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Interactive data visualisation for accounting information: a three-fit perspective

Arif Perdana [a], Alastair Robb [b] and Fiona Rohde[b,c]

[a]Design & Specialised Business Cluster, Singapore Institute of Technology, Singapore, Singapore; [b]UQ Business School, The University of Queensland, Brisbane, Australia; [c]TC Beirne School of Law, The University of Queensland, Brisbane, Australia

ABSTRACT

The volume of freely available accounting information is rapidly becoming overwhelming. To be useful, information needs to be delivered to users in a suitable, relevant, and understandable form. Interactive data visualisation (IDV) can help address this need for useful information by organising accounting information, especially financial reports, into forms with these qualities. Given both their prevalence and their likelihood of being future users of IDV, the purpose of this research is to examine the appropriateness of IDV for non-professional investors' use when they access accounting information. This research uses a 2 × 2 experimental approach involving 404 participants representing non-professional investors from diverse demographic backgrounds. This research suggests that IDV mitigates non-professional investors' restricted investment capabilities by presenting information that is more salient, thus reducing non-professional investors' cognitive effort. This combination allows such investors to better perform both simple and multipart investment tasks. By integrating three information systems' fit perspectives (i.e. task technology, information quality, and cognitive), this research explains IDV's suitability and fit within the accounting domain. We also discuss how the findings can inform practice and span interdisciplinary research into data and information visualisation.

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Interactive media; data visualisation; cognitive theories; task-technology fit; information visualisation; visual analytics

1. Introduction

Individuals are increasingly compelled to find effective and efficient ways to synthesise the growing volumes of available data and information. Enhancing the presentation of data and information using interactive visualisation is important in helping individuals arrive at better decisions. Research into interactive data visualisation (IDV) has been applied to: (1) marketing, where interactive decision environments can influence users' psychological evaluations, choices and performances (Lurie and Mason 2007); (2) accounting, where IDV better provides users with relevant information for decision making (Dilla, Janvrin, and Raschke 2010; Dilla and Raschke 2015); and (3) education, where IDV enhances students' experiences and thus improves learning outcomes (Fouh et al. 2014; Mata, Lazar, and Lazar 2016). In short, IDV helps individuals to more readily obtain and process relevant information, thus improving their decision making.

While potential uses of information presentations and visualisations are relevant to decision making, which data and information visualisations work best for users remains under-researched (Rensink 2014; Goldstone, Pestilli, and Börner 2015). To this end, we assess the value of usability and individuals' mental models and how well visualisations apply to different tasks (Wassink et al. 2008). Because these measures relate directly to the fit (or suitability) of IDV, they are central to our investigation.

We use two information systems' (IS) theories related to fit: task-technology fit (TTF) (Goodhue 1995; Goodhue and Thomspon 1995) and cognitive fit theory (CFT) (Vessey 1991). TTF examines the extent to which specific tasks, technology options, and individuals fit together and thus improve performance. CFT examines how types of information (problem representations) fit with task characteristics (problem-solving tasks) to provide consistent users' problem representations and better problem solving. While these two theories have been widely used in IS research, information quality (IQ) theory could also be considered because it defines which information is fit for use (Wang and Strong 1996; Neely and Cook 2011). Of the three theories listed so far, CFT and IQ apply to a wider sphere of research than TTF, which applies to a narrower technological context.

When drawing on CFT and IQ in the IS field (this field includes accounting information systems [AIS]),

CONTACT Arif Perdana arif.perdana@singaporetech.edu.sg Design & Specialised Business Cluster, Singapore Institute of Technology, Singapore, Singapore
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we must consider the context and the phenomena to which the theory and framework are applied (Benbasat and Zmud 2003; Tate, Evermann, and Gable 2015). TTF and IQ are, perhaps, more perceived than reasoned, whereas cognitive fit might suitably be described as depending on decision making. How perceptions and cognitions, held and used by individuals when they interact with IS, can influence their performance remains somewhat unknown in IS research (Davern 2007; Davern, Shaft, and Te'eni 2012).

IDV permits individuals to customise their presentation interfaces to their tasks. Investigating IDV, therefore, can exemplify technological advancements in IS interfaces that can influence individuals' perceptions, cognitions, and performance. Exploring the suitability of IDV using a three-fit perspective permits a more complete investigation of TTF, IQ, and CFT. Given the prevalence of non-professional investors and their likelihood of being future users of IDV, we study their interactions with IDV (Arnold et al. 2012). We base our investigation on our understanding of TTF, IQ, and cognitive processing to, which leads to the following high-level research question:

To what extent does IDV fit non-professional investors' use?

Using these three theories (i.e. TTF, IQ, and CFT) to examine the concept of fit, leads us to what we call a three-fit perspective taken to understand the extent of its support for the effects of IDV. In this study, we investigate the fit between IDV and non-professional investors, and how their investment decisions relate to the tasks they perform. Drawing on the results of our sample of 404 such investors, we find that IDV enables nonprofessional investors to more quickly accomplish investment tasks, even if those tasks are multipart.[1] Further, IDV permits non-professional investors to filter and focus on the information most pertinent to their tasks. Given that perceptions and cognitions matter in human–computer interactions, our analyses suggest that non-professional investors' performance and fit have a positive relationship. Our findings also agree with the two types of fit in the agent-task-technology (ATT)-fit framework (i.e. user-reality fit, and user-tool fit) (Davern 2007). Drawing from interdisciplinary research may improve the design aspects of IDV and help explain which human cognitive abilities best suit interactivity and visualisation.

This study is set out as follows. First, we discuss the relevant theories, review the IDV-related literature, and develop hypotheses. Second, we present our research method followed by the results of our analysis. Third, we discuss the findings and offer both theoretical and practical contributions. Finally, we introduce the study's limitations, propose future research, and briefly conclude.

2. Background

2.1. Interactive data visualisation (IDV)

Four major terminologies referring to visualisation science appear in the literature, i.e. visual analytics (VA), information visualisation (InfoVis), scientific visualisation (SciVis/ViSC) and interactive data visualisation (IDV). VA uses interactive visual interfaces to facilitate analytical reasoning. VA seeks to help human intelligence understand data by exploiting machine intelligence capabilities to deliver appropriate visualisations (Thomas and Cook 2005; Yi et al. 2007; Goldstone, Pestilli, and Börner 2015; Rensink 2015). InfoViz uses machines to produce and deliver the most suitable, effective and efficient visual representations to help strengthen human cognition (Card, Mackinlay, and Shneiderman 1999). SciVis transforms the symbolic into the geometric, enabling researchers to more easily observe simulations and computations (McCormick, DeFanti, and Brown 1987, 3). Infovis focuses on nonphysical data, whereas Scivis focuses on physical data. While literature attempted to differentiate Infovis and Scivis, both serve the same purpose of enabling knowledge inquiry (Rhyne 2003). IDV refers to visual representations enhanced with interaction capabilities that permit individuals to display multiple visual effects, actively control those presentations, and use those presentations to analyse information (Dilla, Janvrin, and Raschke 2010). The term IDV appears to differentiate the existing static visualisation techniques for decision making.

