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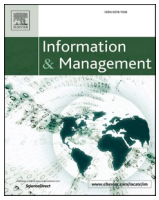

Organizational decision making and analytics: An experimental study on dashboard visualizations

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ABSTRACT

Although analytics have become a widespread practice, we still have minimal knowledge about how dashboards influence decision-makers and through what mechanisms they enhance decision making. In this study, we built on an experiment-based approach with mock-up visualizations and recruited 524 participants, who were divided into two groups (A and B) with variations in their visualizations. We found that the *format, currency*, and *completeness* of information indirectly affect decision making quality by reducing the perceived task complexity and enhancing information satisfaction. Our results contribute to a better understanding of the role of visual representation of information quality on dashboard visualizations.

1. Introduction

Big data analytics (BDA) has been heralded as a key component for businesses to be competitive in an age in which data-driven decision making has become the norm [1]. To cope with the increasing volume of data, a growing number of businesses are now using BDA to gain a competitive edge by enabling their decision makers to take actions based on up-to-date insight [2]. Such insight is typically represented in the form of dashboards, in which large and complex data sets (ie, big data) are analyzed and visualized in an easy-to-comprehend manner [3]. A recent study showed that companies that manage to effectively use analytics to improve performance in marketing and sales are 1.5 times more likely to achieve above-average growth rates and experience a 5 % higher return on sales [4]. As a result, a growing number of enterprises are now using such approaches to enhance key decision tasks [5]. Recent studies also have shown that the use of analytics-based visualizations can allow organizations to track, monitor, and optimize their marketing strategies in real time, improve operational inefficiencies, and boost organizational performance [6]. Building on this trend, a recent survey showed that more than two-thirds of companies are planning to deploy analytics-based visualizations to enhance decision making for core business tasks [7].

This shift toward adopting analytics-based visualizations to support decision making stems from a requirement to make rational decisions in an environment that is information-dense, fast-paced, and highly competitive and in which customers are strongly networked and thus well informed [8]. As a result, there is a growing interest in understanding how the design and use of visualizations can optimize decision making quality in organizational operations.

Despite the rosy promises of visualizations for decision making, deploying analytics approaches for organizational operations is by no means a panacea, and under certain conditions it can result in suboptimal decisions or be unutilized by end users [9]. One key obstacle in successfully leveraging vast amounts of data to inform decision making is the challenge of extracting, selecting, and representing information in a way that the human mind can effectively utilize via visual representations [10]. In this regard, analytics enabled through data visualization plays an essential part in the data discovery process by transforming abstract data into visual elements that can be readily utilized by decision makers [11]. Keim et al. [12] emphasized the importance of combining analytics and visualization to effectively access complex data sets and extend the cognitive abilities of humans. Data visualization aids decision making by increasing understandability [13,14], reducing information overload [15], and helping decision makers interpret and identify patterns in complex datasets [16]. Furthermore, data visualization works as a common language in conversations [17] and aids the communication

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of complex concepts and hypotheses within groups of people [13,18].

Although data visualization is a powerful means for communicating dense and complex information such as that contained in big data, it also is characterized by several quality dimensions that define its effectiveness in terms of user requirements [19]. Prior studies in the information systems discipline have defined a set of dimensions for information quality (IQ) that fall into four main categories: *format, currency, completeness*, and *accuracy* ([20]; Yang et al., 2002; [21,22]). The role of IQ has been a topic studied extensively in relation to user satisfaction [23] and more recently toward decision making [24,25]. However, there is still a lack of knowledge concerning the visual cues of IQ, in the form of dashboard visualizations affects decision making quality [26]. More precisely, we still know very little about how the design of visualizations for decision making affect the perceptions of the intended user and consequently the quality of decision making. IQ dimensions of visual representation have become increasingly important for contemporary organizations, since they can lead to several issues, such as biased decision making, overconfidence, inaccurate understanding of the underlying data, distrust, and overemphasis on certain information [27, 28]. The key assumption in several studies is that simply improving the quality dimensions of information will result in improved decision making. However, we still know little about how each of the underlying dimensions of IQ as presented on analytics visualizations dashboards impacts decision making quality, and specifically through what mechanisms. This problem becomes even more apparent when considering the significant variation in terms of perceived IQ of visual representations used to aid decision making. In other words, how IQ dimensions as embedded in dashboard visualizations affect the quality of decisions made in organizational contexts remains unclear.

In this study, we build on the four dimensions of IQ and seek to understand how they influence decision making quality. According to a study by Janssen et al. [29] that calls for a better understanding of factors that influence decision making quality in the age of analytics and dashboard visualizations, *decision making quality* is defined as the accuracy and correctness of a decision. As data in organizational operations expand and become more complex, the cognitive and time limitations of human agents pose difficulties in making high-quality decisions based on information presented in an unsuitable way. Thus, decision making quality is arguably dependent on the IQ available on dashboard visualizations [29], as well as on the capacity of that information to satisfy informational requirements and reduce the complexity of the decision making task. In this regard, information satisfaction and task complexity go hand in hand, as having sufficient and high-quality information for a given task can reduce the perceived complexity of the task [30]. Prior research on task complexity has indicated that information satisfaction through high IQ availability can reduce perceived task complexity and improve decision making quality [31–33]. Consequently, information satisfaction and perceived task complexity are argued to be the mechanisms through which IQ improves decision making quality.

