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Interactive Data and Information Visualization: Unpacking its Characteristics and Influencing Aspects on Decision-making

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Abstract

Background: *Interactive data and information visualization (IDIV) enhances information presentations by providing users with multiple visual representations, active controls, and analytics. Users have greater control over IDIV presentations than standard presentations and as such IDIV becomes a more popular and relevant means of supporting data analytics (DA), as well as augmenting human intellect. Thus, IDIV enables provision of information in a format better suited to users' decision-making.*

Method: *Synthesizing past literature, we unpack IDIV characteristics and their influence on decision-making. This study adopts a narrative review method. Our conceptualization of IDIV and the proposed decision-making model are derived from a substantial body of literature from within the information systems (IS) and psychology disciplines.*

Results: *We propose an IS centered model of IDIV enhanced decision-making incorporating four bases of decision-making (i.e., predictors, moderators, mediators, and outcomes). IDIV is specifically characterized by rich features compared with standard information presentations, therefore, formulating the model is critical to understanding how IDIV affects decision processes, perceptual evaluations, and decision outcomes and quality.*

Conclusions: *This decision-making model could provide a meaningful frame of reference for further IDIV research and greater specificity in IS theorizing. Overall, we contribute to the systematic description and explanation of IDIV and discuss a potential research agenda for future IDIV research into IS.*

Keywords: Interactive data visualization, information visualization, perceptual evaluation, decision-making, conceptual model.

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Introduction

Information presentation and visualization research has, for some three decades, inspired research in fields such as computer science, IS, psychology, communication, accounting, marketing, and education (e.g., Brucker et al., 2014; Dilla et al., 2010; Lurie & Mason, 2007; Thomas & Cook, 2005; Shmueli et al., 2006; Sundar et al., 2015; Yi et al., 2007). In the literature, two major camps are distinguished: information presentation and information visualization. The computer science and psychology (e.g., cognitive science) fields have long tended to focus on visualizations or visual representation (Goldstone et al., 2015; Thomas & Cook, 2005; Yi et al., 2007). Conversely, information systems, communication, accounting, marketing and education tend to focus on information presentations (Dilla et al., 2010; Jiang & Benbasat, 2007). Information presentation involves delivering and manipulating texts and visuals, whereas information visualization focuses on visual communication. With technological advances, these two research streams are merging and now systems evolve that incorporate interaction techniques that increase the usefulness and relevance of presentations and visualizations for decision-making. This research stream has also developed multiple terms such as interactive media, interactive visualization, and interactive data visualization (IDV), and interactive data and information visualization (IDIV) (Dilla et al., 2010; Perdana et al., 2018; 2019; Sundar et al., 2015; Thomas & Cook, 2005).

More broadly, research into the computer science, psychology, and communication fields help advance understanding of the role interactive presentations and visualizations play in decision-making (Sundar et al., 2015; Thomas & Cook, 2005). Interactivity in presentations and visualizations can be viewed as either being an inherent quality or dependent on the users' perceptions (Sundar et al., 2015). Since technologies cannot be separated from the individuals who use them, both presentation and visualization research are commonly concerned with important questions: Which presentations and visualizations work best and to what extent are they successful? What are the underlying perceptual and cognitive factors that encourage or restrict users' interactions with presentations and visualizations? How should presentations and visualizations be designed to best mitigate users' inadequacies (Rensink, 2014; Sundar et al., 2015). Given these questions, researchers endeavor to combine the insight gained from both information presentation and visualization research programs.

Individuals' differences in cognitive processing ability have been well-documented in the literature (Shah & Miyake, 2006). Because individuals also tend to display limited cognitive ability when processing complex information, providing them with interactive visualizations helps to minimize those limitations (Hullman et al., 2011). IDIV provides rich features that can augment individuals' abilities by helping users to make sense of complex information, directing their reasoning processes, and reducing erroneous inferences when making decisions. IDIV may, therefore, provide greater awareness into decision-making research programs within the IS discipline. In the IS field, including accounting information systems (AIS), the investigation of information presentations, and visualizations frequently involves decision processes, perceptual evaluations, and decision outcomes.

IDIV differs from previously researched information presentations (i.e., graphs and tables presentations). IDIV is part of the data analytics (DA) capability that allows users to acquire more meaningful and contextualized information (Cosic et al., 2012; Ong & Shanks, 2015). IDIV permits selection of multiple types of visualizations, facilitate individuals' active control over their visualizations according to their needs (e.g., concise and seamless navigation); and provide further analytics (e.g., search functions, built-in statistical formulae, machine learning algorithm, and natural language query processing). Overall, IDIV provides both more accessible and enhanced information as well as the tools to explore and augment human intellect (Goldstone et al., 2015).

While research into decision-making, in general, has been well studied in the psychology domain (see, e.g., Brown, 2006; Drechsler et al., 2014; Gigerenzer & Goldstein, 1996; Goodie & Young, 2007; Kahneman, 2003; Tversky & Kahneman, 1974), the narrower context within the IS domain involves specific tasks and the technology may be different. We contend that examining users' interactions with IDIV in an IS domain could create knowledge that can be used to guide additional interdisciplinary research in areas such as audit, risk management, and finance (Rai, 2016). For example, researchers increasingly examine the extent to which IDIV can be used to mitigate risks and uncertainty when making decisions, to improve decision-making outcomes, and to detect fraud (Arnold et al., 2012; Dilla et al., 2010; Dilla & Raschke, 2015; Tang et al., 2016). IDIV also helps enhance nonprofessional investors' sense-making when undertaking investment analysis (Perdana et al., 2018; 2019). Derived from empirical evidence, our proposed model endeavors to offer a conceptual base grounded in judgment and decision-making (Arnott et al., 2006). While we strive to provide a parsimonious model, our model can be further enhanced by understanding which specific IDIV characteristics would be most relevant for particular tasks, and how those characteristics could lead to improved decision-making.

Our aim for this study is to complement the broad psychology studies undertaken within interactive decision environments (e.g., Sundar et al. 2015; Thomas & Cook, 2005; Valkenburg et al., 2016) and to propose a more specific conceptual model of decision-making with IDIV, specific to an IS perspective. To do so, we evaluate IDIV characteristics, their role in supporting the tasks at hand, and the cognition underlying users' interactions with IDIV that contribute to users arriving at decision outcomes. Thus, to guide our study, the following high-level research questions arise, RQ1: *What are the distinct characteristics of IDIV?* RQ2: *Does IDIV influence decision outcomes and, if so, what aspects influence them?*

We examine the findings from related literature and offer propositions that could be tested in future research. Our foci in this study are the antecedents and the consequences of users' interactions with IDIV. Our study does not explain the extent to which users' interactions with IDIV develop and change over time. Thus, we propose using a variance conceptual model to address our research questions (Van de Ven, 2007).

In this study, our model reflects the call from Rai (2016) to extend knowledge via multiple disciplines and to use that knowledge to expand and strengthen IS research. We contribute to the advancement of IDIV research by endeavoring to integrate the literature on the characteristics of interactivity in presentations and visualizations into three common features (i.e., multiple visual representations, active control, and analytics). We contribute to this research area by examining the variance in decision processes, perceptual evaluations, decision outcomes, and the quality attributable to IDIV by specifically delineating decision-making into four bases, namely, predictors, moderators, mediators, and outcomes. We clearly distinguish two routes of information processing when users interact with IDIV, specifically, decision processes and perceptual evaluations. The study of IDIV also promotes the understanding of the intersection of IT artifacts, human characteristics, and tasks (Benbasat & Zmud, 2003). In the era of big data and analytics (BDA), IDIV is becoming part of the everyday business landscape. Consequently, there is a need to ensure any new tools being developed are the most appropriate for the combination of task and user if the organization is going to obtain the desired strategic advantage. We believe that IDIV provides opportunities for researchers to capture a variety of system uses (Burton-Jones & Straub, 2006), therefore, permitting examination of the extent to which users employ IDIV to undertake their tasks.