With technological advances, research has evolved to include interaction techniques that increase the usefulness of, and relevance of presentations and visualisations to, decision making. While these terminologies differ, taken together, they achieve the ultimate purpose of visualisation science. They help users to better understand both the available data and what tasks they can perform to take advantage of machine-generated enhanced visualisations. Visualisations enable users to better make sense of and leverage insight from data.

Visual representations and interactive technologies help users to better understand information and analyse it, even though that information may be complex and/or sizeable (Thomas and Cook 2005). Research into information presentation confirms that domain knowledge and experience can influence decision outcomes and quality. For example, visualisations, from traditional

line charts to pixel-based ones, can improve professional investors' ability. When dealing with large data sets, pixel-based visualisations allow investors to derive more knowledge including ways of decision making that may not occur with traditional visualisation techniques (Ziegler, Nietzschmann, and Keim 2008). Visualisation enhancement benefits both non-experts and experts. When interacting with graphical formats compared with tabular formats, individuals with little accounting experience can thus perform better than their more experienced contemporaries (Cardinaels 2008).

Visualisation enhancements, with the addition of interactive features (e.g. editing and/or changing capabilities), allows non-experts to explore information more fully than when they use traditional presentations (e.g. PDF or HTML files). Using FinVis, an interactive visual and analytics tool, Rudolph, Savikhin, and Ebert (2009) find that it permits non-experts to explore data and to overcome cognitive constraints by allowing users to evaluate return and risks from multiple decisions. Arnold et al. (2012) suggest that IDV should improve the ability of both non-professional and professional investors when they search for information. When interacting with IDV, those who are not expert are likely to evaluate which information is salient and improve more than those who are expert. Because IDV improves their search strategies and risk assessment more than professional investors, non-professional investors gain more from using IDV (Arnold et al. 2012).

2.2. Fit in information systems (IS)

Davern (2007, 56) defines fit in IS as 'The degree of functional correspondence between an agent's knowledge and the structure and features of the environment that specify supported actions and available information relative to a specific task.' TTF and CFT are two theories frequently used to explain fit within IS. TTF explains fit within the scope of a particular technology (Goodhue and Thomspon 1995). TTF suggests that the relationships between tasks, the functionalities of the technology, and the individuals involved affect decision-making performance (Goodhue and Thomspon 1995). Ajayi (2014), for example, examines the fitness between IDV and non-professional investors' characteristics and the decision environment. She finds that the interactivity of presentations enhances the fitness of IDV use, while the visualisation of the presentations has little influences on such fitness. The differing levels of influence are likely caused by task complexity levels.

While Ajayi (2014) investigates the impact of interactivity and visualisation on cognitive load, task fit and accuracy, she does not focus on the fitness of IDV for decision making. This study thus differs from hers in that we study non-professional investors' use of IDV and how well it fits with their information processing and decision making. To determine the fit, we combine IQ and CFT with TTF theory.

Unlike TTF, which considers the fit between individual, technology and tasks, CFT considers only task characteristics to explain fit. CFT suggests that fit occurs when the tasks match individuals' representations of that task. That is, when fit occurs, individuals can process the available information and reduce their cognitive load, thus leading to improved task speed and accuracy (Vessey 1991). While theoretically supported, CFT is used mostly to explain individuals' information processing rather than the characteristics of technology used to deliver the information. We believe that technology characteristics contribute, at least in part, to individuals' information processing.

Both TTF and CFT, however, seem to overlook the inherent and perceived quality of information when they are used to explain fit. While CFT might consider the extent to which information presentations can influence how individuals model their tasks, it does not focus on how well the information fits, nor the extent to which the quality of the information supports the tasks at hand. Similarly, TTF does not consider the quality of the information obtained from a specific technology.

As IQ refers to information that is fit for use, we believe that IQ must be considered when explaining fit in IS, (Wang and Strong 1996; Neely and Cook 2011). IQ is important because it helps users to achieve higher levels of task accuracy. All things being equal, better IQ should enhance decision making (Neely and Cook 2011). The two IQ categories that are particularly relevant to the enhancement of non-professional investors' performance are contextual information quality and representational information quality. The first, referring to value-added-ness and relevancy, and the latter, referring to ease of understanding, and conciseness, are relevant to non-professional investors' perceptions of financial information presentations. Yuan and Wang (2009) and Birt, Mutushamy, and Bir (2017) agree that XBRL-enabled financial statements will enhance accounting information by improving the perspicuity, relevance, and comparability of the information being disclosed.

Jung et al. (2005) suggest that decision-making improvements can be elicited from both higher contextual and representational IQ, for example, contextual IQ allowing users to quickly filter information searches and increasing users' confidence when making investment decisions (Wu, Chuang, and Joung 2008). Jung et al. (2005) finds that time spent on problem solving by

users was substantially reduced by the presence of contextual IQ. While contextual IQ focuses on non-professional investors' information retrieval, representational IQ aligns more closely with their thinking. Higher contextual IQ ensures that the information presentations assist users to better express and translate the meaning of the contained information, and provides feedback about what users should do with the information (Lee 2011). Higher representational IQ helps increase the information's intelligibility (Wang and Strong 1996).

3. Hypotheses development

3.1. IDV and task-technology fit

Ajayi (2014) examines IDV, non-professional investors' characteristics, and task environment, and finds that, while presentations' interactivity enhances how IDV fits, the visualisations of the presentations they have little influence on it. Following TTF theory, and given that non-professional investors are likely to want to lessen task complexity, we expect that the information enhancements permitted by IDV will better support non-professional investors (Hodge and Pronk 2006). We contend that IDV, by improving fit between tasks, non-professional investors' characteristics, and the task environment, can improve non-professionals' performance accuracy.

We speculate that the level of task complexity may cause the apparent disparity between interactivity and visualisation that affects the fit of IDV for non-professional investors. Ajayi (2014) uses a single task to examine the fit between interactivity and visualisation in IDV without considering the levels of task complexity. This approach may adversely affect interpretation the findings because each task may require different levels of interactivity and visualisation. Including task characteristics in IDV studies can better inform designers of visualisation so that they can suitably align IDV with users and their specific purposes (Lam et al. 2012).

Relative to the fit of IDV from the perspective of TTF theory, the following hypotheses support Ajayi's (2014) findings. Unlike Ajayi, our study does not separate interactivity from visualisation but manipulates the data visualisations into two levels, IDV and non-IDV. Further, we incorporate two types of task (i.e. simple and multipart). Both are provided to investigate whether non-professional investors' interactions with IDV are better suited to solving simple or multipart tasks. Better performance of non-professional investors when undertaking such tasks will help clarify whether they obtain better task, technology and individual fit from their interactions with IDV. We again speculate that IDV positively influences non-professional investors' TTF. Further, the better the TTF achieved by non-professional investors' interactions with IDV, the more they should achieve greater task accuracy. Hence, we formulate Hypotheses 1 and 2.

