This resulted in two clear format choices to compare in the field experiment. Furthermore, the findings provided some indications on which parts of the market information system are expected to experience the biggest impact from the change to the intuitive visualisations.

The main conclusion to be derived from the lab experiment is that some of the theoretical effects distilled in the sterile laboratory conditions seem to break in the first encounter with the real-world. Although, undeniably, laboratory experiments are extremely valuable and help to firm up the causal paths between the constructs, researchers have to be careful in extrapolating those findings to the real-world contexts.

5. Field Experiment

The aim of the field experiment was to fulfil the second objective of this research project, i.e. to design, conduct and evaluate a behavioural change intervention with the aim of positively influencing market information system use of small businesses. The intervention was a type of environmental restructuring where the information presentation format was modified. The specific hypotheses and research questions tested by the field experiment are presented next, followed by a detailed description of the experimental design. The chapter concludes with a presentation of the results.

5.1 Introduction (Design)

The use of the Who Buys My Food market information system by small food producers is the target behaviour that was the focus of the field experiment, which introduced a modification to the data presentation format. Intuitive data visualisations are hypothesised to be a better fit with the management style of small businesses and, as a result, an enabler to the increased use of the market information system.

Previous research in this area is mostly limited to a) laboratory experiments with students, using simplified data sets and simplified decision-making tasks, b) field experiments with large companies and c) focus on the adoption or reported use of technology instead of actual use. This makes it difficult to generalise from the findings reported to the very specific and peculiar context of small businesses and their actual use of a bespoke market information system. The lab experiment revealed some inconsistencies with previous studies and offered concrete suggestions for the field experiment, in which symbolic data presentations were replaced with spatial data representations (intuitive visualisations). The field experiment was designed to identify the potential causal effects of different information presentation formats on the use that small food producers make of the information system. The effectiveness of the intervention was evaluated in two ways. First, by comparing objective behavioural metrics. Second, by capturing perceptual measures and other contextually relevant constructs to explain any changes to the use made of the information system by participants in the Who Buys My Food research project. In the following sub-sections the previously reviewed literature is summarised in order to justify the hypotheses tested by the field experiment.

5.1.1 Behavioural change

In the sub-section 2.2.1, Behavioural Change Wheel (BCW) was introduced as a guiding framework for designing theory-based behavioural change interventions (Michie, van Stralen and West, 2011). At the centre of this framework is the Capability-Opportunity-Motivation-Behaviour (COM-B), which guides the behavioural analysis of the target behaviour (Michie, Atkins and West, 2014). According to the COM-B model, behaviours arise as a combination of the three key elements. Capability refers to the ability of a person to conduct a behaviour. Motivation includes both conscious and sub-conscious brain mechanisms which influence the resulting behaviour. Opportunity element denotes physical and social environments in which a person carries out a behaviour. The model acknowledges many possible routes for interventions as indicated by the arrows between the four elements in Figure 34. Detailed behavioural analysis of the target behaviour, the use of a market information system (as shown in Figure 34), identified environmental restructuring, i.e. a modification to a component of the physical environment (the technological artifact) as a viable solution for designing a behavioural change intervention.

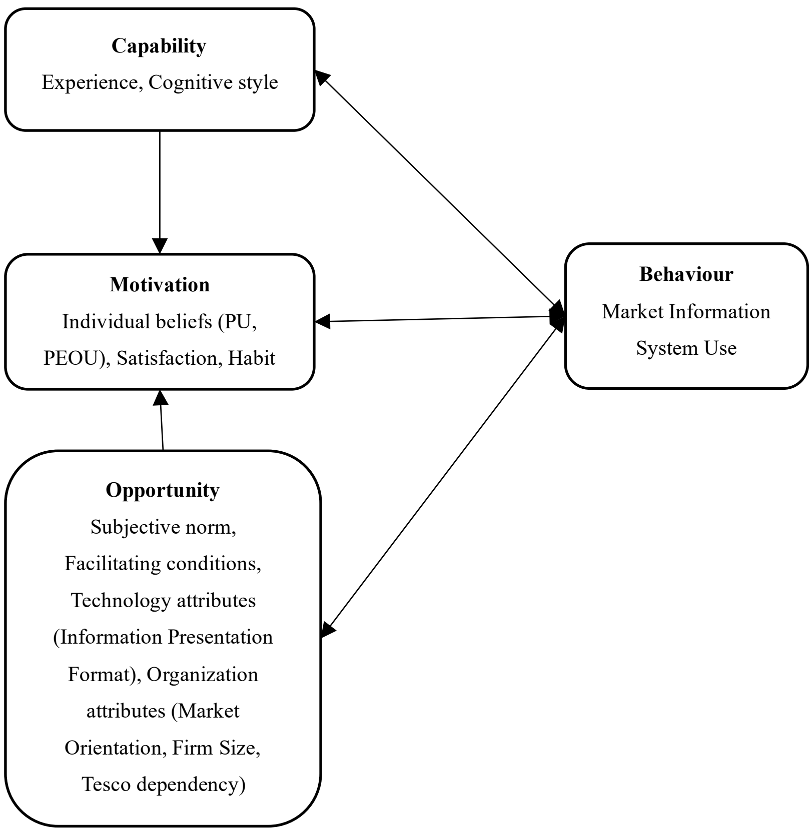


Figure 34 COM-B model with the behavioural analysis of Market Information System Use (adapted from Michie, van Stralen and West, 2011).

Although the general framework shown in Figure 34 indicates how the three main behavioural elements influence each other and the behaviour, it does not provide detailed suggestions about the relationships between the specific constructs that could be tested in order to evaluate the effectiveness of the intervention. For this, findings from the extant IS research on system use are consulted. The baseline model of system use was proposed in the latest comprehensive synthesis of the Unified Theory of Adoption and the Use of Technology (UTAUT) (Venkatesh, Thong and Xu, 2016). However, a key step to increase the relevance and predictive power of the model is to consider the context of the study (March and Smith, 1995; Hong *et al.*, 2014; Burton-Jones and Volkoff, 2017). First, the relevant established constructs have to be chosen depending on the main dependent variable (intention, adoption or use) being studied. Second, a number of additional dimensions for contextualising research studies on system use have been suggested (see e.g. Hong *et al.*, 2014; or Venkatesh, Thong and Xu, 2016), three of which have been identified as relevant for this study: user, technology and organisation attributes (see Figure 35 for the existing relationships suggested by the baseline model). The relevant adjustments made to the baseline model as well as the three additional dimensions of relevant factors are now discussed in turn.

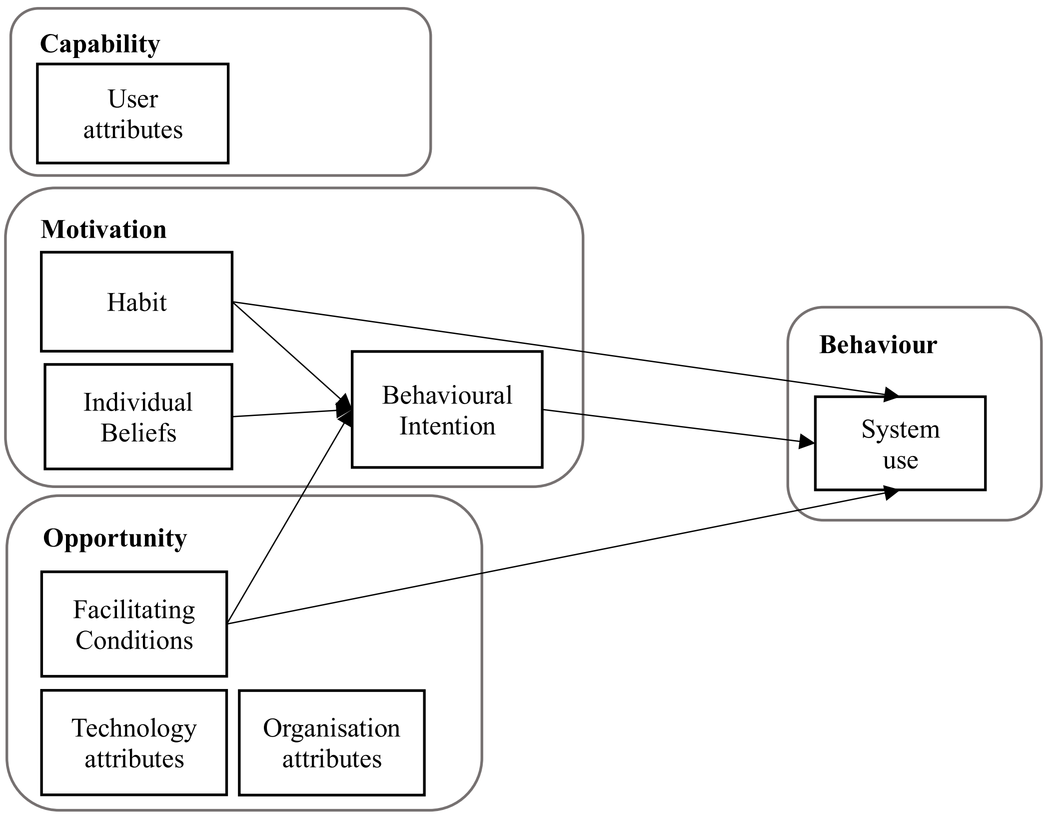


Figure 35 COM-B model combined with the baseline model from UTAUT and the contextual factors.

5.1.1.1 The baseline model

Based on the IS research summarised in the latest synthesis of UTAUT the baseline model of system use includes five key elements (Venkatesh, Thong and Xu, 2016) as shown in Figure 36. However, UTAUT is a theory which includes the determinants of both adoption and continued use behaviour, hence the elements need to be further adjusted for the specific study context. System use is the key dependent variable that is being investigated in this study. However, behavioural intention is also included as a dependent variable to validate previous research findings in the unique context of small businesses. Relationships between the constructs firmly established within previous research are articulated and tested in the unique context of this experiment but they are not formulated as separate hypotheses.

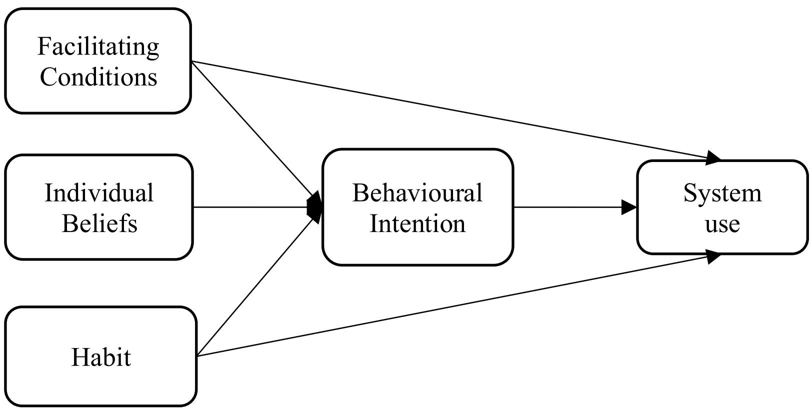


Figure 36 The baseline model of system use (adapted from Venkatesh, Thong and Xu, 2016).

Considerable research has been done regarding the conceptualisation of system use (Burton-Jones and Straub, 2006; Burton-Jones and Grange, 2013; Li, Hsieh and Rai, 2013; Ortiz de Guinea and Webster, 2013). However, the most common approach involves using either the degree of use reported by the users or objective system logs (Burton-Jones and Straub, 2006; Venkatesh *et al.*, 2008; Venkatesh, Thong and Xu, 2016). Since this study is primarily concerned with behavioural change, system use is conceptualised in a behavioural manner as intensity of use (the number of logins). In this view of system use, more logins have positive connotations and denote that system is working appropriately and engaging the end user. Furthermore, to link this study with the laboratory experiment and the research on the impact of information presentation format on user behaviour, duration of use (total time spent on the system) is included as a secondary measure. This second dimension is expected to decrease when the system is well-functioning, since it means that users are able to extract the information they need with greater speed. Furthermore, reported system use measures have been collected in line with previous research for comparative purposes. The specific measurements and comparisons are discussed in more detail in the section 5.2.

According to UTAUT, the central determinant of system use is Behavioural Intention (BI), which is the expression of individual's consciously reasoned and planned action (Fishbein, 1979; Ajzen, 1991). The BI construct is an inheritance from earlier Theories of Reasoned Action (TRA) (Fishbein, 1979) and Planned Behaviour (TPB) (Ajzen, 1991), and the Technology Acceptance Model (TAM) and its further iterations (Davis, 1989; Venkatesh and Davis, 2000; Venkatesh and Bala, 2008). For a long time the intention-behaviour link was said to be "*the most uncritically accepted assumption in social science research in general and IS research in particular*" (Bagozzi, 2007, p. 245). BI is the legacy construct which is important for technology adoption behaviours (Marangunić and Granić, 2015). A related construct of Continuance Intention (CI) was proposed for the specific context of continued system use (Bhattacherjee, 2001; Bhattacherjee and Lin, 2015), but it is merely a subset of the broader BI construct. Although the intention was retained in UTAUT it was shown to lose its predictive power for continued long-term behaviour (Kim, 2009; Lee, 2014), and often results in behaviour-intention gap, with people expressing positive intentions but failing to sustain any behavioural change (Sheeran, 2002; Sheeran and Webb, 2016). In this study the goal is sustained improvement in the use made by small food producers of a bespoke information system designed to support marketing decision-making. All participants in the Who Buys My Food research project have "adopted" the market information system by their participation in the project, thereby expressing a positive BI. However, the starting hypothesis to be tested by the field experiment is that BI is a predictor of actual system use in our context of small businesses. Thus, while BI is retained in the general model, in order to observe if contextually relevant constructs explain how it is formed, our primary hypothesis is:

H1: *There is no relationship between system users' behavioural intention and continued system use.*

A competing determinant of system use is Habit, the introduction of which constituted a considerable paradigm shift in the IS research on technology adoption and use (Kroenung, Eckhardt and Kuhlenkasper, 2017). The Habit construct becomes key for explaining continued long-term behaviour since most of everyday behaviours are driven by unconscious automatic behaviours not reasoned and planned action (Limayem, Hirt and

Cheung, 2007; Evans and Stanovich, 2013). Limayem et al. (2007, p. 709) proposed the IS habit definition as "the extent to which people tend to perform behaviours (use IS) automatically because of learning". Habits are driven by the frequency of past behaviours, the extent of use and satisfaction with the specific piece of technology (Limayem, Hirt and Cheung, 2007). Habit is now acknowledged as an important element of explaining continued use and the behavioural intention (Bhattacherjee and Lin, 2015; Venkatesh, Thong and Xu, 2016; Kroenung, Eckhardt and Kuhlenkasper, 2017), Accordingly, the positive influence of habit on users' system use and behavioural intention is tested in this experiment.

According to the baseline model, the final determinant of system use, are Facilitating Conditions (FC). This construct reflects the degree to which an individual perceives the surrounding organisational and technical infrastructure as supportive of performing the behaviour of using the technology (Venkatesh *et al.*, 2003). When the environment is perceived as more supportive an individual is more likely to use the technology. Perceptions of FC mainly contribute to the formation of beliefs and intentions. For this study, more contextually appropriate and more objective constructs are proposed to explain the resulting behaviour. They are discussed in the sub-section 5.1.1.4 on organisation attributes.

The final part of the baseline model is concerned with the influence of individual beliefs. The main individual beliefs include Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Subjective Norm (SN) and Satisfaction (Bhattacherjee and Lin, 2015; Venkatesh, Thong and Xu, 2016). PU is the degree to which an individual believes that using the system is useful in attaining job related goals (Davis, Bagozzi and Warshaw, 1989). PEOU is the degree of ease of using the system (Venkatesh and Morris, 2000). SN is the degree to which an individual is compelled to act by the feelings expressed by his or her peers about the use of the system (Venkatesh and Morris, 2000). Satisfaction is the affective response of the user based on their previous use of the system (Bhattacherjee, 2001). Satisfaction becomes especially important in the context of continued long-term use since satisfied users are more likely to keep using the system, while dissatisfied users are most likely to discontinue (de Guinea and Markus, 2009; Bhattacherjee and Lin, 2015). Previous research established PU, PEOU and SN as the antecedents of BI, since BI is assumed to mediate their effects to the resulting system use. However, Satisfaction directly exerts an influence on the system use. In seeking to validate these findings from previous studies, the field experiment was used to test for these relationships. Figure 37 below presents the relationships between the baseline constructs in this study.

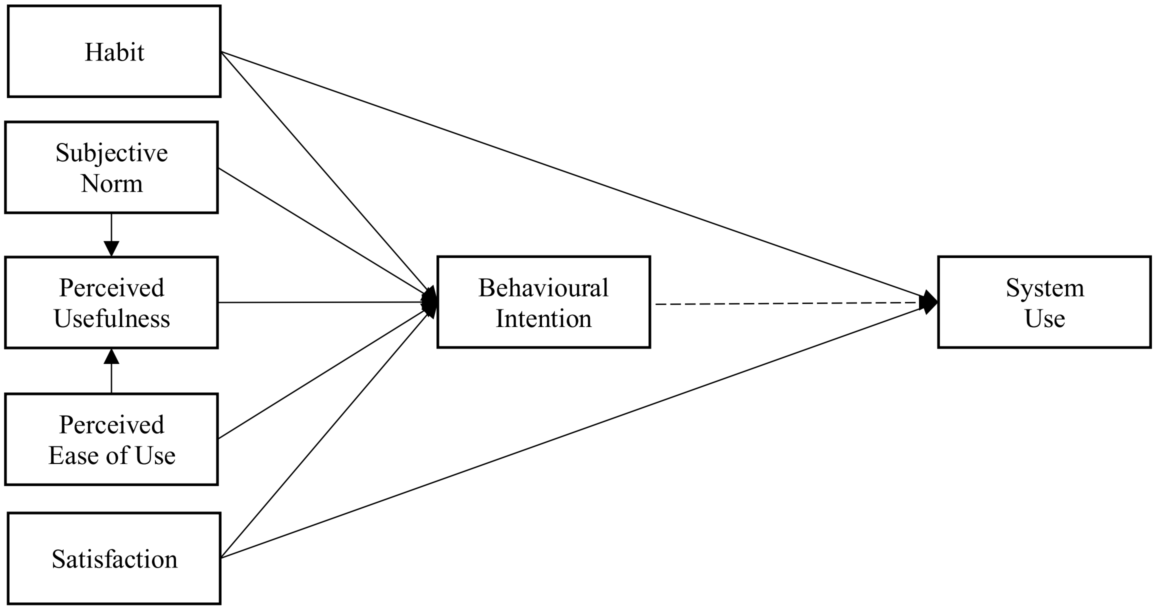


Figure 37 Suggested relationships between the relevant constructs based on the baseline model from UTAUT (adapted from Venkatesh, Thong and Xu, 2016) [dashed line indicates hypothesised nonsignificant relationship].

5.1.1.2 Technology attributes

An important contextual dimension in which the baseline model of system use can be extended is technological attributes (Venkatesh, Thong and Xu, 2016). It has been identified that different technologies used in different situations can have a significant effect on shaping the beliefs and behaviours of the users (Orlikowski, 2000; Hong *et al.*, 2014). In the section 2.2.5, it was argued that a key characteristic of a market information system is the data feeding it and hence the format in which it is presented will have a significant influence on the beliefs and the behaviour of the people using it. This point was further strengthened in Chapter 4, in which the lab experiment revealed that spatial data representations with data labels achieve similar or superior performance to symbolic data representations regardless of the task type. Based on the Cognitive Fit Theory (discussed in detail in the section 4.1.1), if the data representation fits with the nature of the task decisions are made faster and with greater accuracy (Vessey, 1991; Vessey and Galletta, 1991). However, related research concerned with user characteristics has shown that certain data representations facilitate better decision performance and are preferred by certain people regardless of the task type (Engin and Vetschera, 2017; Luo, 2019), which was corroborated in the lab experiment. This finding is extended, and we argue that certain data representations are more suited to the context of small businesses making marketing decisions, operationalised as use of a market information system. Small businesses are known to guide their marketing decisions by informal and intuitive cues (Gilmore, Carson and Grant, 2001; Shepherd, Williams and Patzelt, 2015; Bocconcelli *et al.*, 2018) and struggle with the use of structured and formal data sources (Donnelly *et al.*, 2012, 2015; Wang and Wang, 2020), hence the proposal that intuitive spatial data representations with data labels result in more frequent system use and more favourable emotions and beliefs about the system. The lab experiment demonstrated that spatial data representations with seemingly redundant data labels work particularly well for visualising complex real-world supermarket sales and loyalty card data. This results in the following hypotheses:

H2a: *System use is positively influenced by spatial data representations with data labels*.

H2b: *Perceived usefulness is positively influenced by spatial data representations with data labels.*

H2c: *Perceived ease of use is positively influenced by spatial data representations with data labels*.

H2d: *Satisfaction is positively influenced by spatial data representations with data labels*.

In addition, a related hypothesis is derived concerning the time spent using the market information system. According to the CFT (Vessey, 1991; Vessey and Galletta, 1991), and other research which has examined the impact of data presentation formats on user behaviour (Kelton, Pennington and Tuttle, 2010; Engin and Vetschera, 2017; Kopp, Riekert and Utz, 2018), if the data representation fits the purpose then users spend less time using the system showing the data as they are able to extract the information they need more easily. Accordingly, it is hypothesised that a modified system with spatial data representations with data labels will reduce the total time spent required to access the requisite information.

H2e: *The total time spent on the system is negatively influenced by spatial data representations with data labels*.

Figure 38 presents the hypothesised effects of the data presentation format on system use and individual beliefs. Green arrows indicate newly proposed relationships.

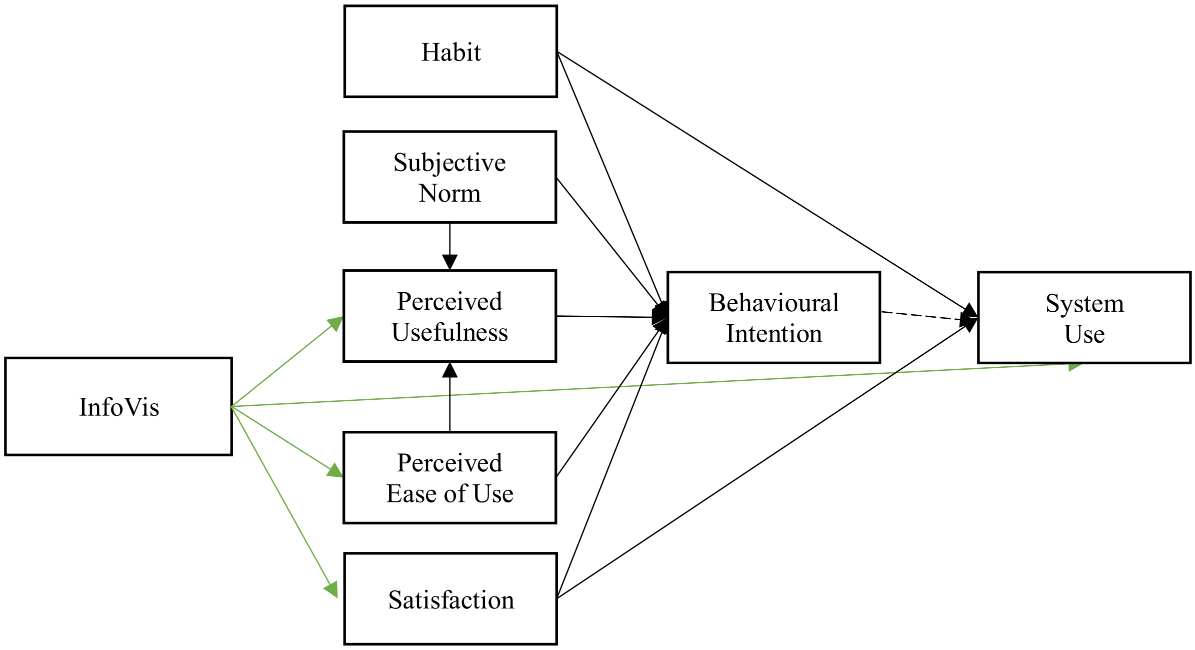


Figure 38 Hypothesised effects of the spatial data representations with data labels (shorted for InfoVis).

Finally, the lab experiment revealed varied effects of the information visualisation formats on the three information areas covered by the information system (product performance, shopper segmentation and store performance). In the experiment, although each report part had an equal number of tasks of various types (in line with the main assumptions of the CFT), different information visualisation formats resulted in different decision-making performance. An important difference between the report parts was the amount of data being visualised putting this finding in line with previous comments that the power of visualisation increases with the increase in the data points on which it is based (Tufte, 2001; Ware, 2012). The consistently varied levels of decision accuracy would indicate that the KPIs and Store Performance parts would benefit from spatial and symbolic (with labels) data representations, respectively, in order to facilitate better decision performance. Luo (2019) has shown that people perform better when using data representations they prefer. Accordingly, it is hypothesised that this increased performance will be expressed in preferences for specific data presentation formats.

H3a: *Symbolic data representation is preferred to spatial data representation for the assessment of product performance.*

H3b: *Spatial data representation is preferred to symbolic data representation for the assessment of store performance.*

5.1.1.3 User Attributes

The characteristics of people using a specific system in a given situation has also been recognised as an important dimension to consider when influencing or explaining system use (Hong *et al.*, 2014; Venkatesh, Thong and Xu, 2016). In the sub-section 2.2.5.2, a case was made for the importance of cognitive style in the context of the use of a market information system. What is more, previous experience has also been shown to be an important factor to include (e.g. Venkatesh and Bala, 2008). They are now discussed in turn.

Cognitive styles are consistent differences among individuals with respect to how they perceive, think and take decisions (Armstrong, Cools and Sadler-Smith, 2012). In other words, they are heuristics that individuals employ to process information about their environment (Kozhevnikov, 2007). Their conceptualisation is based on the dual-processing theories, which posit the existence of two information-processing systems, automatic and intentional. Cognitive styles are employed to measure the tendencies of individuals to employ the two thinking processes (Phillips *et al.*, 2016). The information processing style of individuals seems particularly relevant in the context of a market information system, i.e. a system centred around presenting relevant company, customer and competitor data. Cognitive styles have been shown to exert an influence on the formation of individual beliefs about an information system, such as PU, PEOU and SN (Chakraborty, Hu and Cui, 2008), and also to play a role in individuals' data presentation format preferences and the resulting decision performance (Engin and Vetschera, 2017; Luo, 2019). Therefore, it is hypothesised that cognitive style will play a role in system use depending on the data presentation format, i.e. the change of the format will affect the behaviour of the users in different ways based on their dominating cognitive style. Rational individuals will use the system with spatial data representations with data labels less frequently and for longer periods of time, while experiential individuals will use this same system more frequently and for shorter periods of time.

H4a: *System use increases for experiential individuals exposed to spatial data representations with data labels.*

H4b: *The total time spent using the system decreases for experiential individuals exposed to spatial data representations with data labels.*

Hypotheses 4a-b describe how individuals with different cognitive styles are expected to respond to a change in the data presentation format. However, in the course of the lab it was found that individuals characterised by a dominating rational cognitive style, in general, achieved better decision performance (faster and more accurate decisions) and ranked all data presentation formats higher than experientially inclined individuals. Accordingly, it is hypothesised that individuals with a dominating rational cognitive style will use the system more frequently and perceive it as more useful and easier to use.

H5a: *System use is higher amongst users with a rational cognitive style than those with an experiential cognitive style.*

H5b: *Perceived usefulness is higher amongst users with a rational cognitive style than those with an experiential cognitive style.*

H5c: *Perceived ease of use is higher amongst users with a rational cognitive style than those with an experiential cognitive style.*

The second important user attribute relates to the experience of the user. Previous research has shown the moderating role of experience in the formation of PU and BI, with more experience leading to more favourable beliefs and intentions (Venkatesh and Bala, 2008; Venkatesh, Thong and Xu, 2016). These relationships are tested in the experiment. The proposed relationships between the cognitive style and experience and the baseline model are shown in Figure 39.

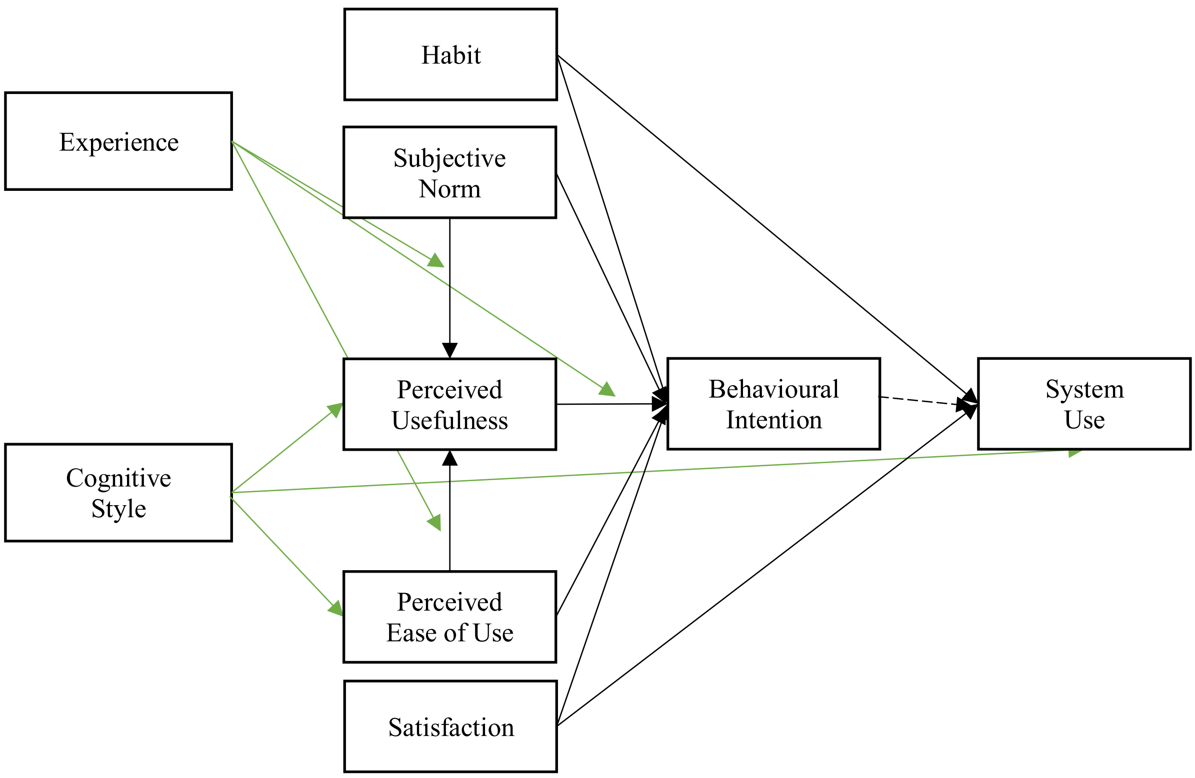


Figure 39 Hypothesised effects of the cognitive style and experience.

Previous research found that people with less experience of traditional systems are more open to new visual interfaces (Cardinaels, 2008; Pajić, 2014). A potential explanation for such behaviour comes from the Status Quo Bias Theory. The theory explains that people have a disproportionate preference to remain in the current situation (status quo) regardless of more optimal options being available (Samuelson and Zeckhauser, 1988). It was shown to play a part in new system introductions or changes (Kim and Kankanhalli, 2009). Since this study involves a change in the information system, it is hypothesised that the resulting preferences will be influenced by the exposure to the two systems. Consequently, it is proposed that people who have experienced the system with spatial data representations with data labels (the treatment group) will express more preference for that system than people who have not experienced it (the control group) when given a side-by-side comparison between the two.

H6: *Exposure to both systems increases preference for the new system*.

5.1.1.4 Organisation attributes

In certain contexts organisational attributes may play a defining role in the system use of individuals (Hong *et al.*, 2014; Venkatesh, Thong and Xu, 2016). Prior research has shown that small businesses constitute a unique context with their own special antecedents of technology adoption and use (e.g. Jeyaraj, Rottman and Lacity, 2006; Ghobakhloo *et al.*, 2011; Morgan-Thomas, 2016; Popovič, Puklavec and Oliveira, 2019). Most of the previous research has focused on studying SME organisation-wide adoption of technology, hence being less relevant here, but there are some factors that could play a salient role in the use of a system by employees of these organisations.

One is firm size, with previous research reporting positive effects found on technology adoption (Jeyaraj, Rottman and Lacity, 2006; Peltier, Zhao and Schibrowsky, 2012; Ramdani, Chevers and Williams, 2013; Länsiluoto *et al.*, 2019). However, due to the homogeneity of our sample in terms of size we did not consider this as important in our context.

Second is firm's strategic orientation. Research into strategic orientations has been prolific (Hakala, 2011). However, market orientation has been studied most extensively in the context of small business performance (Narver and Slater, 1990; Nasution *et al.*, 2011; Covin and Wales, 2012) and identified as an important factor influencing the use of market information (Donnelly *et al.*, 2015; Didonet, Fearne and Simmons, 2020). As such, it was also considered important in the context of technology adoption (Peña, Jamilena and Molina, 2011; Eggers *et al.*, 2017; Länsiluoto *et al.*, 2019). Market orientation (MO) is a complex construct but, in short, its adoption results in resource allocation and business processes that prioritise customer satisfaction and an organisation-wide understanding of customer requirements and competitor behaviour (Narver and Slater, 1990).

Previous research has considered MO to be both an antecedent of technology adoption (Eggers *et al.*, 2017; Länsiluoto *et al.*, 2019) and the result thereof (Peña, Jamilena and Molina, 2011). Interestingly, when MO was modelled as an antecedent of technology adoption it was found to have a negative effect on the adoption of social network sites (Eggers *et al.*, 2017) but a positive effect on the adoption of a performance management system (Länsiluoto *et al.*, 2019). The use of a market information system, which is the subject of this experiment, corresponds very closely with the concept of market orientation, and resembles, to a degree, a performance management system. As a result, it is hypothesised that the degree of firm market orientation is a positive facilitating condition for individual market information system use.