This paper is organized in five sections. After the introduction, Section II defines and proposes the salient features of IDIV, Section III develops the propositions, and Section IV offers research contributions and a possible research agenda. Finally, Section V concludes this study.

Data Analytics, and Interactive Data and Information Visualization: Current Development and Definition

As the technology continues its rapid progress in the era of big data, DA helps overcome economic challenges by assisting industries to understand their past performance, forecast their future performance, detect anomalies and outliers in their financial circumstances, and identify consumer niches (Chen et al., 2012; Chung, 2009; Hou & Gao, 2018; Lee, 2017). DA plays a central role for strategically-focused enterprises pursuing data driven decision-making for competitive advantage and is gaining traction in the Asia Pacific. The Singapore government, for example, has developed an initiative to accelerate DA adoption in small to medium enterprises (SMEs)¹. The Land Transport Authority (LTA) in Singapore uses IDIV to analyze 3.7 million data sets to help overcome public transport supply and demand mismatches². DA incorporating IDIV capabilities could therefore help industries (both large corporations and SMEs) and governments to harness their data and transform it into actionable knowledge.

In the IDIV literature, the conceptual research and its findings diverge somewhat. Such divergence may limit our current understanding of IDIV characteristics, decision processes with IDIV, perceptual evaluations of IDIV, and IDIV use. Past research, for example, has not always agreed on what defines IDIV characteristics (e.g., Downes & McMillan, 2000; Gao et al., 2010; Janvrin et al., 2014; McMillan, 2002; Yi et al., 2007). Different IDIV conceptualization also potentially limits the ability to explain the constructs relevant to users' interactions with IDIV. While IDIV characteristics are generally considered multidimensional, we posit that this multidimensionality can be classified into parsimonious core characteristics. Further, contemporary information presentations with their sophisticated characteristics quite likely impact decision-making differently than standard information presentations. Our ideas resonate, therefore, with the research call from Kelton et al. (2010) to further explore and develop the multidimensionality of contemporary information presentations (i.e., IDIV) in decision-making.

We adopt a narrative review method in this study (Pare et al., 2015; Templier & Pare, 2015). Narrative review is appropriate because our intention is to comprehend the characteristics of IDIV and complement the shortcomings in prior decision-making models on interactive presentations and visualizations. Our conceptualization of IDIV and the proposed decision-making model are derived from a substantial body of literature in IS and psychology.

IDIV Definition

Deriving from the multiple definitions and characteristics of IDIV, we attempt to propose a more coherent and parsimonious definition specific to IS. Current DA tools permit users to explore raw data without any further processing as well as permitting users to process the data via multiple statistical techniques or machine learning algorithms and visualize the information produced. Given that sophisticated information technologies can accommodate both data and information visualization, we believe that the term interactive data and information visualization (IDIV) is more encompassing than IDV. We define IDIV as software that permits individuals to display multiple visual representations, actively control their use of those presentations, and undertake data analyses with those presentations. This definition has two advantages. First, it is parsimonious because it includes three important characteristics of IDIV namely, multiple visual representations, active controls, and analytics.

¹ <https://ie.enterprisesg.gov.sg/Media-Centre/News/2017/10/Govt-making-it-easier-for-SMEs-to-adopt-data-analytics-and-AI--Yaacob>

² <https://www.businesstimes.com.sg/government-economy/singapores-future-economy/tomorrows-companies-today>

Second, this definition clarifies the major difference between IDIV and traditional information presentations or non-IDIV. Although traditional information presentations can consist of multiple visual representations, we argue that such presentations cannot be categorized as IDIV unless they have the other two characteristics: active controls and analytics.

We contend that our conceptualization of active control encompasses ‘interactivity’ from the computer science and psychology fields. For example, active control might be used as an umbrella term for each of modality, message, and source interactivity (Sundar et al., 2015). In this context, the scope of active control includes the availability of interactivity features (i.e., modality interactivity) in media that permits users to engage in information exchanges (i.e., message interactivity), and control relevant information according to their preferences (i.e., source interactivity). Further, we argue that analytics has to be included as an IDIV characteristic because IDIV is one of the capabilities in DA, and in the context of IS, IDIV needs to support users with analytical reasoning (Chen et al., 2012). This characteristic also aligns with the scope of visual representations and interaction technologies suggested by Thomas & Cook (2005), whereby technologies should better help users to analytically understand complex information.

Multiple visual representations, active controls, and analytics describe the IDIV capabilities that can help presentation designers and users find the most efficient and effective ways of acquiring and presenting the relevant information available in organizational data and information stores. Further, sophisticated technologies including interaction and visualization technologies are now available to produce further advanced IDIV. Table 1 presents the scope of the IDIV characteristics and available enabling technologies for IDIV.

Table 1 - IDIV Characteristics and Enabling Technologies for IDIV

Characteristics	Scope	Enabling technologies
Multiple visual representations	IDIV permits users to choose multiple visualizations including graphs, tables, dynamic timelines, maps, pictures, 3D visualizations, spatial, symbolic and/or in combination. This characterization also includes graphics features (e.g., color, shape, size, texture, and orientation) geometric symbols (e.g., point, line, area, surface, volume) , linguistic symbols (text, numerals, punctuation marks), pictorial symbols (images, icons, statistical glyphs) (Baker et al., 2009; Goldstone et al., 2015).	Desktop visualization; holographic display, flexible display.
Active control	Via the interaction with IDIV, users are able to actively control what they want to view, and how they present and exchange the data and information. Active control allows users to explore the visualizations and to further undertake information exchange analyses (McMillan & Hwang, 2002; Coursaris & Sung, 2012).	Traditional mouse recognition, touch screen display, eye tracking control, mouse tracking.
Analytics	IDIV tools have to support users to make sense of increasingly abundant data and information. IDIV enables users to undertake selection, search, exploration, abstraction, filtering, switching, querying, statistical and mathematical calculations (Yi et al., 2007; Clements et al., 2011).	Data engine, analytics engine, natural language processing to data exploration.

While multiple visual representations, active controls, and analytics are the elements of IDIV, in practice, IDIV tools may emphasize one or more characteristics over others. For example, a particular IDIV tool may offer rich visualization options that permit users to actively control the data and information visualizations, but offer few features for undertaking data analyses. Conversely, other IDIV tools may offer few visualization options and active control, but may

feature rich capabilities for undertaking data analyses. To confirm our conceptualization of IDIV and its characteristics. Table 2 presents the three IDIV characteristics that we propose and the degree to which they fit with six currently available IDIV tools.

