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Abstract

Recent advances in machine learning and the availability of big data have made the study of Business Intelligence Systems (BIS) increasingly relevant. BI, which includes processes and methods for improving decision making with the use of fact-based support systems, is reported to be widely used across sectors and different businesses functions. However, most of the research effort centres around the question of how BIS can deliver value to an organisation (Trieu, 2017). Since one of the key determinants of organisational impacts is the actual use of the system, many studies investigate the factors that facilitate more effective use of the information provided. The data presentation format is a promising areas of research (Kelton, Pennington and Tuttle, 2010; Luo, 2019). However, studies conducted thus far tend to rely on laboratory experiments with students and ignore objective usage data, thus reducing the validity and the reliability of the findings (see e.g. Luo, 2019). What is more, the empirical research studies predominantly examine BIS use amongst large businesses neglecting the specific context of SMEs (Arnott, Lizama and Song, 2017; Popovič, Puklavec and Oliveira, 2019). In this research we conduct an online experiment to study the impact of experience on the previously identified relationships between information presentation format, task characteristics and individual differences.

Background

The so-called 'productivity paradox' (e.g. Brynjolfsson, 1993), and other author's claims that 'IT doesn't matter' (Carr, 2003) or that investments in information technology (IT) do not lead to any benefits for the company have long been refuted, and it is widely agreed that IT brings substantial benefits (Kohli and Grover, 2008; Schryen, 2013). They reveal themselves as different organisational impacts, such as improvements in productivity, process optimisation, increased profitability (Schryen, 2013) or less tangible ones, e.g. improved customer service and enhanced customer satisfaction (Kohli and Grover, 2008).

The research into the business value and impacts of IT seems even more relevant in the current business landscape. Rapid technological advancements, exponential growth of the available data, and developments in the field of artificial intelligence are redefining industries all over the world (Gartner, 2017). Companies which successfully embrace and implement the new solutions, such as big data analytics, machine learning (Côrte-Real, Oliveira and Ruivo, 2017) or business intelligence systems (Trieu, 2017) to tackle age-old problems are in a position to reap the benefits offered by IT.

However, it is the large companies that are driving the change and investing billions of dollars within these fields. Outside the technological sectors, small and medium-sized enterprises (SMEs) find it very hard to join this revolution (McKinsey Global Institute, 2017) and adoption rates in the UK remain relatively low (CBI, 2017). Yet, at the same time, they are often described as the backbone of the economy (Gunasekaran, Rai and Griffin, 2011). After all, in the UK they constitute 99.3% of all businesses, employ 60% of the private sector workforce and generate more than half of the private sector turnover (Department for Business, Energy & Industrial Strategy, 2017).

The same situation is visible in the academic community, where larger companies receive substantially more attention from the information systems (IS) researchers. While extant IS research has long recognised that IT per se does not result in performance impacts only its actual use (Orlikowski, 2000; Devaraj and Kohli, 2003), most of the SME IT literature focuses solely on the drivers and barriers to IT adoption (Ghobakhloo *et al.*, 2011; Nguyen, Newby and Macaulay, 2015), i.e. the decision to introduce a technology into the business. This presents a challenging yet very important research opportunity into the post-adoptive actual usage of information technology amongst SMEs, specifically into mechanisms that could improve the IS usage rates among SMEs.

A broader aim of this research is to experimentally test a mechanism for behavioural change of small businesses: from intuitive decision making to evidence-based decision making[1]. The decision-making process is operationalised as the use of a Business Intelligence System (BIS), hence the behaviour we are trying to change is the actual, post-adoptive use of technology. This article describes one step of the environmental restructuring intervention, an intervention where by changing the information system characteristics we aim to improve the use of it. Specifically, it describes an online experiment concerned with information presentation, which is used to inform a subsequent field experiment.

[1] A note on the behavioural change model applied in this research can be found in Appendix.

Introduction

Business intelligence visualisation (BIV) has a long tradition in the decision support systems literature and has been defined as "*the use of computer-supported interactive visual representations of business data to amplify cognition, achieve better data, business and behaviour understanding to improve decision making and business impact*" (Bačić and Fadlalla, 2016, p. 78). An important strand of research within this field is into the effects of information presentation format on decision making, also known as 'tables vs charts' research (Lurie and Mason, 2007; Kelton, Pennington and Tuttle, 2010). Most commonly, two different information presentation formats are compared, and their impact on decision quality (measured by time and accuracy) is examined. The main theoretical basis is a native IS theory of cognitive fit (Vessey, 1991; Vessey and Galletta, 1991), which postulates that if problem representation format fits the nature of the task, then the cognitive fit is achieved and decision task can be completed faster and with better accuracy. The main method utilised for conducting this research are laboratory experiments (Arnott and Gao, 2019), mostly with student samples and simplified decision tasks. As a result, the most commonly quoted limitation of such studies is low relevance to the practice. In this study, we aim to explore the appropriateness of using student samples, and the impact of using extracts from a real business intelligence system (BIS) and real decision tasks. Since it is a real-world scenario, in addition to decision quality variables we also add constructs from information systems (IS) continuance and adoption literature (Bhattacherjee and Lin, 2015) to explore how likely the research subjects are to accept a different format. Two main research questions are explored:

1. How commonly replicated results differ between student and practitioner groups?
2. Do the predictions of the most popular theory and previous research findings hold true when practitioners are used as experimental subjects?

In the next section we discuss the relevant theoretical bases and formulate hypotheses to the questions above.

Theoretical background

This section describes theoretical approaches used in our study. First, the most commonly used theory of cognitive fit is introduced. Second, the theories of status quo bias and automaticity are discussed to formulate hypothesis about how the results differ if students and practitioners are used as experimental subjects.

Cognitive Fit Theory

Cognitive fit theory was a theory developed by Vessey (1991) to resolve the inconsistent findings from previous research on the impact of information presentation on decision making (Benbasat and Dexter, 1986). It is based on a general problem-solving model. The model explains that a problem is solved based on the mental representation of the problem in human working memory. In turn, the mental representation is created from the problem representation and 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.

The general problem-solving model was then adapted to the 'tables vs charts' literature (Vessey, 1991; Vessey and Galletta, 1991). Based on that model, tables or charts (information presentation formats) are 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?).

Although, the predictions of the theory were validated empirically (Vessey and Galletta, 1991), it has received criticism for neglecting design formats, such as charts with data labels (Kopp, Riekert and Utz, 2018) and ignoring individual characteristics of people participating in the tasks (Liu *et al.*, 2014; Engin and Vetschera, 2017), which were later incorporated in the extended cognitive fit model (Kelton, Pennington and Tuttle, 2010). One important decision maker characteristic is their cognitive style, discussed in the next section.

Cognitive Style

Cognitive styles describe consistent differences among individuals with respect to how they perceive, think and take 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 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), 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). A number of conceptualisations of cognitive styles exist. They all measure the tendencies of individuals to employ the two systems for their everyday operations. One of such conceptualisations is Rational-Experiential Index (REI) based on a comprehensive theory of personality, 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). The knowledge of the preferred cognitive style of an individual can inform the more effective 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).

Cognitive styles were used in recent research into information presentation format impact on decision making (Engin and Vetschera, 2017; Luo, 2019). The findings indicate that if the problem representation matches individual's cognitive style the decision performance is improved (Engin and Vetschera, 2017). Moreover, when given a choice, subjects will choose a problem representation that fits their cognitive style (Luo, 2019). However, both of these studies used students as experimental subjects and ignored the impact of previous experiences (skills or knowledge). Few studies tried to incorporate knowledge or previous experience into this area of research (e.g. Cardinaels, 2008; Pajić, 2014) but they still used students as subjects and did not account for real experience of using a specific problem representation regularly, which is the case with practitioners. In related contexts, researchers have also hinted on the role played by experience (Reed *et al.*, 2000; Chen, Fan and Macredie, 2006) but did not examine it in conjunction with cognitive styles. The next two sections introduce theories to formulate hypotheses for using practitioners to try to replicate previous empirical findings. Automaticity theory is introduced to explain the impact on decision quality variables, while status quo theory is used for predicting the impact on IS continuance constructs.

Automaticity Theory

According to the dual-processing paradigm, human behaviour is guided by two main types of processes: conscious and automatic (Bargh and Ferguson, 2000; Evans and Stanovich, 2013). The latter, also referred to as goal-directed automaticity, is characterised by guiding a person's everyday behaviours automatically without the need for active thought (Ortiz de Guinea and Webster, 2013). A most commonly discussed instances of goal-directed automaticity are habits (Aarts and Dijksterhuis, 2000). Habits are widely defined as "*learned sequences of acts that have become automatic responses to specific cues, and are functional in obtaining certain goals or end-states*" (Verplanken and Aarts, 1999, p. 104). In order to develop a habit, three elements are necessary, namely stable context, satisfaction with the outcomes of the behaviour and frequent repetition of the behaviour (Verplanken and Aarts, 1999; Limayem, Hirt and Cheung, 2007).