H7: *System use is positively influenced by the strength of firm's market orientation.*

Finally, an important organisational dimension, relevant in the specific context of our study is the importance of Tesco as a customer. It is well documented that food supply chains are characterised by power imbalance and power dependency, with large retail buyers exercising considerable control and influence over their suppliers (Hingley, 2005; Hingley, Lindgreen and Casswell, 2006). Most importantly, consequences of losing a supermarket contract are much graver for smaller suppliers for whom such a contract can constitute a large share of their income (Hingley, 2005). Recent studies show that the perceived quality of the relationship between (small) food producers and their (larger) retail customer affects their willingness to allocate their scarce resources to sustain such a relationship (Duffy *et al.*, 2013; Malagueño, Gölgeci and Fearne, 2019). Duffy et al. (2013) showed that suppliers in relationships perceived as fair are more willing to use the market information than those who do not. Malagueño et al. (2019) revealed that when retailers are perceived by suppliers as key customers, suppliers allocate more resources which leads to improved performance. Given previous established findings about how supplier-buyer relationships impact small businesses and, in particular decisions regarding resource allocation, it is conceivable that supplier dependency on Tesco could influence their willingness to commit the time and effort necessary to make use of the market information system use. As a result it is proposed that:

H8: *System use is positively influenced by firm's dependency on Tesco.*

Figure 40 shows hypothesised effects of the organisational attributes, which in this context are Facilitating Conditions, on individual continued use of a market information system.

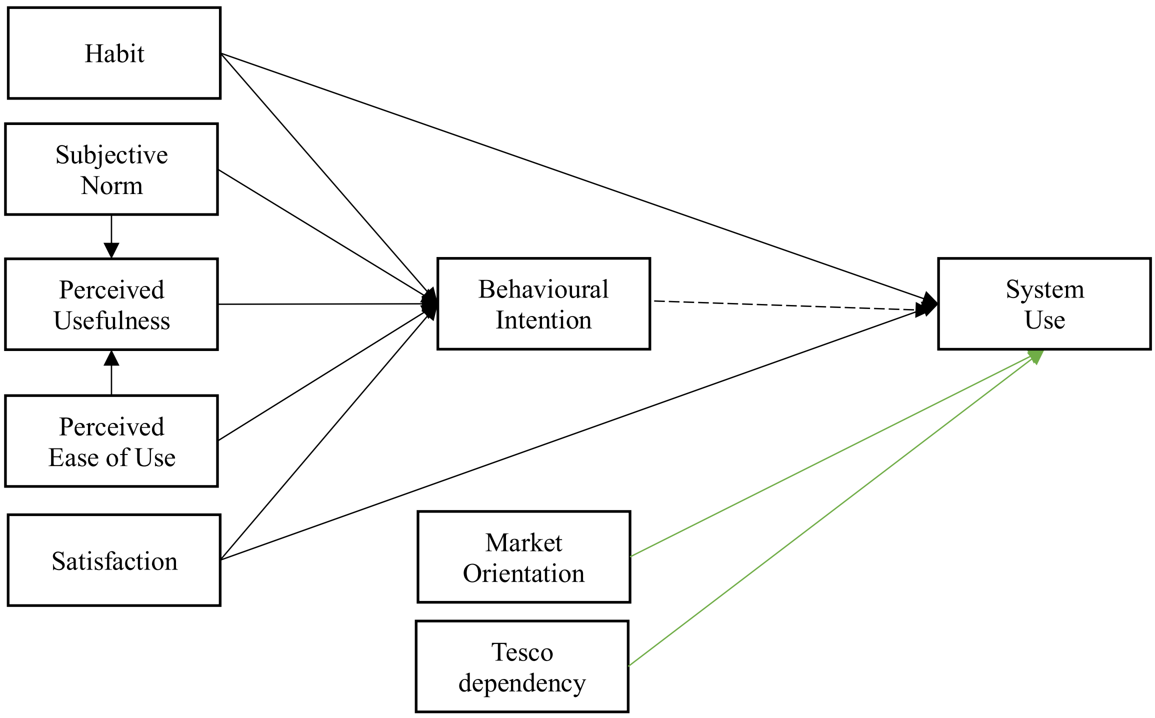


Figure 40 Hypothesised effects of organisational attributes on system use.

5.1.2 Summary of Introduction

This section presented in detail the mechanism of the proposed behavioural change intervention. Based on the COM-B model, environmental restructuring, i.e. a modification to a market information system was identified as a viable route to influencing the target behaviour, i.e. the use of the market information system. However, in order to enrich the evaluation of the intervention, the IS literature was re-visited to support the development of the hypotheses to be tested.

Based on UTAUT, a baseline model of system use was derived consisting of seven key constructs. The model was then enriched by additional factors from three contextual dimensions. They included user (cognitive style and experience), technology (data presentation format) and organisation attributes (strategic firm orientation and Tesco dependency). As shown in the Figure 41, all three exert an influence on the target behaviour. However, they also play a role in the formation of beliefs and intentions. In the next section the method employed to test the hypotheses is described.

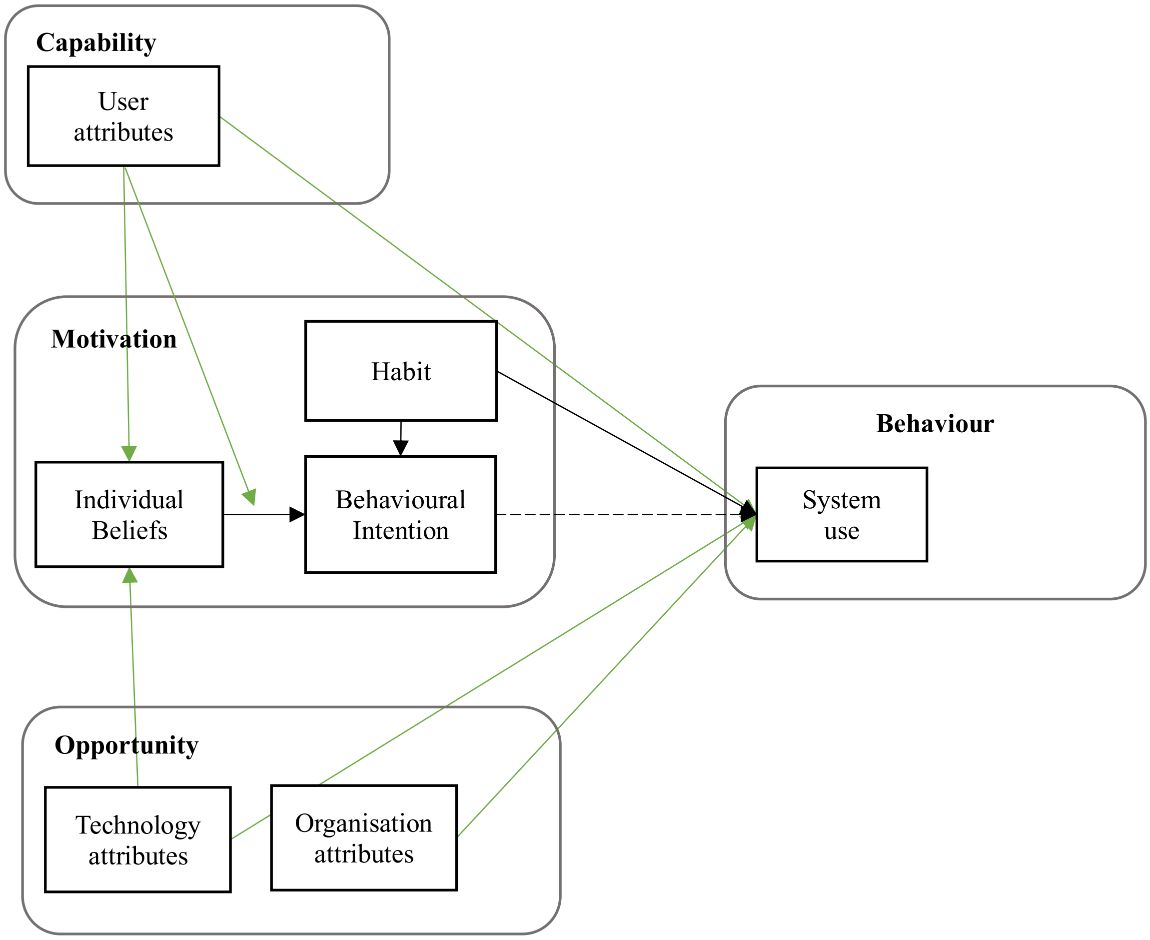


Figure 41 Contextualised UTAUT fit to the COM-B model [new relationships in green].

5.2 Method (Test)

This section details how the field experiment was designed in order to conduct and evaluate a behavioural change intervention. It is noteworthy that because the target behaviour is an extensively studied IS concept, two methods are used to evaluate the behavioural change intervention. First, the causal effects of the experiment are evaluated with typical experimental evaluation methods. Second, following previous IS research, a number of relationships between the constructs are modelled to try to investigate the contextually relevant drivers that can explain system use.

5.2.1 System and visualisations design

The field experiment was conducted as part of the Who Buys My Food (WBMF) project, which provides market information to small food and drink producers supplying a major UK supermarket (Tesco). The market information is provided via an online web-app designed by an external company, referred to as the market information system. The system (from now on referred to as the “old system”) is fed by supermarket loyalty card data – the same data which was used to populate visualisations in the lab experiment. The data is automatically downloaded from Tesco’s online portal, cleaned and uploaded to a database, and, subsequently, presented in a series of screens organised around the information about a) product performance, b) shopper segmentation and c) store performance. Firm’s performance apart from displaying regular diagnostics also includes comparisons against market averages and trends. The informational content of the market information system was discussed in detail in the section 4.2.

To test the impact of the change in the information presentation format on individual system use, an exact replica of the old system (referred to as the “new system”) was created with regard to the general system organisation and functionalities. The only two differences were:

a) the URLs (www.whobuysmyfood.co.uk changed to www.whobuysmyfood.org) and
b) data visualisations (in addition, top menu bar colour was changed from red to black).

The login page, the welcome screen, the contact page, the menu and their content remained the same. The additional texts, such as explanations and little helpers were copied to the word, even if typos and other mistakes in the old system were spotted. The new system was programmed in Python (Django web framework)[11] and deployed in the cloud (AWS EC2 machine)[12]. Mostly identical HTML elements were used to replicate the general look and feel of the old system.

In the old system all but one screen presented the underlying data in the tabular format. The only exception was a series of pie charts (widely discredited as a visualisation choice (e.g. Tufte, 2001; Few, 2007)) summarising store level sales of different formats. Some tables used green and red colouring of cells to indicate values above and below zero. The design of the tables from the old system was used to create “tables” condition in the

[11] For more detail see https://www.djangoproject.com

[12] For more detail see https://aws.amazon.com/ec2

laboratory experiment. In the field experiment the old system is the control group with the prevailing symbolic data representations (or “tables”).

Spatial data representations used in the new system were designed guided by the same principles as discussed in the section 4.2, and additionally informed by the findings from the lab experiment. New spatial data representations were created for KPIs, shopper segmentation and store performance screens. The information in “My Dashboard” and “My Competitors” screens remained presented in a symbolic manner since they only presented answers to questions and a ranking of product names without numerical values. Bar charts, scatterplots and a map were used to create intuitive data visualisations. The data labels were added in an interactive way so as not to overwhelm the visualisation but facilitate that data extraction, which proved to be very important in the lab experiment. Hovering with a mouse over data points displays data labels. The spatial data representations with data labels were programmed with a leading interactive data visualisation package, Plotly,[13] available both in Python and R. The principles and the design of data visualisations used in the new system remained the same as in the data visualisations prepared for the lab experiment. The minor changes are discussed in the rest of this section. As was the case in Chapter 4, lower resolution visualisations are included in the text to help the reader get a basic understanding of what the visualisations looked like. Higher resolution screenshots are included in Appendix D.

[13] For more details see https://plotly.com

As shown in Figure 42, the KPI visualisation remained a series of bar charts summarising the four main indicators. Three changes were made to the visualisation tested in the lab experiment. First, absolute product group values from the bar charts on the left side were extracted into a separate pop-up. This was caused by the reality of working with live data – values for some of the products are very low compared with the product group and the resulting scale would render the bar chart unreadable and meaningless. Second, the colouring of the bars on the right was changed from red/blue to red/green as to remain more faithful to the signalling used in the old system. Finally, the vertical dashed lines indicating changes for the Total Product Group were given a blue hue to help them stand out.

Figure 42 KPI data visualisation in the new system.

As shown in Figure 43, shopper information was presented as a scatterplot tested in the lab experiment. The main change involved replacing the series of vertical dashed lines indicating product group values with a series of black diamond shapes. In addition, the benchmark line was rendered dashed and individual points were given a coloured border to make them stand out in the event of an overlap.

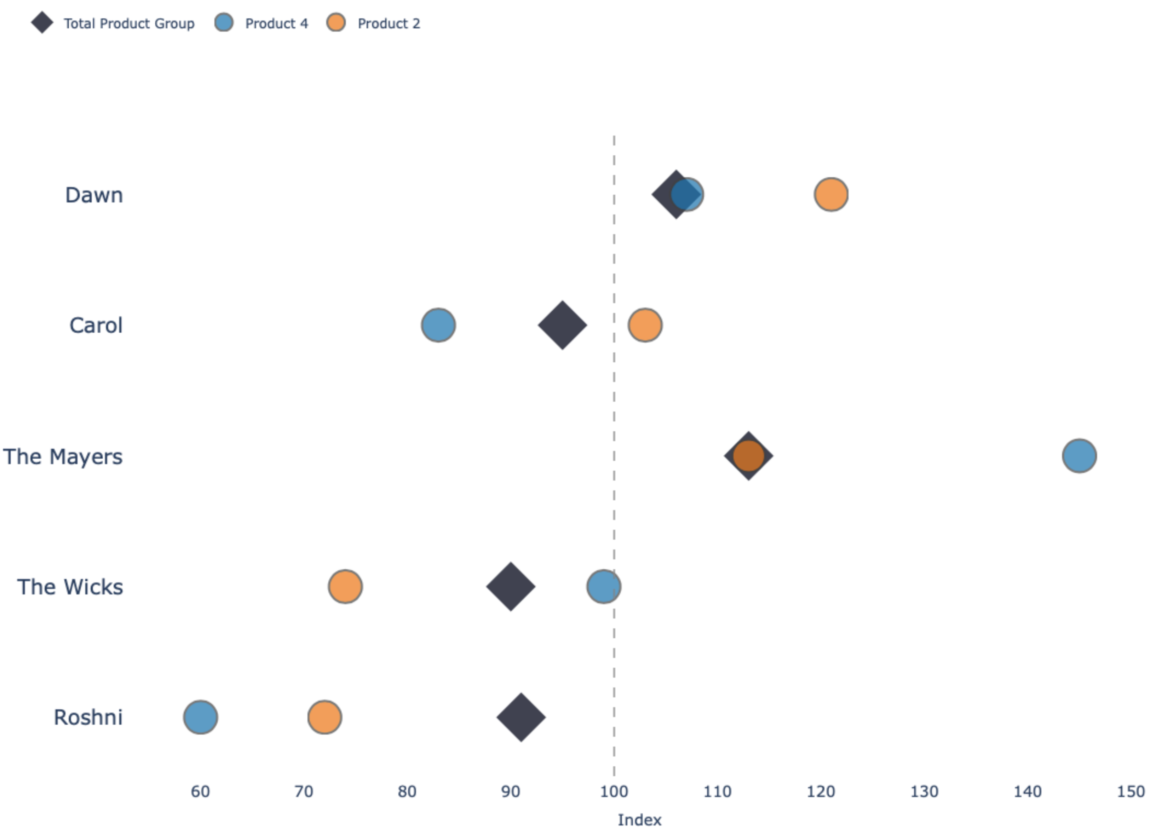


Figure 43 Exemplary shopper segmentation visualisation in the new system.

Figure 44 and Figure 45 present two visualisations used to represent store performance data. They employ the principles tested in the lab experiment, i.e. using bar charts for summaries and a map for individuals stores. The set of bar charts replaced a textual summary description accompanied by a series of pie charts in the old system. The map replaced a table listing sales across individual stores. The store characteristics (format, affluence, coreness and location) were previously represented as separate columns in a table. In the map version the location is represented as the point in space on the map and the postcode is displayed in additional information box when a point is hovered over. The rest of characteristics are represented with colours and can be chosen with the dropdown menu on the left.

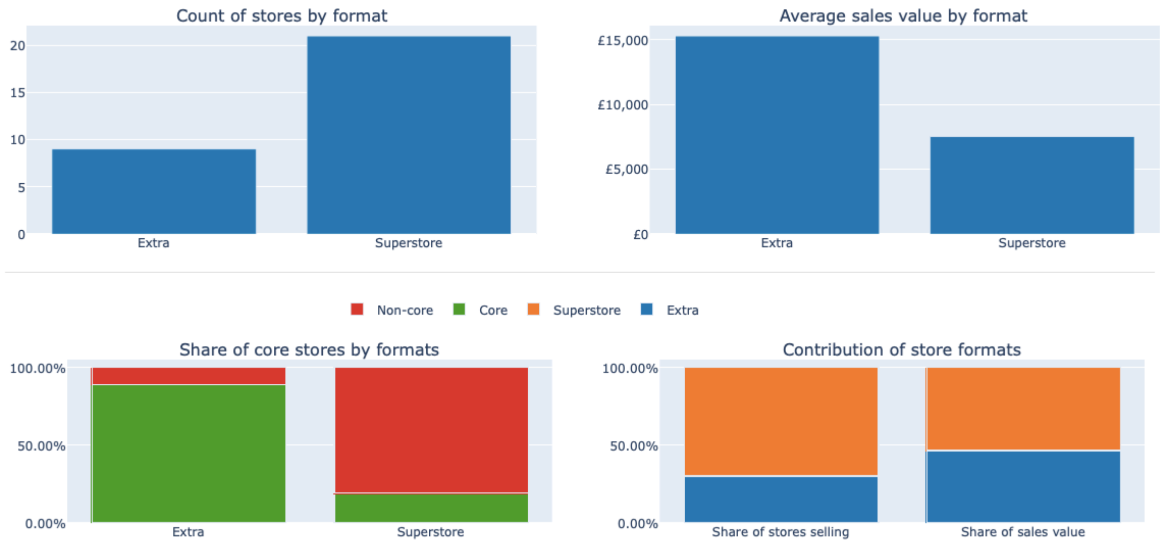


Figure 44 Store performance summary in the new system.

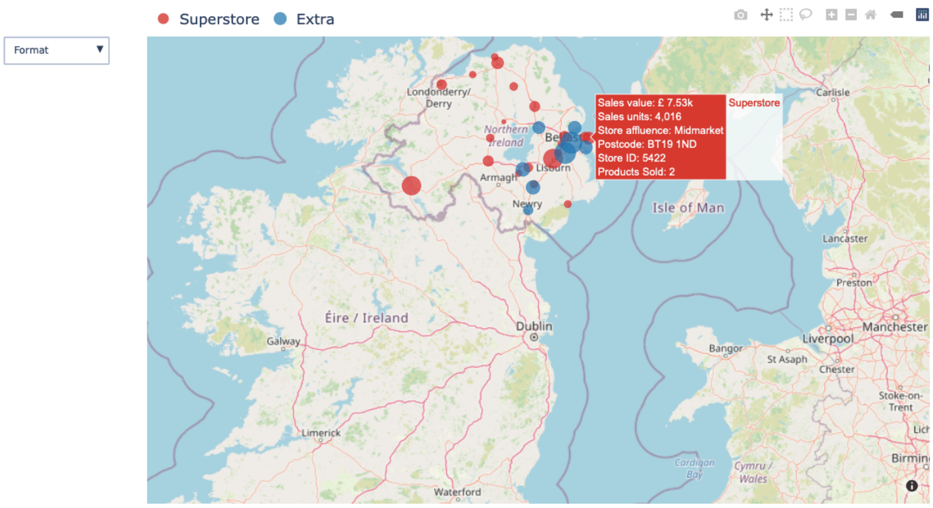


Figure 45 Store performance detailed view in the new system.

5.2.2 Study procedure

The primary purpose of the field experiment was to explore the behavioural response of market information system users to the change in the data presentation format. This required the creation of two groups – a treatment and a control group. Half of the users of the old system was randomly assigned to the new system (the treatment group). The other half was left in the old system for control purposes (the control group). It is acknowledged that many factors, especially in the field context, could exert additional influence on the behaviour of small firms and their employees. Hence, the control group serves as a check on whether what is seen happening to the treatment group is caused by the applied treatment or some other unaccounted for external factor(s). All of the suppliers and their employees agreed to and were aware that they were part of an ongoing research project. However, they were unaware as to the details of the research carried out. The experiment was cleared with the ethics committees in the Norwich Business School and the School of Economics.

Figure 46 presents the timeline of the experiment. Baseline data was collected at the beginning of 2020 (T1). At that time the laboratory experiment was carried out and subsequently the new system was designed and tested. During T1 the first survey was administered to collect data about the individual users of the system and the companies in which they were employed. Users were given a period of four months to use the system. From previous research it was known that suppliers use the system at least once a quarter to prepare for routine quarterly meetings with the supermarket buyer. In May, half of the old system users were randomly assigned to the new system for the period of four months (T2). Then in September, a second survey was distributed to capture individual beliefs, evaluations and intentions. The experiment concluded with a debriefing, i.e. the move of all suppliers to the new system, fixing of the mistakes and the implementation of new features.

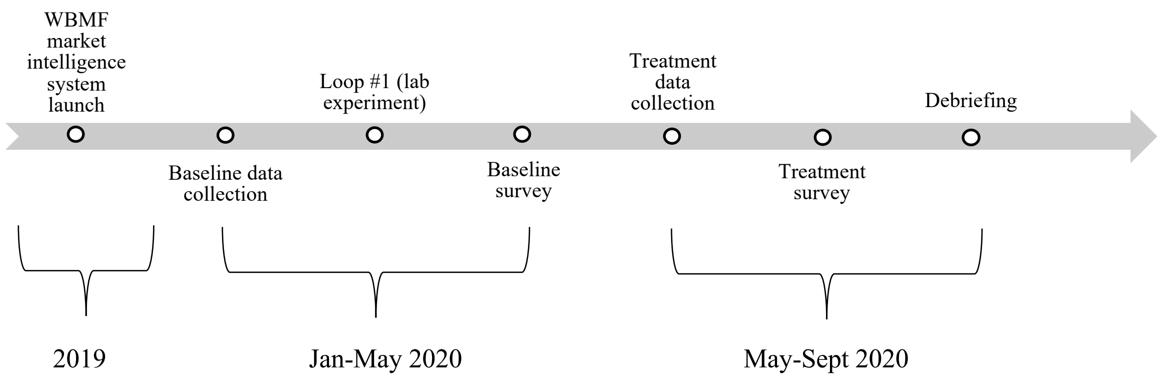


Figure 46 Detailed field experiment timeline.

Before the random assignment to the experimental groups, the sample of participants was stratified to make sure that the two groups were as homogenous as possible with respect to the key characteristics of the users and the firms. These included: above/below median system use at T1, cognitive style, geographical location (Northern Ireland and rest of the UK) and the use of functionality to upload sales data. Previous use is a key predictor of future behaviour. An equal distribution of cognitive style was needed across the experimental conditions to test for the hypothesised responses. The last two characteristics are relevant in the context of the WBMF project. Since the project is funded by Invest Northern Ireland (INI), there is a disproportionate number of Northern Irish companies in our sample who receive additional support in the use of the system from the INI consumer insights team.[14] To account for this the companies in Northern Ireland were equally distributed across the two groups. Since upload of the sales data requires extra effort and thus can be treated as a display of engagement, it was also ensured that companies who did it were equally split between the groups.

In the period of the experiment (Jan-Sept 2020), we strictly controlled our project activities so that they would remain similar across the whole time period. This meant that we carried on with "business as usual" but did not implement any additional activities that could increase the system use and skew the results.

What is more, all of the project-wide communications were carried out at strategic points in time and appropriately adjusted to the experimental groups. The email informing the treatment group about the move purposefully used a neutral language and provided very little details as for the motivations of the change. That information was provided in a bigger message about the project, which underscored the importance of using data to inform marketing decision-making. This allowed us to send almost identical messages to all of the suppliers, but for the URL address, and one sentence informing the treatment group about the change to the new system. As part of the usual project activities, we carried out two additional communications during the treatment period with all of the system users. Their primary aim was to remind the suppliers to use the system and inform them about some additional functionalities. They included:

- a reminder that the systems are automatically sending out email notifications whenever a new report becomes available. It also included instructions on how to

[14] For more details see https://www.nibusinessinfo.co.uk/content/food-and-drink-research-support

add the address to the safe senders list in order to avoid the notifications being classified as spam. All suppliers received the same instructions but the email address to be added to the spam filter was appropriately modified.

- a reminder to upload the sales data and explanation why it is important to consult store level sales data. It also included screenshots of what the systems offer once the data is uploaded by the suppliers. Each group received screenshots from the system they were using at the time.

5.2.3 Measurement

System use, the ultimate dependent variable, was operationalised with two objective behavioural metrics derived from the registered system logs. The first was the number of logins in a given time period as the measure of frequency of use. The second was the total time spent on the site in a given period of time as the measure of duration of use (expressed in the rest of this Chapter in minutes). As explained earlier in the sub-section 5.1.1.1, following previous research it was assumed that higher frequency of use indicates a positive outcome, i.e. better engagement with the system. Conversely, shorter duration of use indicates a positive outcome since a system with better data visualisations is said to facilitate faster information extraction by its user. System logs were collected for each participant for the duration of the whole experiment, i.e. from January 2020 to September 2020. They were then split into two 18-week time periods: baseline (T1 – 06/01/2020 to 10/05/2020) and treatment (T2 – 11/05/2020 to 13/09/2020). System logs were also used to operationalise the Habit construct as the frequency of previous behaviour (Limayem, Hirt and Cheung, 2007).

In addition to the objective behavioural metrics subjective perceptual system usage reports and evaluations, individual and firm characteristics, including control variables for descriptive statistics were also collected via two surveys. The first (baseline) survey was carried out in the middle of the baseline data collection period. The second was distributed at the end of the experiment in September 2020. Table 16 summarises the constructs captured at the corresponding time periods. The item scales are included in Appendix E.

Level	Measurement	T1	T2	Reference
Individual	Perceived Usefulness	√	√	(Davis, 1989)
	Perceived Ease of Use	√	√	(Venkatesh and Morris, 2000)
	Subjective Norm	√	√	(Venkatesh and Morris, 2000)
	Behavioural Intention	√	√	(Bhattacherjee, 2001)
	Satisfaction	√	√	(Bhattacherjee, 2001)
	Cognitive Style	√		(Epstein *et al.*, 1996; Pacini and Epstein, 1999)
	Market Information Experience	√		(Venkatesh and Bala, 2008)
	Systems preferences		√	(Luo, 2019)
	Reported system use	√	√	(Limayem, Hirt and Cheung, 2007; Ruivo, Oliveira and Neto, 2012; Popovič, Puklavec and Oliveira, 2019)
	Actual system use	√	√	(Venkatesh *et al.*, 2008)
	Habit	√		(Limayem, Hirt and Cheung, 2007)
	Gender	√	√	
Company	Family ownership	√		
	Firm age	√		
	Firm size	√		
	Total turnover	√		
	Tesco dependency	√		
	Market orientation	√		(Narver and Slater, 1990)
Both	COVID-19 impact		√	

Table 16 Constructs captured from system logs and in the surveys at the two time periods.

Perceived Usefulness, Ease of Use, Subjective Norm and Behavioural Intention were measured on a seven-point scale ranging from strongly disagree to strongly agree (Davis, 1989; Venkatesh and Morris, 2000; Bhattacherjee, 2001). The Satisfaction construct was measured with relevant items anchored on a seven-point scale (Bhattacherjee, 2001). Cognitive style construct was captured with a reduced number of items (following e.g. Genovese, 2005; Trémolière and Djeriouat, 2019) from the Rational-Experiential Inventory (REI) on a five-point scale ranging from completely false to completely true (Epstein *et al.*, 1996; Pacini and Epstein, 1999). Rational cognitive style was measured with a REI sub-scale, Need for Cognition. Experiential style is measured with the other REI sub-scale, Faith in Intuition. Years of experience of using market information were measured with a seven-point scale ranging from none to more than 5 years. To capture the preferences for the two systems the participants were presented with screenshots of different visualisations side by side and asked which one they preferred. They were asked to express their preference for each visualisation for KPIs, customer segmentation and store performance part as well as in general.

To describe the sample of the companies participating in the research a number of organisational characteristics were captured. They included firm size and age, total turnover in 2019 and whether or not they were family owned. Market orientation was measured on a seven-point scale ranging from strongly disagree to strongly agree (Narver and Slater, 1990). Tesco dependency was measured by asking for the percentage of total sales that was generated with Tesco (a categorical variable in 10% bins), and whether Tesco could be described as a key customer (yes/no). To gauge the impact of the COVID-19 pandemic on our participants and their firms we asked them to report what happened to their total sales, their ability to plan for the long-term, if the pandemic made them make any changes to their core business model and their use of the market information system during lockdown.

5.2.3.1 Reported use vs actual use

In this study a behavioural approach was advocated together with an objective measurement of the target behaviour with the use of system logs. However, since it is a common practice in previous research to base the whole study entirely on reported use, it was decided to collect such data and compare the resulting data sets. Following previous research, our participants were asked to estimate how many times they used the system, and, on average, how much time they spent on each login, over the previous 90 days (Limayem, Hirt and Cheung, 2007; Ruivo, Oliveira and Neto, 2012). They were also asked to rate themselves on a 7-point scale anchored at being a light-heavy user, since previous researchers asked such questions in order to estimate if respondents used a system to a greater extent than an average user (Popovič, Puklavec and Oliveira, 2019). Such measurement items not only assume people can correctly report their behaviour over a significant period of time but can also imagine the behaviour of an "average user" and are able to compare their own behaviour to that average.

In order to compare the reported use with the actual objectively measured system use, we looked at the date of the survey response of each respondent and then generated their actual use data for the previous 90 days. The total time was calculated by multiplying average time spent on site by the number of logins. From the two surveys, 156 valid responses with the estimated reported use have been collected.[15] The results of the comparison of the two metrics are striking.

84% of the number of logins and 91% of time spent reports were inaccurate when compared with the actual objectively captured usage data. Furthermore, as shown in Table 17, an average respondent had a 100% error in their reported number of logins and over 400% error in their reported time spent on site than they actually did. This simple comparison shows the distortion introduced by utilising reported use data rather than objectively measured data.

Variable	Min	Max	Mean	Median	Sd
Number of logins error	0	1,100%	94%	65%	153%
Time spent error	0	11,200%	444%	100%	1,300%

Table 17 Descriptive statistics of the reported use errors.

In addition, Table 18 demonstrates the difficulty posed by questions which ask respondents to self-compare against the unknown averages. First, each of the seven groups contains a respondent that never logged it in a given time frame. Second, the lightest users (groups 1 and 2) seem to be the best in estimating their behaviour against the rest of the cohort. The rest of the evaluations contain some curious reversals. For example, users which rated themselves as 3 used the system more often and for longer periods of time than users which rated themselves higher as a 4. Conversely, users which rated themselves as a 6 used the system less often and for less time than users from the group 5. Finally, there was only a single respondent who deemed themselves as a "heavy user" (rating of 7) despite the fact that four other groups contained people who used the system more often and for longer period of time than the only, self-assigned "heavy user".

[15] In this analysis inactive users were not removed since we only focused on their ability to report their system use not system evaluations relevant for further analysis. Therefore, the number of responses is different than reported in the rest of the study.

Variable	Scale	N	Number of logins				Time spent (minutes)			
			Min	Max	Mean	Sd	Min	Max	Mean	Sd
Light user	1	33	0	17	1.7	3.4	0	126	18.4	36.6
	2	24	0	17	3.4	4.3	0	221	27.8	47.6
	3	31	0	37	7.8	9.3	0	465	84.7	117.0
	4	38	0	39	6.2	8.3	0	390	56.7	86.2
	5	19	0	29	8.4	8.0	0	841	102.0	188.0
	6	10	0	30	6	9.1	0	420	70.5	132.0
Heavy user	7	1	22	22	22	-	198	198	198	-

Table 18 Behavioural metrics of self-rated light/heavy users.

This brief analysis highlights the serious dangers of using reported use metrics and asking users to evaluate themselves against the unknown averages. Such measurements do not accurately represent the behaviour of people and are seriously distorted by the imperfect human memory. Therefore, we proceeded with using only objectively measured system use derived from system logs in all of the analyses.

5.2.4 Participants

50 female [41%] and 73 male [59%] employees of 113 companies were part of the Who Buys My Food project in the experimental period (N = 123). Between 01/01/2020 and 13/09/2020 98 individuals (80%) from 86 companies (76%) were observed to have logged into the market information system at least once.

Time	System users	Responses	Response rate	Companies	Responses	Response rate
T1	99	71	72%	94	70	75%
T2	123	75	61%	113	70	62%

Table 19 Response rate among individuals and companies to the two questionnaires.

As shown in Table 19, at T1 there were 99 system users registered from 94 companies. The number of users and companies using the market information system increased from T1 to T2. However, only the users and companies from T1 were involved in the formal part of the experiment (the control and the treatment groups). The additional companies and their users constituted a naturally occurring third group of participants who were exposed only to the new system ("emergent" group). Since it was unknown at the beginning of the experiment that a) the emergent group would appear and b) how large it would be, it was not included in the formal experiment or the hypothesis testing. However, this group's behaviour and perceptions were investigated in an exploratory manner (see sub-section 5.3.4.1). Table 20 presents the size of experimental groups as assigned at T1, as well as the number of survey responses captured from each group at both times.

Condition	N	T1 survey	T2 survey
Control	55	38	31
Treatment	44	33	28
Emergent	24	0	16

Table 20 Number of participants in each experimental condition; and their responses to the surveys.