Table 2. Examples of Interactive Data and Information Visualization Tools

IDIV Tool	Characteristics	Description
Calcbench (www.calcbench.com)	Multiple Visual Representations (e.g., graph, table, textual, in combination). Active Control (e.g., permits individuals to control visual representations, permits individuals to compare financial statements, permits individuals to perform detailed analytics on financial statements). Analytics (e.g., text search, company search, data query, quick reports).	Calcbench provides access to XBRL-based financial statements drawn from the SEC's corporate financial data repository. Calcbench enables individuals to analyze financial statements by providing several features, such as, financial ratios, financial statements comparisons, chart analyses, industry trends, and collaborative working.
Contexxia (https://www.contexxia.com)	Multiple Visual Representations (e.g., dynamic timeline, numeric line, textual). Active Control (e.g., permits individuals to select the relevant financial and accounting events, permits individuals to create reports, permits individuals to create bookmarks). Analytics (e.g., events searches, concept search, semantic analysis).	Contexxia enables individuals to undertake event analyses, numerical analyses and semantic text comparison of the SEC's XBRL filings
Edgar Dashboard (https://edgar.xbrcloud.com/)	Multiple Visual Representations (e.g., multiple tables, textual, in combination). Active Control (e.g., permits individuals to switch rows and columns, permits individuals to see the detailed elements and properties of reports). Analytics (e.g., text search, data exploration, analyze financial report elements).	Edgar dashboard permits individuals to access, download, view, and analyze XBRL data through a web interface.
Market Watch (http://www.marketwatch.com/tools/stockresearch/marketmap)	Multiple Visual Representations (e.g., market map, trend line charts, candlestick charts, advanced charts, interactive charts, text, or in combination). Active Control (e.g., permits individuals to select the relevant companies' information, permits individuals to select either advanced charts or interactive charts). Analytics (e.g., company search, data exploration).	Market watch provides an intuitive platform of stock market data. It permits individuals to locate companies' information and see detailed historical stock data either using advanced charts or interactive charts
Luminous Cities (http://www.tracemedia.co.uk/luminous)	Multiple Visual Representations (e.g., map display, photo display, textual). Active Control (e.g., permits individuals to browse photos based on the geolocated data) Analytics (e.g., photo display based on users' tag, photo search based on location and period)	Luminous Cities provides a platform to explore geographical landscapes based on the accumulation of photo-tagging on social media.
Tag Galaxy (http://www.taggalaxy.de/)	Multiple Visual Representations (e.g., 3D visualization, photos) Active Control (e.g., permits individuals to search word relationships based on social media tags, and explore the photos linked to particular tags) Analytics (e.g., tag relationship analysis, photo exploration)	Tag Galaxy enables individuals to visually explore word relationships as well as the pictures related to particular words.

IDIV Characteristics and User Interface

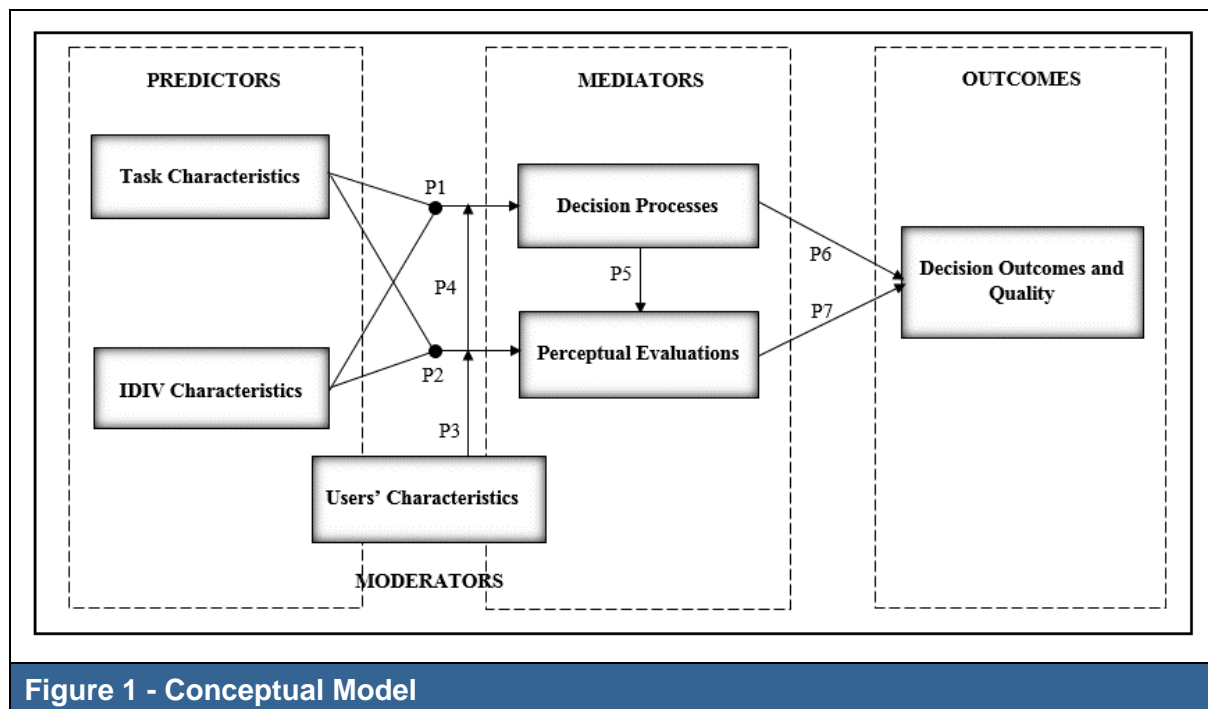
When individuals view visualizations either on paper or by static web presentation, they can only see the graphic as presented and have no control over the visualizations. Therefore, the characteristics presented in Table 2 differentiate static or non-interactive data visualization and IDIV. Apart from the Table 2 examples, some commercially available DA and visualization software (e.g., Tableau, QlikSense, PowerBI, Microstrategy, SAP Lumira) fit with our proposed characteristic by enabling users to visualize their data in multiple visual representations or by combining multiple visuals in a dashboard or story slide deck. Users are also able to actively control the visuals based on provided filters, slicers or parameters. DA software also allow users to conduct deeper analytics by creating their own functions or formulae to further analyze their data and visually display those data and more recently also permit users to further explore data via natural language query.

In summary, this section helps answer RQ1: *What are the distinct characteristics of IDIV?* Based on prior research and confirmed by our observations of currently available IDIV tools, the characteristics that best distinguish IDIV are multiple visual representations, active control, and analytics.

Proposed Model and Its Constructs

Prior studies have attempted to formulate decision-making theories and frameworks for interactive decision environments (e.g., Dilla et al., 2010; Lurie & Mason, 2007; Sundar et al., 2015). The effects of interactive media environments have been described both broadly and specifically. In a broader context, Sundar et al. (2015) proposed four models using their theory of interactive media effects (TIME) to explain the extent to which interactive media affects user psychology. In a more specific context, Lurie & Mason (2007) theorized the role of interactive media in decision-making within the marketing domain. Similarly, within accounting, Dilla et al. (2010) proposed a decision-making model with IDIV.

Multiple views relative to the impact of IDIV on users appear in the above three models (i.e., Dilla et al., 2010; Lurie & Mason, 2007; Sundar et al., 2015), particularly relative to users' and task characteristics. For example, Sundar et al., (2015) acknowledge the role of users to augment their abilities by using interactive media features. The characteristics of users, however, do not receive much attention. This exclusion is possibly due to the model's breadth. While Sundar et al. (2015) provide the overarching theory and model of interactivity and describe how the interactivity features affect cognition when decision-making, they do not consider task characteristics. Similarly, while Lurie & Mason's model does not consider task characteristics, it considers users' characteristics as a construct. In contrast, Dilla et al. (2010) consider task characteristics, users' characteristics, and interactive data visualization characteristics all as antecedents of decision-making.