Hypothesis 1: Non-professional investors who interact with IDV to solve investment tasks report better task-technology fit than non-professional investors who interact with non-IDV to solve the same investment tasks.

Hypothesis 2: When interacting with IDV to undertake investment tasks, non-professional investors' better task-technology fit relative to IDV leads to greater task accuracy compared with non-professional investors' using non-IDV to undertake the same investment tasks.

3.2. IDV and IQ

Non-professional investors' decision making can be improved if they are provided with more relevant information (Pinsker 2007). When financial statements conform with their expected formats, non-professional investors display better information acquisition, make better judgments about financial data, make more accurate financial analyses, and thus make better investment decisions (see Maines and McDaniel 2000; Frederickson and Miller 2004; Hodge, Hopkins, and Wood 2010). Given that financial data are capable of being presented in an IDV format, non-professional investors have viewed companies using XBRL-enabled financial statements positively (Pinsker and Wheeler 2009; Arnold et al. 2012). Such interactive financial statement presentations permit easier information searches by investors (Pinsker and Wheeler 2009; Arnold et al. 2012).

As IDV permits comparisons of multiple financial statements simultaneously in concise presentations, we expect that non-professional investors who interact with XBRL-enabled financial statements will make better-informed decisions, as they can actively control the information because it aligns with their expectations. Following this argument, we investigate the perceived, rather than the inherent, quality of IDV.[2] Because our study focuses on investigating non-professional investors' interactions with IDV, perceptual measures are more relevant than inherent measures of IQ provided by IDV (Jayawardene, Sadiq, and Indulska 2013; Wang and Strong 1996).

Because items in traditional financial statements and those using IDV present equivalent information, this tool does not affect information equivalence. Interactivity and visualisation enhancements, however, make the information in IDV more salient and thus easily

accessible so that users can more readily evaluate the information. IDV permits users to control information presentations and visualisation so that they can select and view the information most relevant to their decision-making needs. While IDV maintains information equivalence and the information is provided in a form that better fits users' needs, they are thought to exhibit more confidence when making investment decisions with IDV. This implies that IDV will have better IQ than non-IDV.

XBRL-enabled financial statements enhance IQ by adding value to the information they disclose using three complementary qualities: improving understandability, being relevant, and being comparable (Yuan and Wang 2009). Wu, Chuang, and Joung (2008) suggest that contextual IQ (i.e. value-added-ness and relevancy) simplifies information searching and increases users' confidence when making investment decisions. Jung et al. (2005) find that users' time spent on problem solving is substantially reduced by the presence of contextual IQ. While it focuses on non-professional investors' information retrieval, representational IQ (i.e. ease of understanding and conciseness) more closely aligns with their information processing abilities. Research into accounting information processing by individuals establishes that, when financial information with higher representational IQ aligns with users' task representations, decision-making performance improves (e.g. Kelton, Pennington, and Tuttle 2010; Kelton and Pennington 2012; Dilla, Janvrin, and Jeffrey 2013). As we noted earlier, because information presented using IDV has better quality than traditional presentations, we contend that IDV should lead to non-professional investors more positively perceiving IQ. The more positive their perceptions when interacting with IDV, the more likely will be their accuracy. Thus, Hypotheses 3 and 4 are presented.

Hypothesis 3: Non-professional investors who interact with IDV to solve investment tasks report better-perceived information quality than non-professional investors who interact with non-IDV to solve the same investment tasks.

Hypothesis 4: When interacting with IDV to undertake investment tasks, non-professional investors' perceived better information quality relative to IDV leads to greater task accuracy compared with non-professional investors' using non-IDV to undertake the same investment tasks.

3.3. IDV and cognitive fit

Information presentations and task characteristics significantly predict decision-making outcomes like task accuracy (Jiang and Benbasat 2007; Speier 2006; Tang et al. 2014). CFT refers to information presentations and task characteristics as problem-solving elements (Vessey 1991). When problem-solving tasks (e.g. task characteristics) align with the problem representation (e.g. information presentations), those problem-solving elements better equip users to consistently apply fitting representations when solving their problems (Vessey 1991). Prior studies have established the fit between information presentations and task characteristics (Kelton, Pennington, and Tuttle 2010; Speier 2006). Specific tasks (e.g. comprehension, comparison, and review) require different information presentations to support better quality decision making (Hard and Vanecek 1991).

CFT is useful for understanding the extent to which users exert cognition when making decisions. Unlike TTF, which specifically acknowledges technology's influence, CFT only measures the effort that users spend in performing their tasks but does not consider how particular technologies influence them. For example, when information presentations and task characteristics are incompatible, users will try harder to understand the information regardless of the presentation technology used. That is, users have to engage in higher thinking than they do when information presentations and task characteristics fit (Vessey 1991). While CFT acknowledges that specific tasks can lead to different fit, unlike TTF, CFT does not consider different technology characteristics. Further, because TTF measures users' perceptions, cognitive fit should be separately investigated from TTF and IQ (Tate, Evermann, and Gable 2015). We expect that IDV can reduce non-professional investors' thinking load. Further, the reduced thinking load afforded by non-professional investors' interactions with IDV likely frees them to devote more time to achieving greater task accuracy. Therefore, we propose Hypotheses 5 and 6:

Hypothesis 5: Non-professional investors who interact with IDV to solve investment tasks report better cognitive fit than non-professional investors who interact with non-IDV to solve the same investment tasks.

Hypothesis 6: When interacting with IDV to undertake investment tasks, non-professional investors' cognitive fit relative to IDV leads to greater task accuracy compared with non-professional investors' using non-IDV to undertake the same investment tasks.

In summary, our research hypotheses compare three-fit perspectives in information systems (see Figure 1). We present the research model in three parts to explain the variables involved in the hypotheses formulation.