Since practitioners used in this study have used the tables repeatedly in the same context to successfully extract information, we expect cognitive fit theory predictions to fail. Namely, the task characteristics and information presentation format do not have to match for performance to be better for people with considerable experience of solving tasks based on tabular data representation. We postulate that student subjects will perform accordingly to the predictions of the cognitive fit theory, but practitioners will not, due to the automatic patterns that they developed through the continuous use of tabular data representations. We hypothesise the following:

Hypothesis 1. When automatic patterns of problem-solving were developed, increased decision making performance is achieved regardless of the fit between task characteristics and problem representation.

Status Quo Bias Theory

The theory of the status quo bias aims to provide explanation for disproportionate preference of people to remain in the current situation (status quo) regardless of more optimal options being available (Samuelson and Zeckhauser, 1988). There are three main categories of reasons that explain the status quo bias: rational decision making, cognitive misperceptions and psychological commitment. Rational decision-making perspective postulates that people assess costs and benefit of switching situations. The costs include transition costs, i.e. costs incurred in adapting to the new situation and uncertainty costs representing perceptions of risks associated with the new situation. Cognitive misperceptions are linked with loss aversion (Kahneman and Tversky, 1979), namely people's perceptions of losses as more painful than equivalent gains. The 'loss' (change) of current situation could be perceived as more significant than it actually is. Finally, three elements contribute to the psychological commitment explanation: sunk costs, social norms and efforts to feel in control.

The status quo bias has been used in the IS literature to explain the resistance of people to accept the introduction of a new system or technology (Kim and Kankanhalli, 2009). Therefore, it is relevant to the current study using practitioners and the BIS they use for their work. Previous research has demonstrated that people will choose a problem representation that fits their cognitive style (Luo, 2019). However, the study ignored the effects of previous experience since it only used students as research subjects. One study provided some initial evidence for this effect, where students with more experience of using the old system were more satisfied with the old system regardless of the improvements brought about by the new interface (Pajić, 2014). Based on that evidence, we propose the following hypothesis to account for the scenario of using practitioners who are used to using a tabular representation for their work:

Hypothesis 2. People with experience of using a certain information representation format will prefer that format regardless of their cognitive style.

The figure below illustrates graphically the models proposed in this study to test the two hypotheses. The next section describes the experimental methodology employed to test it.

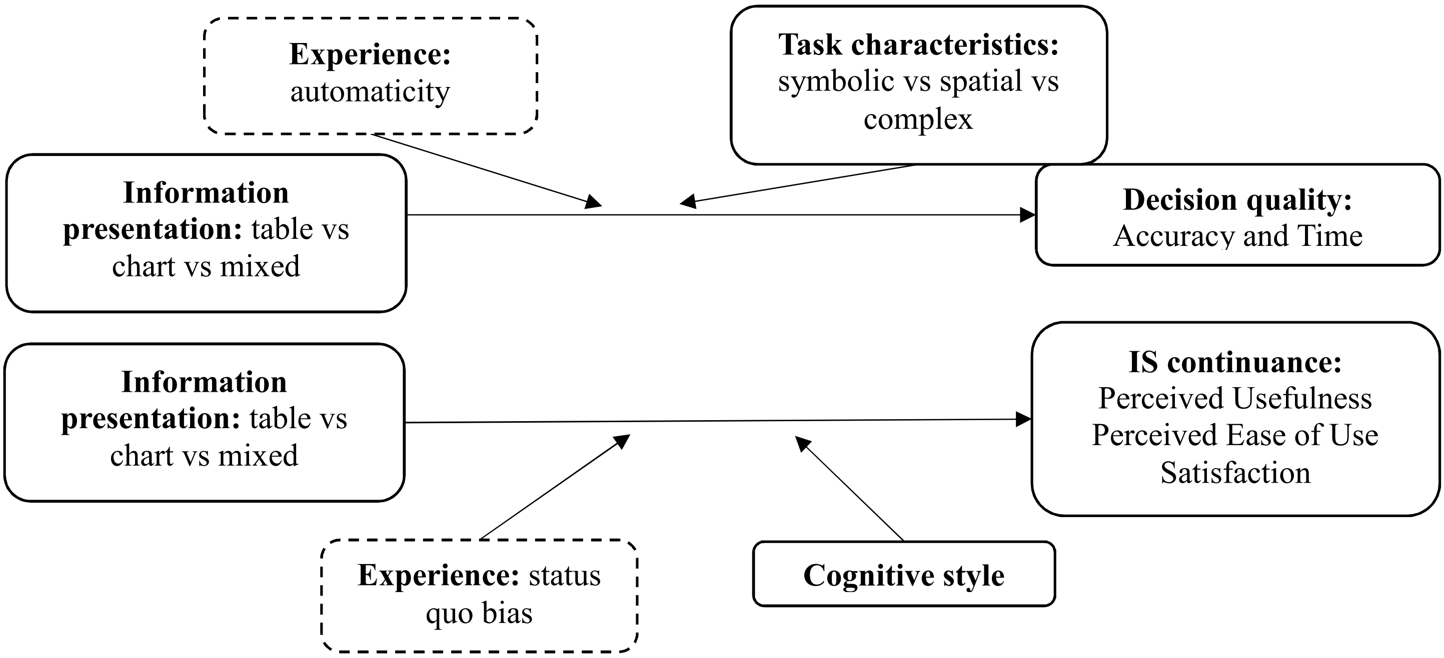

Figure 1 Research models used in this study. Moderators in dashed boxes are predicted to affect practitioners, the others students.