User interfaces (UI) with IDIV characteristics can contribute to decision-making processes by enabling individuals to quickly drill down into their data and generate insight from it. UI has been a common research theme in human computer interaction (e.g., Hartmann et al., 2008; Hasan & Ahmed, 2007; Kumar et al., 2004). An effective UI is considered one of the critical success factors in software, website usability, and decision-making (Turetken et al., 2019; Wen & Lurie, 2019). Wen & Lurie, for example, demonstrate that providing visual boundaries (e.g., color and segmentation) in web based-UI affects consumers' perceptions of product varieties in online shopping environments. Another study notes that UI characteristics of enterprise information systems (EIS) (e.g., navigation, simplicity, and minimal memory load) contribute to users' satisfaction (Ozen & Basoglu, 2006). UI also leads to the successful implementation of EIS (Turetken, et al., 2019). Turetken et al. recommend that (1) UI must fit to the relevant users' tasks; (2) UI has to be consistent and should use familiar user-domain terminology, and (3) Only necessary controls should be placed in UI.

To meet this challenge, we develop a coherent model that complements prior models proposed by Lurie & Mason (2005), and Dilla et al. (2010). Our conceptual model remains parsimonious yet sufficiently comprehensive to promote greater specificity in IS theorizing and provide appropriate recommendations to practice relative to the design aspects and use of IDIV. The conceptual model presented in Figure 1 includes six constructs identified from prior research: (1) IDIV characteristics, (2) task characteristics, (3) users' characteristics, (4) decision processes, (5) perceptual evaluations, and (6) decision outcomes and quality. Table 3 provides the rationale for the constructs' selection.

While we develop a conceptual model with propositions, the operationalization or measurement of variables included in it is beyond the scope of our study. As illustrated in Figure 1, decision-making consists of four essential elements, namely, predictors, moderators, mediators, and outcomes. Predictors consist of the information set or cues presented to users, that is, the statistical properties of the information set, the presentation types, the context of the presentations, and the task characteristics. Because moderators can amplify or diminish the relationships between predictors and mediators, our model incorporates users' characteristics as the moderators. Mediators refer to individual cognitive processes when making evaluations and decisions with the presented information set or

cues, such as decision processes and perceptual evaluations. Outcomes describe the decision outcomes and quality as they relate to system use, information use, and accuracy.

We now turn our attention to describing each of the constructs and relevant variables as proxies of those constructs in the conceptual model. Each construct is described accordingly starting with IDIV characteristics and task characteristics, users' characteristics, decision processes, perceptual evaluations, and decision outcomes and quality. Following the explanation of each of the constructs, we present the theories supporting the nomological net of our conceptual model

Table 3 - Definitions, Scope, and Rationale of Constructs

Constructs in the Conceptual Model	Sources	Definition or Scope	Rationale for Including the Constructs in the Conceptual Model	Relevant factors or variables for constructs
IDIV Characteristics	Dilla et al., (2010); Yi et al., (2007).	IDIV has three essential characteristics, i.e., multiple visual representations, active controls, and analytics. Multiple visual representations provide multiple options for display configurations (graphs, tables, pictures, textual, or in combination). Active controls permit individuals to customize and personalize the information presentations with various visual representations. Analytics permit users to further analyze and manipulate the information.	IDIV characteristics have the potential to influence the decision-making frame (i.e., decision processes, perceptual evaluations, and decision outcomes and quality).	IDIV vs non-IDIV
Task Characteristics	Bonner (2008); Dilla et al. (2010); Kelton et al. (2010).	Using the definition of task from Merriam-Webster.com, that is, "a usually assigned piece of work often to be finished within a certain time". Task characteristics; therefore, refers to the specifications of the assigned piece of work.	The evaluation of information presentations cannot be separated from the characteristics of tasks, suggesting use of task characteristics as one of the antecedents of decision-making with IDIV.	Task type, task complexity, and task environment
Users' Characteristics	Bonner (2008); Venkateshs et al.(2003); Dilla et al. (2010); Hartwick & Barki (1994); Venkatesh et al. (2000); Xiao & Benbasat (2007).	Users' characteristics are personal variables and include domain expertise, domain knowledge, and personal style	Although prior research acknowledges the importance of individual characteristics, this construct's role is diversely used. For example, in AIS, this construct has not been clearly assigned as a predictor or as a moderator. Prior IS research suggests that users' characteristics in decision-making fit the role of moderating variables best.	Novice, expert, professional investors, non-professional investors, decision styles, tolerance for ambiguity, cognitive styles, appetite for risk, and gender.

Table 3 - Definitions, Scope, and Rationale of Constructs

Constructs in the Conceptual Model	Sources	Definition or Scope	Rationale for Including the Constructs in the Conceptual Model	Relevant factors or variables for constructs
Decision Processes	Dilla et al. (2010). Koop & Johnson (2011), Rubinstein (2013).	Effort and time required when making decisions.	Decision processes are distinct from perceptual evaluations. Decision processes capture the effort taken to make decisions, and time spent solving the given tasks.	Cognitive process, information processing strategy such as, search strategy, systematic or heuristic information processing.
Perceptual Evaluations	Arnold et al. (2012); Ghani et al. (2009); Janvrin et al. (2013); van der Heijden, 2013; Weber et al. (2005); Xiao & Benbasat (2007).	Users' perceptions or belief toward particular circumstances and precedes decision outcomes and quality	Based on prior research, perceptual evaluations are used to refer to individuals' perceptions toward IDIV characteristics.	Perceived ease of use, perceived usefulness, and perceived fit
Decision Outcomes and Quality	Burton-Jones & Straub (2006); Bonner (2008); DeLone & McLean (1992; 2003); Xiao & Benbasat (2007).	The consequences of perceptual evaluations and decision processes affected by IDIV characteristics and task characteristics.	Decision outcomes and quality measure the impact of users' interaction with IDIV characteristics and task characteristics when decision-making.	System use (the way the system is used), information use, and accuracy of outcome.

Predictors: IDIV Characteristics and Task Characteristics

From prior IS research on information presentations, two primary constructs affecting decision-making are information presentations (i.e., IDIV characteristics) and task characteristics. The interaction effect of these two constructs on decision outcomes and quality has been well researched (e.g., Frownfelter-Lohrke, 1998; Kelton et al., 2010). As an IT artifact, IDIV cannot be separated from task characteristics (e.g., Benbasat & Zmud, 2003; Dilla et al., 2010; Kelton et al., 2010). This paper intends, therefore, to consider the interaction between IDIV characteristics and task characteristics, as well as the interaction's influence on decision processes, perceptual evaluations, and decision outcomes and quality.

Relative to task characteristics, it has been largely classified as task type, task complexity, and task environment (Kelton et al., 2010). Task type determines the mental processes required when solving tasks (e.g., spatial, symbolic, integrative, selective) (Kelton et al., 2010). Task complexity governs the degree of information load required by the task and the degree of cognitive effort required to accomplish the task (Bonner, 2008). Task environment refers to relevant constraints when accomplishing particular tasks assigned to users (e.g., time, interruptions, familiarity) (e.g., Kelton et al., 2010; Speier et al., 2003; Wheeler & Arunachalam 2009).