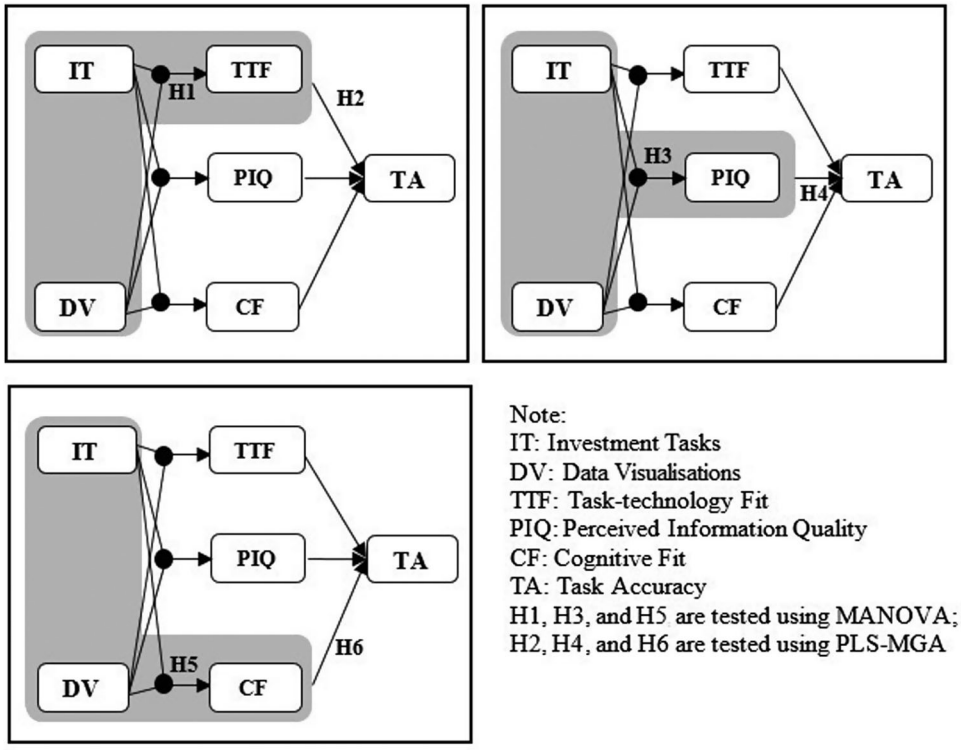

Figure 1. Research model.

4. Research design and participants

4.1. Experimental design

We conducted an experimental study using a 2 × 2 design (i.e. data visualisations vs investment tasks) to test our hypotheses. Independent variables were manipulated using experimental procedures and scenarios. Dependent variables' data were collected using questionnaires and from data derived by comparing participants' answers with model answers to test their accuracy. To increase the robustness of our statistical analyses, we evenly and randomly allocated participants to four conditions: (1) IDV and simple tasks; (2) Non-IDV and simple tasks; (3) IDV and multipart tasks; and (4) Non-IDV and multipart tasks.

4.2. Interactive data and information visualisation platform: Calcbench

We used *Calcbench* to access XBRL-enabled interactive financial statements drawn from the US SEC's corporate financial data repository. *Calcbench*'s interactivity features are multiple visualisations (e.g. graph, table, text, in-combination), active control (e.g. permits individuals to control visual representations, comparisons made from financial statements, detailed analytics performed on financial statements), and analytics derived from text searches, company searches, data queries, quick reports, financial ratios, financial statements comparisons, chart analyses, industry trends and collaborative working (see Appendix A, Figure A1). Appendix A, Figures A2 to A4 displays the comparison of IDV and non-IDV; Appendix A, Figures A5 to A6 displays the experimental instructions.

4.3. Experimental variables

4.3.1. Independent variables

Independent variables in this study are data visualisations (i.e. IDV and non-IDV) and investment tasks (i.e. simple and multipart). We used data visualisations of the actual financial statements retrieved from the SEC. The IDV version was accessed using www.calcbench.com, whereas the non-IDV version was accessed using the SEC website. By using actual financial statements of two large pharmaceutical companies, we sought to improve the generalizability and external validity of the research findings. We used the pseudonyms (i.e. *Apothecary* and *Pharmacy*) to maintain the anonymity of both companies. We manipulated the tasks to replicate basic investment analysis tasks such as calculations (i.e. current ratio) and comparisons (i.e. net earnings and total assets). For the simple tasks, participants undertook simple information acquisitions and calculations whereas, for the multipart tasks, participants were required to find information and calculate financial

Table 1. Experimental tasks.

Experimental tasks	
Simple tasks	Multipart tasks
1. Entering Net Earnings for the two companies	1. Entering Net Earnings for Apothecary and calculating the percentage change (% change Quarter on Quarter) to the Net Earnings attributable to Apothecary
2. Entering the value and/or component to calculating Net Income or Profit Margin for the two companies	2. Calculating the difference of Net Earnings between Apothecary and Pharmacy
3. Entering Total Assets for the two companies	3. Entering Total Assets for Apothecary and calculating the percentage change (% change Quarter on Quarter) to the Net Earnings attributable to Apothecary
4. Entering the value and/or component to calculating Current Ratio for the two companies	4. Calculating the difference of Total Assets between Apothecary and Pharmacy

ratios before comparing analyses (see Appendix A, Table A1). The experimental tasks required participants to interact with IDV or non-IDV. Table 1 details the experiments.

4.3.2. Dependent variables

Before measuring the dependent variables, we required participants to undertake investment analysis tasks. Each provided their perceptions and experiences of solving the specific investment tasks with IDV or non-IDV. The following dependent variables were manipulated and assessed during the experiment.

Task-technology fit refers to the degree to which individuals perceive that using IDV fits with their tasks and their abilities. This variable is based on perceptual measurements captured in a post-task questionnaire using nine reflective items reported on a seven-item Likert-type scale adapted from (Goodhue and Thompson 1995; McGill and Hobbs 2008; Schrier, Erdem, and Brewer 2010; D'Ambra, Wilson, and Akter 2013).

Perceived information quality refers to the degree to which individuals perceive IDV as easy to understand and process, and fitting with their mental representations. This variable is based on perceptual measurements captured in a post-task questionnaire using eight reflective items reported on a seven-item Likert-type scale adapted from (Wang and Strong 1996).

Cognitive fit refers to the degree of individuals' cognitive effort (i.e. cognitive load and cognitive convenience) when acquiring the information from the IDV or non-IDV. The cognitive load is negatively-keyed, whereas cognitive convenience is positively-keyed.[3] This variable is based on self-reported decision processes captured in a post-task questionnaire using six reflective items reported on a seven-item Likert-type scale adapted from (Hong, Thong, and Tam 2004; Kim and Yoo 2000).

Task Accuracy refers to the actual score for individual's answers of the assigned investment tasks. Participants' answers were graded for accuracy based on the model answers. The answers are objective and, because no interpretation is involved in grading, one of the authors can grade all participants' answers.

4.4. Participants

A total of 404 usable responses were collected using a research panel (n = 76), the online crowd-sourcing market: *Amazon Mechanical Turk* (OCM-AMT) (n = 248), and business school students from a major Australian university (n = 80). Students were considered suitable proxies for non-professional investors for three reasons: (1) they are relatively familiar with accounting, investment terminology, and basic investment analysis (Libby, Bloomfield, and Nelson 2002); (2) when conducting investment tasks, they are similar to practitioners unless the tasks require them to make any ethical judgments (Liyanarachchi 2007), and (3) being from a business school, students take mandatory accounting-related courses: *Accounting for Decision Making*, *Financial Accounting for Business*, and *Principles of Financial Accounting*. For both the research panel and OCM-AMT screening, questions were used to ensure that participants suitably represented non-professional investors (see Appendix B for the screening questions). Only those who passed the screening questions could participate in this study. We believe that the participants' diversity improves the generalizability of our research findings. To reward participants for taking the time to be involved in the experiment, we provided a monetary incentive equivalent to AUD $7.5 to 23.