Due to the longitudinal character of this study the sample of respondents fluctuated over time. Twelve users were later excluded from the experimental analyses due to their inactivity throughout the whole project, reducing the Control to 47 and Treatment to 40. It was subsequently learnt that the excluded users either retired, changed jobs or their company had lost their listing with the supermarket. As a result, the number of observations used in different analyses varies. In a similar vein, some companies lost their business with the supermarket thus losing access to the market information system. Table 21 presents some descriptive statistics summarising the experience of the system users in their jobs and in using market information.

Variable (N = 77)	Mean	Sd
Years in a job	4.51	1.71
Experience in using market information	5.57	1.83

Table 21 Descriptive statistics of the experience of research participants.

Table 22 and Table 23 present descriptive statistics of variables characterising the companies involved in this research project. The majority of the companies are family-owned (72%) and have been trading for a considerable amount of time – only 32% of the companies have been trading for less than 10 years. 80% of the companies employ less than 40 people and as can be seen in Figure 47 the majority of businesses have company turnover smaller than £5m.

Variable	Mean	Sd
Number of system users	1.1	0.4
Tesco turnover	£254,621	£364,014
Tesco products	5.7	6.9

Table 22 Descriptive statistics of the firms participating in this study (1).

With regard to Tesco performance, on average the companies had 6 products listed and an average turnover of £250,000. But as can be seen from the relatively large standard deviations that figure varies to a great degree between the businesses, as does the share of turnover with Tesco. Since 96% of respondents deemed Tesco to be their key customer this dimension was dropped from further analysis. Undoubtedly, for most companies Tesco is an important retail customer responsible, on average, for more than 20% of their revenue.

Years trading	**Less than 5 years**	**5-10 years**	**10-15 years**	**15-20 years**	**More than 20 years**
	7%	25%	15%	6%	47%

Family-owned	**Yes**	**No**
	72%	28%

Number of employees	**Less than 10**	**10-20**	**20-30**	**30-40**	**More than 40**	**Don't Know**
	27%	21%	20%	10%	21%	1%

Company turnover (in £ millions)	**<1.5**	**1.5-2.5**	**2.5-3.5**	**3.5-4.5**	**4.5-5.5**	**5.5<**
	38%	14%	12%	10%	8%	17%

Share of turnover with Tesco	**0-10%**	**11-20%**	**21-30%**	**31-40%**	**50-100%**
	21%	32%	28%	11%	8%

Tesco as a key customer	**Yes**	**No**
	96%	4%

Table 23 Descriptive statistics of the firms participating in this study (2).

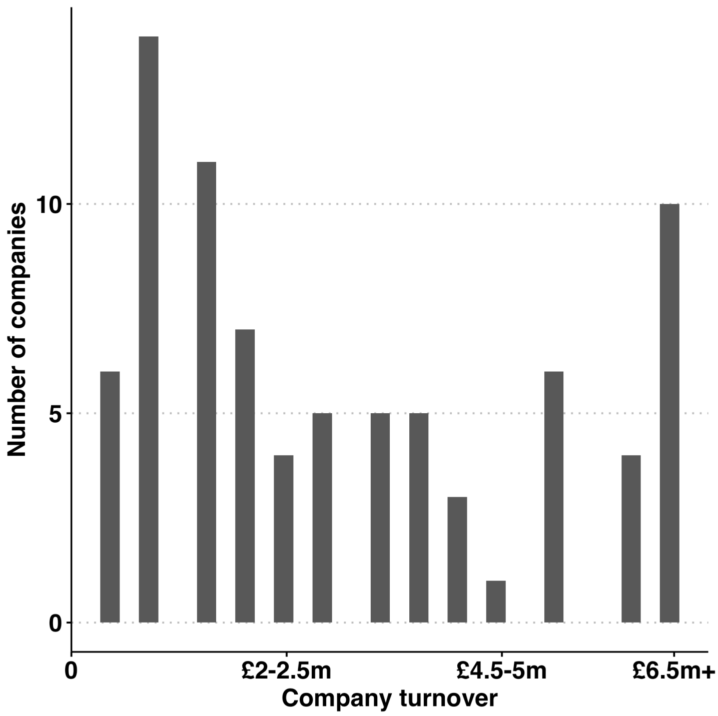


Figure 47 Histogram with company turnover values.

5.3 Results (Evaluate)

This section presents the results of the field experiment. First, the results for the causal effects of the experiment are presented, comparing the behavioural and perceptual responses of the control and treatment groups over time. Second, the preferences for the two systems are summarised. Third, the drivers of actual market information system use in the context of small businesses is explored. Finally, the behaviours and perceptions of the naturally emergent third group of users are explored. Table 24 summarises the results of the hypothesis testing.

Number	Hypothesis	Support	Findings
H1	There is no relationship between system users' behavioural intention and continued system use.	Supported	Insignificant effect.
H2a	System use is positively influenced by spatial data representations with data labels.	Supported	Spatial data representations with data labels offset the general decline in frequency of use.
H2b	Perceived usefulness is positive influenced by spatial data representations with data labels.	Not supported	Insignificant effect.
H2c	Perceived ease of use is positively influenced by spatial data representations with data labels.	Not supported	Insignificant effect.
H2d	Satisfaction is positively influenced by spatial data representations with data labels.	Not supported	Insignificant effect.
H2e	The total time spent on the system is negatively influenced by spatial data representations with data labels.	Not supported	Spatial data representations with data labels offset the general decline in duration of use instead of increasing it.
H3a	Symbolic data representation is preferred to spatial data representation for the assessment of product performance.	Supported	Old system preferred to the new system for the KPIs screen.
H3b	Spatial data representation is preferred to symbolic data representation for the assessment of store performance.	Supported	New system preferred to the old system for the store performance screens.
H4a	System use increases for experiential individuals exposed to spatial data representations with data labels.	Not supported	An insignificant effect was found. But experiential individuals were the only group whose frequency of use increased.
H4b	The total time spent using the system decreases for experiential individuals exposed to spatial data representations with data labels.	Not supported	An insignificant effect was found. The duration of use doubled for experiential users while it decreased for everybody else.
H5a	System use is higher amongst users with a rational cognitive style than those with an experiential cognitive style.	Not supported	Insignificant effect.
H5b	Perceived usefulness is positively influenced by a rational cognitive.	Not supported	Insignificant effect.
H5c	Perceived ease of use is positively influenced by a rational cognitive.	Not supported	Insignificant effect.
H6	Exposure to both systems increases preference for the new system.	Not supported	The opposite direction of the effect was found although they were not significantly different.
H7	System use is positively influenced by the strength of firm's market orientation.	Not supported	Insignificant effect.
H8	System use is positively influenced by firm's dependency on Tesco.	Not supported	Insignificant effect.

Table 24 Summary of the hypotheses and findings.

5.3.1 Experimental results

Table 25 provides descriptive statistics of the system use across the experimental period. In the 36-weeks an "average user" logged in 14 times (once every three weeks) and spent the total of almost two hours using the system. However, this varied greatly between users. In total, 10% of the users did not log in at all. At the other end of the spectrum were the so-called, "heavy users" with a maximum number of logins being 120, which amounts to 3-4 logins every week. There were also people who spent in excess of 35 hours using the system – this is 1,000% more than an average user. These descriptive statistics highlight the heterogeneity in the use of the market information system and the shortcomings of considering reported use or mere adoption instead of actual objectively measured system use.

Variable (N = 87)	Min	Max	Mean	Sd
Frequency of use	1	120	14	20
Duration of use (minutes)	1	1,146	111	177

Table 25 Descriptive statistics of system use over 36 experimental weeks.

5.3.1.1 Behavioural change

Table 26 shows the results of the one-way ANOVA tests conducted to establish if the impact of COVID-19 pandemic was similar on the participants of the experimental conditions. The results show there was no statistically significant difference in the responses from the two groups. The shares of furloughed users were also compared with a two-sided proportions test. Although the treatment group had slightly more furloughed users than the control group, they were furloughed for a shorter period of time, hence equalising the effects.

Item (N = 56)	Control (N = 29)	Treatment (N = 27)	Diff
During the COVID-19 pandemic our total sales increased	3.31	3.15	0.16
During the COVID-19 pandemic it has been impossible to effectively plan for the long-term	3.38	3.41	-0.03
During the COVID-19 pandemic we have made changes to our business model	3.79	3.67	0.12
During the COVID-19 pandemic my use of the WBMF web-app increased	2.48	2.88	-0.40
Share of known furloughed users	10.3%	29.6%	-19.3%
Average furlough length [weeks]	15	12	3

**** p.value < 0.01; ** p.value < 0.05; * p.value < 0.1*

Table 26 The COVID-19 pandemic impact across the experimental conditions.

The next tests are concerned with the effectiveness of the environmental restructuring intervention (information presentation format change) on the system use (H2a and H2d). The data on usage, illustrated in Figure 48, shows that both the frequency and duration of use declined in T2 regardless of the experimental condition.

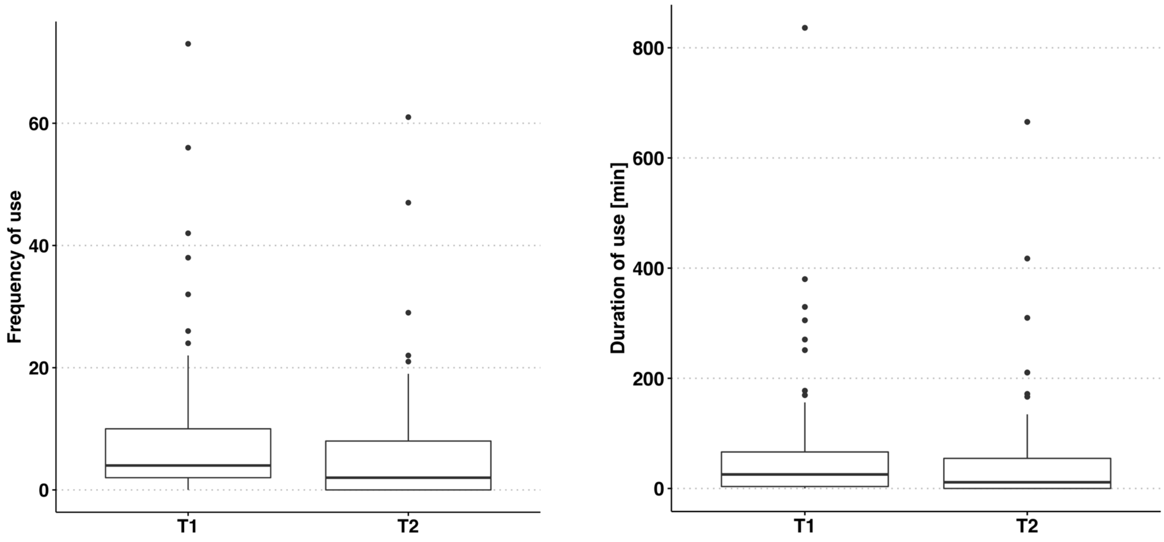


Figure 48 Difference in frequency and duration of system use between time periods.

Figure 49 presents the same data for the two groups and Table 27 shows the statistical (ANOVA) analyses of the usage data, for all users and the two groups.

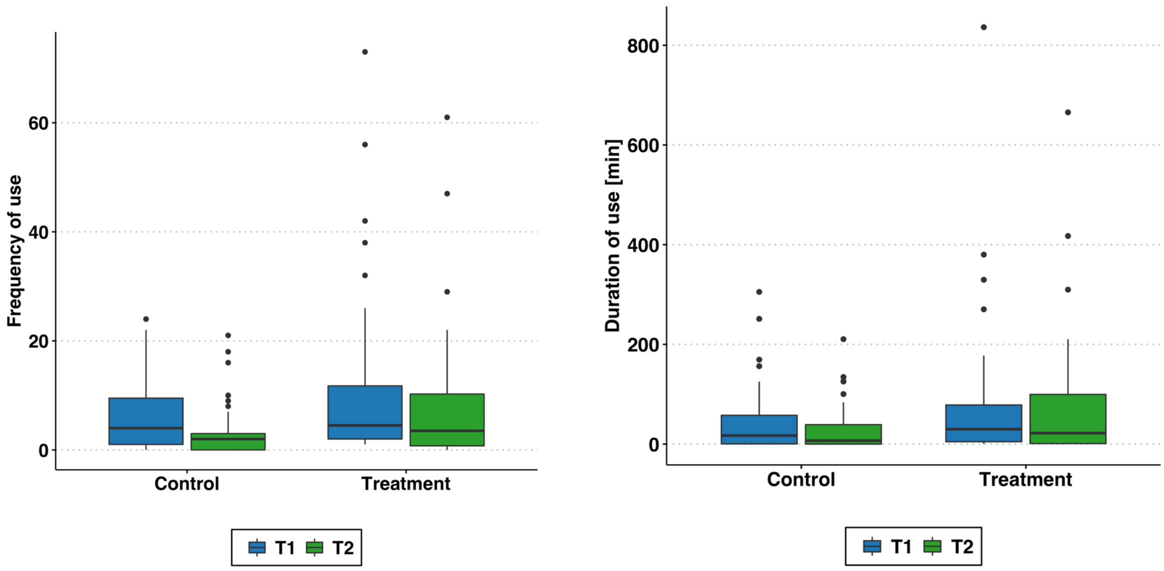


Figure 49 Difference in frequency and duration of system use between time periods by experimental condition.

Condition (N = 87)	**Frequency of use**			**Duration of use (minutes)**		
	T1	**T2**	**Diff**	**T1**	**T2**	**Diff**
Total	8.41	5.63	2.78*	61.1	49.9	11.2
Control	5.83	3.23	2.60**	44.9	28.7	16.2
Treatment	11.40	8.45	2.95	80.2	74.8	5.4

**** p.value < 0.01; ** p.value < 0.05; * p.value < 0.1*

Table 27 Differences in system use between the two time periods by total and experimental conditions.

In general, the frequency of use declined significantly between the two time periods. The same trend is reflected in the behaviour of the users from the control group. However, the change in the presentation format seems to have offset some of the negative general trend, since the drop in frequency of use for the treatment group was not statistically significantly different at T2 from T1. Although system use was hypothesised to increase, the effect of the spatial data representations with data labels is still visible in softening of the negative trend that may well have been caused by COVID-19. The duration of use has decreased both in general, and for the experimental conditions. However, the decline in duration of use was less substantial for the treatment group than the control, which is not what we expected. None of the changes in the duration of use were statistically significant.

The objective of the changes made to the system was not only to change the behaviour of system users but also to understand it better. The experimental data allowed further analysis of user behaviour. Figure 50 and Figure 51 show the density plots of differences in frequency and duration of use between T1 and T2 for each user. Figure 50 shows that the behaviour of most people changed very little over time. However, there was a considerable drop in use by heavy users from T1 (indicated by large negative values on the left of the graph), which was not compensated by the emergence of new heavy users in T2 (just a miniscule “bump” on the right-hand side of the graph).

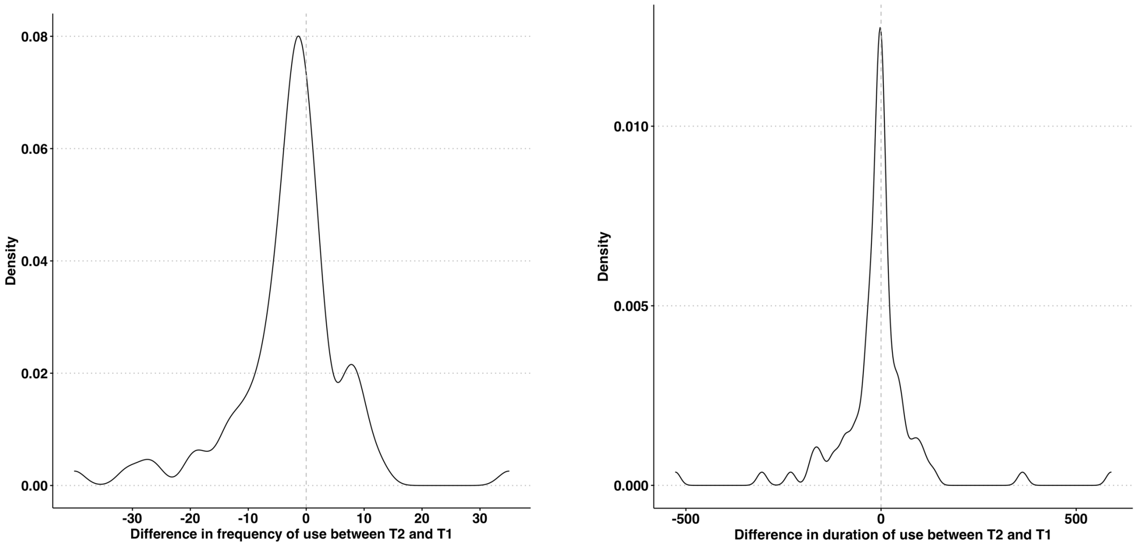


Figure 50 Distribution of the differences in the frequency and duration of system use between T2 and T1.

Figure 51 shows that the treatment condition clearly offset some of the negative trend in T2. Most of the heavy users, the majority of whom were randomly assigned to the treatment group, considerably reduced their use in T2. However, the other substantial difference between the two groups is seen in frequency of use response, ranging from -10 to +10. This is where the effects of the treatment can be seen, with the negative and positive effects, smaller and greater, respectively, as compared with the control group.

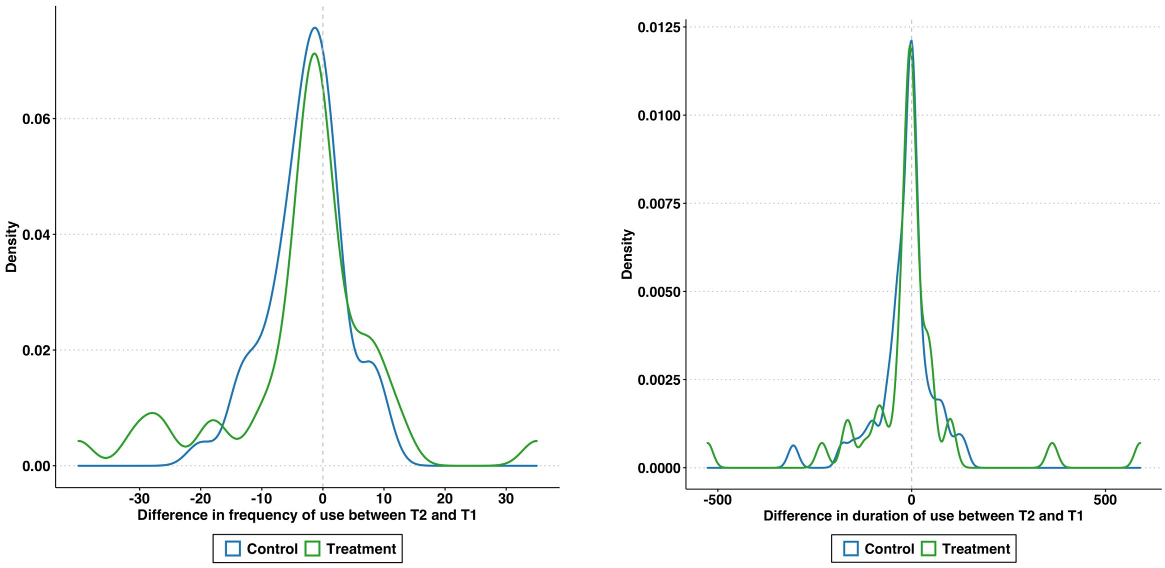


Figure 51 Distribution of the differences in the number of logins and the average session time between T2 and T1 by experimental condition.

The conclusion drawn from this analysis is that H2a is supported. Having controlled for all the known external factors (both expected and unexpected), the frequency of system use was positively influenced by the introduction of spatial data representations with data labels. However, the results fail to support H2d. It was hypothesised that the duration of use would decline for the treatment group but not for the control group, due to the anticipated increase in the ease of system use resulting from the change in the data visualisation. The results show that the treatment group offset some of the general decline in duration of use instead of intensifying, which is the opposite of what was expected.

The impact of cognitive style

The results presented in this section relate to the differing effects of data presentation format on behavioural variables for system users with different cognitive styles (H4a, H4b and H5a). The first step was to establish the psychometric properties of the cognitive styles constructs, as shown in Table 28. One item from the rational cognitive scale was removed due to the low inter-correlation. The Cronbach alpha's were lower than for the student sample in the lab experiment but still within the acceptable range of reliability for the constructs (e.g. Bastian and Haslam, 2010).

Construct	Number of items	α	Mean	Sd	1
1. Rational cognitive style	6	0.50	3.76	0.48	-
2. Experiential cognitive style	5	0.64	2.96	0.58	-0.05

Table 28 Psychometric properties, descriptive statistics and correlation of cognitive styles.

Table 29 shows how the cognitive style were spread across the experimental conditions. Although, we strived to distribute them evenly, with a small sample size, it was not entirely possible. Variables with known effects had to be primarily controlled for in the random allocation, and the control group has a larger share of experiential individuals.

Condition (N = 71)	Cognitive Style	N
Control	Experiential	22
	Rational	11
Treatment	Experiential	15
	Rational	16

Table 29 Spread of cognitive styles across experimental conditions.

The data presented in Table 30 illustrates the broad level of engagement with the system by cognitive style. On average, rational individuals have used the system more frequently and for longer periods of time. The group of rationally inclined users was also characterised by larger standard deviations and maximum values indicating a greater share of heavy users. This is in line with the theoretical expectations as rational cognitive style includes greater use of information in decision-making. However, the differences were not statistically significant, hence the results fail to support H5a.

Cognitive Style (N = 64)	Frequency of use				Duration of use			
	Min	Max	Mean	Sd	Min	Max	Mean	Sd
Experiential	1	87	15.8	16.7	3.2	742	129	164
Rational	1	120	18.3	27.9	1	1146	140	243

**** p.value < 0.01; ** p.value < 0.05; * p.value < 0.1*

Table 30 System use by cognitive style.

Figure 52 demonstrates the behavioural responses of people with different cognitive styles to different data presentation formats. The previously established negative trend seems to be more pronounced for rational individuals in general, but especially in the control group. Experiential individuals seem to respond particularly well to the spatial data representations with data labels by increasing both their frequency and duration of use. It is notable that the system use by rational individuals at T2 declined considerably more than for experiential individuals regardless of the experimental group.

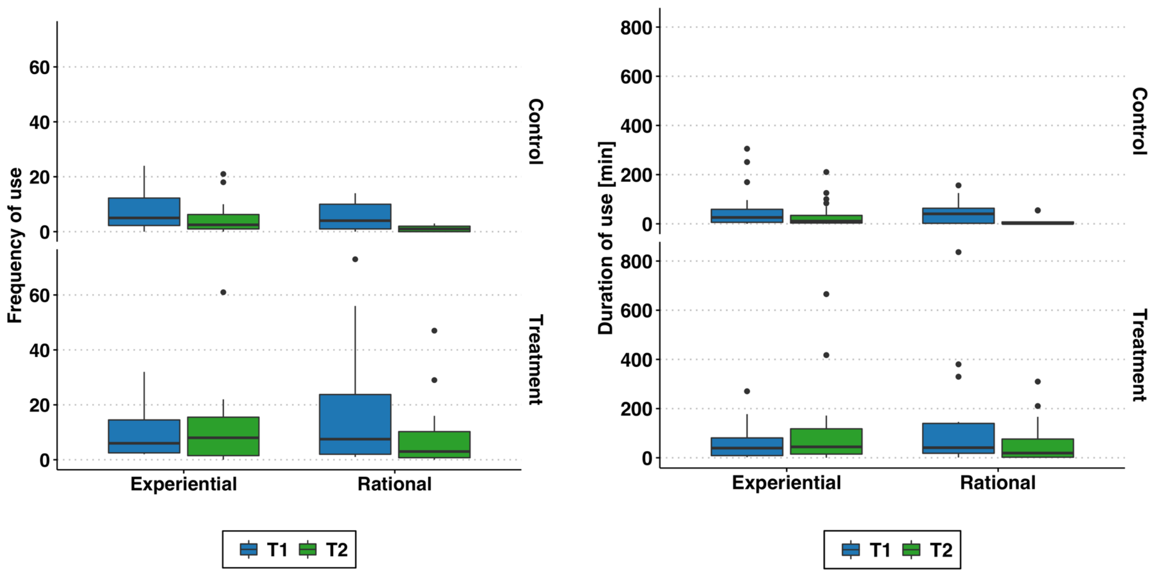


Figure 52 Number of logins and session lengths across time periods, experimental conditions and cognitive styles.

A series of one-way ANOVA tests were conducted to check for differences in behavioural outcomes across the time periods and experimental conditions. As shown in Table 31 none of the differences were found to be statistically significantly different. However, for the control group, both frequency and duration of use declined from T1 to T2 regardless of the cognitive style. The decline was especially pronounced for rational individuals regardless of the experimental group. Interestingly, experiential individuals in the treatment group increased both their frequency and duration of use by 15% and 103%, respectively. At the same time, the rationally inclined individuals reduced their frequency and duration of use by approximately 50%, which is line with the declines in the control group.

Condition (N = 64)	Cognitive Style	Frequency of use			Duration of use		
		T1	T2	Diff	T1	T2	Diff
Control	Experiential	7.32	4.55	2.77	56.5	35.4	21.1
	Rational	5.73	1.09	4.64	47.9	11.8	36.1
Treatment	Experiential	10.00	11.53	-1.53	60.6	123.0	-62.4
	Rational	17.40	8.75	8.65	135.4	60.0	75.4

*** *p.value < 0.01;* ** *p.value < 0.05;* * *p.value < 0.1*

Table 31 Differences in frequency and duration of system use across time periods by experimental conditions and cognitive styles.

None of the statistical tests revealed significant differences, thus failing to support hypotheses H7a and H7b. However, there is some indication that both frequency of use and duration of use have a potential to change positively for the experiential individuals with the change of the data presentation format.

5.3.1.2 Change in beliefs

The final piece of experimental analysis was concerned with the impact of the presentation format on the key individual beliefs (H2b-d). All the relevant constructs had a high Cronbach alpha scores, confirming the reliability of the measurement scales (Table 32).

Construct	Number of items	T1				T2			
		α	1	2	3	α	1	2	3
1. Perceived Usefulness	4	0.96	-			0.95	-		
2. Perceived Ease of Use	4	0.94	0.80	-		0.92	0.44	-	
3. Satisfaction	3	0.83	0.71	0.77	-	0.85	0.67	0.67	-

Table 32 Psychometric properties and correlations of individual beliefs and satisfaction at T1 and T2.

Responses were obtained from 47 system users over the two time periods, 24 from the control group and 23 from the treatment group. Figure 53 shows the predominant lack of substantial change in individual beliefs and emotions across time and experimental conditions. A series of one-way ANOVA tests were conducted to compare the differences in individual beliefs. None of the differences were found to be significantly different.

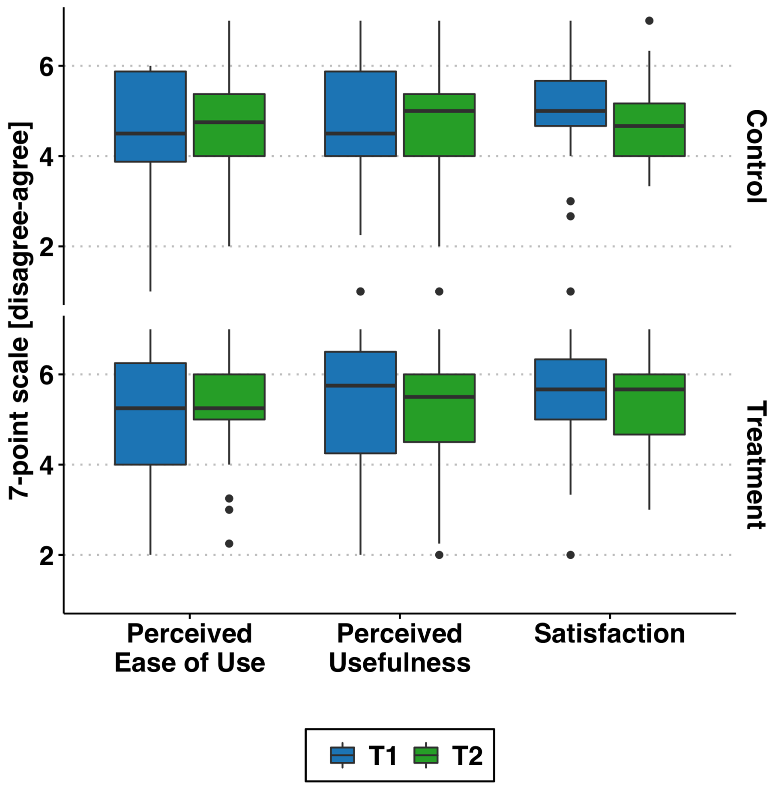


Figure 53 Change in perceptions between time periods by experimental condition.

The differences across time and conditions were minor as shown in Table 33. However, it seems that PU and PEOU have decreased over time for the treatment group while having increased for the control group. This contrasts with the expected effect of the change in the presentation format. Satisfaction has decreased over time regardless of the experimental condition although the decreases were smaller for the treatment group. In summary, the evidence leads us to reject hypotheses 2b-d – the change from the symbolic to spatial data representations with data labels did not positively influence key individual beliefs or emotions.

Condition (N = 47)	**Perceived Ease of Use**			**Perceived Usefulness**			**Satisfaction**		
	T1	**T2**	**Diff**	**T1**	**T2**	**Diff**	**T1**	**T2**	**Diff**
Control	4.61	4.76	-0.15	4.64	4.89	-0.25	5.03	4.81	0.22
Treatment	5.36	5.18	0.18	5.42	5.26	0.16	5.49	5.41	0.08

Table 33 Comparison of system perceptions over time.

5.3.2 Preferences

In addition to the tests of behavioural responses and perceptual changes, participants were also asked to express their preferences for the two systems based on a side-by-side comparison. Participants were asked to choose their preferred option for each part of the system (KPIs, shopper segmentation and store performance) as well as their overall preference. They had the option to express "no preference". It was hypothesised that the response would differ between system parts (H3a and H3b) and between experimental conditions (H6). Figure 54 and Table 34 present the general distribution of preferences overall and across the different parts of the report.

The equality of proportions between the preferences for the old and new system in general and for each report part was tested. The overall evaluation leans towards the old system but the proportions were not statistically significantly different. In terms of the individual parts of the system, as expected, the old system was the favoured choice for the KPIs screen (significantly different at the level of <5%), while the new system was the preferred option for store performance visualisations (significantly different at the level of <10%). The preferences were closely divided for the shopper segmentation part and were not significantly different. These findings result in the acceptance of hypotheses H3a and H3b.

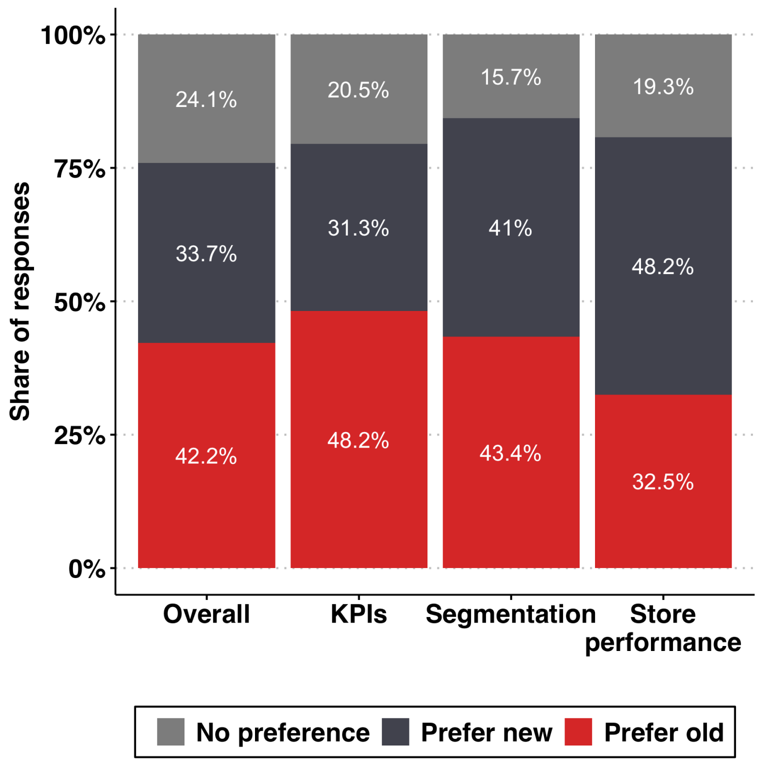


Figure 54 Preferences for the two systems across report parts and in general.

Report part (N = 83)	Prefer Old	Prefer New	No preference
Overall	42.2%	33.7%	24.1%
KPIs	48.2%**	31.3%	20.5%
Segmentation	43.4%	41.0%	15.7%
Store performance	32.5%*	48.2%	19.3%

*** *p.value < 0.01;* ** *p.value < 0.05;* * *p.value < 0.1*

Table 34 Share of preferences across systems and report parts – statistical tests.

Figure 55 and Table 35 illustrate the variation in preferences between experimental conditions. It is important to note that the treatment group had actually used both systems while the control group only saw the screenshots of the new system for the first time when they were asked to answer the questions. It was hypothesised that the control group would suffer from the status quo bias and prefer the old system. However, the results show the opposite, with the treatment group preferring the old system to a slightly higher degree, although the proportions were not significantly different. Therefore, the results failed to support H6. It is also interesting that the treatment group responses are stronger than the control group responses with regard to the KPIs and store performance parts of the system.