Moderators: Users' Characteristics

How users' characteristics influence their interactions with information presentations remains inconclusive. In AIS research, for example, users' characteristics can be either predictors or moderators (e.g., Bonner, 2008; Dilla et al., 2010), whereas in IS research, users' characteristics are generally acknowledged as playing a moderating role in IS acceptance (e.g., Hartwick & Barki, 1994; Venkatesh et al., 2000; 2003; Xiao & Benbasat, 2007). Users' characteristics including domain expertise, domain knowledge, gender, and personal style contribute to incremental variance in decision-making. The relationship between IDIV characteristics, task characteristics and the quality of decision-making appears to be strengthened by users' characteristics. Novice users with limited accounting knowledge, for example, have the potential to benefit most from use of IDIV. The roles of users' characteristics, therefore, appear to accord with the notion of being a moderator because they affect the relationship between two variables (Baron & Kenny, 1986; Cohen & Cohen, 1983; MacKinnon, 2011).

Mediators: Decision Processes and Perceptual Evaluations

We distinguish decision processes and perceptual evaluations in that decision processes are represented by individuals' effort when making decisions (e.g., information processing strategy) and time spent solving tasks (Dilla et al., 2010; Koop & Johnson, 2011; Rubinstein, 2013). Three relevant proxies can be used to measure decision processes, namely, decision time, information search strategy, and actual fit. Decision time reflects the time that users spend solving their tasks with IDIV. Information search strategy reflects whether users process the information systematically or heuristically (Bazerman & Moore, 2009; Tversky & Kahneman, 1974; 2012). Actual fit indicates the actual cognitive effort that individuals apply when interacting with information systems (Tate et al., 2015; Vessey, 1991), as opposed to users' perceptions of fit (Goodhue 1995; Goodhue & Thompson, 1995; Tate et al., 2015).

Perceptual evaluations are adapted from prior studies investigating users' preferences when they decide whether to use IT artifacts or the information obtained from IS. Three relevant variables can be used as proxies for perceptual evaluations, namely, perceived ease of use, perceived usefulness, and perceived fit. The first two variables are adopted from the technology

acceptance model (TAM) (Davis, 1989; Davis et al., 1989) and perceived fit is adopted from task technology fit (TTF) (Goodhue, 1995; Goodhue & Thompson, 1995).

Outcomes: Decision Outcomes and Quality

This study posits that decision processes and perceptual evaluations can potentially influence decision outcomes and quality. Three relevant variables can be used to explicate decision outcomes and quality, namely, system use, information use, and accuracy. System use describes the activity of understanding, applying, and employing the available IT artifacts for a given tasks. Systems use can involve the method of use, extent of use, proportion of use, duration of use, frequency of use, decision to use, voluntariness of use, variety of use, specificity of use, appropriateness of use, and dependence on use (Burton-Jones & Straub, 2006). Information use is “the physical and mental acts humans employ to incorporate information into their knowledge base or knowledge structure” (Spink & Cole 2006, p. 28). Information use, however, involves obtaining information from particular IS and incorporating that information into their decision-making. Accuracy is an objective measure of the extent to which individuals accurately accomplish their assigned tasks using IDIV. Accuracy in this context relates to the decisions being made by users being optimal as a consequence of IDIV use. Given the notion of IDIV, both systems use and information use are central to effective IDIV use.

Underlying theories supporting the relationships between constructs in the conceptual model

Apart from providing the rationale for construct selection in the model, our nomological net for the model aligns with four applicable theories: information-processing theory (Card et al., 1983; Newell & Simon, 1972), TIME (Sundar, et al. 2015), cognitive fit theory (CFT) (Vessey, 1991), and task-technology fit theory (TTF) (Goodhue, 1995; Goodhue & Thompson, 1995). First, the purpose of our model reflects the idea of information-processing theory. Both IS and humans can be described as information-processing systems. Information-processing theory explains that the interactions between humans and computers can be divided into three interacting subsystems: perceptual, motor, and cognitive subsystems (Card, et al. 1983; Newell & Simon, 1972). When the given cues and tasks are simple, users will carried them out by perceptual systems, which, in turn, will activate motor systems. When the given cues and tasks are complex, however, the cognitive systems will activate motor systems.

Second, the relationships between IDIV characteristics, decision processes and perceptual evaluations are supported by TIME, whereby, interactive interfaces can lead to greater perceptual bandwidth as well as cognitive processing (Sundar et al., 2015). Third, in the IS research domain, cognitive fit theory (CFT) and task-technology fit (TTF) provide relevant explanations of the interaction effects between IDIV characteristics and task characteristics on decision processes, perceptual evaluations, and decision outcomes and quality. CFT suggests that the alignment between types of information and types of tasks leads to better fitness between individuals’ mental representations and, thus, better problem solving (Vessey, 1991). In this context, we argue that individuals’ mental representations can be best described as part of decision processes. Whereas TTF suggests that the alignment between task, technology and individuals’ abilities leads to stronger fit perceptions (Goodhue, 1995; Goodhue & Thompson, 1995).

Propositions

Recall in our model that we illustrate decision-making with IDIV as having four essential elements: predictors, moderators, mediators, and outcomes. In the following subsections, we offer seven propositions describing the relationships between each construct within the four elements within the IDIV context.

IDIV Characteristics and Task Characteristics' Relationships with Decision Processes and Perceptual Evaluations

While there is a substantial body of research investigating users' interactions with information presentations, such research does not always clearly distinguish between perceptual evaluations, decision processes, decision outcomes and the quality of those decisions. Recall that perceptual evaluation describes how an individual perceives or evaluates particular circumstances, which precedes their decision outcomes and quality (Xiao & Benbasat, 2007). Decision processes involve decision time and cognitive effort, that is, the extent to which individuals process and acquire the information from particular IS (e.g., Hong et al., 2005; Koop & Johnson, 2011; Rubinstein, 2013), while decision *outcomes* and quality arise when individuals use the IS or accomplish their decision-making tasks with the information obtained from the IS (Xiao & Benbasat, 2007). In short, perceptual evaluations, decision processes, and decision outcomes and their quality are distinct concepts. Perceptual evaluations and decision processes have the potential to help users arrive at appropriate decision outcomes and quality.

The Relationships between IDIV Characteristics, Task Characteristics and Decision Processes

Opinions diverge somewhat on how to assign effort and time as either decision processes or decision outcomes and quality variables. Concerning decision-making with provided cues or tasks, effort is associated with the extent to which individuals process the information prior to making decisions (Koop & Johnson, 2011; Xiao & Benbasat, 2007). The effort taken to arrive at decision outcomes and the time spent accomplishing the tasks indicates that the process of deliberation precedes decisions (Koop & Johnson, 2011; Rubinstein, 2013). Effort and time, therefore, appear to be most appropriately classified as reflecting decision processes rather than reflecting decision outcomes and quality.

The interactions between IDIV characteristics, task characteristics, and decision processes have attracted significant research. As part of any decision-making process the decision maker must ensure they acquire the most appropriate information and integrate the information in a timely manner. For example, animation using realistic images, gradual transitions, and parallel navigation result in less decision time than that using abstract images, abrupt transitions, and sequential navigation (Gonzalez & Kasper, 1997). Interactive presentations permitting individuals to use search features help them to acquire and integrate information (Hodge et al., 2004). Assuming the task requires the acquisition and integration of information, an IDIV allows for more efficient and effective information gathering and integration through the combination of animation and interactive presentation. Overall, studies demonstrate that IDIV characteristics and task characteristics can determine the extent to which users apply strategies to acquire and process information. Thus, we offer the following proposition.