5. Results

5.1. Pilot test

Before the main experiment, we conducted a pilot test using 48 postgraduate students from a large Australian university to ensure that the experimental materials and procedures were reliable and understandable. We required participants to interact with IDV or non-IDV to solve specific investment tasks and also complete both a treatment manipulation check and an instructional manipulation check to establish construct and statistical conclusion validity (Oppenheimer, Meyvis, and Davidenko 2009). Appendix B lists the manipulation check questions. The results indicate that participants found the experimental procedure to be understandable

because their responses fell in the 5 to 7 range in a seven-item scale representing strongly disagree to strongly agree). Following the manipulation check, we assessed the reliability of the perceptual measurement using Cronbach's Alpha with the result showing that TTF scores 0.957 (9 items); Cognitive Fit has a Cronbach's alpha of 0.934 (6 items), and Perceived Information Quality scores 0.900 (8 items). All Cronbach's alpha results for the measures are therefore reliable and consistent (Cronbach's alpha >.7) (Tabachnick and Fidell 2007).

5.2. Participants demographics

The three sources of participants were students, a research panel, and OCM-AMT. The sample comprised slightly more women than men with ages ranging from 18 to 60, averaging 24 for the students, 42 for the research panel, and 37 for the OCM-AMT. Academically, the percentage of participants having accounting or finance qualifications from the research panel was 7% and from OCM-AMT was 4%, with the remainder were distributed across other qualifications. Students with accounting or finance qualifications differed somewhat with 18% and 24%, respectively, while 58% were distributed across other backgrounds. More than half of the students (72%) and the research panel (54%) had prior accounting knowledge, while more than half of OCM-AMT's participants (53%) had no prior accounting knowledge. Participants from the three sources were relatively familiar with investment terminologies (e.g. current assets, liabilities, and ratios). Most participants from the research panel and the OCM-AMT were risk averse, whereas less than 50% of students were risk averse.

5.3. Factor analysis

To help ensure our measurement items appropriately reflected each construct, we conducted an exploratory factor analysis (EFA) (Tabachnick and Fidell 2007), using the whole dataset (n = 404) used for the main experiment. The EFA results indicate that the measurement items can be grouped into four constructs. All items proposed to measure TTF loaded on to one factor. We identified two measurement factors for perceived IQ. Two items were separate from the other items. Such separation indicates that the items measured both dimensions of IQ (i.e. representational IQ and contextual IQ). Four of the six items proposed to measure cognitive fit loaded on to one factor. For the remaining two measurement items the correlation coefficient for cognitive fit were less than 0.50, thus indicating that they were unrelated to any of the other groups and were subsequently dropped from the remainder of the analysis. Table 2 shows the rotated component matrix of the exploratory factor analysis.

Table 2. Rotated component matrix.

	Component			
Variables	1	2	3	4
TTF1	**.779**	.294	−.114	.156
TTF2	**.647**	.195	−.189	.598
TTF3	**.728**	.186	−.055	.343
TTF4	**.565**	.141	−.170	.692
TTF5	**.704**	.370	−.026	.181
TTF6	**.744**	.247	−.112	.202
TTF7	**.794**	.304	−.181	.100
TTF8	**.663**	.262	−.092	.270
TTF9	**.587**	.188	−.221	.610
Perceived IQ1	.348	**.753**	−.150	.099
Perceived IQ2	.346	**.801**	−.177	.111
Perceived IQ3	.294	.288	−.111	**.797**
Perceived IQ4	.447	.638	−.191	.216
Perceived IQ5	.342	.713	−.065	.407
Perceived IQ6	.294	.277	−.118	**.798**
Perceived IQ7	.274	**.623**	−.027	.507
Perceived IQ8	.321	**.764**	−.117	.218
CF1	−.113	−.078	**.870**	−.130
CF2	−.055	−.063	**.898**	−.105
CF3	−.151	−.112	**.889**	−.061
CF4	−.160	−.150	**.868**	−.048
CF5[a]	.052	.467	−.468	.365
CF6[a]	.024	.404	−.430	.419

[a]dropped items.

5.4. Results of the effect of IDV and investment tasks on non-professional investors' TTF, perceived IQ, and cognitive fit

A MANOVA examined the interaction effects of financial statements' visualisations (IDV vs non-IDV) and investment tasks (simple vs multipart) on individuals' TTF, perceived IQ, and cognitive fit. Before undertaking MANOVA analysis, we undertook four tests to ensure the data fulfilled the normal MANOVA assumptions.[4]

Table 2 presents the results of the MANOVA analysis. Our analysis shows that both IDV and non-IDV significantly affect non-professional investors' TTF, perceived IQ, and cognitive fit. All the p values for each dependent variable were below 0.05. The contribution of the data visualisations to the variance of each dependent variable were 49%, 8% and 49% respectively (see Table 3). To further examine what effect IDV and non-IDV might have on TTF, perceived IQ, and cognitive fit, we investigated the estimated marginal means of the independent variables (see Figure 2). The three graphs of estimated marginal means indicate that participants who undertook either simple or

Table 3. Test of between-subject effects for the effect of data visualisations and investment tasks on individuals' TTF, Perceived IQ, and Cognitive Fit.

Source	Dependent variable	df	F	Sig.*	Partial eta squared	Observed power
Data Visualisation (DV) – (Interactive vs NonInteractive)	TTF	1	384.055	.000	.490	1
	Perceived IQ	1	387.028	.000	.492	1
	Cognitive Fit	1	37.513	.000	.086	1
Investment Tasks (IT) – (Simple vs Multipart)	TTF	1	1.202	.274	.003	.194
	Perceived IQ	1	1.422	.234	.004	.221
	Cognitive Fit	1	2.161	.142	.005	.311
DV x IT	TTF	1	13.691	.000	.033	.958
	Perceived IQ	1	15.016	.000	.036	.972
	Cognitive Fit	1	13.505	.000	.033	.956

*significant at both 0.05 and 0.01 (computed using alpha = .05).