Methodology

Study design

To test the hypotheses formulated above, we have designed an online between-subject experiment. We have taken extracts from a Business Intelligence System deployed and used by approximately 80 small food businesses. The system consists of a number of modules presenting the following data: company performance, wider market performance, customer and competitor data. All of the data is presented in a tabular format.

To design the experiment, we used the tables extracted from the system ('tables' condition) and created graphical visualisations ('charts' condition) and enhanced them with data labels (‘mixed’ condition)[2]. Next, we prepared a set of 18 information extraction tasks, commonly performed in practice. The tasks are both simple (symbolic and spatial) and complex in nature to reflect the variety of scenarios faced by practitioners using this system. There are six tasks of each type.[3]

As a result, we use a 3x3x2 (Information Presentation: tables, charts, mixed x Task Characteristics: symbolic, spatial, complex x Experience: low and high) between-subject design. Each subject begins the experiment by being randomly allocated to one of the information presentations conditions (tables, charts or mixed) and then performs 18 information extraction tasks of spatial, symbolic and complex nature. Each task is presented as a separate screen to guarantee that time taken to answer was not obstructed by additional questions. An extract from real performance data from a major UK supermarket is used to populate the visualisations in all of the conditions to ensure a link to the practice. After completing the tasks, each participant is asked a number of questions related to their cognitive styles, perceptions of the visualisations and demographics.

Measurement

We measure the decision quality with time taken to submit an answer and by considering the errors in the subjects’ choices. Apart from the objective decision quality measures, we also used a number of subjective perceptual measurements. Preferences for a presentation format is evaluated using IS continuance constructs, which answers the call for linking information presentation literature with the extant IS literature (Bačić and Fadlalla, 2016). They include: Perceived Usefulness, Perceived Ease of Use and Satisfaction – the most commonly used predictors for technology acceptance and continuance. The items were measured with a 7-point scale adapted for the purpose of this experiment from the original scales (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).

Participants

The subjects were recruited using an online platform, Prolific. 87 female [59%] (age: $\mu = 23.1$, $\sigma = 6.4$) and 60 male [41%] (age: $\mu = 26.8$, $\sigma = 9.2$) students took part, with a screening applied for UK nationality and student status. Participants were enrolled on the following degree courses: 97 bachelor [66%], 29 masters [20%], 13 other [9%] and 9 PhD [6%]. An experienced pool consisted of 80 female [54%] (age: $\mu = 40.9$, $\sigma = 10.0$) and 68 male [46%] (age: $\mu = 37.4$, $\sigma = 9.7$) participants, with a screening applied for UK nationality, full-time employment in managerial positions. Participants came from a variety of industries, with the most common being 14 education [9.5%], 13 manufacturing [8.8%], 12 retail [8.1%], 7 IT [4.7%] and 6 construction [4%]. The survey lasted 15 minutes and participants were rewarded with £2.

Preliminary Findings

This is still work in progress so only few aspects of the study were examined, and exclusively in descriptive manner. However, the preliminary findings already highlight some interesting aspects.

[2] Exemplary visualisations used can be found in the Appendix.
[3] Exemplary tasks used can be found in the Appendix.

As predicted by the cognitive fit theory, for the student pool tables facilitate shortest times for symbolic tasks while charts enable shortest completion times for spatial tasks. However, the differences are minor and ANOVA analysis indicates the differences are not statistically significant. But a statistically significant difference is revealed when it comes to complex tasks, this is clearly visible in the Figure 2. Tables are by far the worst choice for complex tasks and there is no difference between charts and the mixed condition. This is a very important point because hardly any work in real-life scenario is simple in nature and yet many systems keep utilising tables to present the relevant information.

However, a somewhat different picture emerges when we look at the results for the experienced subject pool. Here, clearly tables are the best choice for symbolic tasks but also, they seem to facilitate shortest times for spatial tasks (differences not statistically significant). As for students tables seem to be the worst choice for complex tasks but unlike for students, charts seem to perform better than the mixed condition.