P1: The extent to which decision processes vary depends on the interaction effect between IDIV characteristics and task characteristics.

The Relationships between IDIV Characteristics, Task Characteristics and Perceptual Evaluations

Different decision outcomes and quality are preceded by multiple perceptual evaluations. For example, individuals' perceptions toward IS have the potential to influence their decisions to use IS (Xiao & Benbasat, 2007). The psychology literature indicates that, when making decisions, individuals largely depend on their beliefs about the given cues and tasks (Mellers et al., 1998). This result reflects the information-processing theory notion that the given cues or tasks will be processed by either perceptual or cognitive systems to activate behavior via motor systems (Card, et al., 1983; Newell & Simon, 1972). In the research, perceptual evaluations of IS have been examined via a substantial number of studies using the technological acceptance model (TAM) (Davis, 1989; Davis et al., 1989). TAM indicates that individuals intend to use an IS when it helps facilitate the individuals' work (i.e., perceived usefulness) and are easy to use (i.e., perceived ease of use).

While the impact of interactive information presentations and visualizations on perceptual evaluations and decision-making is generally accepted (Chung & Nah, 2009; Huang et al., 2013; Locke et al., 2015), prior studies have used multiple proxies for perceptual evaluations. For example, in the communication field, the use of interactivity and customization features in the media increases perceived user satisfaction (Chung & Nah, 2009). Interactive data facilitates easy and rapid financial analysis and is perceived by users to be accurate and efficient. (Locke et al., 2015). Marketing research also finds that individuals likely perceive higher trustworthiness when interacting with e-tailer websites that provide search and feedback functions (Huang et al., 2013). As noted earlier, when interacting with information presentations and visualizations, the characteristics of the tasks at hand cannot be separately examined. The interaction effect and fit between IDIV characteristics and task characteristics therefore primarily determines perceptual evaluations and is consequently worthy of investigation. Thus, the following proposition is offered:

P2: The extent to which perceptual evaluations vary depends on the interaction effect between IDIV characteristics and task characteristics.

The Moderating Effects of Users' Characteristics

Along with IDIV characteristics and task characteristics, a further component of the input of the decision-making model is users' characteristics. These primary characteristics considered here are domain expertise (i.e., non-professionals vs professionals) and domain knowledge (i.e., visualization knowledge, tasks-specific experience, accounting or auditing knowledge). Relative to domain expertise, non-professional investors attract much attention because of their particular characteristics: their inexperience (Pinsker, 2007), their limited knowledge of financial information (Maines & McDaniel, 2000), and their reliance on simplified information (Hodge & Pronk, 2006). The use of IDIV is credited with improving non-professional investors' decision-making ability. IDIV can potentially improve the ability of both non-professional and professional investors when searching for information. Non-professional investors however gain greater benefits through improving their search strategies and risk assessments compared with their professional counterparts (Arnold et al. 2012).

Prior research generally confirms that domain knowledge (visualization knowledge, tasks-specific experience, accounting or auditing knowledge) can influence perceptual evaluations and decision outcomes and quality, e.g., a, users' understanding of, and familiarity with, graphs could influence their speed of information recognition and acquisition (Shah & Freedman, 2011). Users' experiences with specific tasks also contribute to the quality of decision-making

(Bierstaker & Thibodeau 2006). Divergent conclusions from prior studies, however, are still to be fully resolved. Raschke & Steinbart (2008) for example identified that those who possess task-specific experience perform similarly to their counterparts when interacting with misleading graphs, even though both cohorts had graph design training. In contrast, Cardinaels (2008) found that individuals with little accounting experience perform better than their more experienced counterparts when interacting with graphical formats than with tabular formats. In short, information presentations offer benefits to both inexperienced and experienced individuals. Concerning IDIV, however, we posit that those who are inexperienced and have less domain knowledge appear to benefit most from IDIV.

Relative to the preceding examples, this study observes that users' characteristics are moderators rather than predictors (Baron & Kenny 1986). Users' characteristics therefore can explain the relationships between information presentations, task characteristics, decision processes, perceptual evaluations, and decision outcomes and quality. This notion also aligns with research in psychology and IS investigating the role of users' characteristics as moderators rather than predictors (Baron & Kenny, 1986; Venkatesh et al., 2000; 2003; Xiao & Benbasat, 2007). In light of such argument, the following two propositions arise.

P3: Users' characteristics moderate the relationship between IDIV characteristics, task characteristics and perceptual evaluations.

P4: Users' characteristics moderate the relationship between IDIV characteristics, task characteristics and decision processes.

We speculate that the operationalization of these two propositions may provide insightful findings to inform both theory and practice. Regarding the position of novices versus experts for example, those who are not expert are likely to exhibit more salient perceptual evaluations than those who are expert. Similarly, those who are not expert are likely to exhibit greater improvements in their decision processes than those who are expert. The difference between novice and experienced individuals when interacting with technology has also been described in the Theory of Technology Dominance (TTD) (Arnold & Sutton, 1998). TTD suggests that novice users tend to rely more heavily on technology compared to more experienced users. While TTD explains the difference in the level of reliance as it relates to technology, our conceptual model can highlight improvements to decision processes and perceptual enhancements when interacting with IDIV.

The Relationships between Decision Processes, Perceptual Evaluations, and Decision Outcomes and Quality

While research has attempted to suggest a decision-making framework with IDIV, it does not clearly distinguish between decision processes, decision outcomes, and the quality of those outcomes. Bonner (2008) argued that processes and performance are two distinct decision outcomes. We argue that processes should be distinguished from performance. Decision processes precede decision outcomes and quality and should, therefore, be viewed separately. Following this line of argument, this study proposes that decision-making with IDIV can be more comprehensively explained if the decision processes, the decision outcomes, and quality are each examined separately.

While research into IDIV explaining the relationships between decision processes, perceptual evaluations, and decision outcomes and quality is limited, such relationships have been formulated and empirically tested in other contexts, such as studies about recommendation

agents, decision aids, information exchanges, and IS success. Decision processes can potentially influence perceptual evaluations. Both decision processes and perceptual evaluations also likely simultaneously influence decision outcomes and quality. Xiao & Benbasat (2007) suggest that, when using recommendation agents, consumers' decision processes appear to lead to consumers arriving at more positive evaluations concerning greater perceived ease of use and greater perceived usefulness. Relative to the relationship between perceptual evaluations and decision outcomes and quality, users' positive evaluations of the security of e-commerce websites leads to intentions to use B2C e-commerce (Hartono et al., 2014). In a different context, Xu et al. (2014) find that better perceived decision quality leads to positive intentions to reuse a particular recommendation agent. In light of these findings, we believe that for IDIV, the relationships between decision processes, perceptual evaluations, and decision outcomes and quality may follow a similar pattern. The following propositions are, therefore, presented:

P5: Better decision processes lead to more positive perceptual evaluations of IDIV.

P6: Better decision processes permit users to accomplish better decision outcomes and quality.

P7: More Positive perceptual evaluations permit users to accomplish better decision outcomes and quality.

To summarize, propositions 1 to 7 are formulated to help answer RQ2: Does IDIV influence decision outcomes and, if so, what aspects influence them? Both IDIV characteristics and task characteristics are proposed to be associated with decision processes and perceptual evaluations, which are in turn moderated by users' characteristics. Subsequently, decision processes and perceptual evaluations can influence decision outcomes and quality.