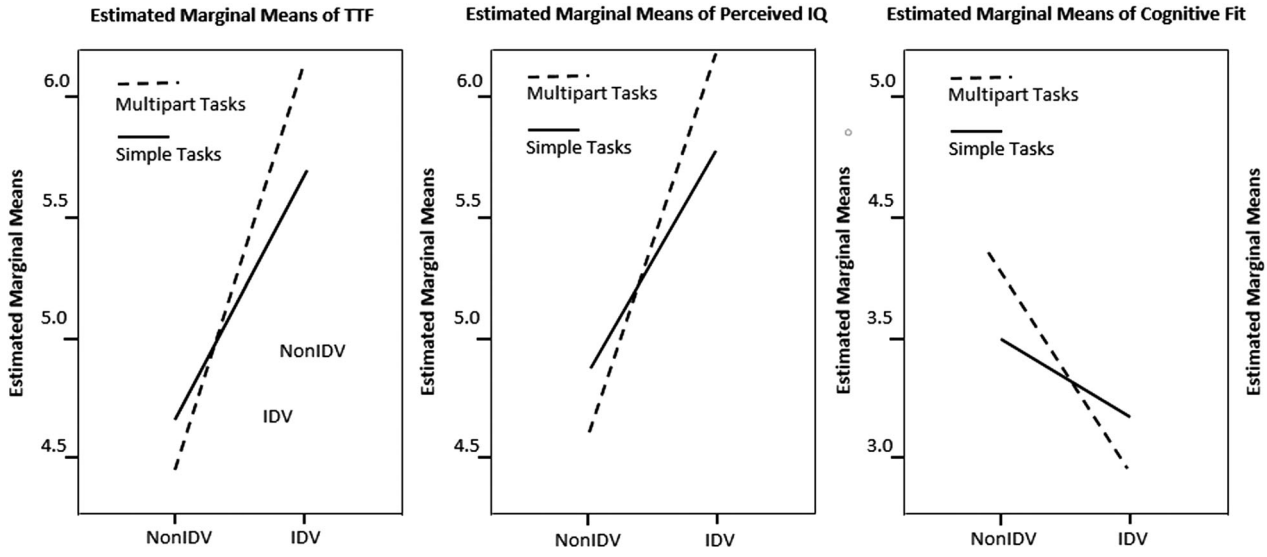

Figure 2. Estimated marginal means of independent variables against dependent variables.

multipart tasks, and who used IDV, held more positive TTF, perceived IQ, and cognitive fit. The observed power of 1 indicates that our experimental manipulation of data visualisations successfully detected the effects of data visualisations on TTF, perceived IQ, and cognitive fit.

In contrast, investment tasks had no significant effects on non-professional investors' TTF, perceived IQ, and cognitive fit. Investment tasks' contribution to the variance between investment tasks and cognitive fit is low, with an observed power below 50% and, as such, caution should be exercised when interpreting the results. While the individual effects of the independent variables are somewhat different, the interaction effects of both IDV and investment tasks on non-professional investors' TTF, perceived IQ, and cognitive fit remain significant. The contribution of both independent variables to non-professional investors' TTF, perceived IQ, and cognitive fit was low (<5%). The independent variables in this study account for some 95% of the interaction effects between independent variables and dependent variables.

To further test our hypotheses, we undertook a contrast analysis comparing the experimental groups (i.e. IDV with simple tasks, and IDV with multipart tasks) and control groups (i.e. non-IDV with simple tasks, and non-IDV with multipart tasks). We assigned weighting coefficients for each group to be compared (1 vs −1) and zero weight coefficients for groups that were not involved in the comparisons. We assigned the coefficients for the three contrasts of the experimental and control groups as follows: IDV and Simple Tasks; Non-IDV and Simple Tasks; IDV and Multipart Tasks; and Non-IDV and Multipart Tasks. The three contrasts are, contrast 1: 1,−1,0,0; contrast 2: 0,0,1,−1, and contrast 3: 1,−1,1,−1 (see Table 4 for descriptive statistics of each group compared).

The contrast test shows that H1, H3, and H5 were supported ($p < .01$). The results suggest that non-professional investors who used IDV for solving both simple and multipart tasks had stronger TTF, perceived IQ, and cognitive fit than those who used non-IDV when solving the same simple or multipart tasks.

Table 4. Contrast test for each comparable group.

Hypotheses	Variables	Contrast	Value of contrast	Std. Error	t	df	Sig. (1-tailed)*
H1	TTF	1	1.149	0.105	10.933	197.731	.000*
		2	1.683	0.099	16.966	154.093	.000*
		3	2.832	0.144	19.597	350.235	.000*
H3	Perceived IQ	1	1.05	0.094	11.131	196.625	.000*
		2	1.564	0.094	16.71	176.983	.000*
		3	2.614	0.133	19.673	372.835	.000*
H5	CF	1	0.416	0.148	2.801	198.554	.006*
		2	1.139	0.149	7.639	199.607	.000*
		3	1.554	0.21	7.39	398.16	.000*

*Significant at both 0.05 and 0.01 (computed using alpha = .05).

5.5. Results of the relationship between non-professional investors' TTF, perceived IQ, cognitive fit, and task accuracy

While H1, H3, and H5 confirm that the interactions between the independent variables and dependent variables (i.e. TTF, perceived IQ, and cognitive fit) were significant, the relationships between TTF, perceived IQ, cognitive fit, and task accuracy are yet to be examined. H1, H3, and H5 show that the experimental groups differ significantly from the control group. To show more completely the three-fit perspective, we conducted a PLS multigroup analysis (Hair et al. 2014) comparing the relationships between non-professional investors' TTF, perceived IQ, and cognitive fit, and task accuracy with the data visualisations (IDV vs non-IDV) and investment tasks (simple vs multipart). Before the analysis, we assessed the reliability of measurement items, the convergent validity, and the discriminant validity for each variable. Our assessment indicated that all measurement items were reliable (<50%), the research model was reflective (AVE greater than 0.50) (Fornell and Larcker 1981), and each variable was distinct from each other (HTMT <0.85) (Hair et al. 2010; Henseler, Sarstedt, and Ringle 2015).

After analysing the measurement model and verifying the construct validity, the data set was divided into two subsets: IDV and non-IDV use, resulting in 202 items for each. The two subsets were then used to assess the structural model using multigroup analysis. We performed a bootstrap analysis using a resampling technique of 1000 random samples to determine the significance of the relationships. The results of the structural model between IDV and non-IDV examined whether the relationships between variables in each group were different. To resolve the proposed hypotheses, this study used alphas, namely, 0.05 and 0.1 to accommodate the relatively small sample size, particularly when analysing multiple comparisons. They require the equal distribution of sample size to each comparable group. Using fewer restrictive alphas is acceptable for small sample sizes (Lavrakas 2008); Table 5 presents the path coefficients, t statistics of the PLS results for each group, and the *p*-value of the multigroup comparison between IDV and non-IDV use.

Table 5. Path coefficients and A 4 × 4 multigroup comparison for variables in research model.

	IDV		NonIDV	
Relationships	Simple Path coefficients/ *p*-value	Multipart Path coefficients/*p*-value	Simple Path coefficients/*p*-value	Multipart Path coefficients/*p*-value
Panel A				
TTF → Task Accuracy	.510/.000*	.292/.000*	.276/.206	−0.5474453
Perceived IQ → Task Accuracy	.353/.000*	.575/.000*	.167/.159	−0.8275862
CF → Task Accuracy	.422/.000*	.663/.000*	.219/.100	.122/.093
Panel B				
Relationships		Path difference and *p*-value (IDV Simple vs IDV Multipart)	Path difference and *p*-value (IDV Simple vs NonIDV Simple)	Path difference and *p*-value (IDV Simple vs NonIDV Multipart)
TTF → Task Accuracy		.218/.984	.234/.266	.661/.003*
Perceived IQ → Task Accuracy		.221/.043	.186/.135	.546/.032*
CF → Task Accuracy		.241/.001*	.203/.136	.300/.006*
Relationships		Path difference and *p*-value (IDV Multipart vs NonIDV Simple)	Path difference and *p*-value (IDV Multipart vs NonIDV Multipart)	Path difference and *p*-value (NonIDV Simple vs NonIDV Multipart)
TTF → Task Accuracy		.016/.709	.443/.072*	.427/.841
Perceived IQ → Task Accuracy		.407/.003	.767/.000*	.360/.840
CF → Task Accuracy		.444/.000*	.541/.000*	.097/.663

*significant at .05 (one-tailed).