Task / Format	Total (n = 148)	Tables (n = 50)	Charts (n = 46)	Mixed (n = 52)
Symbolic	28.6 (27.7)	24.5 (18.3)	30.4 (23.6)	30.8 (36.8)
Spatial	26.0 (26.2)	27.3 (28)	24.8 (18.4)	25.8 (30)
Complex	55.9 (41.7)	65.1 (47) ***[4]	51.6 (42.3)	50.8 (33.7)

Table 1 Average time taken to complete the tasks for different conditions for the student subject pool (standard deviations reported in parentheses).

Task / Format	Total (n = 148)	Tables (n = 51)	Charts (n = 48)	Mixed (n = 49)
Symbolic	34.5 (31.9)	27.8 (31.2)***	43.0 (37.7)	33.1 (23.4)*
Spatial	27.7 (26.5)	26.2 (19.9)	28.4 (22.9)	28.6 (34.6)
Complex	60.6 (58.2)	66.0 (65.3)**	54.1 (42.8)	61.4 (62.8)

Table 2 Average time taken to complete the tasks for different conditions for the experienced subject pool (standard deviations reported in parentheses).

[4] Statistical significance levels reported in the following manner: *** <0.01, ** <0.05, *<0.1.

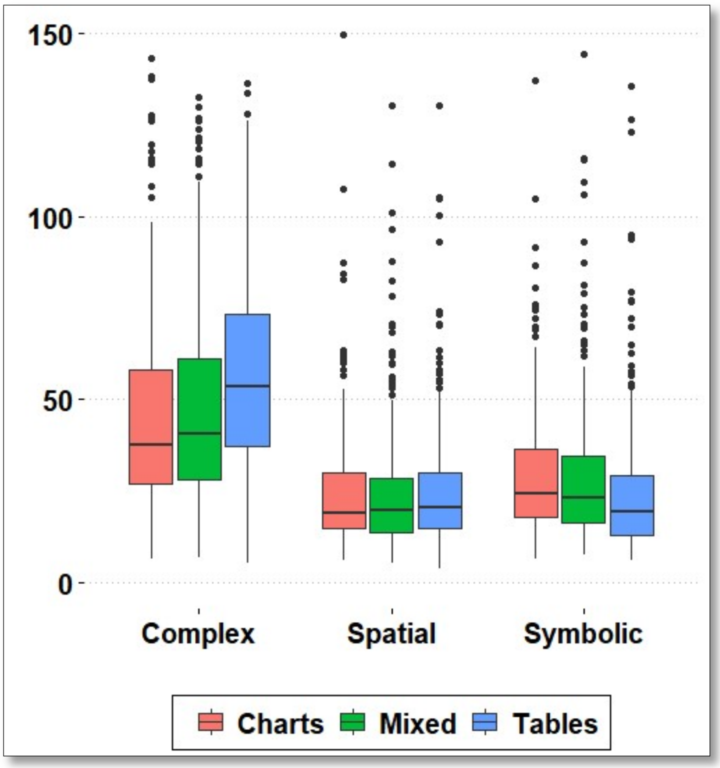

Figure 2 Boxplot for time taken to answer across conditions the student sample (the vertical axis presents time taken to complete the tasks (in seconds).