Contributions and Research Agenda

Research Contributions

In this paper, we have formulated propositions guided by validated theories concerning perceptual evaluations of decision tasks using IDIV. We expect that the propositions should contribute to the advancement of research related to IDIV. More specifically, this paper offers the four following contributions to research.

First, guided by previous work on information-processing theory (Card et al., 1983; Newell & Simon, 1972), we clearly delineate the decision-making elements into predictors, moderators, mediators and outcomes. Such delineation helps clarify several concerns arising from prior investigations of perceptual evaluations and decision-making³. In addition, decision processes appear to be classified by several studies as outcomes of decision-making. This paper classifies: (1) IDIV characteristics and task characteristics as predictors; (2) users' characteristics as moderators; (3) decision processes and perceptual evaluations as mediators, and (4) decision

³ These involve focusing on predictors and outcomes of decision-making, mixing predictors with moderators, and mediators with outcomes, and giving insufficient attention to mediators.

outcomes and quality as outcomes. More appropriately, these constructs should be investigated sequentially, so that predictors precede mediators and outcomes.

Second, this study provides the foundations to enhance understanding of the mediating role that decision processes and perceptual evaluations play. Such understanding is important because mediators explain the underlying mechanism between predictors and outcomes. The route for decision-making, whether via decision processes or perceptual evaluations, potentially affects the decision outcomes. We contend that this contribution will better inform both theory and practice. Recall that, in Section III: The Conceptual Model and its Constructs, we suggest three relevant proxies of decision processes, namely, time spent, information processing strategy, and actual fit.

Third, we believe our conceptualization may improve practice because it provides greater insight into decision processes and perceptual evaluations and thus helps identify the constructs that can best explain the outcomes of users' interactions with IDIV. In our model, we incorporate perceived fit as one of the proxies of perceptual evaluations and actual fit as one of the proxies in decision processes. Empirical findings from investigations into both perceptual fit and actual fit are important for helping presentation and visualization designers align IDIV with users' tasks, expectations and cognitive style. Benefits include enhancing visualizations and giving individuals' greater choice and control over the visualizations that best suit their specific tasks. Further, IDIV is increasingly important for supporting DA.

Appropriate data visualizations can reduce the level of difficulty faced by individuals when comprehending such information. While the relevancy of visualizations largely depends on the users' mental models and their specific tasks, they are often generated by designers who may have different mental models from users (Bačić & Fadlala, 2016). This implies that the relevancy of visualizations relates to the alignment between the graphic designers' mental models, the users' mental models, and the purpose of the visualizations when supporting specific tasks.

While the relevancy of visualizations is important, the attractiveness of visualizations also matters because it can generate higher interest from stakeholders seeking to invest in companies that present their information with visualizations (Latham & Tello, 2016). Such interest occurs because investment decision-making is not always rational; individuals may use heuristic decision-making (Monti et al., 2012) or be attracted by visual representations (Baron et al., 2006). Providing relevant and attractive IDIV features and UI, therefore, warrants implementations that address both rational and heuristic aspects of decision-making.

Fourth, IDIV is now the essential feature of DA tools (data visualizations, and machine learning). Organizations and individuals are able to leverage their data via these tools permitting them solve their business problems. With intuitive UI, DA tools allow both expert and novice users to generate insights from their data using IDIV. Further, the ability of novice to readily switch from one visualization to other visualizations using IDIV will benefit them to arrive at satisfying visualization experiences. This could make novice more heuristically adept when solving their problems using IDIV (Perdana et al, 2018; Luo, 2019).

Fifth, while DA has recently found favor, research related to understanding DA's capabilities and the interactions between individuals and IDIV remains limited (Jiang et al., 2019). Jiang et al, for example, reviewed just 10 papers in the field of DA and Business Intelligence, and 12 papers related to Human Computer Interactions. Given the potential uptake of DA research, we provide articulated propositions to help comprehend individuals' interactions with IDIV with the intention that those propositions motivate further research effort in an expanding field.

Overall, this paper proposes a high-level, theory-driven conceptual model wherein the specific constructs and variables explain the context in which this model may be applied. The conceptual model in this study is intended to serve as a basis for future research on users' interactions with IDIV. In the next section, this study proposes several areas where further investigation is warranted.

Table 4 - Proposed Model and the Potential Research Contributions

Elements	Constructs	Potential Theory and Practical Contributions
Predictors and Mediators	IDIV Characteristics, Task Characteristics, Decision Processes, Perceptual Evaluations	<ul style="list-style-type: none"> IDIV characteristics may need to vary depending on the characteristics associated with a particular task. We argue that the more difficult the tasks the more likely users will use multiple IDIV characteristics. They are also likely to use multiple visualization to make sense of the data and use analytics to find more insights. Perceptual evaluations may vary depending on whether IDIV characteristics align with task characteristics. Our argument align with TTF theory. When particular tasks can be solved effectively with IDIV, the more likely they will have favorable perceptual evaluations.
Predictors, Moderators, and Mediators	IDIV Characteristics, Task Characteristics, Users' Characteristics, Decision Processes, Perceptual Evaluations	<ul style="list-style-type: none"> The route for decision-making, whether via decision processes or perceptual evaluations, is clearly distinguished. Help facilitate alignment of graphic designers' mental models, the users' mental models, and the purpose of the visualizations when supporting specific tasks. The design aspect of IDIV, for example, is essential to facilitate users' choice when solving their tasks. The three IDIV characteristics must be seamlessly combined (Luo, 2019).
Mediators and Outcomes	Decision Processes, Perceptual Evaluations, Decision Outcomes and Quality	<ul style="list-style-type: none"> IDIV features and UI warrant potential implementations addressing both the rational and heuristic aspects of decision-making. For example, expert or frequent users of data visualizations will have more favorable perceptual evaluations and better decision process than that of novice users. Novice users, however, may benefit from IDIV characteristics by making them more heuristically adept (Luo, 2019; Perdana et al., 2018).

Research Agenda

The proposed conceptual model in this paper (see Figure 1) specifically examines the relationships between IDIV characteristics, task characteristics, users' characteristics, decision processes, perceptual evaluations, and decision outcomes and their quality. Prior research in information presentations in disciplines such as IS, psychology, communication, AIS, marketing, and information visualizations, provides an important foundation for this conceptual model. This paper proposes that it provides a more nuanced understanding of the mechanisms that influence decision-making with IDIV. Future work may examine and further improve the theoretical development of this model. The following subsections offer suggestions for such research.

Testing the Conceptual Model

Future research should empirically validate the directions of the relationships among the constructs within the IDIV context, either for a partial conceptual model or for the complete conceptual model (including predictors, moderators, mediators, and outcomes). The proposed model is an associative model, wherein constructs within the predictors always precede constructs within the mediators (recall, Figure 1). Considering the nature of the conceptual model, experimental research appears appropriate to validate pieces of this model.