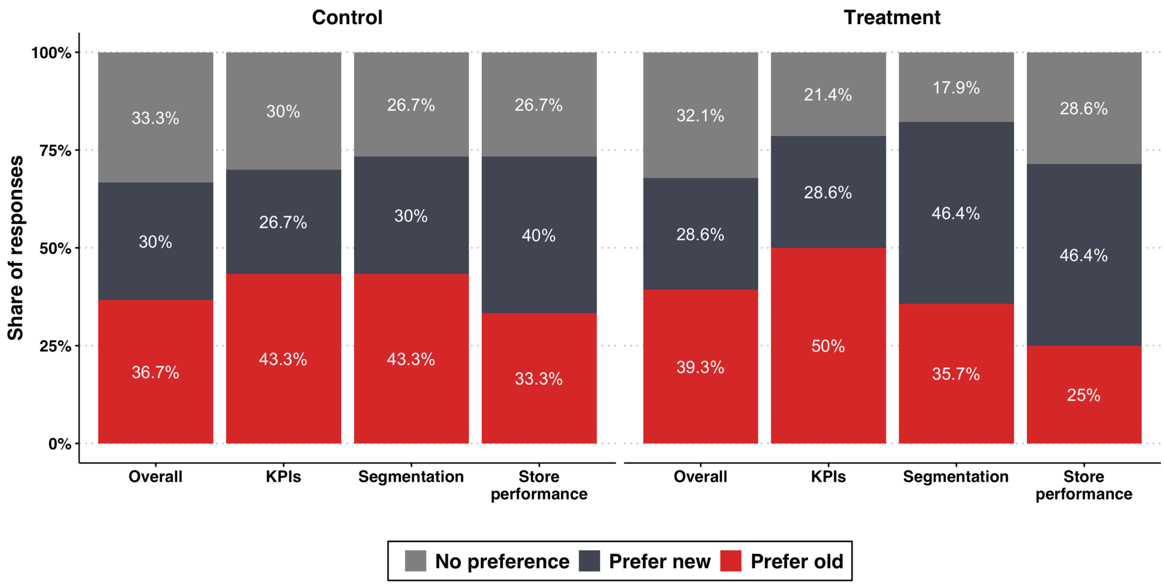


Figure 55 Preferences for the two systems by experimental groups.

Condition	Report part	Prefer old	Prefer new	No preference
Control (N = 30)	**Overall**	36.7%	30.0%	33.3%
	KPIs	43.3%	26.7%	30.0%
	Segmentation	43.3%	30.0%	26.7%
	Store performance	33.3%	40.0%	26.7%
Treatment (N = 28)	**Overall**	39.3%	28.6%	32.1%
	KPIs	50.0%	28.6%	21.4%
	Segmentation	35.7%	46.4%	17.9%
	Store performance	25.0%	46.4%	28.6%

**** p.value < 0.01; ** p.value < 0.05; * p.value < 0.1*

Table 35 Preferences for the two systems by experimental conditions.

Given the unexpected higher preference for the old system among the treatment group, the objective behavioural measures were explored to see if they differed between people who expressed different preferences. Interestingly, as shown in Table 36, people who preferred the old system after the exposure to the new system were the heaviest users in general, but their use declined with the switch. Those who preferred the new system after the exposure were medium users, but their use doubled after the switch. Those with no preference were the lowest users but their number of logins declined while session length remained the same. The sample is very small, but these numbers would suggest that to a degree past behaviour of people is reflected in their preferences. None of the groups contained a disproportionate share of individuals with a certain cognitive style and none of the differences were statistically significantly different.

Overall preference (N = 28)	Number of logins			Average session length			Cognitive Style		
	T1	T2	Diff	T1	T2	Diff	E	R	NA
Old	21.4	14.4	7.0	181	153	28	46%	46%	8%
New	6.3	12.1	-5.8	19	116	-97	38%	38%	24%
No preference	10.4	6.0	4.4	51	25	26	44%	56%	0

**** p.value < 0.01; ** p.value < 0.05; * p.value < 0.1*

Table 36 Behavioural responses and preferences for the two systems among the treatment group.

5.3.3 Explaining use – technology and organisation attributes

The purpose of this part of the analysis was to explore the behavioural drivers of market information system use, in the specific context of small businesses. This was done by validating previous research findings and investigating the role played by the contextual factors in explaining commonly used constructs in system use, i.e. system use and behavioural intention, to which we added additional contextual user, technology and organisation attributes, i.e. cognitive style, information presentation format, firm's market orientation and Tesco dependency.

Table 37 illustrates the psychometric properties and correlations of the constructs used on both the individual and firm level. The psychometrics for cognitive style were reported in Table 28. All of the constructs had a very reliable level of Cronbach alpha around 0.90.

Construct	Scale items	T1 (N = 71)			T2 (N = 76)								
		α	Av	Sd	α	Av	Sd	1	2	3	4	5	6
1. Perceived Usefulness	4	-	-	-	0.95	4.88	1.31	-					
2. Perceived Ease of Use	4	-	-	-	0.92	4.84	1.08	0.46	-				
3. Satisfaction	3	-	-	-	0.85	5.01	0.96	0.68	0.67	-			
4. Behavioural Intention	4	0.94	5.44	1.69	0.89	5.33	1.33	0.65	0.39	0.62	-		
5. Subjective Norm	4	-	-	-	0.98	4.88	1.39	0.68	0.39	0.42	0.69	-	
6. Market orientation	10	0.86	4.94	0.92	-	-	-	-0.19	0.00	0.03	0.04	-0.08	-

Table 37 Psychometric evaluations and descriptive statistics of constructs captured at both T1 and T2.

In order to explain system use multiple linear regression was used with frequency of use and behavioural intention as dependent variables. The focus was on explaining the behaviour at T2, with the use of appropriate constructs collected either at T1 or T2. In order to explain the frequency of system use at T2, behavioural intention expressed at T1 was used since the intention is assumed to be a predictor of future action. However, satisfaction expressed at T2 was used as its levels is assumed to shed light on the past behaviour. Organisational attributes were added in additional models.

This results in three separate multiple regression calculations, as shown in Table 38. Model 1 is the hypothesised baseline model which explained almost 39% of the variance in actual frequency of market information system use. The Habit construct was the only statistically significant predictor, thus supporting previous findings. Interestingly, the effect of Satisfaction was much stronger than that of Habit yet insignificant, thus contrasting previous findings. The BI variable was not only found to be insignificant but also its effect was negatively related to system use indicating, as predicted, its irrelevance for continued actual system use (supporting H1). Models 2 and 3 included organisational attributes of market orientation and Tesco dependency, but neither of the effects was statistically significant leading to the rejection of H7 and H8.

Explaining system use

	Dependent variable:		
	System use		
	(1)	(2)	(3)
Habit	0.549***	0.570***	0.558***
	(0.096)	(0.094)	(0.102)
Satisfaction	1.926	1.845	2.168
	(1.285)	(1.248)	(1.504)
Behavioural Intention	-0.424		
	(0.823)		
Market Orientation		1.032	
		(1.740)	
Tesco Turnover (share)			-0.168
			(0.684)
Constant	-5.851	-13.315	-8.957
	(7.244)	(10.858)	(8.117)
Observations	52	51	45
R^2	0.425	0.453	0.433
Adjusted R^2	0.389	0.418	0.391
Residual Std. Error	9.213 (df = 48)	9.112 (df = 47)	9.744 (df = 41)
F Statistic	11.832*** (df = 3; 48)	12.980*** (df = 3; 47)	10.428*** (df = 3; 41)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 38 Multiple linear regression analyses with system use as a dependent variable.

Behavioural intention at T2 was explained with the relevant individual beliefs as well as satisfaction captured at T2. The aim here is to understand what shapes continuance intention to use a market information system after a substantial amount of time since its adoption. Following previous research, the moderating role of contextually relevant experience, i.e. experience with using market information, was also tested.

As shown in Table 39, two models explaining continuance intention at T2 were tested. Model 1 demonstrated that in the context of continued market information system use by small businesses, only two constructs, Satisfaction and Subjective Norm, were significant in explaining the BI thus offering support for previous research findings. The model explained almost 65% of variance in BI. The effects of Habit and PU were minimal, and PEOU had a small negative effect contrasting previous research findings. The addition of Experience as a moderator (Model 2) actually decreased the explanatory power of the model offering no support for previously established role of experience.

Explaining behavioural intention		
	Dependent variable:	
	Behavioural Intention	
	(1)	(2)
Habit	-0.0002	0.003
	(0.009)	(0.010)
Satisfaction	0.582***	0.612***
	(0.182)	(0.212)
Perceived Usefulness	0.080	-0.062
	(0.127)	(0.310)
Perceived Ease of Use	-0.143	-0.159
	(0.138)	(0.171)
Subjective Norm	0.515***	0.462***
	(0.106)	(0.123)
Experience		-0.149
		(0.309)
Usefulness:Experience		0.023
		(0.056)
Constant	0.232	1.306
	(0.574)	(1.880)
Observations	59	52
R^2	0.675	0.645
Adjusted R^2	0.645	0.588
Residual Std. Error	0.830 (df = 53)	0.880 (df = 44)
F Statistic	22.059*** (df = 5; 53)	11.401*** (df = 7; 44)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 39 Multiple linear regression analyses with behavioural intention as a dependent variable.

Three models were tested to explain Perceived Usefulness (Table 40). Model 1, which explained almost 47% of the variation, demonstrated significant positive relationships between PEOU, SN and PU thus confirming previous findings. The effect of SN was twice that of PEOU indicating the relative importance of the perception of the social context to the individual beliefs with regard to technology in shaping the beliefs about the system's usefulness. The hypothesised effect of user cognitive style was not found to be significant (Models 2 and 3). Therefore, H5b was rejected. What is more, the addition of experience led to a reduction in the explained variance, which is in contrast to previous findings.

Explaining perceived usefulness

	Dependent variable:		
	Perceived Usefulness		
	(1)	(2)	(3)
Perceived Ease of Use	0.287^{**}	0.284^{*}	0.676
	(0.132)	(0.151)	(0.550)
Subjective Norm	0.524^{***}	0.519^{***}	0.263
	(0.103)	(0.113)	(0.448)
Rational Cognitive Style		-0.059	
		(0.313)	
Experience			0.131
			(0.411)
Experience:PEOU			-0.074
			(0.094)
Experience:Subjective Norm			0.048
			(0.077)
Constant	1.007	1.045	0.384
	(0.610)	(0.737)	(2.419)
Observations	59	52	52
R^2	0.484	0.438	0.447
Adjusted R^2	0.466	0.403	0.387
Residual Std. Error	1.031 (df = 56)	1.097 (df = 48)	1.112 (df = 46)
F Statistic	26.285^{***} (df = 2; 56)	12.466^{***} (df = 3; 48)	7.435^{***} (df = 5; 46)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 40 Multiple linear regression analyses with perceived usefulness as a dependent variable.

Finally, simple linear regression was used to test the effect of cognitive style on the perceived ease of use. The results are presented in Table 41 and show that cognitive style had no statistically significant impact on perceived ease of use, resulting in the rejection of H5c.

Explaining perceived ease of use

	Dependent variable:
	Perceived Ease of Use
Rational Cognitive Style	0.293
	(0.315)
Constant	4.766***
	(0.200)
Observations	52
R^2	0.017
Adjusted R^2	-0.003
Residual Std. Error	1.116 (df = 50)
F Statistic	0.866 (df = 1; 50)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 41 Linear regression analyses with perceived ease of use as a dependent variable.

5.3.4 Exploratory analysis

5.3.4.1 'Emergent' user group

As explained earlier (see section 5.2.4), an unexpected user group emerged during the course of the experiment (N = 24). These were the users that were added to the WBMF project over the course of T2, which means they had no experience of the old system. No formal hypotheses were proposed for this group, but the opportunity was taken to compare their behaviour and perceptions with the treatment group.

Table 42 presents the descriptive statistics of the two variables describing system use for the emergent group and the treatment group. Two things stand out. First, the average and maximum frequency of use of the emergent group were far below the values for the treatment group. Second, the duration of use of the emergent group far exceeded the treatment group. These two facts might point to a highly differential behaviour of users at the beginning of their system use (users from the emergent group at most used the market information system for 17 weeks) and reflect the length of time it takes new users to get accustomed with the system.

Group	Frequency of use				Duration of use			
	Min	Max	Mean	Sd	Min	Max	Mean	Sd
Treatment	1	61	8.5	12.8	1	665	74.8	131.0
New	1	24	4.9	5.3	2.5	885	74.5	176.0

Table 42 The comparison of behavioural metrics of the new group with the treatment groups.

Table 43 shows the comparative results for individual beliefs. Consistently, the emergent group perceives the system to be less useful and less easy to use than the treatment group. They were also less satisfied and less inclined to use it in the future than the treatment group. Interestingly, their perception of the subjective norm was also lower. Again, this might suggest different interplay of factors at the beginning of system use. New users are struggling with making sense of the system but may also need more time to secure a buy-in from important peers in their organisations.

Group	Perceived Usefulness	Perceived Ease of Use	Satisfaction	Subjective Norm	Behavioural Intention
Treatment	5.29	5.17	5.40	5.28	5.87
New	4.75	4.91	4.92	5.09	5.30

Table 43 The comparison of perceptual metrics of the new group with the treatment group.

Finally, the preferences for the two systems were compared (see Figure 56 and Table 44). The emergent group, which had no experience of the old system, expressed stronger preference for it than both the control and the treatment group. The only part of the system which they found more appealing in the new version was the part covering store performance.

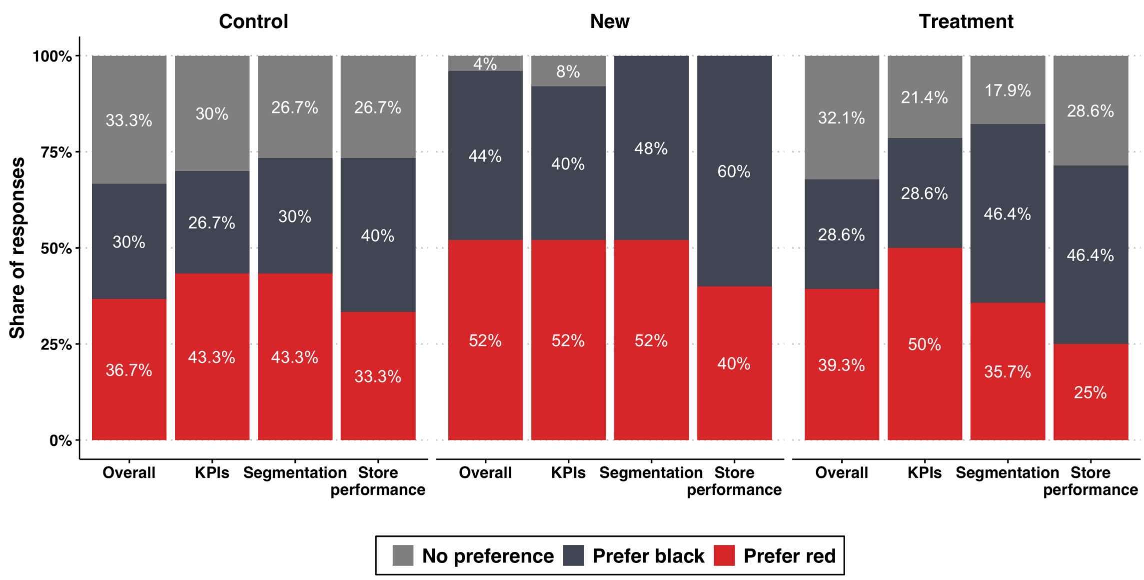


Figure 56 Preferences for the two systems by experimental groups.

Condition	Report part	Prefer red	Prefer black	No preference
Control	**Overall**	36.7%	30.0%	33.3%
	KPIs	43.3%	26.7%	30.0%
	Segmentation	43.3%	30.0%	26.7%
	Store performance	33.3%	40.0%	26.7%
New	**Overall**	52.0%	44.0%	4.0%
	KPIs	52.0%	40.0%	8.0%
	Segmentation	52.0%	48.0%	0
	Store performance	40.0%	60.0%	0
Treatment	**Overall**	39.3%	28.6%	32.1%
	KPIs	50.0%	28.6%	21.4%
	Segmentation	35.7%	46.4%	17.9%
	Store performance	25.0%	46.4%	28.6%

**** p.value < 0.01; ** p.value < 0.05; * p.value < 0.1*

Table 44 Preferences for the two systems by experimental conditions.

5.3.4.2 Impact of COVID-19

The experimental period of this study coincided with the global pandemic of COVID-19 that had a particularly disruptive effect on UK food industry (see e.g. FSA, 2020; Mintel, 2020c; ONS, 2020; Perkins, 2020). Steps were taken to control for its impact between the experimental groups. However, it is likely that the general decline in the use of the market information system was at least partially the result of the serious disruptions caused by the global pandemic and the series of national lockdowns and restrictions, which have been implemented across the UK. Therefore, further analysis was conducted of the data collected on the impact of COVID-19 pandemic on our sample of small businesses, from the supplier survey and the loyalty card (performance) data for their products.

As shown in Figure 57, COVID-19 had a considerable and heterogenous impact on the small businesses involved in this experiment. Participants were asked what happened to their sales and their ability to plan during the COVID-19 pandemic. First, the dichotomous impact on total sales stands out. For 40% of companies the pandemic was a negative event, while for 55% it had positive influences. The situation is more homogenous when it comes to business planning, with 70% of businesses agreeing that it was very difficult, almost impossible, to effectively plan anything for the long-term. However, it is noteworthy that there is a group of businesses that have not agreed with the statements about the impossibility of long-term planning and the necessity to implement changes to the business model (c. 30% and c. 25%, respectively), implying they carried on with "business as usual" throughout the pandemic.

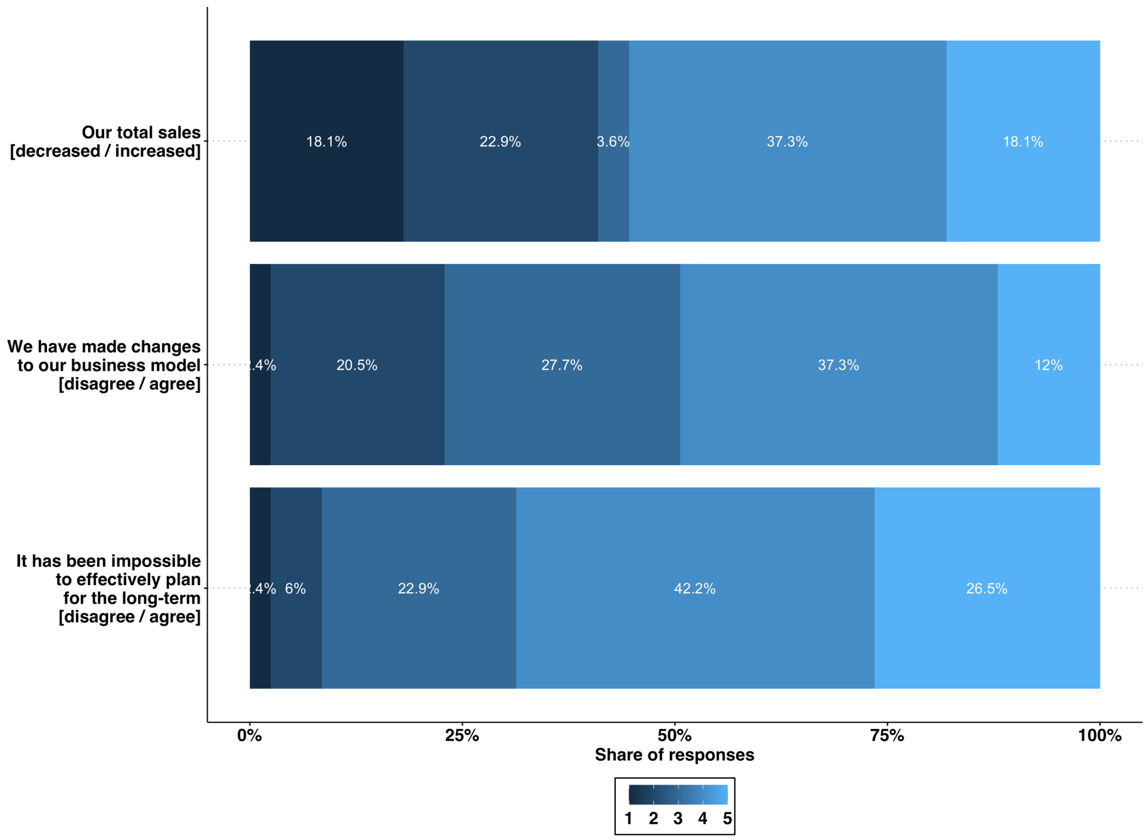


Figure 57 Summary of responses to questions about COVID-19 impact.

The discovery of the dichotomous impact of the pandemic on total sales prompted the examination of the relevant loyalty card (performance) data for the products of involved businesses. Descriptive statistics for the year-on-year changes in total sales of all products listed, for the 26 weeks from 16/03/2020 up to 13/09/2020 and the corresponding period 12 months before are reported in Table 45.

Sales Increased?	N	Min	Max	Median	Mean	Sd
No	37 (33%)	-64%	-0.1%	-25%	-27%	2%
Yes	76 (67%)	1%	2,880%	24%	81%	331%

Table 45 Descriptive statistics of COVID-19 impact on supermarket sales of the participating companies.

The majority of companies (67%) experienced a considerable growth in their Tesco sales during the COVID-19 pandemic and the national lockdown. However, it is notable that the average growth and decline in year-on-year sales were substantial, with companies either loosing or adding approximately a quarter of their supermarket sales. Undoubtedly, this highlights the pressure the companies were under during the time of the experiment.

Furthermore, since almost 30% of the companies had not used the market information system during the mentioned 26 weeks, in an organic way, two groups emerged of system users and non-users. Their average sales growth was compared and then further broken down by companies with growing and declining sales. The summary is shown in Table 46. Two interesting findings emerge. First, non-users experienced both greater declines and smaller gains in sales units. Second, decreasing sales were associated with twice the total time spent using the system. This indicates the crisis-related system use, with companies turning to data and information only when the situation deteriorates rather than consulting it regularly.

System use	Sales Increased?	N	Median sales change	Median time duration of use
Users	No	24 (21%)	-23%	44 mins
	Yes	57 (50%)	27%	24 mins
Non-users	No	13 (12%)	-29%	-
	Yes	19 (17%)	18%	-

Table 46 Average supermarket sales change and average duration of use.

Throughout the pandemic a regular contact was maintained with a number of companies involved in the WBMF project. From that contact it became evident that meeting the production demands (when sales grew) or attempting to replace dwindling supermarket sales by pivoting the business model, most often towards e-commerce, required considerable time and effort. This left the companies with less time available for routine or discretionary duties, such as consulting market information. If the findings about the impact on sales are juxtaposed with the anecdotal evidence from the communications with the companies, then it is safe to say that the pandemic had a substantial negative impact on the use of the market information system, which in turn is likely to have had an impact on the reliability of the field experiment.

5.4 Summary of Chapter 5

The field experiment involved the design, test and evaluation of a behavioural change intervention. The intervention modified part of the physical environment, the technological artifact, with the objective of positively influencing the behaviour and attitudes of system users. After the baseline data collection period, half of the users were randomly assigned and moved to the exact replica of the system but for the way the information was presented. The experiment was evaluated primarily through behavioural data derived from the system logs, supplemented by data from two surveys which were used to enrich the study and help to evaluate the effectiveness of the intervention. The experiment revealed a number of expected and unexpected findings.

First, symbolic data representations with data labels (the treatment condition) were found to have a positive effect on system use, both frequency and duration. The treatment group countered the general negative trend and decreased their system use to a lesser and statistically insignificant degree. This finding demonstrates the scope for simple yet targeted interventions to improve system use among small businesses.

Second, although the differences were not statistically significant, people with different cognitive styles seem to have responded in different ways. Rational individuals decreased their use considerably. At the same time, experiential individuals in the treatment condition were the only group of users who actually increased their use, both frequency and duration. This would indicate that behavioural change interventions should be mindful of user cognitive characteristics.

Third, different data presentation formats are preferred for different purposes.

Symbolic and spatial (with data labels) data representations were the favourite for the KPIs and store performance parts of the system, respectively. Interestingly, the overall preferences for the two systems were reflected in the behavioural responses, with people who preferred the old system decreasing their behaviour when moved to the new system. The opposite happened for people with positive preferences towards the new system.

Finally, it was established that continued individual system use in the context of small businesses is driven by different factors than suggested by prior research. The only statistically significant predictor of frequency of use was the automatic habitual learnt response. The emotive response had a large effect but was found to be an insignificant predictor. The rational component (the continuance intention) not only had a negative effect but was also statistically insignificant. Furthermore, it was apparent that small business employees form their attitudes towards continued system use in a different manner than expected. The two significant predictors were their emotions and beliefs about the social environment – the usually proclaimed rationally formed individual beliefs had small insignificant effects. Interestingly, firm's market orientation or Tesco dependency were not found to have played a role in driving individual continued system use.

6. Discussion

This chapter summarises the most important contributions and findings from the two experiments. I analyse which findings correspond to and which contrast with the expectations based on previous research. This detailed analysis provides answers to the project research questions relating to the influence of information presentation format and the cognitive styles on behaviour. This chapter is structured as follows. First, a brief recap of the aim and objectives of this study is followed by the description of how it was conducted. Second, the three sets of theoretical contributions offered by the experiments are analysed. Third, the methodological contributions are described. Finally, the practical implications for small businesses and IS practitioners are presented.

6.1 Research summary

The aim of this study was to help small food businesses be more competitive by increasing their use of structured market information, which is vital for their effective marketing decision-making. The use of data for decision-making was operationalised as the use of a market information system, which collates, summarises and displays the relevant market information. This project had two objectives, which involved the design, test and evaluation of a) market information system modifications and b) a behavioural change intervention.

A behavioural lens was used as the main theoretical framework to view this problem and guide the identification and design of a theory-based behavioural change intervention. Through the theoretical analysis of the target behaviour modifications to the data presentation format were identified as a viable route for an effective behavioural change intervention. As a result, two broad research questions emerged. First, in what way does data presentation format play a role in the actual use of a market information system by small businesses. Second, to what degree are behavioural and attitudinal differences towards the market information system use expected among people with different cognitive styles.

In order to realise the study objectives and attempt to find answers to the research questions, the design science (DS) paradigm and design science research methodology (DSRM) were adopted. DS is a research paradigm for the simultaneous creation of new knowledge and the delivery of something of practical value and relevance for the wider community. DSRM offers a systematic and rigorous procedure for applying the DS paradigm. At its heart it contains the so-called design loops, where potential solutions to the previously identified problem are designed, tested and evaluated. DSRM was used to formulate two experiments, one in the laboratory and one in the field, to realise the study objectives and gather evidence for the research questions.

Each experiment investigated a set of detailed hypotheses, which collectively provide evidence for the broad project research questions. What is more, the laboratory experiment was used to inform the field experiment. The main findings, and how they relate to previous research are summarised in the section 6.2 on theoretical contributions. That section is followed by two more sections which discuss the contributions of this project to knowledge about experimental research methods as well as the practical implications of the main findings.

6.2 Theoretical contributions

In this sub-section, the key theoretical contributions of this study are summaries and explained. The main findings from the lab and field experiments are brought together and discussed in the relevant thematic sections organised around the broad research questions. First, the role played by information presentation format in actual market information system use is discussed. Second, the influence of cognitive style on the actual market information system use and beliefs about the system is summarised. Finally, the role of the contextual factors relevant to small businesses in explaining the broad theoretical concepts, such as the behaviour of system use and the beliefs about the system, are discussed.

6.2.1 Information presentation format and behaviour

The first theoretical contribution of this study is the answer to the research question about market information presentation format and its influence on the resulting behaviour of people accessing and using the market information via an information system. The evidence for this research question came from both the lab and field experiments. In line with previous research, the results suggest that in a controlled environment certain data presentation formats result in better decision-making performance for certain decision-making tasks (Kelton, Pennington and Tuttle, 2010). However, that line of inquiry was extended to field based IS constructs. The findings from the field experiment demonstrated that the intuitive information presentation format (spatial data representations with data labels) plays a positive role in the actual information system use among small businesses, thus facilitating a behavioural change (Bačić and Fadlalla, 2016; Henke *et al.*, 2016; Hassan, 2019).

The findings from the laboratory experiment show that data presentation format influences the resulting decision-making performance measured by speed and accuracy. In line with the Cognitive Fit Theory (CFT) and previous research (Vessey, 1991; Vessey and Galletta, 1991; Gettinger *et al.*, 2013), participants who used a symbolic data presentation format (tables) achieved faster and more accurate decisions for symbolic tasks. However, contrary to the CFT propositions participants failed to achieve improved decision-making performance for spatial tasks when spatial data representations (charts) were used. Instead, tables resulted in significantly faster and more accurate decisions regardless of the task type. This contradictory finding warrants an explanation.

CFT posits that when a fit occurs between data presentation format and the nature of the decision-making task, then decision-making performance is improved (Vessey, 1991; Vessey and Galletta, 1991). However, there is another dimension to this problem omitted in the CFT, namely the data itself which is used to construct a table or a chart. In the lab experiment real-world data sets and real-world tasks were used in order to satisfy previous criticisms of artificial and simplified data sets and tasks (Lurie and Mason, 2007). As a result, the complexity which is inherent in the field contexts made its way into the study. Data complexity is expressed as either the number of data points (rows), data length, or the number of dimensions (columns), data width. It is believed that spatial data representations work particularly well when displaying large data sets (Lycett, 2013; Abbasi, Sarker and Chiang, 2016; Henke *et al.*, 2016) and the effectiveness of the tables ends at 20-30 data points (Tufte, 2001). However, such observations are concerned with the "length" of the data not its "width". A finding from the post-hoc analysis of the data from the experiment sheds additional light on this problem. The accuracy of decisions made using charts is highest for visualisations of segmentation data (a single scatterplot), then KPIs (series of eight bar charts) and finally stores (a series of twelve bar charts). These findings suggest that when a data set has many dimensions (columns), the spatial data representation introduces too much complexity, while a table condenses it into a more understandable picture. Altogether these findings suggest that the visualisation complexity, which is the result of the data complexity, especially its width not only length might, at times, be more important than the nature of the task, and the resulting cognitive fit. This warrants further research, in order to extend the applicability of the CFT in more real-world contexts and thus broaden the boundary of this theory.

Furthermore, expecting shortcomings of the previous research when real-world data and tasks are used, more complex presentation formats and complex tasks were explored.

Obviously, real-world contexts are far more complex than controlled laboratory settings. In line with previous research, when seemingly redundant data labels were added to charts, the resulting decision-making performance was better than for ordinary charts for both spatial and symbolic tasks (Kopp, Riekert and Utz, 2018). This insight was taken further, and a comparison was made between the performance achieved with charts with labels and tables only to discover that charts with labels matched decision performance of tables for spatial and complex tasks. This implies that a small visualisation modification yields a significant improvement in decision performance achieved with charts.

The findings from the laboratory experiment clearly demonstrate that information presentation format affects behaviour, in this case the decision-making performance. They also highlight a few shortcomings of the CFT and its definition of "fit", which might be more complex, especially when real-world context is introduced to the study. First, data complexity, especially its width seems to play a role, in some instances, more important than the task type. It could be added as the third dimension to the original model. Second, data labels, which, according to the CFT and related theories, are redundant (Vessey, 1991; Vessey and Galletta, 1991; Kopp, Riekert and Utz, 2018), actually equalise decision performance achieved with either tables or charts regardless of the task type. Spatial data representations with data labels seem to offer "the best of the both worlds": spatial representation to facilitate the extraction of spatially related information but also symbolic representations to allow for fast and accurate extraction of specific values. This insight constituted the basis for the experimental conditions in the field experiment – tables acted as the control condition while charts with labels were the treatment condition.

The review of the research on small businesses characteristics, decision-making and marketing style revealed that small businesses are guided by informal and intuitive cues and struggle to make use of formalised and structured data in their marketing decision-making (Gilmore, Carson and Grant, 2001; Donnelly *et al.*, 2015; Hutchinson *et al.*, 2015; Shepherd, Williams and Patzelt, 2015; Bocconcelli *et al.*, 2018). Spatial data representations make use of the extensive sub-conscious and intuitive neural structure (Tory and Moller, 2004; Ware, 2012; Hoffman, Singh and Prakash, 2015), and the laboratory experiment demonstrated that equal or better decision performance can be achieved with charts with labels as compared against ordinary tables. These findings were synthesised, and it was hypothesised that the modification of the data representations (from symbolic tables to intuitive charts with labels) has the scope to positively influence the behaviour of the employees of small businesses accessing the market information system. System users log into the market information system in order to extract information, so conceptually each login is a single or a series of information extraction tasks which constituted the crux of the laboratory experiment thus offering further ground for such an extension. It was expected that a system which is better suited to the users' characteristics would facilitate more logins, to extract more information, but reduce the total time spent in the system, since a better format allows for faster information extraction.

The field experiment provides evidence of the positive effect of the intuitive information presentation format on the behaviour of actual market information system use among the employees of small businesses. The effect was not pronounced exactly as expected due to the general decline in system use over the experimental period. It was caused by some external out-of-control factors. The COVID-19 pandemic is one of the valid explanations, especially as the additional exploratory analysis revealed its varied and yet considerable impact. Nevertheless, it was found that the change of the data visualisation format to the spatial data representations with data labels significantly offset the negative trend in use on both measured dimensions, frequency and time.

First, frequency of use remained approximately at the same level across the experiment for the treatment group while it declined significantly in the control group. In the context of information system actual use, this supports the claims made by previous researchers that different tools commonly used by large businesses must be adjusted for the specific context of small businesses (McCartan-Quinn and Carson, 2003; Wang and Wang, 2020). Furthermore, with the use of the behavioural lens and the design science paradigm, the results demonstrate that there is a rigorous and systematic way to theoretically create such adjustments. Although the adjustments could be deemed relatively simple, compared to one-to-one data interpretation services investigated by previous researchers (O'Connor and Kelly, 2017), they show that a targeted, theory-based system modification can nevertheless yield significant effects. Unlike previous interventions (e.g. Baird, Davidson and Mathiassen, 2017; O'Connor and Kelly, 2017), which were mostly concerned with conscious and rational endeavours, such as training and individual support (Santhanam *et al.*, 2013), this study shows that connecting with the more sub-conscious and automatic processing, recognised as modus operandi of small businesses, is a valid route for an effective behavioural change intervention among small businesses.