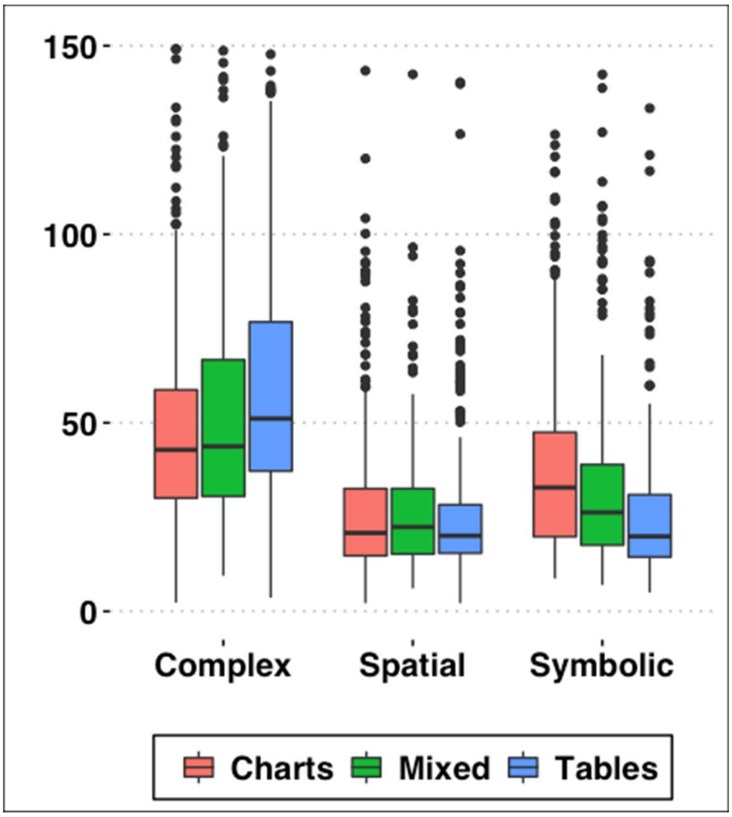

Figure 3 Boxplot for time taken to answer across conditions for the experienced sample the vertical axis presents time taken to complete the tasks (in seconds).

We also examined the perceptions of the subject pools about the visualisations they encountered. The participants perceived the visualisations to be relatively useful and easy to use and reported to be quite satisfied (averages around five on a seven-point scale). However, the perceptual measures are particularly interesting when contrasted with the objectively obtained results. For example, for the student subject pool, charts and mixed conditions facilitated very similar times to extract information but charts are perceived to be significantly more difficult to use resulting in less satisfied participants, which would indicate the mixed charts to be best for complex tasks.

However, for the experienced subject pool tables receive highest rankings on all measures, despite the fact that charts facilitated better performance on some tasks.

Variable / format	Total	Tables	Charts	Mixed
Ease of Use	5 (1.3)	5.1 (1.2)	4.6 (1.3)***	5.3 (1.2)
Usefulness	5.5 (1.3)	5.4 (1.4)	5.2 (1.2)	5.7 (1.3)
Satisfaction	5.3 (1.3)	5.4 (1.4)	5.0 (1.3)**	5.6 (1.1)

Table 3 Averages and standard deviations for perceptual measures across conditions for the student pool.

Variable / format	Total	Tables	Charts	Mixed
Ease of Use	5.1 (1.2)	5.4 (1.1)	5.0 (1.1)	5.0 (1.2)
Usefulness	5.6 (1.1)	5.8 (1.1)	5.5 (1.0)	5.6 (1.1)
Satisfaction	5.5 (1.2)	5.6 (1.4)	5.2 (1.2)	5.5 (1.1)

Table 4 Averages and standard deviations for perceptual measures across conditions for the experienced pool.