Table 6. Summary of hypotheses testing results.

Panel A: Hypotheses tested with MANOVA			Support
Nonprofessional investors who interact with IDV to solve investment tasks			
Hypothesis 1: report better task-technology fit			Full
Hypothesis 3: report better cognitive fit			Full
Hypothesis 5: report better perceived information quality			Full
than nonprofessional investors who interact with nonIDV to solve the same investment tasks.			
	Results		
Panel B: Hypotheses tested with PLS	Relational Analysis	Comparison Analysis	Support
When interacting with IDV to undertake investment tasks, nonprofessional investors'			
Hypothesis 2: perceived better task-technology fit relative to IDV leads to greater task accuracy	Significant	Significant	Full
Hypothesis 4: cognitive fit relative to IDV leads to greater task accuracy	Significant	Significant	Full
Hypothesis 6: perceived better information quality relative to IDV leads to greater task accuracy	Significant	Significant	Full
compared with nonprofessional investors' using nonIDV to undertake the same investment tasks.			

The results of the multigroup analysis indicate that, for both group 1 and group 2, the contributions of TTF, perceived IQ, and cognitive fit to the task accuracy were within the range, 30% to 67% ($p < .05$). However, for groups 3 and 4, the contributions of TTF, perceived IQ, and cognitive fit to task accuracy were not significant (see, Table 5; Panel A). The comparison between groups 1 and 4 indicates that the contribution of TTF, perceived IQ, and cognitive fit to task accuracy was significantly different. Similarly, TTF, perceived IQ, and cognitive fit were significantly higher for group 2 than group 4. Cognitive fit was only significant for group 2 (see, Table 5, Panel B). These findings indicate that non-professional investors are better served by IDV when performing simple or multipart tasks than non-IDV. To fully support the hypotheses related to the multigroup comparison of relational analyses, we considered the significance of both path coefficients and the multigroup comparisons. Thus, H2, H4, and H6 were fully supported. Table 6 summarises the hypotheses testing results.

6. Discussions and contributions

By investigating and integrating the three-fit perspectives, we provide further understanding of how data visualisations fit non-professional investors' use. That is, we compared analyses for interaction effects between the independent and dependent variables (i.e. TTF, perceived IQ, and cognitive fit). We also investigated whether enhanced TTF, perceived IQ, and cognitive fit arising from non-professional investors' interactions with IDV lead to greater task accuracy. After comparing differences between the experimental groups (IDV) and control groups (non-IDV), the hypotheses in this study were fully supported.

We first analyzed the interaction effects of the independent variables and the dependent variables, finding that non-professional investors perceived better TTF, better cognitive fit, and better IQ when interacting with IDV to solve simple or multipart tasks than did non-professional investors using non-IDV. Prior research suggests that TTF enhances users' belief in utilising IDV and the use of IDV helps reduce users' cognitive load leading to better cognitive fit (Ajayi 2014). Further, when interacting with IDV, users are able to quickly search and filter the most relevant information (Arnold et al. 2012). Our research assessed IDV's capabilities by measuring users' perceived information quality, finding that IDV can help enhance financial statement information quality. Taken together, our results enhance our understanding of the role of three-fit perspectives in IDV via users' perceptual enhancements that otherwise have been separately investigated in the literature.

To complement our first analysis, we analyzed how the three-fit perspectives related to task accuracy. Task accuracy is an essential outcome variable when investigating IDV (Tang et al. 2014). While Ajayi's (2014) research finds that two essential features of IDV, namely interactive and visualisation appeared to have no significant effect on task accuracy. Our research, however, finds that IDV enables non-professional investors to achieve greater task accuracy. Better task accuracy is likely achieved due to less cognitive effort exerted by non-professional investors as confirmed by our hypotheses (H3 and H5). Our analysis also indicates that when interacting with IDV to perform investment tasks, non-professional investors' TTF, perceived IQ, and cognitive fit indicated greater accuracy than non-professional investors interacting with non-IDV to solve the same tasks. Next, we present how this paper contributes theoretically and practically to research.

6.1. Theoretical contributions

Our theoretical contributions are fourfold: First, our study captures the breadth of individual fit when using information systems with specific IT and multiple

tasks. Much of the IS and AIS theory (including CFT and IQ, Tate, Evermann, and Gable 2015) was adapted from other disciplines (e.g. psychology, marketing, and computer science). Unlike CFT and IQ, TTF is a native IS theory because it considers the interactions between technology, tasks, and users. When applying theories from other disciplines to IS, the phenomena to which the theories are being applied must be examined. This applies to our focus, which is accounting where non-professional investors use the interactive features of IDV to control and switch financial statement presentations from yearly to quarterly or vice versa.

Second, our findings suggest that fit can enable non-professional investors to achieve two outcomes: first, to explore their information while interacting with financial statements and thus improve their performance; and second, to achieve greater task accuracy when compared with their interactions with non-IDV. Unlike prior research that largely applied TTF either as a mediating variable (e.g. Lee, Cheng, and Cheng 2007; D'Ambra, Wilson, and Akter 2013) or as the dependent variable of the task, technology, and individuals' characteristics set, our study examines the three-fit perspective's role in simultaneously improving performance across data visualisations and investment tasks. Unlike studies that investigated TTF's relationships with task, technology, and individuals' characteristics, we examined the effect of technology and tasks characteristics on TTF, as well as its relationship with task accuracy. Further, we involved the individual characteristics of non-professional investors to better analyse the relationship between cause and effect more thoroughly. This is important because the three-fit perspective extends the investigation beyond a simple relational analysis.

Third, our study contributes to understanding fit categories. The investigation of the three-fit categories concur with the ATT fit framework (Davern 2007). As IDV can be used to support substantive tasks like analysing financial information and comparing financial statements across companies, user-reality fit, and user-tool fit of the ATT framework support our findings. Our results accord with user-reality fit in that non-professional investors' characteristics match the available information in IDV to achieve greater task accuracy when solving investment tasks. Regarding user-tool fit, we found that non-professional investors' characteristics match IDV characteristics by providing more salient and relevant information than is the case with non-IDV.