Second, the field experiment revealed that the change of the visualisation format allowed the treatment group to retain the total time spent on the system, while it declined for everybody else. This is in contrast to the negative effect reasoned from the research on the impacts of data presentation format on decision-making performance (Vessey, 1991; Vessey and Galletta, 1991) and the findings from the laboratory experiment. Perhaps the assumption derived from the laboratory research was too simplistic for the actual field context, where various types of "uses" have been discovered in previous research (e.g. Lallmahomed *et al.*, 2013; Bagayogo, Lapointe and Bassellier, 2014; Arnott, Lizama and Song, 2017; Goutas, Hess and Sutanto, 2020), and the theory of "effective use" is being developed (Burton-Jones and Grange, 2013; Burton-Jones and Volkoff, 2017). It could be that in the field context, a more effective market information system reduces the time for individual information extraction tasks but, at the same time, encourages extracting more information thus increasing total time spent. The design of this study did not allow for such a nuanced investigation. On the other hand, it is an important contribution highlighting that expectations from the "clean" laboratory setting are not easily transferable to the field contexts. More advanced conceptualisation of the system use is undoubtedly a ripe avenue for future research, which is discussed further in the section 7.2. Nevertheless, the different behavioural response between the experimental groups in terms of the total time spent provides further support for the hypothesis that information presentation format influences the target behaviour.

In light of the findings from the two experiments, there appears to be enough evidence to answer the first research question. Information presentation format plays an important role in actual market information system use among small businesses. It is also evident that the use of the behavioural lens as a theoretical framework to study the actual system use by small businesses can yield novel and interesting findings. A more proactive research methodology which involves artifact modifications proved to be a valid alternative to the standard action research or descriptive studies.

6.2.2 Information presentation format and cognitive styles

The second theoretical contribution of this study revolves around finding evidence to answer the second research question about the behavioural and attitudinal differences between people with different cognitive styles towards the use of a market information system. Cognitive styles, which describe how individuals perceive information, think and take decisions (Kozhevnikov, 2007; Armstrong, Cools and Sadler-Smith, 2012) were identified in the literature review as a potentially important construct in the context of individuals making use of a market information system. The two experiments offer some evidence that indeed the knowledge of a person's cognitive style sheds additional explanations on their resulting decision-making performance, visualisation preferences and behaviour of using a market information system. However, the results are not fully consistent with previous research, nor are they consistent between the two experiments. Furthermore, a number of findings were not statistically significant, which means we have to be cautious in drawing definite conclusions and further research is required in order to sustain or disprove our findings. The summary of the main contributions and explanations for the contradictory findings are offered below.

Based on previous research it was expected that specific information presentation formats would facilitate better decision-making performance for people with specific cognitive styles (Engin and Vetschera, 2017; Luo, 2019). However, the results show that people achieved significantly better decision-making performance with tables regardless of their cognitive style. This was further confused in evaluations of the visualisations, since none of the differences in preferences were statistically significant. Overall, these findings are in contrast to previous research (Engin and Vetschera, 2017; Luo, 2019) but an unexpected set of differences between experiential and rational individuals was found that was not suggested by previous researchers. In general, individuals who according to the Rational-Experiential Inventory (REI) (Epstein *et al.*, 1996; Pacini and Epstein, 1999) were classified as rationally inclined solved the decision-making tasks faster, more accurately and evaluated all three types of visualisations more favourably than experientially inclined individuals. This suggests that the conceptualisation of cognitive styles used in this study could be responsible for the disparity with previous research, where different conceptualisations were used.

Engin and Vetschera (2017) used Cognitive Style Index (CSI) (Allinson and Hayes, 1996, 2011) which captures if people acquire information in a conscious or unconscious way. Luo (2019) employed a Verbaliser-Visualiser Questionnaire (VVQ) (Kirby, Moore and Schofield, 1988) which describes learning styles; whether people prefer to learn information using text or images. Both of these scales are relatively narrow in scope in that they focus on the mode in which information is acquired. Hence the opposite extremes from the scales (conscious-unconscious and verbalise-visualise) are said to match with symbolic and spatial data representations. The REI scale, which was employed in this study, is a broader and more comprehensive measure (Epstein *et al.*, 1996; Pacini and Epstein, 1999). It captures the degree to which individuals tend to operate (acquire information, think, make decisions) using the two modes of processing information, as suggested by the underlying two systems thinking model of human cognition (Sloman, 2002; Kahneman, 2012). REI is composed of two scales, the Faith in Intuition and the Need for Cognition. In the literature review it was reasoned that spatial data representations, which are said to be interpreted by the sub-conscious processes of the visual system (Tory and Moller, 2004; Ware, 2012; Hoffman, Singh and Prakash, 2015), would result in less effortful and more effective information extraction for individuals with higher scores on the Faith in Intuition. As it turns out that correspondence was not reflected in the experiments. Rather, broader preferences for, and the capability in the use of structured data in decision-making were captured. Rational individuals exhibit a strong need to acquire information from formal sources and do so best with tables but are equally comfortable with other data representations. For experiential individuals a mere change in data presentation format does not facilitate less effortful and more effective information extraction; they also did best with the default tables but performed worse than rational individuals. This warrants further research into which, if any, visualisations, or additional design elements, such as storytelling or interactive features (Kosara and Mackinlay, 2013; Perdana, Rob and Rohde, 2018; Nadj, Maedche and Schieder, 2020) can increase the effectiveness of communication with experiential individuals.

The findings from the field experiment were only partially consistent with the laboratory experiment results. What is more, none of the differences found in the field experiment were statistically significant. However, they are discussed anyway since there is an indication of some correspondence to previous research findings and theory.

First, the general behaviour of rational individuals seems to have been different to the experiential ones. On the whole, rationally inclined individuals used the market information system more frequently and spend more time than the experiential individuals, which was previously suggested but only with reported use data (Chakraborty, Hu and Cui, 2008). This resembles the finding that rational individuals achieved better decision-making performance in the laboratory experiment. It also suggests that the REI classification allowed a broad differentiation between the two groups of individuals, those more and less inclined to use the data embodied in the market information system.

Second, different behavioural responses to the experimental treatment seem to have been observed from individuals with different cognitive styles. Despite the general decline in system use over the experimental period, experiential individuals in the treatment group were the only group of individuals whose system use increased. This is consistent with previous laboratory experiment which suggested that certain data representations can positively affect individuals with different cognitive styles (Engin and Vetschera, 2017; Luo, 2019). This indicates that the change in the presentation format, from the default tables to charts with labels, could have been a good fit for experiential individuals which resulted in a positive influence on their behaviour. It is noteworthy that the opposite of this effect did not materialise, namely rational individuals in the control (tables) group did not retain or increase their system use as expected. They were actually the group that decreased their use to the highest degree. These findings would indicate that the influence of the external confounding factors was not equally distributed among individuals with different cognitive styles, and the change in visualisation format was able to offset that influence only to a degree.

In conclusion, findings from the two experiments contributed towards the second broad study research question. There is very little statistically significant evidence that there are differences in behavioural and attitudinal responses by individuals with different cognitive styles. Although many results seem to be in the right direction as suggested by previous findings and the theory, most of them were not statistically significant. However, the study findings do not indicate that individual characteristics should be disregarded in future research of technology use by small businesses, merely that cognitive style plays a lesser role than expected.

6.2.3 Context in explaining system use

The final theoretical contribution of this study revolves around the importance of context in studying the behaviour of system use and the formation of commonly modelled beliefs about information systems. Previous research has highlighted the importance and difficulties associated with incorporating the contextually relevant variables in the study of system use (March and Smith, 1995; Hong *et al.*, 2014; Venkatesh, Thong and Xu, 2016; Burton-Jones and Volkoff, 2017). This is the first study to extend the baseline UTAUT model to investigate actual individual system use in the context of a market information system and small businesses. Previous research in the small business context mostly focused on adoption, used reported use data and did not focus on individuals (Ruivo, Oliveira and Neto, 2012; Ruivo *et al.*, 2013; e.g. Popovič, Puklavec and Oliveira, 2019). This study has revealed a number of interesting correspondences and contrasts with the previous research mostly carried out in the context of larger businesses.

As expected in the case of continued individual system use, as time passes, automatic and emotional mechanisms become gradually more important than conscious rational ones

(Limayem, Hirt and Cheung, 2007; Kim, 2009; Lee, 2014). However, the findings from this study revealed that the habit construct was the only statistically significant predictor of continued system use by individuals from small businesses. Satisfaction, the emotional component, in line with previous research, had a large positive effect but did not satisfy the threshold for statistical significance thus decreasing our confidence in this relationship (Bhattacherjee and Lin, 2015). Tellingly, the behavioural intention construct was not statistically significant, which is in stark contrast to previous research and the general consensus on the importance of the intentions in explaining behaviour (Lee, 2014; Bhattacherjee and Lin, 2015; Venkatesh, Thong and Xu, 2016). This offers further evidence on how different the world of small businesses is, and that the knowledge gathered in large business context is not readily transferrable to small businesses (McCartan-Quinn and Carson, 2003; Morgan-Thomas, 2016; Wang and Wang, 2020). To explain the actual use of technology among small businesses the automatic processes come first, emotions come second, and the rational decision-making seems to lose any influence whatsoever.

A very similar picture emerges when considering how the individual beliefs about system use are formed in this context. Although the focus of this study was on the behaviour itself, Behavioural Intention (BI) was modelled as the dependent variable to contrast small business context with previous research (e.g. Bhattacherjee and Lin, 2015; Mouakket, 2015; Venkatesh, Thong and Xu, 2016; Huang, 2019), which places great importance on the intention, accepting the assumption that intention leads to behaviour (Bagozzi, 2007; Sheeran and Webb, 2016). For the BI, in line with previous research, two equally important explanatory variables were the emotive Satisfaction and the belief in Subjective Norm (SN), the perception of the influence of the social environment (Bhattacherjee and Lin, 2015; Venkatesh, Thong and Xu, 2016). The rational evaluations of the market information system, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), had miniscule insignificant effects in contrast with previous research (Mouakket, 2015; Venkatesh, Thong and Xu, 2016). These findings highlight, again, the importance of emotive and environmental factors rather than the conscious and rational ones in the context of market information system use among small businesses.

Finally, a puzzling set of findings relates to the firm-related characteristics, namely market orientation and Tesco dependency, both of which were found to be insignificant predictors of individual system use. Although IS researchers recommend adding contextually relevant organisational factors to modelling individual system use (Venkatesh, Thong and Xu, 2016), this study is the first to use such a characteristic to explain individual system use of small business employees.

Extending previous research findings to our context, a significant and positive effect was expected of market orientation which is an important variable used in the context of small business technology adoption (Peña, Jamilena and Molina, 2011; Eggers *et al.*, 2017; Länsiluoto *et al.*, 2019). Especially that market orientation construct should embody the same activities that are performed while interacting with the market information system – understanding customer needs and wants, customer satisfaction, competitor activities. What is more, the system enables the information to be easily shared within the businesses. One explanation for this no effect could be the uncovered disparity between reported behaviour and actual behaviour (reported in the sub-section 5.2.3.1 and further discussed in the section 6.3). The respondents could be reporting the strategic orientation of their business as inaccurately as they reported their system use behaviour. At the same time, it is feasible that the businesses involved would use other tools, in addition to the market information system, to realise certain elements of their market orientation thus remaining uncaptured in this study. Further studies are required to understand this contrasting finding by examining, in an objective manner, the activities that are assumed to give rise to the market orientation.

Based on previous research, which showed that the type of supplier-buyer relationship determines resources allocation and market information use (Duffy *et al.*, 2013; Malagueño, Gölgeci and Fearne, 2019), it was expected that Tesco dependency would have a significant and positive effect on individual system use. The lack of the expected effect reveals a more nuanced relationship between how small businesses actually allocate their scarce resources and the monetary importance of the retail customers. It is conceivable that other variables such as the desire to grow certain revenue streams or performance with other retailers exert stronger influence on the resulting individual behaviour. Alternatively, there might have not been enough variability in the data, since most of the respondents deemed Tesco to be a key customer and for very few companies Tesco accounted for more than forty percent of their turnover.

In summary, the findings discussed in this sub-section are in line with what we would expect when investigating the world of small businesses. Their context is unlike that of large businesses and special considerations have to be made to account for it. The analyses provide further evidence for the importance of different considerations for small businesses, especially around the interventions aiming at increasing not only adoption but continued and sustained system use.

6.3 Methodological contributions

This study offers a number of contributions in terms of the methodology employed. First, it was demonstrated that Design Science (DS) paradigm and Design Science Research Methodology (DSRM) (Hevner, March and Park, 2004; Peffers *et al.*, 2007) can be successfully used to design rigorous and theory-based interventions in the small business research. Although the use of DS in information systems research has been gaining popularity, its use is scarce in other social science domains (Hevner, March and Park, 2004; Nunamaker *et al.*, 2015; Holzer *et al.*, 2020; Silic and Lowry, 2020). A number of previous studies implemented various interventions to assist small businesses in the adoption and use of technology (e.g. Baird, Davidson and Mathiassen, 2017; O'Connor and Kelly, 2017), but the results of the experiments reported in this study show that DS approach can offer a more proactive and involved alternative that pays more attention to the IT artifact itself. After all, the technological artifact is central to any research dealing with technology use. This study showed how the experimental method can be employed in the small business context in order to increase the causal inferences (Harrison and List, 2004; Neuman, 2014). What is more, thanks to the laboratory experiment informing the design decisions made in the field context, it was not necessary to rely purely on previous research findings from other contexts. Rather it was possible to adjust them in a controlled and rigorous way to ensure their effectiveness and relevance.

Second, further evidence was added to the importance of using objectively captured actual system use data. This study illustrated the dangers stemming from using reported use data, equating adoption with use or ending the study on intention, which is assumed to always lead to behaviour (Bagozzi, 2007; Limayem, Hirt and Cheung, 2007; Ruivo, Oliveira and Neto, 2012; Ortiz de Guinea and Webster, 2013; Morgan-Thomas, 2016; Popovič, Puklavec and Oliveira, 2019). Reported use collected in a manner consistent with previous research (e.g. Limayem, Hirt and Cheung, 2007; Ruivo, Oliveira and Neto, 2012; Popovič, Puklavec and Oliveira, 2019), has revealed substantial discrepancies from the objectively measured behaviour. A very small proportion of individuals were able to correctly estimate their system use, with an average error hovering around 100%. The comparison against an unknown average resulted in a similar distortion of results. This study is the first to compare reported and actual system use measurements, which is surprising as the findings highlight a considerable weakness of fully depending on reported use data. However, the findings are consistent with the established extant psychological research on heuristics and biases, which has shown how limited are humans' abilities to estimate values, and how selective is human memory (e.g. Gilovich, Griffin and Kahneman, 2002; Kahneman, 2012; Montibeller and Winterfeldt, 2015).

What is more, collecting market information system use data from the system logs revealed a great heterogeneity in actual use among the participating individuals and businesses. While several users logged in only once in the experimental period, others, so-called "heavy users", used the system 1,400% more frequently, and for 1,000% longer periods of time than the average user. This also added further evidence to the intention-behaviour gap debate (Sheeran, 2002; Sheeran and Webb, 2016; Kroenung, Eckhardt and Kuhlenkasper, 2017). According to the commonly accepted view, all of the small business were adopters of the market information system and, according to the data collected, they all had an intention to use the system, but not all did. Furthermore, the findings revealed that it was considerably easier to explain variance in the intention construct than the objectively measured continued system use. Further research is required to identify determinants of continued system use among small businesses. These points are especially important for studying the effects of technology on organisational performance, where, in a processual sense, the act of actual usage is an absolute prerequisite to any positive performance impacts (Devaraj and Kohli, 2003). More on this in Chapter 7 on future work.

Finally, the study demonstrated that the use of real-world data and decision-making tasks in a laboratory experiment might result in findings contradictory to previous research and prompt new investigations (Samuelson and Zeckhauser, 1988; Lurie and Mason, 2007). This links to the older but still relevant debate on the value of laboratory experiments with student participants (e.g. Schwenk, 1982). Findings from the controlled and neutral laboratory settings have an enormous theoretical value, but in disciplines like management or information technology, they realise their full potential when enhanced with a link to the real-world. Ideally when combined with a field experiment set where real business operate in the real world (Harrison and List, 2004; Nunamaker *et al.*, 2015). Otherwise, they risk the fate of the famous Coca Cola blind tastes, which "despite their objectivity (or, more aptly, because of it) proved to be grossly irrelevant" (Samuelson and Zeckhauser, 1988, p. 11). As Coca Cola researchers discovered, the finding from the laboratory setting that customers prefer new experimental flavour did not translate into any business success as customers in their actual behaviour were influenced by the packaging and branding to a greater extent than by the taste alone. Thus the real-world setting rendered the laboratory finding utterly irrelevant.

6.4 Practical implications

This study delivered practical contributions on two dimensions, tangible and conceptual. On the tangible level, a systematically developed and rigorously tested market information system was designed, tested, evaluated and delivered to the end users. In the research process actual visualisations were developed and refined, and then an actual market information system was developed, deployed and is now used every day by more than a hundred small UK food businesses. The current version of the system is the result of two experiments in order to optimise the effectiveness of the information extraction for the small food businesses and their employees. This is one of the key aspects of the DS paradigm, where part of the delivered value comes from the relevance of the research outcomes to practice and the ability of practitioners to make active use of them (Hevner, March and Park, 2004; Peffers *et al.*, 2007; Nunamaker *et al.*, 2015).

As a result, the aim of this study was achieved. By designing a market information system adjusted for the specific context of SMEs they have been given a tool with the scope of assisting them in becoming more competitive during the technological revolution of the 21st century (Chen, Chiang and Storey, 2012; Watson, 2014; Henke *et al.*, 2016; Davenport, 2018; McKinsey Analytics, 2018; Cam, Chui and Hall, 2019; Rai, Constantinides and Sarker, 2019; Peters and Duncan, 2020; Ågerfalk, 2020). Specifically, small UK food producers have been armed with market information they are able to consult and from which they are capable of extracting useful insights. This gives them an indispensable leverage during such a turbulent economic situation caused by the COVID-19 pandemic (Mintel, 2020c; ONS, 2020; Perkins, 2020). But also during the intensifying range rationalisations among the UK supermarkets, notably led by Tesco, which is hitting hardest the smallest businesses (Barclays, 2018; Holmes, 2020). Having the accurate and reliably-sourced information on their consumers and competitors activities, small brands are enabled to build fairer relationships with their large supermarket customers, which is a key determinant of their subsequent success and performance (Malagueño, Gölgeci and Fearne, 2019). Securing access to the understandable data is a first step in the long journey to generate competitive advantage with data analytics, but it is a fundamental first step.

Furthermore, on the conceptual level, a number of findings came into light which could prove useful for future visualisation and system designers as well as small business managers. First, the findings emphasise the importance of applying user-centred design principles in the design of data visualisations and market information systems (Gulliksen *et* *al.*, 2003; Norman, 2013). Visualisations have to be designed carefully and flexibly to account for the complexity of the data feeding them, the tasks they are supposed to facilitate and the specific user characteristics. For visualisations, undoubtedly “one size does not fill all”, as the results demonstrated that various parts of the system require data presented in different ways. Being mindful and considerate to individual characteristics of the users is also key in the wider design of information systems, including market information systems.

What is more, the results suggest that workplace systems designed to encourage users to regular initial use, and which evoke certain emotions are more likely to result in a long-term continued use. It seems that the rational evaluations, such as ease of use, have a lesser impact than the ability of the system to facilitate habitual system use, and the subsequent satisfaction which does not necessarily have to stem from work related outcomes (Kroenung, Eckhardt and Kuhlenkasper, 2017; Liu *et al.*, 2017). The findings also suggest that small business managers play a substantial role in facilitating continued system usage. The cultivation of the right social environment, the one where employees feel technology and data use is valued, is a very important factor in enhancing market information system use. The findings agree with other recommendations that top management support is crucial for utilising market information in small businesses (e.g. Hutchinson *et al.*, 2015), and the importance of the general “data culture” of organisations in continued system and data use (Díaz, Rowshankish and Saleh, 2018; Waller, 2020).

7. Limitations and Future Research Directions

7.1 Study limitations

This study was designed and conducted to reveal causal inferences that would contribute to the knowledge base around data visualisation, technology use and decision-making in small business practice. At the same time, it sought to deliver outcomes with practical value and relevance to small business practitioners. However, there were inherent limitations with the chosen approach.

First, specifically because of the focused and targeted nature of this study, its external validity is limited. Although an attempt was made to re-validate findings from a wider research base as well as contribute new knowledge, both of the experiments were contextualised for a specific data source coming from Tesco (which is only one supermarket, albeit the largest in the UK), a specific market information system and a small subset of small food and drink businesses. Therefore, the extent to which the findings are generalisable to other contexts is questionable.

Second, the experimental approach, which offers numerous benefits, has its drawbacks. The field experiment was implemented to complement and extend the findings from the controlled environment of the laboratory experiment. However, any field experiment is subject to the confounding effect of unknown variables, which cannot be controlled as effectively as in the laboratory setting (Giannoccaro, 2013; Neuman, 2014). This was further exacerbated by the outbreak of the global pandemic of COVID-19 set to cause the worst economic crisis since the Great Depression (Gopinath, 2020), especially in the retail sector (BRC, 2021; CRR, 2021). Although, the food retail sector has experienced growth during the pandemic, the systemic changes and strains on supply chains and food producers operations were unprecedented and unevenly distributed (Mintel, 2020c; BRC, 2021). Consequently, the small sample size in the field study, combined with the unknown external influences could have been the reason behind a number of statistically insignificant findings, which suggest extra caution should be exercised in the interpretation of the results and the inferences drawn. Further validations using larger samples would strengthen the initial findings from this study.

Third, the study included a set of implicit assumptions relating to the determinants of system use, the conceptualisation of system use and its impacts. By focusing on only one element (Opportunity) of the COM-B framework, it was implicitly assumed that participants had the right skills (Capability) and motivation (Motivation) to use the system. Arguably, they were justified, since the participants in this study gain access to the system exclusively at their own agency (indicating some Motivation) and are trained upon enrolment (meaning some Capability is acquired). However, future studies targeting more than one behavioural component would offer the potential for further insights in this area and the design of more effective interventions. Furthermore, a relatively simple and limited conceptualisation of system use was used based on frequency of logins and time spent using the system. Based on the previous research it was assumed that more logins and less time spent indicate positive reflections of system use. However, the results shed some doubt on such a conceptualisation derived from the theories mostly tested in the laboratory settings. More nuanced conceptualisation could be employed to reveal additional detail about actual system use among small businesses. This point is further discussed as a potentially fruitful avenue for future work in the next section.

Finally, previous studies which rely on the intention to use were criticised for ignoring or assuming away the potential intention-behaviour gap. However, this study was also limited in that it ended on the act of using the system. The main source of this was the limited scope of what a doctoral research project could feasibly achieve in the time given. It remains for future work to investigate if that actual system use translates into any organisational and individual performance gains.

7.2 Future research directions

Despite the limitations outlined above, this study has generated a number of interesting and relevant (theoretically, methodologically and practically) findings, some of which warrant further research.

First, the study finding could lead to relevant extensions and validations in new contexts. The argument for more evidence-based marketing decision-making applies to other functional areas and sectors with distinct structural and/or organisational contexts, such as tourism or hospitality, in which there are a large number of small family firms offering services rather than manufacturing a product. Such studies could get closer to achieving technology “integration” within the specific socio-technical context rather than its impersonal “deployment” (Morgan-Thomas, 2016; Mateescu and Elish, 2019). A good starting point would be in-depth investigations to understand the drivers of use and non-use of technology by small businesses in their specific socio-technical contexts (Orlikowski, 2007; Orlikowski and Scott, 2008; Morgan-Thomas, 2016; Sergeeva *et al.*, 2017). The findings from such explorations could then directly guide the design of targeted interventions enabling more effective use, which leads to another avenue for future work.

It remains to be seen whether behavioural change interventions which target more than one behavioural element at a time, as suggested by the COM-B framework, can be successfully applied. Previous studies have shown how to increase the Capability by demonstrating the importance of training and IT support on the resulting use (Santhanam *et al.*, 2013; T. Hazen *et al.*, 2014; Retana *et al.*, 2018). In a similar vein, gamification offers a way to target the Motivation component, although the research is still in early stages (Liu *et al.*, 2017; Karahanna, Xin Xu, *et al.*, 2018; Khan, 2020; Silic and Lowry, 2020). This study has shown how simple system modifications offer a way to target the Opportunity component. Future studies could build on these singular findings by integrating the components and developing complex interventions. The real challenge for system designers lies in their ability to account for the broader, systemic picture in which every act of technology use occurs. A complex intervention might include system modifications which make the system easier to use and better suited to the user and their characteristics, embed gamification elements to increase intrinsic motivation to use it, supported by efforts to develop the necessary skills to use the system. The ultimate real challenge is to design an inclusive workplace information system that works as a systemic support mechanism which cultivates and fosters intrinsic motivation.

Third, it is vital that future researchers of actual technology use among small businesses build on the findings with regard to the importance of objectively collected usage data and the heterogeneity of use that this study revealed. More complex and nuanced conceptualisations of system use could be developed. Examples of such attempts exist in the wider IS literature, with researchers developing a theory of effective use as opposed to simply "more use" (Burton-Jones and Grange, 2013; Burton-Jones and Volkoff, 2017), studying different individual or organisational use patterns (Ortiz de Guinea and Webster, 2013; Arnott, Lizama and Song, 2017) or investigating collective use, i.e. individual use that gives rise to higher-level usage in work groups (Negoita, Lapointe and Rivard, 2018). There are very few studies in the small business domain that looked at use patterns (Baird, Davidson and Mathiassen, 2017; Popovič, Puklavec and Oliveira, 2019), which is the necessary starting point for new knowledge about technology use. Furthermore, as this study has shown, it is key that future studies focus on the actual, objectively measured, use of technology not its reported use. There is scope for such approaches to reveal very interesting findings, particularly as advances in technology enable state-of-the-art fine-grained data collection methods (Cecez-Kecmanovic *et al.*, 2014; Brinberg *et al.*, 2021). Perhaps the most striking demonstration comes from Brinberg et al. (2021) and their "Human Screenome Project". Researchers collected over six million smartphone screenshots from 132 users (a screenshot was taken every 5 seconds) to investigate, in an unprecedent way, smartphone usage behaviour. The results highlighted how different are the digital lives we lead when we look at the individual instead of average use. Instead of depending on aggregated and de-contextualised system logs or reported data the researchers conducted a fine-grained analysis of the screenshots to reveal very heterogenous engagement patterns that exist not only between people but also within the behaviour of each person. This detail would have been lost in any typical data aggregation. The arguments for relying on reported use and average usage metrics now appear all but redundant.

Finally, future research could go a step further than this study and investigate what kind of actual technology use (or use patterns) lead to positive impacts on organisational performance (Chen, Chiang and Storey, 2012; Schryen, 2013; Trieu, 2017). The actual use of technology, in a processual sense, is an essential element for any kind of performance impacts to materialise (Delone and McLean, 2003; Devaraj and Kohli, 2003). However, previous research which investigated performance impacts of technology among small businesses treated technology "use" either dichotomously as adoption (adopted or not) (e.g. Länsiluoto *et al.*, 2019), or used reported use data (e.g. Popovič, Puklavec and Oliveira, 2019). The findings of this study show the serious shortcomings of both of these approaches. Heterogeneity of system use among "adopters" is simply too great, while reported use too inaccurate to use them as reliable measures for investigating performance impacts.

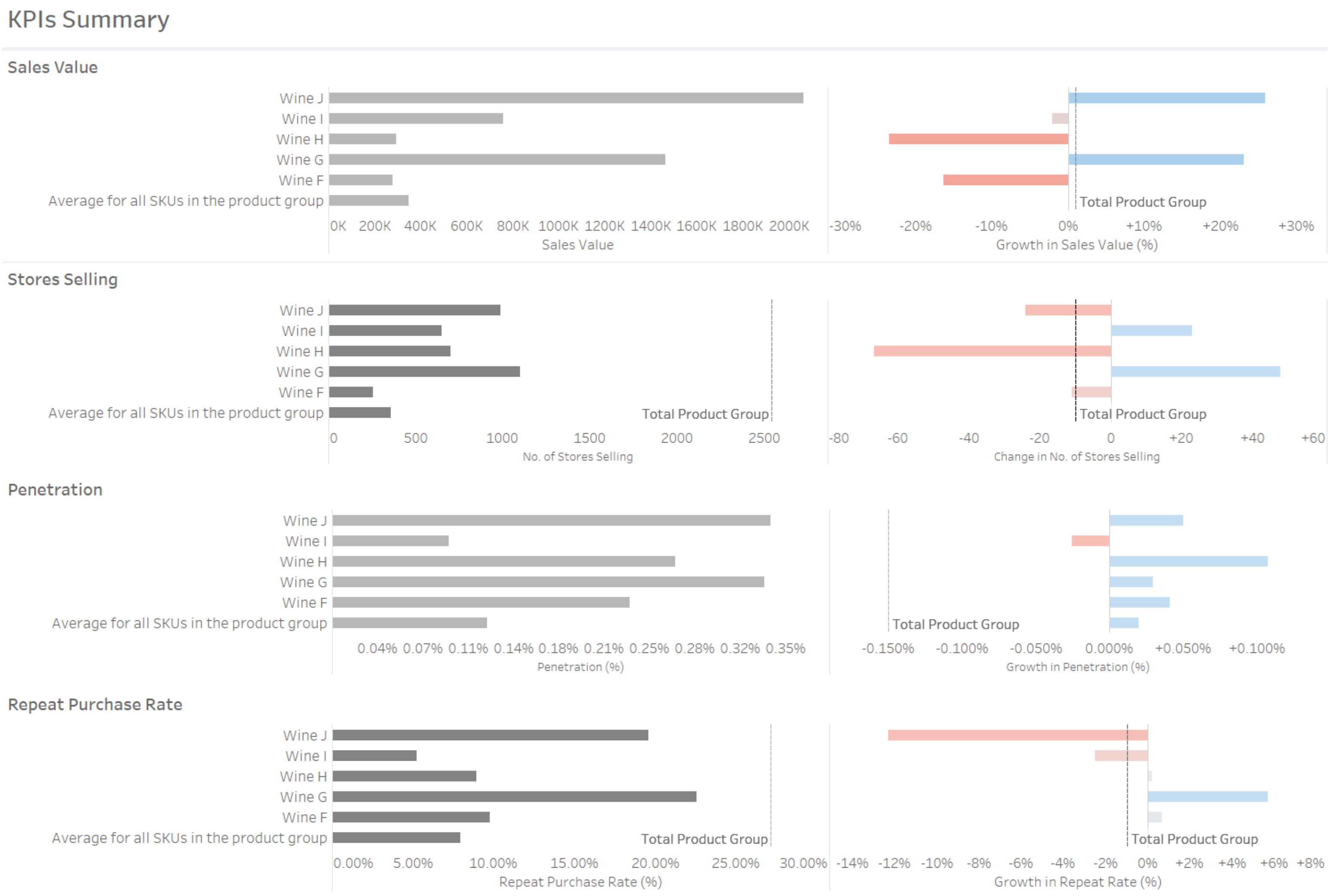
Appendix A

Appendix A contains high resolution screenshots of visualisations used in the laboratory experiment. It contains the same examples from the tables and charts conditions shown within Chapter 4.

KPIs Summary

Product Name	Growth in Sales Value (%)	Penetration (%)	Growth in Penetration (%)	No. of Stores Selling	Growth in No. of Stores Selling (%)	Repeat Purchase Rate (%)	Growth in Repeat Rate (%)
Wine E	-35.29%	0.13%	-38.57%	320	-10.64%	6.75%	57.71%
Wine D	8.72%	0.04%	8.53%	308	12.41%	6.42%	33.00%
Wine C	3.99%	0.52%	10.56%	1,104	36.63%	8.65%	-11.83%
Wine B	-19.06%	1.28%	-17.33%	1,659	5.40%	8.02%	-12.71%
Wine A	7.54%	0.71%	13.68%	862	2.01%	12.22%	-4.53%
Total Product Group	1.04%	10.98%	-0.15%	2,543	-1.05%	27.15%	-0.98%
Average for all SKUs in the product group		0.12%		357		7.92%	

KPIs Summary in tables condition.

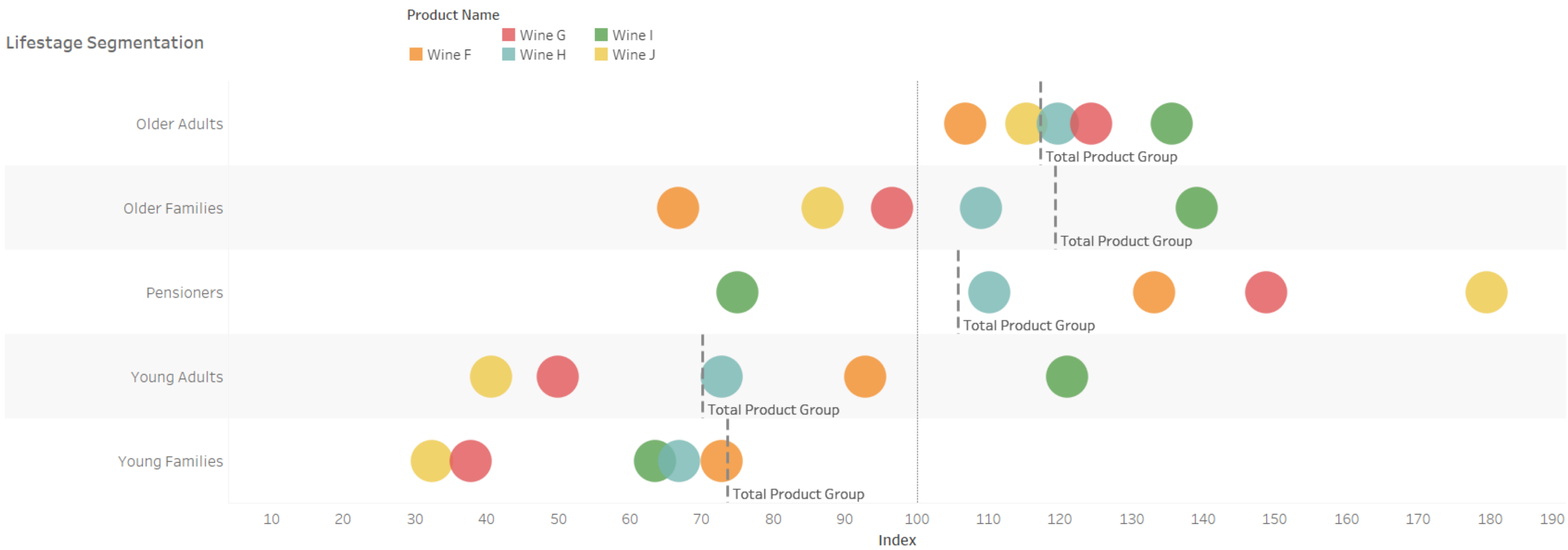


KPIs Summary in charts condition.