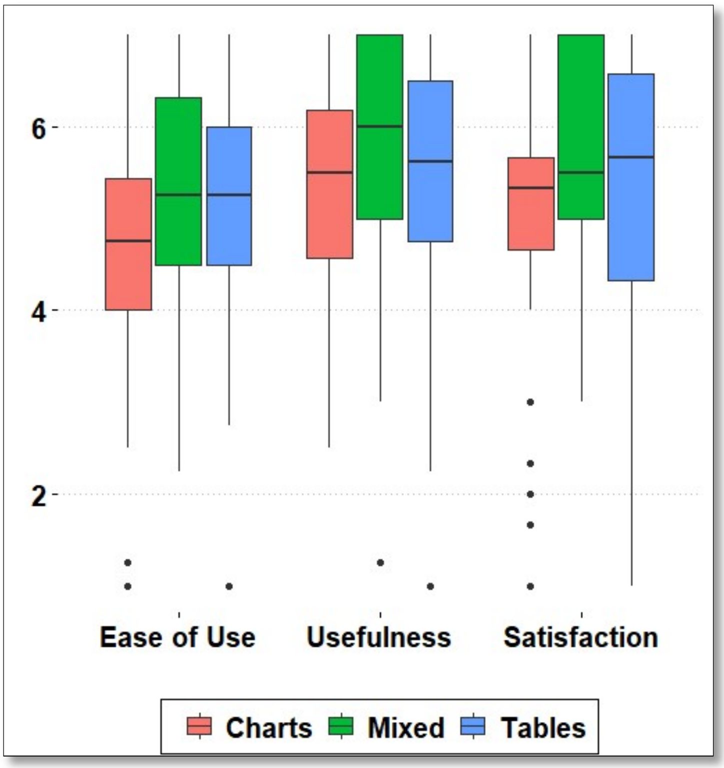

Figure 4 Boxplots for perceptual measures across conditions for the student pool

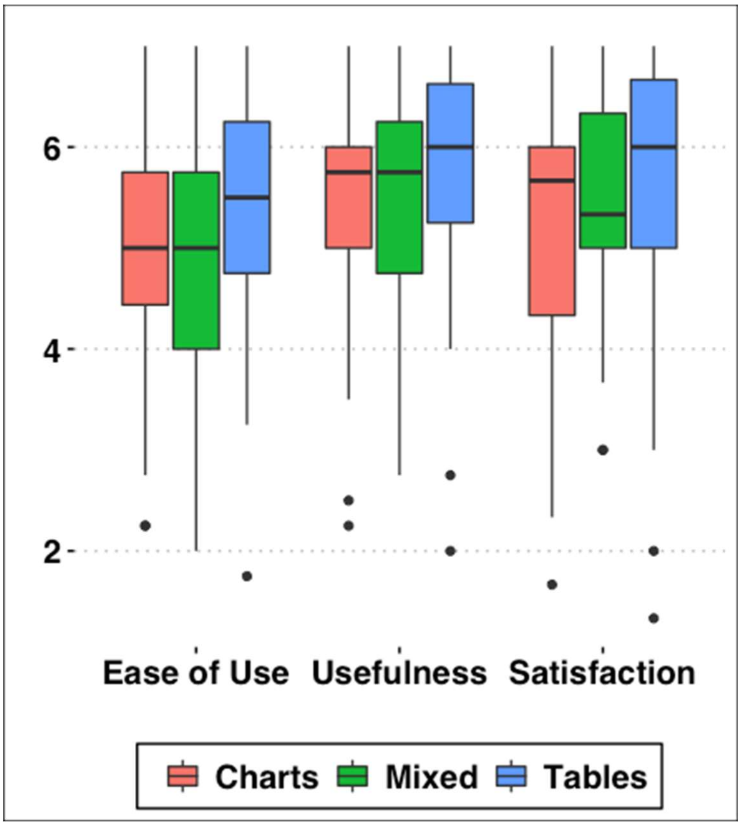

Figure 5 Boxplots for perceptual measures across conditions for the experienced pool

Conclusions

Although a significant portion of data remains to be analysed, the preliminary results highlight the importance of rigorous experimental analysis before the implementation of an information system. In this study, we report an online experiment which is used to inform a design and deployment of a visualisation-driven Business Intelligence System (BIS) which is to be used by approximately 80 small food businesses. Initial findings reveal that most commonly used tables are not effective (in terms of time) for complex information acquisition tasks. What is more, it is only through the combination of objective and subjective measures that additional nuances are revealed. Finally, the preliminary findings hint that certain mechanisms might be biasing more experienced participants towards tables both in terms of perceptions and objective performance.

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Appendix

Behavioural Change Model

Behavioural change is approached with a COM-B (Capability-Opportunity-Motivation -> Behaviour) model (Michie, van Stralen and West, 2011). COM-B model postulates that there are three components which constitute a behaviour, and interventions can be targeted at any combination of them. Michie et al. (2011) explain that every behavioural change intervention has to start with a theoretical analysis of the behaviour in the specific context, which for us is BIS use by small businesses. Then interventions are chosen to influence specific constructs which were determined to be antecedents of a certain behaviour. The figure below presents the theoretical analysis of BIS use.