Fourth, to complement the substantial body of IS research using TTF, IQ, and CFT, our research more specifically theoretically explains fit. Regarding TTF, our research generally confirms the literature's finding that the alignment among tasks, technology, and individuals can lead to positive TTF, perceived IQ, and cognitive fit. Therefore, because of non-professional investors' restricted capabilities, we theorise that IDV helps them solve either simple or multipart tasks. To complement TTF, we use CFT to provide evidence that IDV users expend less cognition to perform simple or multipart tasks when interacting with information obtained using IDV than non-professional investors using non-IDV. In addition, the IQ perspective affirms that the information obtained from IDV fits well with non-professional investors' use. Our research also theoretically explains the extent to which the three-fit perspective produces better task accuracy. The three-fit perspective can predict the outcomes of decision making that occurs when non-professional investors hold positive TTF, perceived IQ, and cognitive fit; they are likely to perform both their simple and multipart tasks more accurately.

6.2. Practical contributions

Organisations are increasingly dealing with growing volumes of data, including their own accounting data. Producing relevant information and learning from those data is challenging, not just for the organisations and their internal decision making, but also for external data consumers. Organisations increasingly need to deliver and disclose their related accounting information to their external users (e.g. potential investors). As such external users are likely to interact with volumes of financial information from many companies, the presentations of accounting information should enable them to more readily acquire the understanding necessary to support their decision making. Further, different external users have different abilities when interacting with financial information (e.g. professional investors vs non-professional investors). Professional investors may be familiar with sophisticated financial analyses and decision tools, whereas non-professional investors may have little access to such analyses and tools. Therefore, organisations need to consider both types of investors when seeking to attract more investment funds. Considering the prevalence of non-professional investors, we believe that providing an interactive-enabled environment for their decision making is relevant and practical. Data visualisation can also be accessed by large numbers of non-professional investors when visualisations are affordable and widely accessible. Our findings emphasise the value of IDVs in the accounting field because of their capacity to alleviate the restricted abilities of non-professional investors.

We contend that our research may also provide insight into other disciplines such as cognitive

psychology and computer science visualisations. Understanding sophisticated human perceptions remains an ongoing question to cognitive scientists in general, and a compelling question about data visualisations in particular (Goldstone, Pestilli, and Börner 2015). This is because these scientists seek to understand how the human brain works with visualisations (Goldstone, Pestilli, and Börner 2015). Similarly, in computer science, human perceptions and cognitive capability are important in generating effective visualisations for decision making (Kalawsky 2009). Because our experimental IDV materials consisted of three features (i.e. active control, multiple visualisation, and analytics), we suggest that IDV equipped with them leads to positive perceptions of TTF and IQ, and cognitive fit. Adding our findings to interdisciplinary research may help improve the design of IDV and permit better understanding of how best to leverage human cognitive abilities and intellect with visualisations.

7. Limitations and future research

While the results of our research findings are encouraging, three limitations arise: First, our experiment was strictly controlled within the accounting domain with our manipulated IDV and tasks being specific to financial statements and basic investment tasks. Further, we used the existing IDV features provided by *Calcbench* without any further manipulations. We also did not distinguish which IDV features (i.e. multiple visualisations, active control, or analytics) most benefited non-professional investors. Second, the measurements of all variables including TTF, CFT, and IQ were adapted from the literature. Because the measurement items can be classified as both personal perceptions and traits, they may introduce bias. Third, while the findings were derived from a diverse range of participants, we did not undertake a PLS multigroup comparison analysis based on the participants' origins (students, research panel, and OCM-AMT) because of our restricted sample size. When undertaking such a comparative analysis, the sample should be divided into their sources and other factors being considered (i.e. IDV and task characteristics), which leads to significantly expanded comparisons (i.e. 12 × 12). This research should thus be viewed as a basis for future research with a broader experimental setting. Further, the study captures a snapshot, rather than a dynamic view of fit (Davern 2007).

Future research may compensate for these limitations by identifying, expanding or manipulating other features in IDV, and investigating the features that most benefit users. Regarding the measurement limitations, future research could answer the call from Tate, Evermann, and Gable (2015) suggesting that CFT can be used to investigate actual fit. The measurement of actual fit, therefore, requires measurement tools that cannot be consciously manipulated and are not susceptible to subjectivity and demand effect bias. While measuring the cognitive effort using, for example, neuro-imaging tools (e.g. fMRI, EEG) may suit interdisciplinary research, gaining such insight from findings remains costly and outside the capacity of most researchers (Dimoka et al. 2012). Future research could also study the dynamic view of fit, for example, by focusing on how individual learning likely adjusts fit and increases familiarity of the technology and the task environment (Davern 2007). Investigating the dynamic view of fit could improve our understanding of how individuals adapt to technologies and task environments to maintain their fit over time.

8. Concluding remark

This study has answered the high-level research question: To what extent does IDV fit non-professional investors' use? Our results confirm that IDV offers relevant functionality for non-professional investors to undertake their tasks. When using IDV to solve their tasks, non-professional investors perceive more positive TTF, IQ, and cognitive fit than when using non-IDV. Further, these variables are relevant predictors of task accuracy. In conclusion, we suggest that conditions such as information in a fit-for-use form, and the abilities of the technologies to generate conducive environments, need to be more fully developed. IDV, for example, must provide functionalities that fit individuals' abilities and their specific tasks. A more complementary fit between IDV, tasks, and non-professional investors will likely lead to greater and better IDV use.

Notes

1. Given the exploratory nature of this study, we assessed the effect of IDV as a whole, rather than assessing which components of IDV contributed most to the non-professional investors' performance, e.g. interactivity, visualisations, etc.
2. Inherent quality reflects the quality of the characteristics or attributes of the data or information in their own right (Wang and Strong 1996). Wang and Strong (Wang and Strong 1996) propose four dimensions the inherent quality of data and information i.e. accuracy, believability, objectivity, and reputation. Jayawardene, Sadiq, and Indulska (2013) suggest that inherent quality reflects the representational nature of the data or information and remains dependent on users' perceptions.

3. In the analyses, therefore, the cognitive load measurement has to be reverse coded.
4. Relative to those tests, our 404 sample size is sufficient to satisfy the multivariate normality assumption (Tabachnick and Fidell 2007). The correlation coefficient (0.747) between each variable (TTF, CF and perceived IQ) was below the threshold for multicollinearity (<0.80) (Stevens 2009). The result of Box's test of equality of covariance matrices indicated a violation of the assumptions of the equal variance of covariance ($p < .05$). The randomised and even participant allocation mitigated this violation thus permitting robust interpretation of the data (Hair et al. 2010; Tabachnick and Fidell 2007). The results of Levene's test for equality of error variance indicated a violation of the assumption of equality of error variance ($p < .05$). We mitigated this violation by the use of a more stringent alpha when accepting or rejecting the MANOVA hypotheses (= 0.001) (Tabachnick and Fidell 2007).

Disclosure statement

No potential conflict of interest was reported by the authors.

ORCID

Arif Perdana http://orcid.org/0000-0002-1260-240X
Alastair Robb http://orcid.org/0000-0002-3177-7854

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