Lifestage Summary

Product Name	Young Adults	Young Families	Older Families	Older Adults	Pensioners
Wine E	73	80	145	128	69
Wine D	59	50	145	136	87
Wine C	84	105	150	119	53
Wine B	77	104	134	109	85
Wine A	60	90	153	119	82
Total Product Group	70	74	119	117	106

Shopper segmentation in tables condition.



Shopper segmentation in charts condition.

Total

	Number of Stores	Total Sales	Rate of Sales
Total	801	£688,530	£23.37

Format

	Number of Stores	Total Sales	Rate of Sales
Dotcom	6	£6,704	£23.05
Express	176	£30,569	£6.77
Extra	255	£319,494	£29.49
Metro	19	£10,937	£17.47
Superstore	344	£320,825	£25.83

Affluence

	Number of Stores	Total Sales	Rate of Sales
Midmarket	315	£332,269	£28.59
No Affluence Stores	142	£29,916	£8.10
Price Sensitive	130	£74,985	£17.69
Super Upmarket Stores	49	£69,258	£28.57
Unclassified	73	£40,762	£17.29
Upmarket	86	£139,666	£33.40

Region

	Number of Stores	Total Sales	Rate of Sales
Borders	11	£3,314	£19.17
Central Scotland	45	£15,670	£12.59
East Anglia	96	£198,504	£62.01
London	203	£133,127	£17.57
Midlands	89	£82,992	£23.83
North East	20	£17,504	£20.81
North Scotland	26	£14,093	£18.58
North West	85	£49,599	£16.01
Northern Ireland	29	£10,982	£10.78
South East	67	£62,361	£22.40
South West	26	£22,211	£23.84
Wales	52	£37,340	£20.55
Yorkshire	49	£39,247	£21.27

Store performance (1) in tables condition.

Extra stores

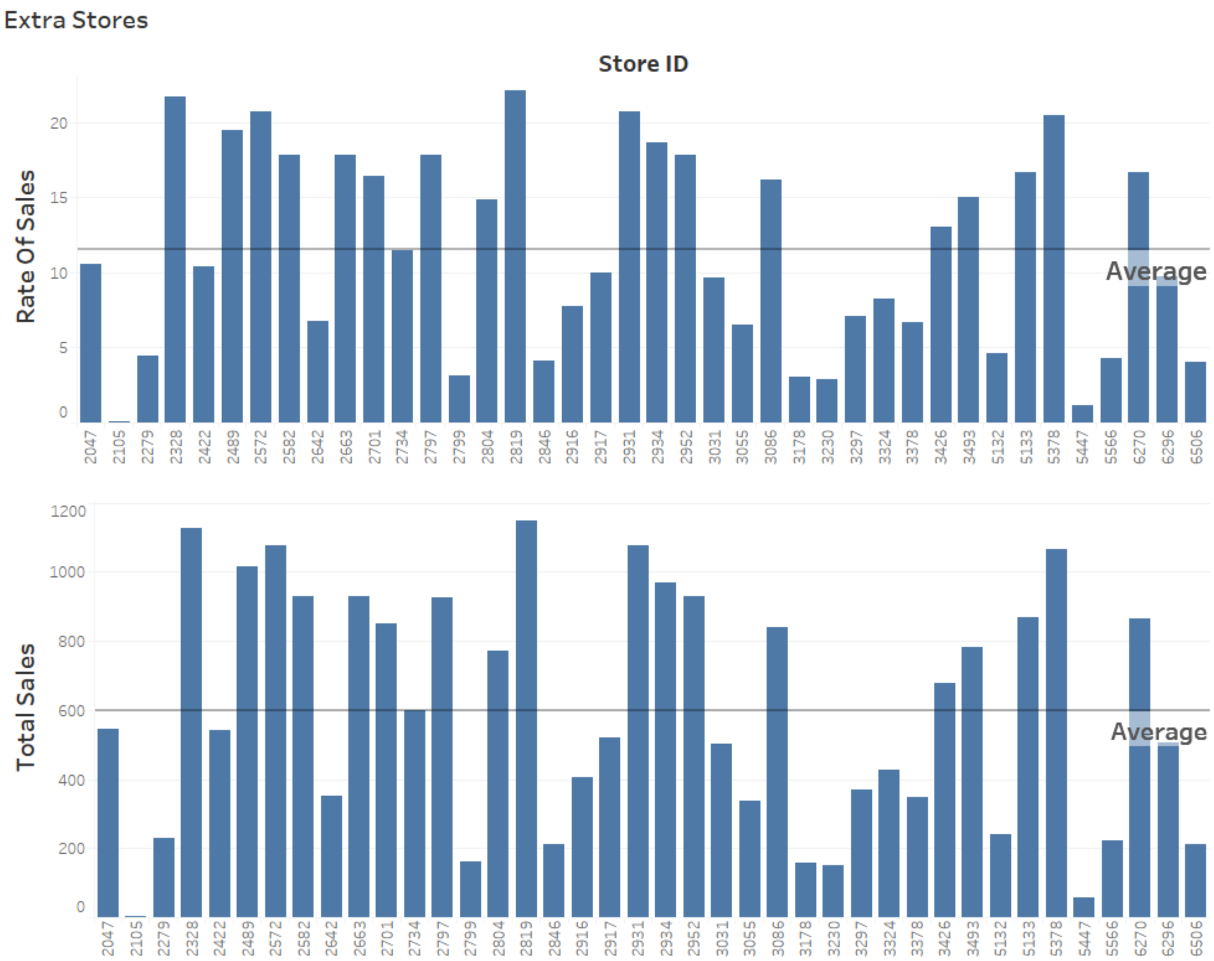
Store ID	Rate of Sales	Total Sales
2039	£23.00	£1,196
2073	£29.40	£1,529
2128	£19.87	£1,033
2136	£38.12	£1,982
2141	£19.15	£996
2164	£26.77	£1,392
2361	£7.15	£372
2371	£30.44	£1,583
2436	£56.73	£2,950
2569	£9.92	£516
2587	£4.85	£252
2638	£17.17	£893
2804	£16.42	£854
2819	£17.92	£932
2846	£23.67	£1,231
2898	£27.12	£1,410
3008	£15.63	£813
3107	£24.42	£1,270
3177	£53.75	£2,795
3290	£29.60	£1,539
3345	£16.88	£878
3377	£14.83	£771
5031	£11.81	£614
5249	£2.52	£131
5447	£6.83	£355
5528	£14.69	£764
5652	£24.52	£1,275
5745	£1.69	£88
5851	£17.65	£918
5852	£25.56	£1,329
5904	£13.83	£719
5992	£33.92	£1,764
6025	£9.50	£494
6161	£4.42	£230
6193	£10.83	£563
6419	£17.17	£893
6476	£13.46	£700
6504	£19.63	£1,021
6785	£6.08	£316
6810	£20.69	£1,076
Average	£19.44	£1,011

Stores from 5 regions

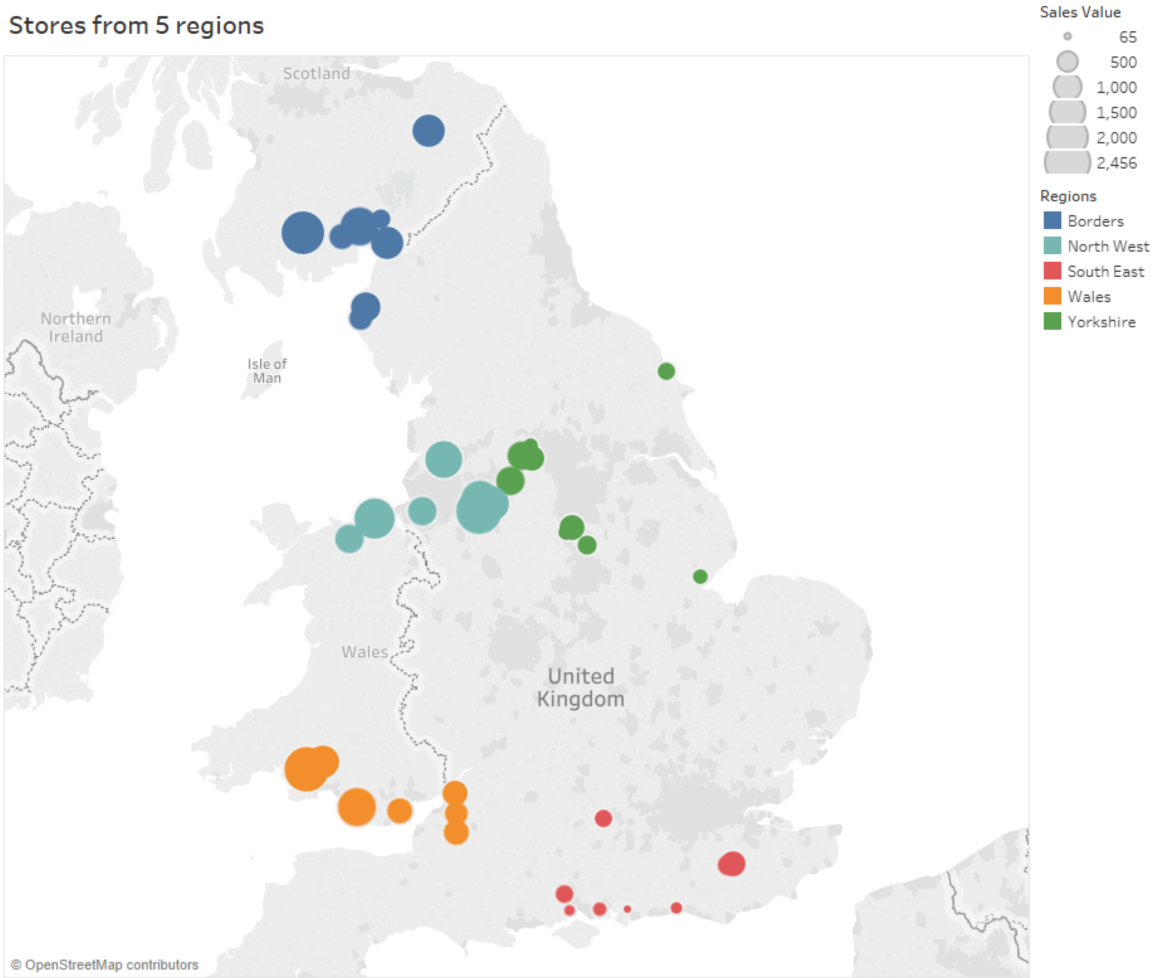
Store ID	Region	Sales
2105	Borders	£2,050
2166	Borders	£3,797
2172	Borders	£2,822
2877	Borders	£15,847
3145	Borders	£3,719
4351	Borders	£574
5275	Borders	£111
6179	Borders	£242
2265	South East	£964
2445	South East	£1,735
2718	South East	£332
2722	South East	£244
2757	South East	£116
5222	South East	£100
6077	South East	£205
6554	South East	£100
2142	North West	£1,199
2701	North West	£274
2943	North West	£330
2992	North West	£575
5148	North West	£460
6025	North West	£494
6232	North West	£22
6797	North West	£306
2676	Wales	£428
2880	Wales	£2,314
2913	Wales	£563
5249	Wales	£131
5438	Wales	£1,038
5652	Wales	£1,275
6331	Wales	£619
6475	Wales	£220
2168	Yorkshire	£274
2204	Yorkshire	£1,654
2286	Yorkshire	£1,906
2392	Yorkshire	£854
2693	Yorkshire	£507
2814	Yorkshire	£225
4362	Yorkshire	£1,884
6130	Yorkshire	£263

Store performance (2-3) in tables condition.

Store performance (1) in charts condition.



Store performance (2) in charts condition.



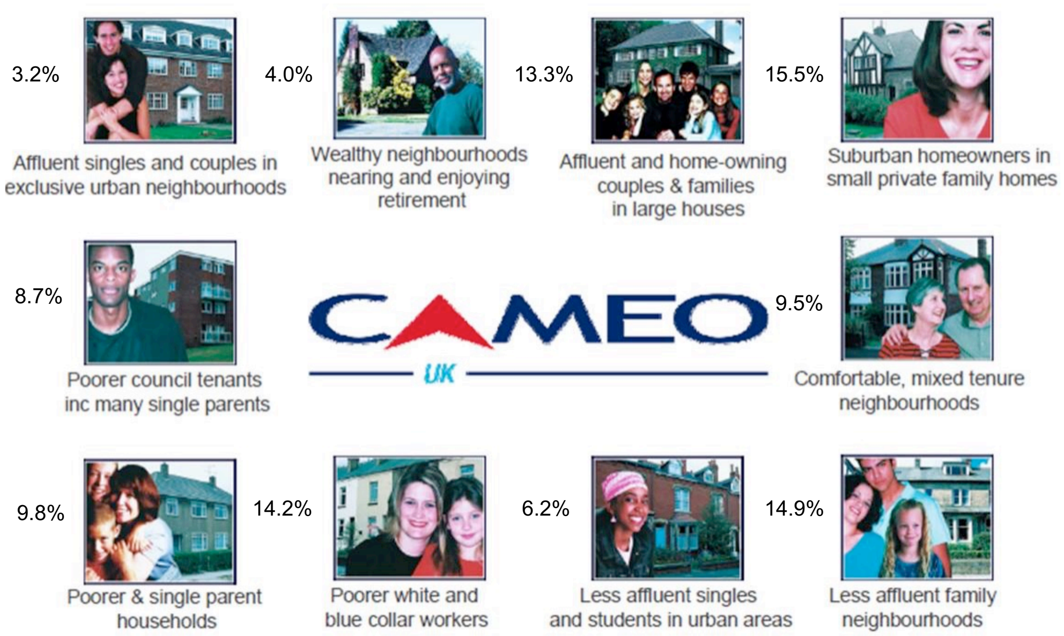
Store performance (3) in charts condition.

Appendix B

Appendix B contains explanations on four different types of shopper segmentations (according to dunnhumby and Tesco) used in the Who Buys My Food project.

Lifestage segment	% shoppers	Age & family
Young Adults	20%	Adults aged 20-39 with no children
Older Adults	17%	Adults aged 40-59 with no children
Young families	23%	Adults with all children under 10
Older families	21%	Adults with one or more child over 10
Pensioners	19%	Adults over 60 with no children

Lifestage shopper segmentation at dunnhumby and Tesco.



Cameo shopper segmentation at dunnhumby and Tesco.

Lifestyle segment	% shoppers	Description
Convenience	14%	Regard food as fuel, are busy and rely heavily on the microwave
Finer Foods	14%	Time conscious, enjoy luxury products and are willing to experiment
Kids Choice	9%	Young families influenced by the needs of children
Mainstream	31%	Have broad tastes and favour established brands
Price Sensitive	24%	Look primarily for value and rely on staple foods
Traditional	8%	Enjoy the art of cooking but rely on a fixed shopping list so less likely to buy on impulse

Lifestyle (detailed) shopper segmentation at dunnhumby and Tesco.

Family segment	% shoppers	Description
Roshni	21%	Balancing work and socialising makes for busy, interesting but occasionally challenging lives for young people without children
The Wicks	18%	Tired, stressed and stretched, lower affluent families find life a battle
The Mayers	13%	Busy, stressed and stretched, higher affluent families are trying to do it all
Carol	19%	Life is simpler for the lower affluent empty nesters
Dawn	29%	The high affluent post family have both the money and time to enjoy themselves

Five Families shopper segmentation at dunnhumby and Tesco.

Appendix C

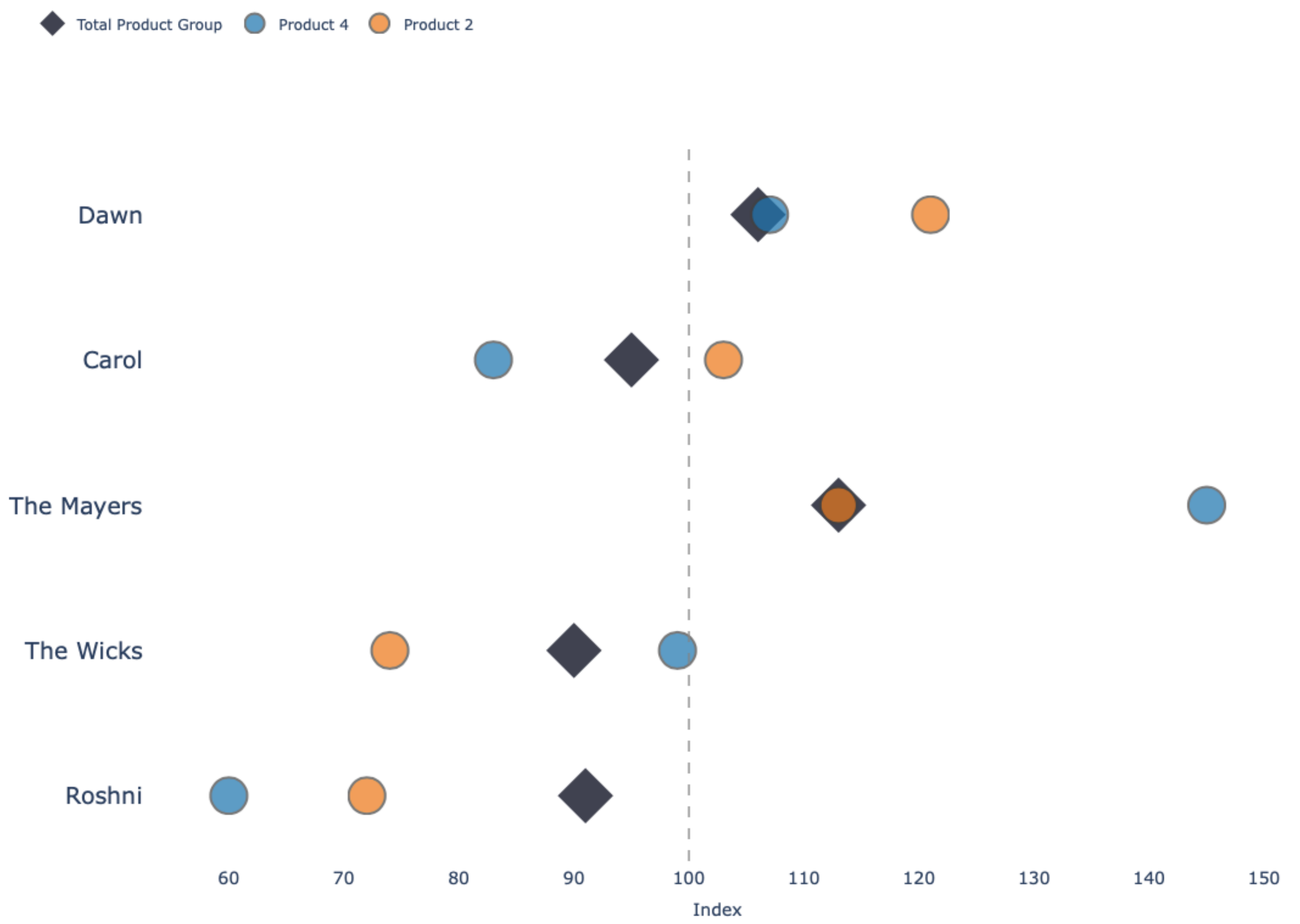
Appendix C contains survey items used in the laboratory experiment.

Measurement Items
Need for Cognition
I enjoy intellectual challenges
I am not very good at solving problems that require careful logical analysis
I am not a very analytical thinker
I prefer complex to simple problems
I don't reason well under pressure
I have no problem thinking things through carefully
Knowing the answer without having to understand the reasoning behind it is good enough for me
Faith in Intuition
I like to rely on my intuition
I often go with my instincts when deciding on a course of action
I can usually feel when something is not right or wrong even if I can't explain how I know
I suspect my hunches are inaccurate as often as they are accurate
I think it is foolish to make important decisions based purely on gut feelings
Perceived Usefulness
Using the [condition: tables / charts / charts with labels] improved my decision performance
Using the [condition] improved my productivity
Using the [condition] improved my decision effectiveness
I found the [condition] to be useful for the task.
Perceived Ease of Use
My interactions with the [condition] were clear and understandable
Interacting with the [condition] did not require a lot of mental effort
I found the [condition] to be easy to use
I found it easy to get from the [condition] what I need
Satisfaction
How do you feel about using the [condition] for the tasks you were given: Very dissatisfied/Very satisfied
How do you feel about using the [condition] for the tasks you were given: Very displeased/Very pleased
How do you feel about using the [condition] for the tasks you were given: Very frustrated/Very contended

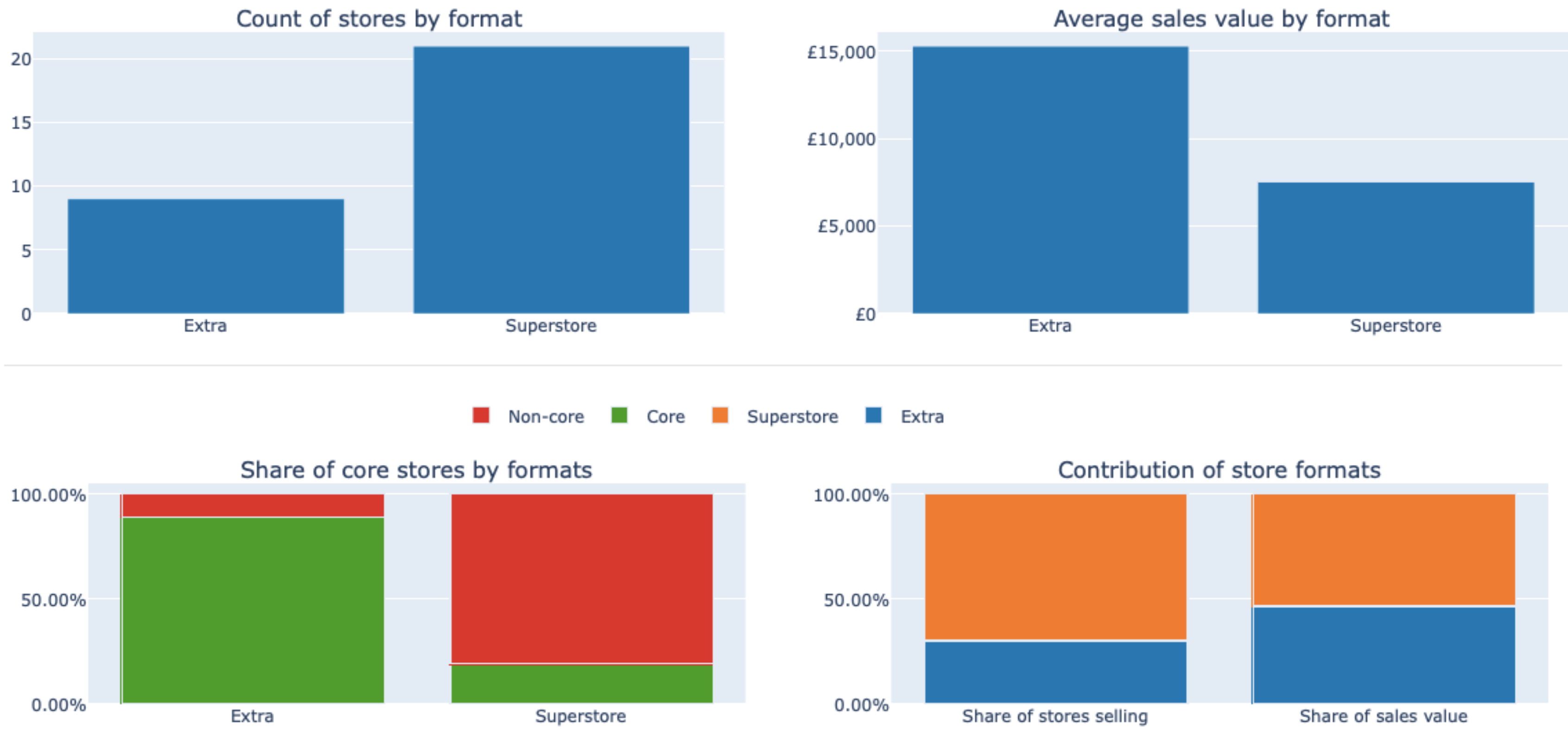
Appendix D

Appendix D contains higher quality visualisations used in Chapter 5.

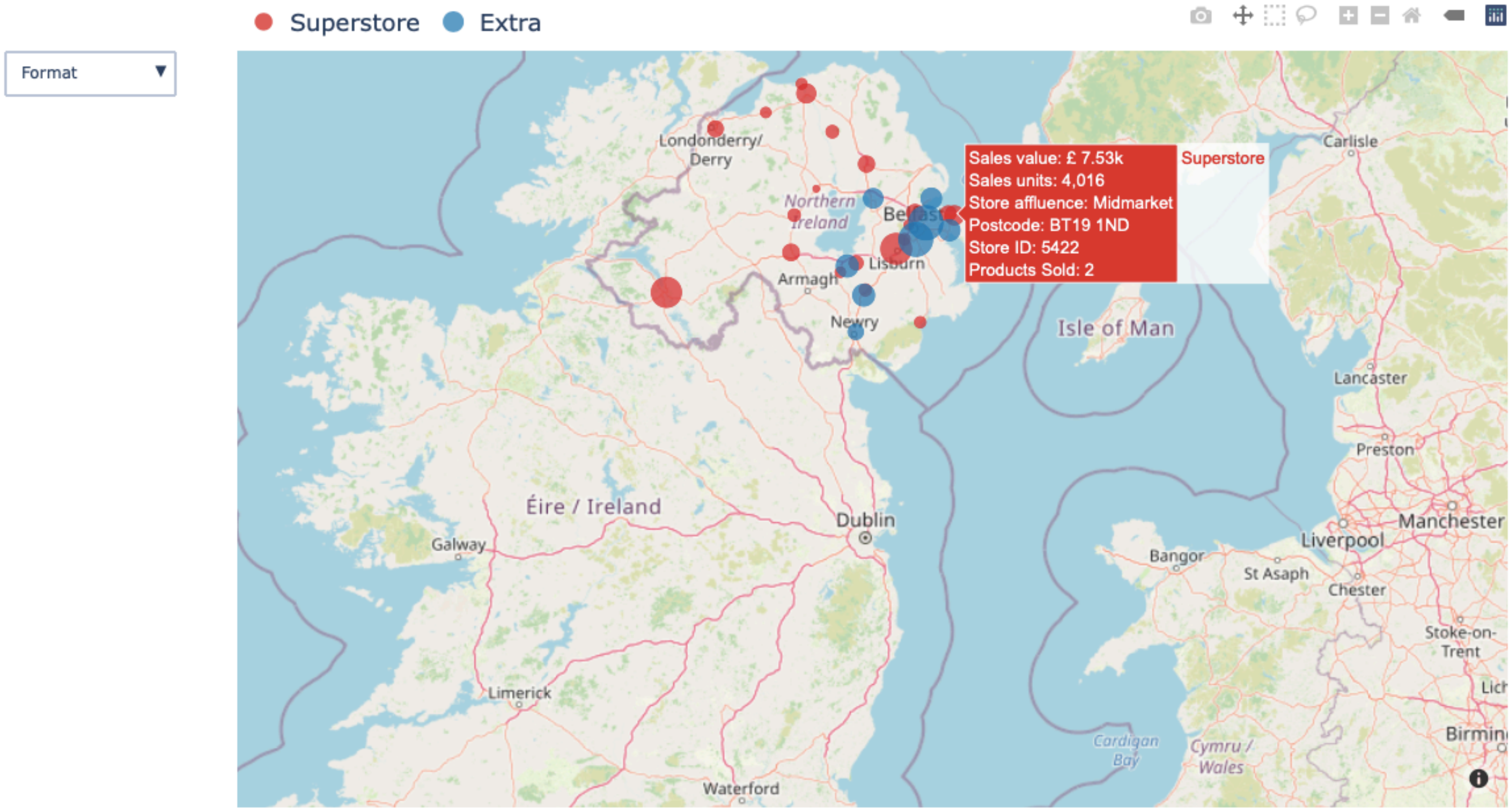
KPIs summary in the new system.



A shopper segmentation view in the new system.



Store performance summary in the new system.



Detailed store performance view in the new system.

Appendix E

Appendix E contains survey items used in the field experiment.

Measurement Items
Need for Cognition
I enjoy intellectual challenges
I am not very good at solving problems that require careful logical analysis
I am not a very analytical thinker
I prefer complex to simple problems
I don’t reason well under pressure
I have no problem thinking things through carefully
Knowing the answer without having to understand the reasoning behind it is good enough for me
Faith in Intuition
I like to rely on my intuition
I often go with my instincts when deciding on a course of action
I can usually feel when something is not right or wrong even if I can’t explain how I know
I suspect my hunches are inaccurate as often as they are accurate
I think it is foolish to make important decisions based purely on gut feelings
Perceived Usefulness
Using the WBMF web-app improved my decision performance
Using the WBMF web-app improved my productivity
Using the WBMF web-app improved my decision effectiveness
I found the WBMF web-app to be useful for the task.
Perceived Ease of Use
My interactions with the WBMF web-app were clear and understandable
Interacting with the WBMF web-app did not require a lot of mental effort
I found the WBMF web-app to be easy to use
I found it easy to get from the WBMF web-app what I need
Satisfaction
How do you feel about using the WBMF web-app for the tasks you were given: Very dissatisfied/Very satisfied
How do you feel about using the WBMF web-app for the tasks you were given: Very displeased/Very pleased
How do you feel about using the WBMF web-app for the tasks you were given: Very frustrated/Very contended
Subjective Norm
People who influence my behaviour at work think that I should use the WBMF web-app
People who influence my behaviour at work would welcome my continued use of the WBMF web-app in my work
People who are important to me at work think that I should use the WBMF web-app
People who are important to me at work would welcome my continued use of the WBMF web-app in my work
Behavioural Intention
I intend to continue using the WBMF web-app rather than discontinue its use
I plan to continue using the WBMF web-app in my job
My intentions are to continue using the WBMF web-app rather than manually processing our Tesco data
I intend to continue using the WBMF web-app rather than manually processing our Tesco data
System preferences
Which system do you prefer for KPIs screen?
Which system do you prefer for segmentation?
Which system do you prefer for store performance?
Overall, which system do you prefer?

Reported system use
In the last 3 months (90 days), approximately how many times have you used the WBMF web-app?
On overage, how many minutes would you say you spend on the WBMF web-app each time you use it?
Overall, how do you rate the intensity of your use of the WBMF web-app?

Market Information Experience
How many years of experience do you have in the use of market information?

Market Orientation
Our business objectives are driven by customer satisfaction
We monitor and evaluate the attitude of staff towards delivering customer satisfaction
We measure customer satisfaction frequently
We are aware of customer needs and wants
We respond rapidly to competitive actions
Our business pays close attention to industry and market trends
We target opportunities for competitive advantage
All of our business functions are integrated in serving the needs of our customers
Market information is shared with all of the functions of the business
There is a culture of mutual cooperation between the different functions in our business

COVID-19 impact
During the COVID-19 pandemic our total sales: decreased a lot / increased a lot
During the COVID-19 pandemic our Tesco sales: decreased a lot / increased a lot
During the COVID-19 pandemic it has been impossible to effectively plan for the long-term
During the COVID-19 pandemic we have made changes to our business model
Have you been furloughed? If yes, for how many weeks have you been furloughed since March 2020?
During the COVID-19 pandemic my use of the WBMF web-app: decreased a lot / increased a lot

Family ownership
Is the company a family-owned business?

Firm age
For how many years has the company been trading?

Number of employees
What is the total number of employees in your company?

Total turnover
What was your total turnover in 2019?

Glossary

WBMF – Who Buys My Food, a collaborative action research project.

BCW – Behavioural Change Wheel.

COM-B – Capability-Opportunity-Motivation-Behaviour, a model of behaviour.

DS – Design Science.

DSRM – Design Science Research Methodology.

KPI – Key Performance Indicator.

ICT – Information and Communication Technology.

IS – Information System.

IT – Information Technology.

SME – Small and Medium Sized Enterprise.