Recent technological advances permit researchers to manipulate both IDIV characteristics and task characteristics. The availability of such features enables researchers to investigate the interaction effects between IDIV characteristics and task characteristics, and their impact on decision processes, perceptual evaluations, and decision outcomes and quality. Researchers should also more closely examine the role of users' characteristics when interacting with IDIV. For example, P2 and P3 raise prospects for further examination of whether experts and novices exhibit different decision processes and perceptual evaluations when interacting with IDIV. Experts are not only knowledgeable of their domain, they also have more visual literacy skills than novices. If significant differences are confirmed, future research could investigate which IDIV characteristics best fit with experts or novices, and which IDIV features better support particular tasks than others. Understanding how experts and novices interact with IDIV, for example, could help IDIV designers to deliver the IDIV features most relevant for different user characteristics. We contend that addressing such questions will provide an insight into rich measures of system use (Burton-Jones & Straub, 2006). We believe that IDIV provides a rich environment for IS studies to investigate the relationship between IT artefacts, task characteristics, and individual characteristics. This rich environment should contribute to the empirical findings that further advance the IS discipline (Benbasat & Zmud, 2003).

A substantial body of research in information presentations has tested relationships between predictors and outcomes, for example, the effect on accuracy caused by the interaction between information presentations and task characteristics. It appears that, when users process information prior to arriving at decision outcomes (e.g., accuracy), their underlying cognition is overlooked. In both IS and AIS research, the processes that apparently mediate the relationship between predictors and outcomes in decision-making seem to be paid scant attention. Our proposed model uses validated theories from the psychology field to articulate the apparent missing link in the relationships. We expect that our model provides an avenue for future research to empirically test the effects on both decision processes and perceptual evaluations of the interaction between IDIV characteristics and task characteristics.

Future research could investigate reliable and valid measurement variables within decision processes such as information processing strategy and actual fit. While current research largely uses self-reported decision processes as measures, using this type of measure may bias any findings. Exploring the potential of interconnected technologies (e.g., brain sensors, eye tracking, mouse tracking) that can more precisely observe individuals' decision processes could provide more insightful findings for IDIV research programs. Investigation of these constructs and variables could also improve knowledge about how individuals process information when interacting with IDIV to arrive at decision outcomes and quality.

Prior research in IS largely incorporated system use, information use, and accuracy as the relevant variables to measure decision outcomes and quality (e.g., Bonner, 2008; Burton-Jones & Straub, 2006; DeLone & McLean, 1992; 2003; Jiang & Benbasat, 2007). Few studies propose sense-making as a relevant variable for evaluating the outcome of individual interactions with

data visualization (e.g., Baker et al., 2009; Parsons & Sedig, 2013). In the context of IDIV, the availability of IDIV enables individuals to amplify their analytical capabilities. Via IDIV data is presented as meaningful and intuitive visuals enhancing individuals' ability to make better sense of complex data (Baker et al., 2009; Petterson, 2014). Incorporating sense-making as the relevant variable in the model could help researchers to comprehend how perceptual evaluations and decision process lead to better decision- making with visualization.

Enhancing the Conceptual Model

This paper endeavors to develop a parsimonious conceptual model. We identify three important areas for further development: first, further investigation of decision processes and perceptual evaluations; second, further investigation of users' characteristics; and third, extending the model to investigate continuance decisions of IDIV use.

The first area that we highlight is decision processes and perceptual evaluations. In the conceptual model we incorporate information processing strategy and actual fit as the two relevant proxies for decision processes (see Section: Proposed Model and its Constructs). Relative to information processing strategy, using IDIV to support individuals when making decisions should help them to overcome bounded rationality. Concerning IDIV, little is known of the extent to which users process the information available from IDIV, particularly whether users apply heuristic or systematic information processing. Future research could examine the role of both IDIV characteristics and task characteristics with leveraging heuristic, or enhancing systematic information processing.

Relative to actual fit, we concur with Tate et al., (2015) that both TTF and Cognitive Fit are appropriate theories to study IS fit at the individual level. While cognitive fit is concerned with the actual fit related to the cognitive effort that individuals apply when accomplishing their tasks with IDIV (Tate et al. 2015), TTF can be used to investigate individuals' perceptions of IDIV characteristics and tasks characteristics (Goodhue 1995; Goodhue & Thompson, 1995). While researchers have used cognitive fit (Vessey, 1991) to study information visualizations, their research did not incorporate important IDIV characteristics such as, active control and analytics.

Relative to individuals' perceptions, we highlight three areas that could be further explored: perceived information quality, perceived uncertainty and perceived risk. The notion of fitness for use in the information quality (IQ) field implies that information is perceived to be high quality when it is informative, relevant, and applicable to support decision-making (Wang & Strong 1996). Despite much research having been conducted to investigate IQ from the perceptual perspective in the area of IS (Jayawardene et al. 2013), limited attention has been paid to IQ relative to users' interactions with IDIV (Perdana et al., 2019). Future research may investigate, for example, (1) whether or not perceived information quality is dependent on interactivity features; and (2) whether users' perceived information quality can be enhanced by using interactivity features.

Relative to perceived uncertainty and perceived risk, we contend that IDIV permits individuals to reduce uncertainty and mitigate risks. Individuals will make decisions more confidently when they can search relevant information. Because IDIV has the potential to ensure that relevant information is more easily available, IDIV may reduce individuals' uncertainty and, in turn, help them achieve improved decision outcomes and quality. Huang et al. (2013), for example, find that those with access to interactive data are likely to be more trusting in the information provided on e-tailer websites. These higher levels of trust are reflected through lower perceived uncertainty towards the available information. More recently, Dilla et al., (2015) support the potential for using interactive data to detect fraud. Given that IDIV has the potential to reduce

uncertainty, we contend that IDIV can shape individuals' notions of the provided information. Further, these notions can be reflected by lower users' perceived uncertainty.

The second area that could benefit from investigation is users' characteristics. The characteristics could include domain expertise, domain knowledge, gender, and personal style. Further investigation may be needed to examine how IDIV complements particular users' characteristics. In AIS, for example, research involving participants such as non-professional investors versus professional investors, or participants with high-level prior accounting or auditing knowledge versus participants with low-level prior accounting or auditing knowledge may prove insightful for the practical purposes of IDIV. Another users' characteristic that may warrant investigation is individuals' appetite for risk. In line with the previous arguments about perceived risk, investigating individuals' appetite for risk (e.g., risk averse, risk neutral, risk taker) could further enrich the development of the proposed conceptual model. Appetite for risk has the potential to explain the relationships between IDIV characteristics, task characteristics, and perceived risks as they relate to assessing whether or not risk averse individuals are more likely to have lower perceived risk when interacting with IDIV.

The third area that may provide an avenue for future research is extending the model to investigate how users' behavior changes over time when interacting with IDIV. This extension would have to be viewed from a process model perspective rather than variance model perspective (Van de Ven, 2007). More specifically, when explaining the continuance decisions of IDIV use, apparently recursive relationships occur between decision outcomes and quality, decision processes, and perceptual evaluations. Incorporating intentional behavior and/or habit perspective(s) when explaining the process view of IDIV continuance decisions may provide insight into whether repetitive use of IDIV leads to better decision processes, more positive perceptual evaluations, and heightened dependency on IDIV.

Concluding Remark

While research into IDIV is relatively well-documented in the human computer interaction, psychology, communication, and marketing fields, research has yet to provide a parsimonious model of the extent to which individuals' interactions with IDIV affects their decision processes, perceptual evaluations, and decision outcomes and quality. Drawing on multiple findings from diverse literature, while at the same time attempting to provide comprehensive understanding, our proposed model helps to summarize complex decision-making into parsimonious researchable constructs specific to IS. This paper proposes a conceptual model to better understand IDIV characteristics and thus enhance decision processes, perceptual evaluations, and decision outcomes and quality.

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