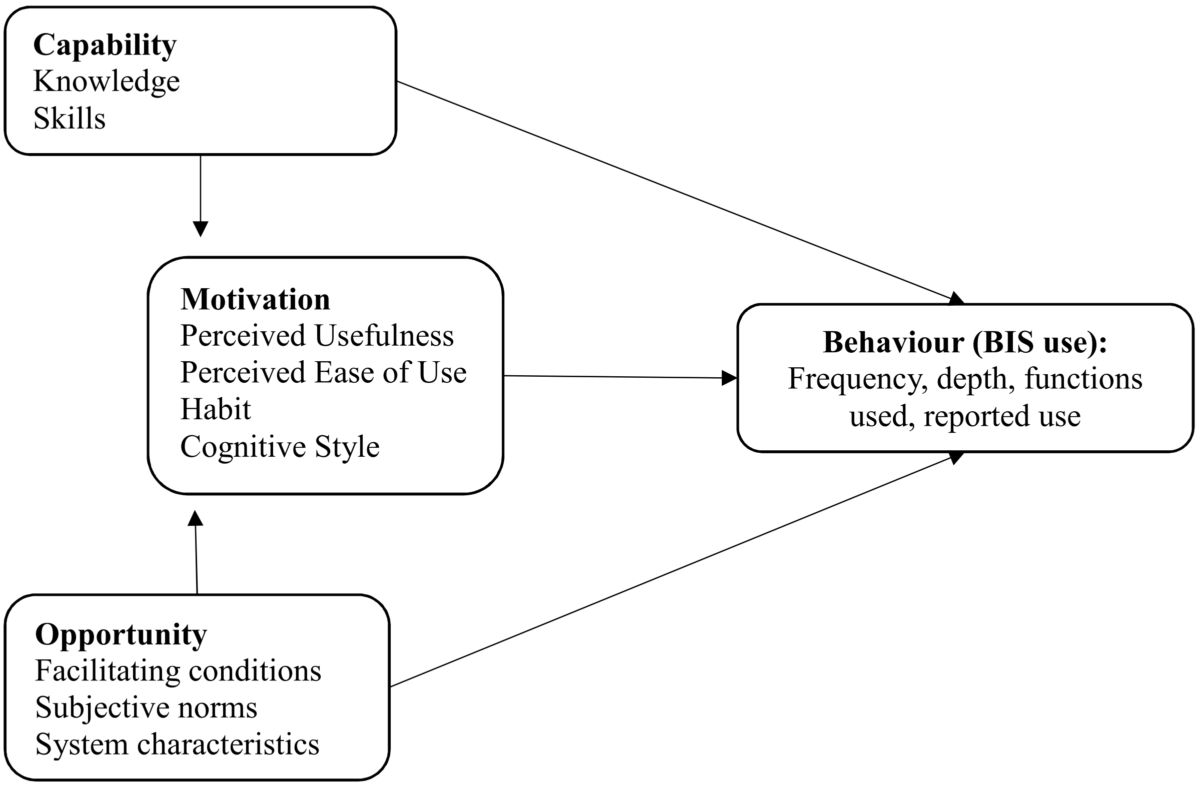

Figure 6 COM-B model applied to IS continuance behaviour, Business Intelligence System use.

The environmental restructuring intervention aims at changing the system characteristics and thus impacting the motivation component and ultimately leading to the increased BIS use. It involves three distinct stages:

1. A change of the mode of delivery from offline to online.
2. An online experiment to determine an ‘optimal’ presentation format.
3. A field experiment where half of the companies are switched to a system that presents information in a way determined to be best in the online experiment.

In stage 1 we observe which companies adopt a new system and which do not. We also examine the impact the change had on the actual and reported use of the business intelligence.

In stage 2 we determine how the business intelligence should be presented in order to facilitate effective information extraction. We examine how different information presentation formats impact decision quality (accuracy, time) and users' perceptions of the visualisations.

In stage 3 we switch half of the companies from the old table-based system to a new visualisation-driven system. We observe how users deal with the change, and what impact it has on their behaviour. Finally, we link the use of the system with objectively measured organisational performance.

Information Presentation Conditions

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 7 'Tables' condition

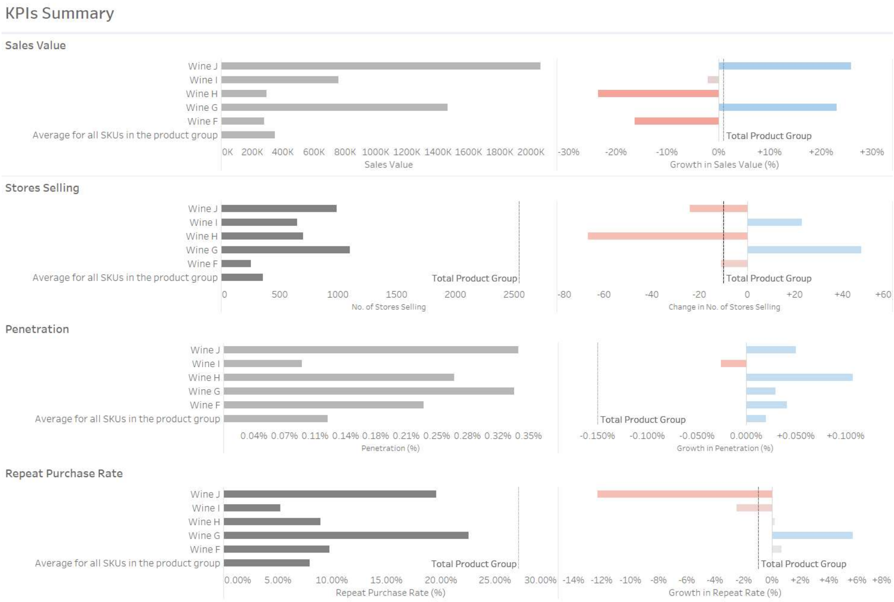

Figure 8 'Charts' condition

Figure 9 'Mixed' condition

Exemplary tasks

Symbolic:

- What is the penetration of product X?
- What is the repeat purchase rate of product X?

Spatial:

- Is the sales growth for product X higher than for the total product group?
- Is the number of stores selling for product X higher than the average for all SKUs in the product group?

Complex:

- Which product is at the greatest risk of being delisted? (Hint: 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)
- Which product is most likely to have their number of stores selling increased? (Hint: a 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)