List of References

1. Abbasi, A., Sarker, S. and Chiang, R. (2016) ‘Big Data Research in Information Systems: Toward an Inclusive Research Agenda’, *Journal of the Association for Information Systems*, 17(2), pp. i–xxxii.
2. Abebe, M. (2014) ‘Electronic commerce adoption, entrepreneurial orientation and small- and medium-sized enterprise (SME) performance’, *Journal of Small Business and Enterprise Development*, 21(1), pp. 100–116.
3. Adamou, B. (2018) *Games and Gamification in Market Research: Increasing Consumer Engagement in Research for Business Success*. KoganPages.
4. Ågerfalk, P. J. (2020) ‘Artificial intelligence as digital agency’, *European Journal of Information Systems*, 29(1), pp. 1–8.
5. Aggarwal, R., Kryscynski, D., Midha, V. and Singh, H. (2015) ‘Early to Adopt and Early to Discontinue: The Impact of Self-Perceived and Actual IT Knowledge on Technology Use Behaviors of End Users’, *Information Systems Research*, 26(1), pp. 127–144.
6. Ajzen, I. (1985) ‘From Intentions to Actions: A Theory of Planned Behavior’, in *Action Control*. Berlin: Springer (SSSP Springer Series in Social Psychology).
7. Ajzen, I. (1991) ‘The Theory of Planned Behavior’, *Organizational Behavior and Human Decision Processes*, 50, pp. 179–211.
8. Allinson, C. and Hayes, J. (1996) ‘The Cognitive Style Index: A Measure of Intuition-Analysis For Organizational Research’, *Journal of Management Studies*, 33(1), pp. 119–135.
9. Allinson, C. and Hayes, J. (2011) ‘The Cognitive Style Index: Technical Manual and User Guide’.
10. Alpkan, L., Yilmaz, C. and Kaya, N. (2007) ‘Market Orientation and Planning Flexibility in SMEs: Performance Implications and an Empirical Investigation’, *International Small Business Journal*, 25(2), pp. 152–172.
11. Alshaikh, M., Naseer, H., Ahmad, A. and Maynard, S. B. (2019) ‘Toward Sustainable Behaviour Change: An Approach for Cyber Security Education Training and Awareness’, in *ECIS 2019 Proceedings*, pp. 1–14.
12. Ambalov, I. A. (2018) ‘A meta-analysis of IT continuance: An evaluation of the expectation-confirmation model’, *Telematics and Informatics*, 35(6), pp. 1561–1571.

13. Armstrong, S. J., Cools, E. and Sadler-Smith, E. (2012) 'Role of Cognitive Styles in Business and Management: Reviewing 40 Years of Research: Role of Cognitive Styles in Business and Management', *International Journal of Management Reviews*, 14(3), pp. 238–262.
14. Arnott, D., Lizama, F. and Song, Y. (2017) 'Patterns of business intelligence systems use in organizations', *Decision Support Systems*, 97, pp. 58–68.
15. Aronoff, C. (2004) 'Self-Perpetuation Family Organization Built on Values: Necessary Condition for Long-Term Family Business Survival', *Family Business Review*, 17(1), pp. 55–59.
16. Arrow, K. J. (1994) 'Methodological Individualism and Social Knowledge', *The American Economic Review*, 84(2), pp. 1–9.
17. Ates, A., Garengo, P., Cocca, P. and Bititci, U. (2013) 'The development of SME managerial practice for effective performance management', *Journal of Small Business and Enterprise Development*, 20(1), pp. 28–54.
18. Atkins, L. and Michie, S. (2015) 'Designing interventions to change eating behaviours', in *Proceedings of the Nutrition Society*, pp. 164–170.
19. Bačić, D. and Fadlalla, A. (2016) 'Business information visualization intellectual contributions: An integrative framework of visualization capabilities and dimensions of visual intelligence', *Decision Support Systems*, 89, pp. 77–86.
20. Bagayogo, F., Lapointe, L. and Bassellier, G. (2014) 'Enhanced Use of IT: A New Perspective on Post-Adoption', *Journal of the Association for Information Systems*, 15(7), p. 361-387.
21. Bagozzi, R. (2007) 'The Legacy of the Technology Acceptance Model and a Proposal for a Paradigm Shift.', *Journal of the Association for Information Systems*, 8(4), pp. 244–254.
22. Baird, A., Davidson, E. and Mathiassen, L. (2017) 'Reflective Technology Assimilation: Facilitating Electronic Health Record Assimilation in Small Physician Practices', *Journal of Management Information Systems*, 34(3), pp. 664–694.
23. Baker, J., Jones, D. R. and Burkman, J. (2009) 'Using Visual Representations of Data to Enhance Sensemaking in Data Exploration Tasks', *Journal of the Association for Information Systems*, 10(7), pp. 533–559.
24. Barba-Sánchez, V., Jimenez-Zarco, A. I. and Martinez-Ruiz, M. P. (2007) 'Drivers, Benefits and Challenges of ICT Adoption by Small and Medium Sized Enterprises

(SMEs): A Literature Review', *Problems and Perspectives in Management*, 5(1), pp. 103–114.

25. Barclays (2018) *Scale, Disruption and Brexit: A new dawn for the UK food supply chains?* Barclays.
26. Barker, F., Atkins, L. and de Lusignan, S. (2016) 'Applying the COM-B behaviour model and behaviour change wheel to develop an intervention to improve hearing-aid use in adult auditory rehabilitation', *International Journal of Audiology*, 55(sup3), pp. S90–S98.
27. Barki, H., Titah, R. and Boffo, C. (2007) 'Information System Use–Related Activity: An Expanded Behavioral Conceptualization of Individual-Level Information System Use', *Information Systems Research*, 18(2), pp. 173–192.
28. Barnes, D., Clear, F., Dyerson, R., Harindranath, G., Harris, L. and Rae, A. (2012) 'Web 2.0 and micro-businesses: an exploratory investigation', *Journal of Small Business and Enterprise Development*, 19(4), pp. 687–711.
29. Bastian, B. and Haslam, N. (2010) 'Excluded from humanity: The dehumanizing effects of social ostracism', *Journal of Experimental Social Psychology*, 46, pp. 107–113.
30. Bayfield, J. (2018) *The UK grocery market: ripe for disruption*. Aviva.
31. BEIS Committee (2018) *Small businesses and productivity*. 15. House of Commons, Business, Energy and Industrial Strategy Committee.
32. Benbasat, I. and Barki, H. (2007) 'Quo vadis, TAM?', *Journal of the Association for Information Systems*, 8(4), pp. 211–218.
33. Benbasat, I. and Dexter, A. S. (1986) 'An Investigation of the Effectiveness of Color and Graphical Information Presentation under Varying Time Constraints', *MIS Quarterly*, 10(1), pp. 59–83.
34. Benton, T. (2014) *Philosophical Foundations of the Three Sociologies*. Routledge.
35. Betsch, C. and Kunz, J. J. (2008) 'Individual strategy preferences and decisional fit', *Journal of Behavioral Decision Making*, 21(5), pp. 532–555.
36. Bhattacherjee, A. (2001) 'Understanding Information Systems Continuance: An Expectation-Confirmation Model', *MIS Quarterly*, 25(3), pp. 351–370.
37. Bhattacherjee, A. and Lin, C.-P. (2015) 'A unified model of IT continuance: three complementary perspectives and crossover effects', *European Journal of Information Systems*, 24(4), pp. 364–373.

38. Bhattacherjee, A. and Premkumar, G. (2004) ‘Understanding Changes in Belief and Attitude toward Information Technology Usage: A Theoretical Model and Longitudinal Test’, *MIS Quarterly*, 28(2), pp. 229–254.
39. Blankson, C., Motwani, J. G. and Levenburg, N. M. (2006) ‘Understanding the patterns of market orientation among small businesses’, *Marketing Intelligence & Planning*, 24(6), pp. 572–590.
40. Blankson, C. and Omar, O. E. (2002) ‘Marketing practices of African and Caribbean small businesses in London, UK’, *Qualitative Market Research: An International Journal*, 5(2), pp. 123–134.
41. Block, J. H. (2012) ‘R&D investments in family and founder firms: An agency perspective’, *Journal of Business Venturing*, 27(2), pp. 248–265.
42. Blohm, I. and Leimeister, J. M. (2013) ‘Gamification: Design of IT-Based Enhancing Services for Motivational Support and Behavioral Change’, *Business & Information Systems Engineering*, 5(4), pp. 275–278.
43. BMG Research and Durham University (2015) *Digital Capabilities in SMEs: Evidence Review and Re-survey of 2014 Small Business Survey respondents*.
44. Bocconcelli, R., Cioppi, M., Fortezza, F., Francioni, B., Pagano, A., Savelli, E. and Splendiani, S. (2018) ‘SMEs and Marketing: A Systematic Literature Review: SMEs and Marketing’, *International Journal of Management Reviews*, 20(2), pp. 227–254.
45. Borgatti, S. P. and Foster, P. C. (2003) ‘The Network Paradigm in Organizational Research: A Review and Typology’, *Journal of Management*, 29(6), pp. 991–1013.
46. BRC (2021) *Briefly Opened Stores Boost Christmas Sales*.
47. Brinberg, M., Ram, N., Yang, X., Cho, M.-J., Sundar, S. S., Robinson, T. N. and Reeves, B. (2021) ‘The idiosyncrasies of everyday digital lives: Using the Human Screenome Project to study user behavior on smartphones’, *Computers in Human Behavior*, 114, p. 106570.
48. Bruque, S. and Moyano, J. (2007) ‘Organisational determinants of information technology adoption and implementation in SMEs: The case of family and cooperative firms’, *Technovation*, 27(5), pp. 241–253.
49. Burton-Jones, A. and Grange, C. (2013) ‘From Use to Effective Use: A Representation Theory Perspective’, *Information Systems Research*, 24(3), pp. 632–658.

50. Burton-Jones, A. and Straub, D. W. (2006) 'Reconceptualizing System Usage: An Approach and Empirical Test', *Information Systems Research*, 17(3), pp. 228–246.
51. Burton-Jones, A. and Volkoff, O. (2017) 'How Can We Develop Contextualized Theories of Effective Use? A Demonstration in the Context of Community-Care Electronic Health Records', *Information Systems Research*, 28(3), pp. 468–489.
52. Cam, A., Chui, M. and Hall, B. (2019) *Global AI Survey: AI proves its worth, but few scale impact*. McKinsey & Company.
53. Campbell, D. J. (1988) 'Task Complexity: A Review and Analysis', *The Academy of Management Review*, 13(1), pp. 40–52.
54. Cardinaels, E. (2008) 'The interplay between cost accounting knowledge and presentation formats in cost-based decision-making', *Accounting, Organizations and Society*, 33(6), pp. 582–602.
55. Carrasco-Hernández, A. and Jiménez-Jiménez, D. (2013) 'Can Family Firms Innovate? Sharing Internal Knowledge From a Social Capital Perspective', *Electronic Journal of Knowledge Management*, 11(1), pp. 30–37.
56. Carter, J. (2001) *Developing e-Commerce Systems*. Englewood Cliffs, NJ: Prentice Hall.
57. Cearley, D., Burke, B., Smith, D., Jones, N., Chandrasekaran, A., Lu, C. and Karamouzis, F. (2020) *Top 10 Strategic Technology Trends for 2020: A Gartner Trend Insight Report*. Gartner.
58. Cecez-Kecmanovic, D., Galliers, R. D., Henfridsson, O., Newell, S. and Vidgen, R. (2014) 'The sociomateriality of information systems: current status, future directions', *MIS Quarterly*, 38(3), pp. 809–830.
59. Chaffey, D. (2009) *E-business and E-commerce Management Strategy, Implementation and Practice*. 4th edn. Harlow: Pearson Education.
60. Chakraborty, I., Hu, P. J.-H. and Cui, D. (2008) 'Examining the effects of cognitive style in individuals' technology use decision making', *Decision Support Systems*, 45(2), pp. 228–241.
61. Chen, H., Chiang, R. H. L. and Storey, V. C. (2012) 'Business Intelligence and Analytics: From Big Data to Big Impact', *MIS Quarterly*, 36(4), pp. 1165–1188.
62. Chirico, F. and Nordqvist, M. (2010) 'Dynamic capabilities and transgenerational value creation in family firms: The role of organizational culture', *International Small Business Journal*, 28(5), pp. 487–504.

63. Clements, J. A. and Boyle, R. (2018) ‘Compulsive technology use: Compulsive use of mobile applications’, *Computers in Human Behavior*, 87, pp. 34–48.
64. Covin, J. G. and Wales, W. J. (2012) ‘The Measurement of Entrepreneurial Orientation’, *Entrepreneurship Theory and Practice*, 36(4), pp. 677–702.
65. Croson, R. (2005) ‘The Method of Experimental Economics’, *International Negotiation*, 10(1), pp. 131–148.
66. CRR (2021) *The Crisis in Retailing - Check Latest Closures & Job Losses*.
67. Davenport, T. H. (2018) ‘From analytics to artificial intelligence’, *Journal of Business Analytics*, 1(2), pp. 73–80.
68. Davis, F. D. (1989) ‘Perceived usefulness, perceived ease of use, and user acceptance of information technology’, *MIS Quarterly*, 13(3), pp. 319–340.
69. Davis, F. D., Bagozzi, R. P. and Warshaw, P. R. (1989) ‘User Acceptance of Computer Technology: A Comparison of Two Theoretical Models’, *Management Science*, 35(8), pp. 982–1003.
70. Davis, R., Campbell, R., Hildon, Z., Hobbs, L. and Michie, S. (2015) ‘Theories of behaviour and behaviour change across the social and behavioural sciences: a scoping review’, *Health Psychology Review*, 9(3), pp. 323–344.
71. De Massis, A., Frattini, F. and Lichtenthaler, U. (2012) ‘Research on Technological Innovation in Family Firms: Present Debates and Future Directions’, *Family Business Review*, 26(1), pp. 10–31.
72. Dekimpe, M. G. (2020) ‘Retailing and retailing research in the age of big data analytics’, *International Journal of Research in Marketing*, 37(1), pp. 3–14.
73. Delen, D. and Zolbanin, H. M. (2018) ‘The analytics paradigm in business research’, *Journal of Business Research*, 90, pp. 186–195.
74. Delone, W. H. and McLean, E. R. (2003) ‘The DeLone and McLean Model of Information Systems Success: A Ten-Year Update’, *Journal of Management Information Systems*, 19(4), pp. 9–30.
75. Department for Business, Energy & Industrial Strategy (2019) *Business Population Estimates for the UK and Regions 2019*.
76. Deregowski, J. (1968) ‘Pictorial recognition in subjects from a relatively pictureless environment’, *African Social Research*, 5, pp. 356–364.
77. Deterding, S., Dixon, D., Khaled, R. and Nacke, L. (2011) ‘From Game Design Elements to Gamefulness: Defining “Gamification”’, in. *MindTrek*, Tampere,

Finland, pp. 1–7.

78. Devaraj, S., Easley, R. F. and Crant, J. M. (2008) ‘Research Note —How Does Personality Matter? Relating the Five-Factor Model to Technology Acceptance and Use’, *Information Systems Research*, 19(1), pp. 93–105.
79. Devaraj, S. and Kohli, R. (2003) ‘Performance Impacts of Information Technology: Is Actual Usage the Missing Link?’, *Management Science*, 49(3), pp. 273–289.
80. Díaz, A., Rowshankish, K. and Saleh, T. (2018) *Why data culture matters*. McKinsey Quarterly.
81. Díaz-Chao, Á., Sainz-González, J. and Torrent-Sellens, J. (2015) ‘ICT, innovation, and firm productivity: New evidence from small local firms’, *Journal of Business Research*, 68(7), pp. 1439–1444.
82. Dickson, G. W., Senn, J. A. and Chervany, N. L. (1977) ‘Research in Management Information Systems: The Minnesota Experiments’, *Management Science*, 23(9), pp. 913–923.
83. Didonet, S. R., Fearne, A. and Simmons, G. (2020) ‘Determining the presence of a long-term/short-term dilemma for SMEs when adopting strategic orientation to improve performance’, *International Small Business Journal: Researching Entrepreneurship*, 38(2), pp. 90–110.
84. Didonet, S. R., Simmons, G., Díaz-Villavicencio, G. and Palmer, M. (2016) ‘Market Orientation’s Boundary-Spanning Role to Support Innovation in SMEs’, *Journal of Small Business Management*, 54(1), pp. 216–233.
85. Dilla, W., Janvrin, D. J. and Raschke, R. (2010) ‘Interactive Data Visualization: New Directions for Accounting Information Systems Research’, *Journal of Information Systems*, 24(2), pp. 1–37.
86. Dominici, A., Boncinelli, F. and Marone, E. (2019) ‘Lifestyle entrepreneurs in winemaking: An exploratory qualitative analysis on the non-pecuniary benefits’, *International Journal of Wine Business Research*, 31(3), pp. 385–405.
87. Donnelly, C., Simmons, G., Armstrong, G. and Fearne, A. (2012) ‘Marketing planning and digital customer loyalty data in small business’, *Marketing Intelligence & Planning*, 30(5), pp. 515–534.
88. Donnelly, C., Simmons, G., Armstrong, G. and Fearne, A. (2015) ‘Digital loyalty card “big data” and small business marketing: Formal versus informal or complementary?’, *International Small Business Journal*, 33(4), pp. 422–442.

89. Duffy, R., Fearne, A., Hornibrook, S., Hutchinson, K. and Reid, A. (2013) ‘Engaging suppliers in CRM: The role of justice in buyer–supplier relationships’, *International Journal of Information Management*, 33(1), pp. 20–27.
90. van Duin, S. and Bakhshi, N. (2018) *Artificial Intelligence*. Deloitte.
91. Dunn, B. (1996) ‘Family Enterprises in the UK: A Specia Sector?’, *Family Business Review*, 9(2), pp. 139–155.
92. Durkin, M., McGowan, P. and McKeown, N. (2013) ‘Exploring social media adoption in small to medium-sized enterprises in Ireland’, *Journal of Small Business and Enterprise Development*, 20(4), pp. 716–734.
93. Eddleston, K. A., Kellermanns, F. W. and Sarathy, R. (2008) ‘Resource Configuration in Family Firms: Linking Resources, Strategic Planning and Technological Opportunities to Performance’, *Journal of Management Studies*, 45(1), pp. 26–50.
94. Eddleston, K. A., Otondo, R. F. and Kellermanns, F. W. (2008) ‘Conflict, Participative Decision-Making, and Generational Ownership Dispersion: A Multilevel Analysis’, *Journal of Small Business Management*, 46(3), pp. 456–484.
95. Edge (2020) *Future Retail Disruption Report*. Edge by Ascential.
96. Eggers, F., Hatak, I., Kraus, S. and Niemand, T. (2017) ‘Technologies That Support Marketing and Market Development in SMEs—Evidence from Social Networks’, *Journal of Small Business Management*, 55(2), pp. 270–302.
97. Engin, A. and Vetschera, R. (2017) ‘Information representation in decision making: The impact of cognitive style and depletion effects’, *Decision Support Systems*, 103, pp. 94–103.
98. Epstein, S. (2003) ‘Cognitive-Experiential Self-Theory of Personality’, in *Handbook of Pyschology: Volume 5 Personality and Social Psychology*. John Wiley & Sons, Inc.
99. Epstein, S., Pacini, R., Denes-Raj, V. and Heier, H. (1996) ‘Individual Differences in Intuitive-Experiential and analytical-Rational Thinking Styles’, *Journal of Personality and Social Psychology*, 71(2), pp. 390–405.
100. Erevelles, S., Fukawa, N. and Swayne, L. (2016) ‘Big Data consumer analytics and the transformation of marketing’, *Journal of Business Research*, 69(2), pp. 897–904.
101. Eurostat (2020) *Small and Medium-Sized Enterprises (SMEs)*.

102. Evans, J. St. B. T. and Stanovich, K. E. (2013) ‘Dual-Process Theories of Higher Cognition: Advancing the Debate’, *Perspectives on Psychological Science*, 8(3), pp. 223–241.
103. Few, S. (2007) ‘Save the Pies for Dessert’, *Visual Business Intelligence Newsletter*.
104. Fishbein, M. (1979) ‘A theory of reasoned action: Some applications and implications’, in. *Nebraska Symposium on Motivation*, pp. 65–116.
105. Fisher, M. and Raman, A. (2018) ‘Using Data and Big Data in Retailing’, *Production and Operations Management*, 27(9), pp. 1665–1669.
106. Frias-Martinez, E., Chen, S. Y. and Liu, X. (2009) ‘Evaluation of a personalized digital library based on cognitive styles: Adaptivity vs. adaptability’, *International Journal of Information Management*, 29(1), pp. 48–56.
107. FSA (2020) *The COVID-19 consumer research*. Food Standards Agency.
108. FSB (2017) *Digital skills gap in small firms holding back productivity*.
109. Fuller, P. B. (1994) ‘Assessing Marketing in Small and Medium-sized Enterprises’, *European Journal of Marketing*, 28(12), pp. 34–49.
110. Gallagher, J., Ashley, P. and Needleman, I. (2020) ‘Implementation of a behavioural change intervention to enhance oral health behaviours in elite athletes: a feasibility study’, *BMJ Open Sport & Exercise Medicine*, 6(1), pp. 1–6.
111. Genovese, J. E. C. (2005) ‘Paranormal beliefs, schizotypy, and thinking styles among teachers and future teachers’, *Personality and Individual Differences*, 39(1), pp. 93–102.
112. Genpact (2020) *Consumer Packaged Goods and Retail in the Age of Instinct*. Genpact.
113. Gettinger, J., Kiesling, E., Stummer, C. and Vetschera, R. (2013) ‘A comparison of representations for discrete multi-criteria decision problems’, *Decision Support Systems*, 54(2), pp. 976–985.
114. Gettinger, J., Koeszegi, S. T. and Schoop, M. (2012) ‘Shall we dance? — The effect of information presentations on negotiation processes and outcomes’, *Decision Support Systems*, 53(1), pp. 161–174.
115. Ghobakhloo, M., Hong, T. S., Sabouri, M. S. and Zulkifli, N. (2012) ‘Strategies for Successful Information Technology Adoption in Small and Medium-sized Enterprises’, *Information*, 3(1), pp. 36–67.

116. Ghobakhloo, M. and Hong Tang, S. (2013) 'The role of owner/manager in adoption of electronic commerce in small businesses: The case of developing countries', *Journal of Small Business and Enterprise Development*, 20(4), pp. 754–787.

117. Ghobakhloo, M., Sabouri, M. S., Hong, T. S. and Zulkifli, N. (2011) 'Information Technology Adoption in Small and Medium-sized Enterprises; An Appraisal of Two Decades Literature', *Interdisciplinary Journal of Research in Business*, 1(7), pp. 53–80.

118. Giannoccaro, I. (ed.) (2013) *Behavioral issues in operations management: new trends in design, management, and methodologies*. London: Springer.

119. Gibson, J. J. (1979) *The Ecological Approach to Visual Perception*. New York: Psychology Press.

120. Gilmore, A., Carson, D. and Grant, K. (2001) 'SME marketing in practice', *Marketing Intelligence & Planning*, 19(1), pp. 6–11.

121. Gilovich, T., Griffin, D. W. and Kahneman, D. (eds) (2002) *Heuristics and biases: the psychology of intuitive judgment*. Cambridge, U.K. ; New York: Cambridge University Press.

122. Gomes, C. *et al.* (2019) 'Computational sustainability: computing for a better world and a sustainable future', *Communications of the ACM*, 62(9), pp. 56–65.

123. Goodhue, D. L. and Thompson, R. L. (1995) 'Task-Technology Fit and Individual Performance', *MIS Quarterly*, 19(2), pp. 213–236.

124. Gopinath, G. (2020) 'The Great Lockdown: Worst Economic Downturn Since the Great Depression – IMF Blog', *IMFBlog*.

125. Goutas, L., Hess, B. and Sutanto, J. (2020) 'If erring is human, is system use divine? Omission errors during post-adoptive system use', *Decision Support Systems*, 130, p. 113225.

126. Greenberg, J. and Tomlinson, E. C. (2004) 'Situated Experiments in Organizations: Transplanting the Lab to the Field', *Journal of Management*, 30(5), pp. 703–724.

127. Grewal, D., Roggeveen, A. L. and Nordfält, J. (2017) 'The Future of Retailing', *Journal of Retailing*, 93(1), pp. 1–6.

128. Grover, V., Chiang, R. H. L., Liang, T.-P. and Zhang, D. (2018) 'Creating Strategic Business Value from Big Data Analytics: A Research Framework', *Journal of Management Information Systems*, 35(2), pp. 388–423.

129. Groves, K., Vance, C. and Choi, D. (2011) ‘Examining Entrepreneurial Cognition: An Occupational Analysis of Balanced Linear and Nonlinear Thinking and Entrepreneurship Success’, *Journal of Small Business Management*, 49(3), pp. 438–466.

130. de Guinea, A. O. and Markus, M. L. (2009) ‘Why Break the Habit of a Lifetime? Rethinking the Roles of Intention, Habit, and Emotion in Continuing Information Technology Use’, *MIS Quarterly*, 33(3), pp. 433–444.

131. Gulliksen, J., Göransson, B., Boivie, I., Blomkvist, S., Persson, J. and Cajander, Å. (2003) ‘Key principles for user-centred systems design’, *Behaviour & Information Technology*, 22(6), pp. 397–409.

132. Gunnell, J. J. and Ceci, S. J. (2010) ‘When emotionality trumps reason: A study of individual processing style and juror bias’, *Behavioral Sciences & the Law*, 28(6), pp. 850–877.

133. Hakala, H. (2011) ‘Strategic Orientations in Management Literature: Three Approaches to Understanding the Interaction between Market, Technology, Entrepreneurial and Learning Orientations: Orientations in Management Literature’, *International Journal of Management Reviews*, 13(2), pp. 199–217.

134. Halilovic, S. and Cicic, M. (2013) ‘Understanding determinants of information systems users’ behaviour: a comparison of two models in the context of integrated accounting and budgeting software’, *Behaviour & Information Technology*, 32(12), pp. 1280–1291.

135. Harrison, G. W. and List, J. A. (2004) ‘Field Experiments’, *Journal of Economic Literature*, 42(4), pp. 1009–1055.

136. Hassan, N. R. (2019) ‘The origins of business analytics and implications for the information systems field’, *Journal of Business Analytics*, 2(2), pp. 118–133.

137. Hatak, I., Kautonen, T., Fink, M. and Kansikas, J. (2016) ‘Innovativeness and family-firm performance: The moderating effect of family commitment’, *Technological Forecasting and Social Change*, 102, pp. 120–131.

138. Hatak, I. R. and Roessl, D. (2015) ‘Relational Competence-Based Knowledge Transfer Within Intrafamily Succession: An Experimental Study’, *Family Business Review*, 28(1), pp. 10–25.

139. Henke, N., Bughin, J., Chui, M., Manyika, J., Saleh, T., Wiseman, B. and Sethupathy, G. (2016) *The age of analytics: Competing in a data-driven world*. McKinsey Global

Institute.

140. Hernández-Linares, R., Kellermanns, F. W. and López-Fernández, M. C. (2018) ‘A note on the relationships between learning, market, and entrepreneurial orientations in family and nonfamily firms’, *Journal of Family Business Strategy*, 9(3), pp. 192–204.

141. Hevner, A., March, S. and Park, J. (2004) ‘Design science in information systems research’, *MIS Quarterly*, 28(1), pp. 75–105.

142. Hingley, M. (2005) ‘Power to all our friends? Living with imbalance in supplier–retailer relationships’, *Industrial Marketing Management*, 34, pp. 848–858.

143. Hingley, M., Lindgreen, A. and Casswell, B. (2006) ‘Supplier-Retailer Relationships in the UK Fresh Produce Supply Chain’, *Journal of International Food & Agribusiness Marketing*, 18(1–2), pp. 49–86.

144. Hochberg, J. and Brooks, V. (1962) ‘Pictorial Recognition as an Unlearned Ability: A Study of One Child’s Performance’, *The American Journal of Psychology*, 75(4), pp. 624–628.

145. Hodgkinson, G. P., Sadler-Smith, E., Sinclair, M. and Ashkanasy, N. M. (2009) ‘More than meets the eye? Intuition and analysis revisited’, *Personality and Individual Differences*, 47(4), pp. 342–346.

146. Hoffman, D. D., Singh, M. and Prakash, C. (2015) ‘The Interface Theory of Perception’, *Psychonomic Bulletin & Review*, 22(6), pp. 1480–1506.

147. Holmes, H. (2020) *Delistings: have supermarket product ranges shrunk for good?*, *The Grocer*.

148. Holzer, A., Kocher, B., Bendahan, S., Vonèche Cardia, I., Mazuze, J. and Gillet, D. (2020) ‘Gamifying knowledge sharing in humanitarian organisations: a design science journey’, *European Journal of Information Systems*, 29(2), pp. 153–171.

149. Hong, W., Chan, F. K. Y., Thong, J. Y. L., Chasalow, L. C. and Dhillon, G. (2014) ‘A Framework and Guidelines for Context-Specific Theorizing in Information Systems Research’, *Information Systems Research*, 25(1), pp. 111–136.

150. Hossain, M. A. and Quaddus, M. (2012) ‘Expectation-confirmation theory in information system research: a review and analysis.’, in *Information Systems Theory: Explaining and Predicting our Digital Society*. Springer Science * Business Media.

151. Howley, P., Buckley, C., O Donoghue, C. and Ryan, M. (2015) ‘Explaining the economic “irrationality” of farmers’ land use behaviour: The role of productivist attitudes and non-pecuniary benefits’, *Ecological Economics*, 109, pp. 186–193.
152. Hsieh, C. and Lin, B. (1998) ‘Internet commerce for small businesses’, *Industrial Management & Data Systems*, 98(3), pp. 113–119.
153. Huang, Y.-M. (2019) ‘Examining students’ continued use of desktop services: Perspectives from expectation-confirmation and social influence’, *Computers in Human Behavior*, 96, pp. 23–31.
154. Hutchinson, K., Donnell, L. V., Gilmore, A. and Reid, A. (2015) ‘Loyalty card adoption in SME retailers: the impact upon marketing management’, *European Journal of Marketing*, 49(3/4), pp. 467–490.
155. Hwang, M. I. (2014) ‘Disentangling the Effect of Top Management Support and Training on Systems Implementation Success: A Meta-Analysis’, *Communications of the Association for Information Systems*, 35(2), pp. 19–37.
156. Igbaria, M., Zinatelli, N., Cragg, P. and Cavaye, A. L. M. (1997) ‘Personal Computing Acceptance Factors in Small Firms: A Structural Equation Model’, *MIS Quarterly*, 21(3), pp. 279–305.
157. IGD (2018) *The Online Store of the Future: How to prepare your business and win*. IGD.
158. IGD (2019) *Digital Retail Models of the Future*. IGD.
159. IRI (2017) *Back to Growth: Big Data Collaboration*. IRI Worldwide.
160. Isenberg, T., Isenberg, P., Jian Chen, Sedlmair, M. and Moller, T. (2013) ‘A Systematic Review on the Practice of Evaluating Visualization’, *IEEE Transactions on Visualization and Computer Graphics*, 19(12), pp. 2818–2827.
161. Jaskiewicz, P., Combs, J. G. and Rau, S. B. (2015) ‘Entrepreneurial legacy: Toward a theory of how some family firms nurture transgenerational entrepreneurship’, *Journal of Business Venturing*, 30(1), pp. 29–49.
162. Jasperson, J. S., Carter, P. E. and Zmud, R. W. (2005) ‘A Comprehensive Conceptualization of Post-Adoptive Behaviors Associated with Information Technology Enabled Work Systems’, *MIS Quarterly*, 29(3), pp. 525–557.
163. Jaworski, B. J. and Kohli, A. K. (1993) ‘Market Orientation: Antecedents and Consequences’, *Journal of Marketing*, 57(3), pp. 53–70.

164. Jeyaraj, A., Rottman, J. W. and Lacity, M. C. (2006) ‘A review of the predictors, linkages, and biases in IT innovation adoption research’, *Journal of Information Technology*, 21(1), pp. 1–23.
165. Jones, O., Macpherson, A., Thorpe, R. and Ghecham, A. (2007) ‘The evolution of business knowledge in SMEs: conceptualizing strategic space’, *Strategic Change*, 16(6), pp. 281–294.
166. Jones, P., Simmons, G., Packham, G., Beynon-Davies, P. and Pickernell, D. (2014) ‘An exploration of the attitudes and strategic responses of sole-proprietor micro-enterprises in adopting information and communication technology’, *International Small Business Journal*, 32(3), pp. 285–306.
167. Kahneman, D. (2012) *Thinking Fast and Slow*. Penguin Books.
168. Karahanna, E., Benbasat, I., Bapna, R. and Arun, R. (2018) ‘Opportunities and Challenges for Different Types of Online Experiments’, *MIS Quarterly*, 42(4), pp. iii–x.
169. Karahanna, E., Xin Xu, S., Xu, Y., Zhang, N. (Andy), Xu, Y., Hong Kong University of Science and Technology, Zhang, N. (Andy), and Harbin Institute of Technology (2018) ‘The Needs–Affordances–Features Perspective for the Use of Social Media’, *MIS Quarterly*, 42(3), pp. 737–756.
170. Karali, E., Brunner, B., Doherty, R., Hersperger, A. M. and Rounsevell, M. D. A. (2013) ‘The Effect of Farmer Attitudes and Objectives on the Heterogeneity of Farm Attributes and Management in Switzerland’, *Human Ecology*, 41(6), pp. 915–926.
171. Kellermanns, F. W., Eddleston, K. A., Sarathy, R. and Murphy, F. (2012) ‘Innovativeness in family firms: a family influence perspective’, *Small Business Economics*, 38(1), pp. 85–101.
172. Kelton, A. S., Pennington, R. R. and Tuttle, B. M. (2010) ‘The Effects of Information Presentation Format on Judgment and Decision Making: A Review of the Information Systems Research’, *Journal of Information Systems*, 24(2), pp. 79–105.
173. Khan, A. (2020) ‘From Elements to Structures: An Agenda for Organisational Gamification’, *European Journal of Information Systems*, 29(6), pp. 621–640.
174. Kim (2009) ‘The Integrative Framework of Technology Use: An Extension and Test’, *MIS Quarterly*, 33(3), p. 513.
175. Kim, H.-W., Chan, H. C. and Chan, Y. P. (2007) ‘A balanced thinking–feelings model of information systems continuance’, *International Journal of Human-Computer*

Studies, 65(6), pp. 511–525.

176. Kim, H.-W. and Kankanhalli, A. (2009) 'Investigating User Resistance to Information Systems Implementation: A Status Quo Bias Perspective', *MIS Quarterly*, 33(3), pp. 567–582.
177. Kim, S. H., Jang, S. Y. and Yang, K. H. (2017) 'Analysis of the Determinants of Software-as-a-Service Adoption in Small Businesses: Risks, Benefits, and Organizational and Environmental Factors', *Journal of Small Business Management*, 55(2), pp. 303–325.
178. Kirby, J. R., Moore, P. J. and Schofield, N. J. (1988) 'Verbal and visual learning styles', *Contemporary Educational Psychology*, 13(2), pp. 169–184.
179. König, A., Kammerlander, N. and Enders, A. (2013) 'The Family Innovator's Dilemma: How Family Influence Affects the Adoption of Discontinuous Technologies by Incumbent Firms', *Academy of Management Review*, 38(3), pp. 418–441.
180. Kopp, T., Riekert, M. and Utz, S. (2018) 'When cognitive fit outweighs cognitive load: Redundant data labels in charts increase accuracy and speed of information extraction', *Computers in Human Behavior*, 86, pp. 367–376.
181. Kosara, R. and Mackinlay, J. (2013) 'Storytelling: The Next Step for Visualization', *Computer*, 46(5), pp. 44–50.
182. Kozhevnikov, M. (2007) 'Cognitive styles in the context of modern psychology: Toward an integrated framework of cognitive style.', *Psychological Bulletin*, 133(3), pp. 464–481.
183. Kroenung, J., Eckhardt, A. and Kuhlenkasper, T. (2017) 'Conflicting behavioral paradigms and predicting IS adoption and non-adoption – The importance of group-based analysis', *Computers in Human Behavior*, 67, pp. 10–22.
184. Lallmahomed, M. Z. I., Ab.Rahim, N. Z., Ibrahim, R. and Rahman, A. A. (2013) 'Predicting different conceptualizations of system use: Acceptance in hedonic volitional context (Facebook)', *Computers in Human Behavior*, 29(6), pp. 2776–2787.
185. Lam, H., Bertini, E., Isenberg, P., Plaisant, C. and Carpendale, S. (2012) 'Empirical Studies in Information Visualization: Seven Scenarios', *IEEE Transactions on Visualization and Computer Graphics*, 18(9), pp. 1520–1536.

186. Länsiluoto, A., Joensuu-Salo, S., Varamäki, E., Viljamaa, A. and Sorama, K. (2019) 'Market Orientation and Performance Measurement System Adoption Impact on Performance in SMEs', *Journal of Small Business Management*, 57(3), pp. 1027–1043.
187. Lashley, C. and Rowson, B. (2010) 'Lifestyle businesses: Insights into Blackpool's hotel sector', *International Journal of Hospitality Management*, 29(3), pp. 511–519.
188. Lee, W.-K. (2014) 'The temporal relationships among habit, intention and IS uses', *Computers in Human Behavior*, 32, pp. 54–60.
189. Lee, Y., Kozar, K. A. and Larsen, K. R. T. (2003) 'The Technology Acceptance Model: Past, Present, and Future', *Communications of the Association for Information Systems*, 12, pp. 752–780.
190. Lewis-Beck, M. S., Bryman, A. and Futing Liao, T. (2004) *The SAGE Encuclopedia of Social Science Research Methods*. Sage Publications.
191. Li, X., Hsieh, J. J. P.-A. and Rai, A. (2013) 'Motivational Differences Across Post-Acceptance Information System Usage Behaviors: An Investigation in the Business Intelligence Systems Context', *Information Systems Research*, 24(3), pp. 659–682.
192. Limayem, M., Hirt, S. G. and Cheung, C. M. K. (2007) 'How Habit Limits the Predictive Power of Intention: The Case of Information Systems Continuance', *MIS Quarterly*, 31(4), pp. 705–737.
193. Lin, N. (2017) 'Building a Network Theory of Social Capital', in *Social Capital: Theory and Research*.
194. Liu, D., Santhanam, R., Webster, J., Webster, J., and Queen's University (2017) 'Toward Meaningful Engagement: A Framework for Design and Research of Gamified Information Systems', *MIS Quarterly*, 41(4), pp. 1011–1034.
195. Liu, S., Cui, W., Wu, Y. and Liu, M. (2014) 'A survey on information visualization: recent advances and challenges', *The Visual Computer*, 30(12), pp. 1373–1393.
196. Lloyds Bank (2019) *UK Business Digital Index*.
197. Luo, W. (2019) 'User choice of interactive data visualization format: The effects of cognitive style and spatial ability', *Decision Support Systems*, 122, p. 113061.
198. Lurie, N. H. and Mason, C. H. (2007) 'Visual Representation: Implications for Decision Making', *Journal of Marketing*, 71(1), pp. 160–177.
199. Luse, A., McElroy, J. C., Townsend, A. M. and DeMarie, S. (2013) 'Personality and cognitive style as predictors of preference for working in virtual teams', *Computers*

in Human Behavior, 29(4), pp. 1825–1832.

200. Lycett, M. (2013) '"Datafication": making sense of (big) data in a complex world', *European Journal of Information Systems*, 22(4), pp. 381–386.
201. Ma, K.-L., Liao, I., Frazier, J., Hauser, H. and Kostis, H.-N. (2012) 'Scientific Storytelling Using Visualization', *IEEE Computer Graphics and Applications*, 32(1), pp. 12–19.
202. Makridakis, S. (2017) 'The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms', *Futures*, 90, pp. 46–60.
203. Malagueño, R., Gölgeci, I. and Fearne, A. (2019) 'Customer categorization, relational justice and SME performance in supermarket supply chains', *Supply Chain Management: An International Journal*, 24(3), pp. 417–429.
204. Manyika, J. (2017) *What's now and next in analytics, AI, and automation*. McKinsey Global Institute.
205. Marangunić, N. and Granić, A. (2015) 'Technology acceptance model: a literature review from 1986 to 2013', *Universal Access in the Information Society*, 14(1), pp. 81–95.
206. March, S. T. and Smith, G. F. (1995) 'Design and natural science research on information technology', *Decision Support Systems*, 15(4), pp. 251–266.
207. Marchand, D. A. and Peppard, J. (2013) 'Why IT Fumbles Analytics', *Harvard Business Review*, 91(1–2), pp. 104–114.
208. Marcketti, S. B. (2006) 'An Exploratory Study of Lifestyle Entrepreneurship and Its Relationship to Life Quality', *Family and Consumer Sciences Research Journal*, 34(3), pp. 241–259.
209. Mason, T. (2020) *Why grocers must invest in digital for post-lockdown growth | Comment & Opinion | The Grocer*.
210. Mateescu, A. and Elish, M. C. (2019) *AI in Context: The Labor of Integrating New Technologies*. Data&Society.
211. Mazzarol, T., Reboud, S. and Soutar, G. N. (2009) 'Strategic planning in growth oriented small firms', *International Journal of Entrepreneurial Behavior & Research*, 15(4), pp. 320–345.
212. McAfee, A. and Brynjolfsson, E. (2012) 'Big Data: the management revolution', *Harvard Business Review*, 10, pp. 60–69.

213. McCartan-Quinn, D. and Carson, D. (2003) ‘Issues which Impact upon Marketing in the Small Firm’, *Small Business Economics*, 21, pp. 201–213.
214. McGaughey, S. L. (1998) ‘Realising the Marketing Advantages of International Standard-Setting Activities: Opportunities for Innovative Technology-Based SMEs’, *Journal of Marketing Management*, 14(8), pp. 897–925.
215. McKenzie, B., Burt, S. and Dukeov, I. (2018) ‘Introduction to the special issue: technology in retailing’, *Baltic Journal of Management*, 13(2), pp. 146–151.
216. McKiernan, P. and Morris, C. (1994) ‘Strategic Planning and Financial Performance in UK SMEs: Does Formality Matter?’, *British Journal of Management*, 5(Special Issue), pp. S31–S41.
217. McKinsey Analytics (2018) *Crossing the frontier: How to apply AI for impact*. McKinsey & Company.
218. McKinsey Global Institute (2017) *Artificial Intelligence: The Next Digital Frontier?* McKinsey Global Institute.
219. Michie, S., Atkins, L. and West, R. (2014) *The Behaviour Change Wheel: A Guide to Designing Interventions*. London: Silverback Publishing.
220. Michie, S. and Johnston, M. (2012) ‘Theories and techniques of behaviour change: Developing a cumulative science of behaviour change’, *Health Psychology Review*, 6(1), pp. 1–6.
221. Michie, S., Johnston, M., Francis, J., Hardeman, W. and Eccles, M. (2008) ‘From Theory to Intervention: Mapping Theoretically Derived Behavioural Determinants to Behaviour Change Techniques’, *Applied Psychology*, 57(4), pp. 660–680.
222. Michie, S., Richardson, M., Johnston, M., Abraham, C., Francis, J., Hardeman, W., Eccles, M. P., Cane, J. and Wood, C. E. (2013) ‘The Behavior Change Technique Taxonomy (v1) of 93 Hierarchically Clustered Techniques: Building an International Consensus for the Reporting of Behavior Change Interventions’, *Annals of Behavioral Medicine*, 46(1), pp. 81–95.
223. Michie, S., van Stralen, M. M. and West, R. (2011) ‘The behaviour change wheel: A new method for characterising and designing behaviour change interventions’, *Implementation Science*, 6(42), pp. 1–11.
224. Mingers, J., Mutch, A. and Willcocks, L. (2013) ‘Critical Realism in Information Systems Research’, *MIS Quarterly*, 37(3), pp. 795–802.
225. Mintel (2019) *Supermarkets UK*. Mintel.

226. Mintel (2020a) *Online Grocery Retailing UK*. Mintel.

227. Mintel (2020b) *Supermarkets UK: Inc Impact of COVID-19*. Mintel.

228. Mintel (2020c) *The impact of COVID-19 on Food and Drink*. Mintel.

229. Montibeller, G. and Winterfeldt, D. von (2015) 'Cognitive and Motivational Biases in Decision and Risk Analysis', *Risk Analysis*, 35(7), pp. 1230–1251.

230. Morgan-Thomas, A. (2016) 'Rethinking technology in the SME context: Affordances, practices and ICTs', *International Small Business Journal*, 34(8), pp. 1122–1136.

231. Moriarty, J., Jones, R., Rowley, J. and Kupiec-Teahan, B. (2008) 'Marketing in small hotels: a qualitative study', *Marketing Intelligence & Planning*, 26(3), pp. 293–315.

232. Morton, M. S. S. and Stephens, J. A. (1968) 'The impact of interactive visual display systems on the management planning process', *Sloan Management School Working Papers*, pp. 356–368.

233. Motwani, J. G., Jiang, J. J. and Kumar, A. (1998) 'A comparative analysis of manufacturing practices of small vs large West Michigan organizations', *Industrial Management & Data Systems*, 98(1), pp. 8–11.

234. Mouakket, S. (2015) 'Factors influencing continuance intention to use social network sites: The Facebook case', *Computers in Human Behavior*, 53, pp. 102–110.

235. Nadj, M., Maedche, A. and Schieder, C. (2020) 'The effect of interactive analytical dashboard features on situation awareness and task performance', *Decision Support Systems*, 135, p. 113322.

236. Narver, J. C. and Slater, S. F. (1990) 'The Effect of a Market Orientation on Business Profitability', *Journal of Marketing*, 54(4), pp. 20–35.

237. Nasution, H. N., Mavondo, F. T., Matanda, M. J. and Ndubisi, N. O. (2011) 'Entrepreneurship: Its relationship with market orientation and learning orientation and as antecedents to innovation and customer value', *Industrial Marketing Management*, 40(3), pp. 336–345.

238. Negoita, B., Lapointe, L. and Rivard, S. (2018) 'Collective information systems use: a typological theory', *MIS Quarterly*, 42(4), pp. 1281–1301.

239. Neuman, L. (2014) *Social Research Methods: Qualitative and Quantitative Approaches*. 7th edn. Pearson Education.

240. Nguyen, T. H. (2009) 'Information technology adoption in SMEs: an integrated framework', *International Journal of Entrepreneurial Behavior & Research*, 15(2),

pp. 162–186.

241. Nguyen, T. H., Newby, M. and Macaulay, M. J. (2015) 'Information Technology Adoption in Small Business: Confirmation of a Proposed Framework', *Journal of Small Business Management*, 53(1), pp. 207–227.
242. Nguyen, T. H. and Waring, T. (2013) 'The adoption of customer relationship management (CRM) technology in SMEs: An empirical study', *Journal of Small Business and Enterprise Development*, 20(4), pp. 824–848.
243. Nielsen (2018) *Future Opportunities in FMCG E-Commerce: Market Drivers and Five-Year Forecast*. Nielsen.
244. Nordqvist, M. and Melin, L. (2010) 'Entrepreneurial families and family firms', *Entrepreneurship & Regional Development*, 22(3–4), pp. 211–239.
245. Norman, D. (2013) *The design of everyday things: Revised and expanded edition.* Constellation.
246. Nunamaker, J. F., Briggs, R. O., Derrick, D. C. and Schwabe, G. (2015) 'The Last Research Mile: Achieving Both Rigor and Relevance in Information Systems Research', *Journal of Management Information Systems*, 32(3), pp. 10–47.
247. Nunamaker, J. F., Chen, M. and Purdin, T. D. M. (1990) 'Systems Development in Information Systems Research', *Journal of Management Information Systems*, 7(3), pp. 89–106.
248. O'Connor, C. and Kelly, S. (2017) 'Facilitating knowledge management through filtered big data: SME competitiveness in an agri-food sector', *Journal of Knowledge Management*, 21(1), pp. 156–179.
249. O'Dwyer, M., Gilmore, A. and Carson, D. (2009) 'Innovative marketing in SMEs: an empirical study', *Journal of Strategic Marketing*, 17(5), pp. 383–396.
250. Oliver, R. L. (1980) 'A Cognitive Model for the Antecedents and Consequences of Satisfaction', *Journal of Marketing Research*, 17, pp. 460–469.
251. ONS (2020) *Coronavirus and the impact on output in the UK economy*. Office for National Statistics.
252. van Oorschot, J. A. W. H., Hofman, E. and Halman, J. I. M. (2018) 'A bibliometric review of the innovation adoption literature', *Technological Forecasting and Social Change*, 134, pp. 1–21.
253. Orlikowski, W. J. (2000) 'Using Technology and Constituting Structures: A Practice Lens for Studying Technology in Organizations', *Organization Science*, 11(4), p. 25.

254. Orlikowski, W. J. (2007) ‘Sociomaterial Practices: Exploring Technology at Work’, *Organization Studies*, 28(9), pp. 1435–1448.
255. Orlikowski, W. J. and Iacono, C. (2001) ‘Research commentary: Desperately seeking the “IT” in IT research—A call to theorizing the IT artifact’, *Information Systems Research*, 12(2), pp. 121–134.
256. Orlikowski, W. J. and Scott, S. V. (2008) ‘Sociomateriality: Challenging the Separation of Technology, Work and Organization’, *The Academy of Management Annals*, 2(1), pp. 433–474.
257. Ortiz de Guinea, A. and Webster, J. (2013) ‘An Investigation of Information Systems Use Patterns: Technological Events as Triggers, the Effect of Time, and Consequences for Performance’, *MIS Quarterly*, 37(4), pp. 1165–1188.
258. Pacini, R. and Epstein, S. (1999) ‘The relation of rational and experiential information processing styles to personality, basic beliefs, and the ratio-bias phenomenon’, *Journal of Personality and Social Psychology*, 76(6), pp. 972–987.
259. Pajić, D. (2014) ‘Browse to search, visualize to explore: Who needs an alternative information retrieving model?’, *Computers in Human Behavior*, 39, pp. 145–153.
260. Peffers, K., Tuunanen, T., Rothenberger, M. A. and Chatterjee, S. (2007) ‘A Design Science Research Methodology for Information Systems Research’, *Journal of Management Information Systems*, 24(3), pp. 45–77.
261. Peltier, J. W., Schibrowsky, J. A. and Zhao, Y. (2009) ‘Understanding the Antecedents to the Adoption of CRM Technology by Small Retailers’, *International Small Business Journal*, 27(3), pp. 307–336.
262. Peltier, J. W., Zhao, Y. and Schibrowsky, J. A. (2012) ‘Technology adoption by small businesses: An exploratory study of the interrelationships of owner and environmental factors’, *International Small Business Journal*, 30(4), pp. 406–431.
263. Peña, A. I. P., Jamilena, D. M. F. and Molina, M. Á. R. (2011) ‘Impact of Market Orientation and ICT on the Performance of Rural Smaller Service Enterprises’, *Journal of Small Business Management*, 49(3), pp. 331–360.
264. Perdana, A., Rob, A. and Rohde, F. (2018) ‘Does Visualization Matter? The Role of Interactive Data Visualization to Make Sense of Information’, *Australasian Journal of Information Systems*, 22, pp. 1–34.
265. Pérez, D. and Duréndez, A. (2007) ‘Managerial behaviour of small and medium-sized family businesses: an empirical study’, *International Journal of*

Entrepreneurial Behavior & Research, 13(3), pp. 151–172.

266. Perkins, C. (2020) *What impact is coronavirus having on the UK grocery market?*, *The Grocer*.
267. Peters, G. and Duncan, A. D. (2020) *100 Data and Analytics Predictions Through 2024*. Gartner.
268. Peters, M., Frehse, J. and Buhalis, D. (2009) ‘The importance of lifestyle entrepreneurship: A conceptual study of the tourism industry’, *PASOS Revista de turismo y patrimonio cultural*, 7(3), pp. 393–405.
269. Phillips, W. J., Fletcher, J. M., Marks, A. D. G. and Hine, D. W. (2016) ‘Thinking styles and decision making: A meta-analysis’, *Psychological Bulletin*, 142(3), pp. 260–290.
270. Pike, W. A., Stasko, J., Chang, R. and O’Connell, T. A. (2009) ‘The Science of Interaction’, *Information Visualization*, 8(4), pp. 263–274.
271. Pitkänen, I., Parvinen, P. and Töytäri, P. (2014) ‘The Significance of the New Venture’s First Sale: The Impact of Founders’ Capabilities and Proactive Sales Orientation: New Venture’s First Sale’, *Journal of Product Innovation Management*, 31(4), pp. 680–694.
272. Plummer, D. *et al.* (2019) *Gartner’s Top Strategic Predictions for 2020 and Beyond: Technology Changes the Human Condition*. Gartner.
273. Polites, G. and Karahanna, E. (2012) ‘Shackled to the Status Quo: The Inhibiting Effects of Incumbent System Habit, Switching Costs, and Inertia on New System Acceptance’, *MIS Quarterly*, 36(1), pp. 21–42.
274. Polites, G., Serrano, C., Thatcher, J. B. and Matthews, K. (2018) ‘Understanding social networking site (SNS) identity from a dual systems perspective: an investigation of the dark side of SNS use’, *European Journal of Information Systems*, 27(5), pp. 600–621.
275. Popovič, A., Puklavec, B. and Oliveira, T. (2019) ‘Justifying business intelligence systems adoption in SMEs’, *Industrial Management & Data Systems*, 119(1), pp. 210–228.
276. Power, D. J., Heavin, C., McDermott, J. and Daly, M. (2018) ‘Defining business analytics: an empirical approach’, *Journal of Business Analytics*, 1(1), pp. 40–53.
277. Rai, A., Constantinides, P. and Sarker, S. (2019) ‘Next-Generation Digital Platforms: Toward Human-AI Hybrids’, *MIS Quarterly*, 43(1), pp. iii–ix.

278. Ramdani, B., Chevers, D. A. and Williams, D. A. (2013) 'SMEs' adoption of enterprise applications A technology-organisation-environment model', *Journal of Small Business and Enterprise Development*, 20(4), pp. 735–753.
279. Rao, A. S. and Verweij, G. (2017) *Sizing the prize: What's the real value of AI for your business and how can you capitalise?* PwC.
280. Reani, M., Davies, A., Peek, N. and Jay, C. (2018) 'How do people use information presentation to make decisions in Bayesian reasoning tasks?', *International Journal of Human-Computer Studies*, 111, pp. 62–77.
281. Reani, M., Peek, N. and Jay, C. (2019) 'How different visualizations affect human reasoning about uncertainty: An analysis of visual behaviour', *Computers in Human Behavior*, 92, pp. 55–64.
282. Reijonen, H. (2010) 'Do all SMEs practise same kind of marketing?', *Journal of Small Business and Enterprise Development*, 17(2), pp. 279–293.
283. Reinartz, W., Wiegand, N. and Imschloss, M. (2019) 'The impact of digital transformation on the retailing value chain', *International Journal of Research in Marketing*, 36(3), pp. 350–366.
284. Reinecke, K. and Bernstein, A. (2013) 'Knowing What a User Likes: A Design Science Approach to Interfaces that Automatically Adapt to Culture', *MIS Quarterly*, 37(2), pp. 427–453.
285. Reinsel, D., Gantz, J. and Rydning, J. (2018) *The Digitization of the World from Edge to Core*.
286. Retana, G. F. *et al.* (2018) 'Technology Support and Post-Adoption IT Service Use: Evidence from the Cloud', *MIS Quarterly*, 42(3), pp. 961–978.
287. Robson, K., Plangger, K., Kietzmann, J. H., McCarthy, I. and Pitt, L. (2016) 'Game on: Engaging customers and employees through gamification', *Business Horizons*, 59(1), pp. 29–36.
288. Rogers, E. M. (2003) *Diffusions of innovations*. London: Free Press.
289. Roper, S. and Hart, M. (2018) *State of Small Business Britain Report 2018*. Enterprise Research Centre.
290. Rorty, R. (1982) *Consequences of Pragmatism*. Minneapolis: University of Minnesota Press.
291. Ruivo, P., Oliveira, T., Johansson, B. and Neto, M. (2013) 'Differential Effects on ERP Post-Adoption Stages across Scandinavian and Iberian SMEs', *Journal of*

Global Information Management, 21(3), pp. 1–20.

292. Ruivo, P., Oliveira, T. and Neto, M. (2012) 'ERP use and value: Portuguese and Spanish SMEs', *Industrial Management & Data Systems*, 112(7), pp. 1008–1025.
293. Ryan, R. M. and Deci, E. L. (2000) 'Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being', *American Psychologist*, 55(1), pp. 68–78.
294. Saket, B., Endert, A. and Demiralp, C. (2018) 'Task-Based Effectiveness of Basic Visualizations', *arXiv:1709.08546 [cs]*.
295. Samuelson, W. and Zeckhauser, R. (1988) 'Status quo bias in decision making', *Journal of Risk and Uncertainty*, 1(1), pp. 7–59.
296. Santhanam, R., Yi, M., Sasidharan, S. and Park, S.-H. (2013) 'Toward an Integrative Understanding of Information Technology Training Research across Information Systems and Human-Computer Interaction: A Comprehensive Review', *AIS Transactions on Human-Computer Interaction*, 5(3), pp. 134–156.
297. Schryen, G. (2013) 'Revisiting IS business value research: what we already know, what we still need to know, and how we can get there', *European Journal of Information Systems*, 22(2), pp. 139–169.
298. Schwenk, C. R. (1982) 'Why sacrifice rigour for relevance? A proposal for combining laboratory and field research in strategic management', *Strategic Management Journal*, 3(3), pp. 213–225.
299. Seaborn, K. and Fels, D. I. (2015) 'Gamification in theory and action: A survey', *International Journal of Human-Computer Studies*, 74, pp. 14–31.
300. Segel, E. and Heer, J. (2010) 'Narrative Visualization: Telling Stories with Data', *IEEE Transactions on Visualization and Computer Graphics*, 16(6), pp. 1139–1148.
301. Sergeeva, A., Huysman, M., Soekijad, M., van den Hooff, B., Soekijad, M., Vrije Universiteit Amsterdam, van den Hooff, B., and Vrije Universiteit Amsterdam (2017) 'Through the Eyes of Others: How Onlookers Shape the Use of Technology at Work', *MIS Quarterly*, 41(4), pp. 1153–1178.
302. Shaft, T. M. and Vessey, I. (2006) 'The Role of Cognitive Fit in the Relationship between Software Comprehension and Modification', *MIS Quarterly*, 30(1), pp. 29–55.
303. Sheeran, P. (2002) 'Intention—Behavior Relations: A Conceptual and Empirical Review', *European Review of Social Psychology*, 12(1), pp. 1–36.

304. Sheeran, P. and Webb, T. L. (2016) ‘The Intention-Behavior Gap: The Intention-Behavior Gap’, *Social and Personality Psychology Compass*, 10(9), pp. 503–518.

305. Shepherd, D. A., Williams, T. A. and Patzelt, H. (2015) ‘Thinking About Entrepreneurial Decision Making: Review and Research Agenda’, *Journal of Management*, 41(1), pp. 11–46.

306. Shrader, C. B., Mulford, C. L. and Blackburn, V. L. (1989) ‘Strategic and Operational Planning, Uncertainty, and Performance in Small Firms’, *Journal of Small Business Management*, 27(4), pp. 45–60.

307. Silic, M. and Lowry, P. B. (2020) ‘Using Design-Science Based Gamification to Improve Organizational Security Training and Compliance’, *Journal of Management Information Systems*, 37(1), pp. 129–161.

308. Simmons, G., Armstrong, G. A. and Durkin, M. G. (2008) ‘A Conceptualization of the Determinants of Small Business Website Adoption: Setting the Research Agenda’, *International Small Business Journal: Researching Entrepreneurship*, 26(3), pp. 351–389.

309. Skinner, B. F. (1953) *Science and Human Behaviour*. London: Collier Macmillan Publishers.

310. Sloman, S. A. (2002) ‘Two Systems of Reasoning’, in *Heuristics and biases: the psychology of intuitive judgment*. Cambridge, U.K. ; New York: Cambridge University Press.

311. Soror, A. A., Hammer, B. I., Steelman, Z. R., Davis, F. D. and Limayem, M. M. (2015) ‘Good habits gone bad: Explaining negative consequences associated with the use of mobile phones from a dual-systems perspective: Good habits gone bad’, *Information Systems Journal*, 25(4), pp. 403–427.

312. Speier, C. (2006) ‘The influence of information presentation formats on complex task decision-making performance’, *International Journal of Human-Computer Studies*, 64(11), pp. 1115–1131.

313. Spillan, J. E. and Ziemnowicz, C. (2003) ‘Strategic Management in Small Retail Businesses: The Case of Guatemala’, *International Small Business Journal: Researching Entrepreneurship*, 21(4), pp. 461–478.

314. Statista (2017) *Customer loyalty schemes in the UK*. Statista.

315. Statista (2020a) *Big data*. Statista.

316. Statista (2020b) *Supermarkets in the UK*. Statista.

317. Sykes, T. A. and Venkatesh, V. (2017) 'Explaining Post-Implementation Employee System Use and Job Performance: Impacts of the Content and Source of Social Network Ties', *MIS Quarterly*, 41(3), pp. 917–936.
318. Sykes, T. A., Venkatesh, V. and Gosain, S. (2009) 'Model of Acceptance with Peer Support: A Social Network Perspective to Understand Employees' System Use', *MIS Quarterly*, 33(2), pp. 371–393.
319. T. Hazen, B., Kung, L., G. Cegielski, C. and Allison Jones-Farmer, L. (2014) 'Performance expectancy and use of enterprise architecture: training as an intervention', *Journal of Enterprise Information Management*, 27(2), pp. 180–196.
320. Teets, J. M., Tegarden, D. P. and Russell, R. S. (2010) 'Using Cognitive Fit Theory to Evaluate the Effectiveness of Information Visualizations: An Example Using Quality Assurance Data', *IEEE Transactions on Visualization and Computer Graphics*, 16(5), pp. 841–853.
321. Thatcher, J. B. *et al.* (2018) 'Mindfulness in Information Technology Use: Definitions, Distinctions, and a New Measure', *MIS Quarterly*, 42(3), pp. 831–847.
322. The Grocer (2020) *Britain's Biggest Brands 2020: the top 100*, *The Grocer*.
323. Thong, J. Y. L. (1999) 'An Integrated Model of Information Systems Adoption in Small Businesses', *Journal of Management Information Systems*, 15(4), pp. 187–214.
324. Tory, M. and Moller, T. (2004) 'Human factors in visualization research', *IEEE Transactions on Visualization and Computer Graphics*, 10(1), pp. 72–84.
325. Trémolière, B. and Djeriouat, H. (2019) 'Love is not exactly blind, at least for some people: Analytic cognitive style predicts romantic beliefs', *Personality and Individual Differences*, 145, pp. 119–131.
326. Trieu, V.-H. (2017) 'Getting value from Business Intelligence systems: A review and research agenda', *Decision Support Systems*, 93, pp. 111–124.
327. Tufte, E. R. (2001) *The Visual Display of Quantitative Information*. 2nd edn. Cheshire, Conneticut: Graphics Press.
328. Turel, O. (2015) 'Quitting the use of a habituated hedonic information system: a theoretical model and empirical examination of Facebook users', *European Journal of Information Systems*, 24(4), pp. 431–446.
329. Turel, O. and Serenko, A. (2012) 'The benefits and dangers of enjoyment with social networking websites', *European Journal of Information Systems*, 21(5), pp. 512–

528.

330. UK Government (2020a) *Furlough scheme cut-off date extended to 19 March*, *GOV.UK*.
331. UK Government (2020b) *PM announces easing of lockdown restrictions: 23 June 2020*, *GOV.UK*.
332. UK Government (2020c) *Prime Minister's statement on coronavirus (COVID-19): 23 March 2020*, *GOV.UK*.
333. Venkatesh, V. and Bala, H. (2008) 'Technology Acceptance Model 3 and a Research Agenda on Interventions', *Decision Sciences*, 39(2), pp. 273–315.
334. Venkatesh, V., Brown, Maruping, and Bala (2008) 'Predicting Different Conceptualizations of System Use: The Competing Roles of Behavioral Intention, Facilitating Conditions, and Behavioral Expectation', *MIS Quarterly*, 32(3), pp. 483–502.
335. Venkatesh, V. and Davis, F. D. (2000) 'A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies', *Management Science*, 46(2), pp. 186–204.
336. Venkatesh, V. and Morris, M. G. (2000) 'Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior', *MIS Quarterly*, 24(1), pp. 115–139.
337. Venkatesh, V., Morris, M. G., Davis, G. B. and Davis, F. D. (2003) 'User Acceptance of Information Technology: Toward a Unified View', *MIS Quarterly*, 27(3), pp. 425–478.
338. Venkatesh, V., Thong, J. Y. L. and Xu, X. (2012) 'Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology', *MIS Quarterly*, 36(1), pp. 157–178.
339. Venkatesh, V., Thong, J. Y. L. and Xu, X. (2016) 'Unified Theory of Acceptance and Use of Technology: A Synthesis and the Road Ahead', *Journal of the Association for Information Systems*, 17(5), pp. 328–376.
340. Venkatesh, V., Zhang, X. and Sykes, T. A. (2011) '"Doctors Do Too Little Technology": A Longitudinal Field Study of an Electronic Healthcare System Implementation', *Information Systems Research*, 22(3), pp. 523–546.
341. Vessey, I. (1991) 'Cognitive Fit: A Theory-Based Analysis of the Graphs Versus Tables Literature*', *Decision Sciences*, 22(2), pp. 219–240.

342. Vessey, I. and Galletta, D. (1991) 'Cognitive Fit: An Empirical Study of Information Acquisition', *Information Systems Research*, 2(1), pp. 63–84.
343. Waller, D. (2020) '10 Steps to Creating a Data-Driven Culture', *Harvard Business Review*, 6 February.
344. Wang, S. and Wang, H. (2020) 'Big data for small and medium-sized enterprises (SME): a knowledge management model', *Journal of Knowledge Management*, 24(4), pp. 881–897.
345. Wang, Y., Meister, D. B. and Gray, P. H. (2013) 'Social Influence and Knowledge Management Systems Use: Evidence from Panel Data', *MIS Quarterly*, 37(1), pp. 299–313.
346. Ware, C. (2012) *Information Visualization: Perception for Design*. 3rd edn. Boston: Morgan Kaufmann.
347. Watson, H. J. (2014) 'Tutorial: Big Data Analytics: Concepts, Technologies, and Applications', *Communications of the Association for Information Systems*, 34, pp. 1247–1268.
348. Watson, J. B. (1957) *Behaviorism*. Transaction Publishers.
349. Welsh, J. A. and White, J. F. (1981) 'A small business is not a little big business', *Harvard Business Review*, 4, pp. 18–26.
350. Widmeyer, G. R. (1992) 'Building an Information System Design Theory for Vigilant EIS', *Information Systems Research*, 3(1), pp. 36–59.
351. Wolcott, P., Kamal, M. and Qureshi, S. (2008) 'Meeting the challenges of ICT adoption by micro-enterprises', *Journal of Enterprise Information Management*, 21(6), pp. 616–632.
352. Wood, R. E. (1986) 'Task complexity: Definition of the construct', *Organizational Behavior and Human Decision Processes*, 37(1), pp. 60–82.
353. Woodfield, P. and Husted, K. (2017) 'Intergenerational knowledge sharing in family firms: Case-based evidence from the New Zealand wine industry', *Journal of Family Business Strategy*, 8(1), pp. 57–69.
354. Wu and Lederer (2009) 'A Meta-Analysis of the Role of Environment-Based Voluntariness in Information Technology Acceptance', *MIS Quarterly*, 33(2), p. 419.
355. Yang, S., Wang, B. and Lu, Y. (2016) 'Exploring the dual outcomes of mobile social networking service enjoyment: The roles of social self-efficacy and habit', *Computers in Human Behavior*, 64, pp. 486–496.

356. Zahra, S. A., Neubaum, D. O. and Larrañeta, B. (2007) 'Knowledge sharing and technological capabilities: The moderating role of family involvement', *Journal of Business Research*, 60(10), pp. 1070–1079.
357. Zhang, J. (1997) 'The Nature of External Representations in Problem Solving', *Cognitive Science*, 21(2), pp. 179–217.
358. Zhou, D., Chuang, T. and Nakatani, K. (2009) 'An exploratory study of the extent of information technology adoption in SMEs: an application of upper echelon theory', *Journal of Enterprise Information Management*, 22(1/2), pp. 183–196.
359. Zuboff, S. (2019) *The age of surveillance capitalism*. Profile Books.