The present study was conducted to explore how the different IQ dimensions can indirectly influence decision making quality using analytics-based visualization. Although there has been some empirical work on the role of IQ in relation to decision making performance, there remains still a lack of understanding regarding how IQ attributes presented in the form of visual formats, such as dashboards, influence decision making quality [29]. Since the use of dashboards is becoming increasingly embedded in contemporary organizational operations and decision making, it is important to understand what aspects of IQ contribute to improving decisions [27,34]. In addition, although some prior studies assumed a direct relationship between IQ and decision making, there is a growing understanding of the effects of underlying mechanisms (i.e., indirect effects). Thus, in this study we explore how information satisfaction and perceived task complexity mediate the effect of IQ dimensions from dashboard visualizations to decision making quality. Doing so can enable us to better understand how decision makers interact with dashboards that present complex information in condensed visualizations, as well as how to optimally design such interfaces to meet the needs of decision makers. From a practical perspective, understanding these points also can enable contemporary organizations to design analytics-based visualizations in an optimal way without the risk of investing large sums on analytics that are not meaningful for key decision makers. The context of organizational decision making is also important, given the significant and long-term financial commitments tied to decisions, which have important ramifications for the future survival of the organization [35]. Thus, this article builds on the following research questions:

RQ1: *What aspects of IQ on analytics-based visualizations influence decision making quality in an organizational setting?* and

RQ2: *What is the role of information satisfaction and task complexity in mediating the above relationships?*

To answer these questions, this study builds on an experiment using mock-up visualizations accompanied by decision making tasks. Specifically, we have developed four decision making tasks related to organizational operations, along with two variations (A and B) of the four visualizations that accompany each task. We built on the IQ dimensions of format, currency, completeness, and accuracy to create variations A and B of the visualizations. We collected data from 524 individuals who were invited to complete one of the two variations of the four decision making tasks and accompanying dashboard visualizations. After each task, respondents were asked to select an answer for the decision making choice, assess the information provided on the dashboard, and provide some information about the task and their perceptions of their decision making quality.

By quantitatively analyzing these data through a conceptual research model by means of partial least squares, we showcase the significance of how IQ dimensions influence information satisfaction and perceived task complexity and in turn affect decision making quality. Specifically, we find that the format, currency, and completeness of information provided on dashboard visualizations positively contribute to information satisfaction. In turn, these dimensions have direct and indirect effects through information satisfaction on reducing perceived task complexity. In other words, the format, currency, and completeness of information on dashboards influence decision makers by prompting changes in perceptions of the complexity of tasks and in satisfying informational requirements. These changes in perception then influence decision making quality.

Information satisfaction has a positive effect on decision making quality, whereas perceived task complexity has an inverse effect, in which the lower the perceptions, the better the decision making quality. Based on the study results, we discuss some important implications that can help guide future research and practice. The novelty of the study is twofold, on the one hand by examining the impact and mechanisms through which visual representations of IQ influence decisions at the organizational level and on the other hand by setting the study in a realistic context tied to decision making tasks and respective visualizations on analytics dashboards.

The rest of the paper is structured as follows. Section 2 presents the literature synthesis by first describing how dashboard visualization has been introduced in the organizational context and their significance and then providing an overview of how visualization influences decision making of individuals as well as some important caveats of the process. The section concludes with a theoretical synthesis of how IQ, satisfaction, and task complexity are associated and their impact on decision making quality. Section 3 introduces our conceptual research model, which stems from the discussed literature and the corresponding theories. Section 4 provides an overview of the process of developing scenarios and designing the survey used to test the research model, and Section 5 discusses the study results, describing the analysis method, measurement model, and structural model. Section 6 closes by discussing the findings in light of the research model and its implications for research and practice, along with limitations of this research and

suggestions for future work.

2. Background

2.1. BDA dashboards in organizational operations

An increasing number of businesses are striving to use BDA to analyze available data and aid decision making [36]. BDA can be defined as the process of applying advanced analytic techniques to big data [37], referring to the process of analyzing raw data to extract information from massive data sets [38]. The end products of such analytics approaches are represented predominantly in the form of dashboards. These dashboards visualize key information to help decision makers utilize synthesized and contextualized information in a concise manner [39]. Through these dashboards, decision makers can extract meaningful patterns [16], generate information, and gain an understanding of business processes [6]. Moreover, analytics-based dashboards have been found to significantly improve decision making, reduce risks, and uncover insights from data that otherwise go unnoticed [37].

Within the context of organizational operations, analytics-based dashboards have been gradually becoming a core component of decision making. Specifically, Hallikainen et al. [6] emphasized the importance of customer and partner relations in firm operations and described how the use of dashboards can enhance these relations by providing up-to-date and concentrated information with key collaborators. In addition, dashboards allow for the generation of rich insight into prospective customers and enhance informed decision making about prospective actions that can be taken to improve market positioning [6]. To survive in a competitive environment, companies must leverage analytics-based insight in the form of dashboards to maintain an overview of emerging developments in key areas of operations [40]. A recent study by Akhtar et al., [41] highlights that the most successful organizations are data-driven, with the ability to dynamically monitor and visualize data-driven insights pertaining to such activities as production runs, supply chain interaction, transportation, and logistics. Analytics-based dashboards also can help optimize business processes related to industrial customers [42] by revealing and capitalizing on company changes [37] and enhancing sales growth [6]. As such, an increasing number of organizational core activities are informed by data provided through analytics-based dashboards.

An organization's overall capability for sensemaking in the complex and continuously evolving business environment can be increased through the use of dashboards and data-driven decision making [43]. In the organizational context, dashboards are being increasingly acknowledged as one of the more important analytical tools that allow managers to visually identify trends, patterns, and anomalies about operations as well as to monitor, plan, and execute future decisions [44]. Gustafson and Pomirleanu [45] recently suggested that dashboard visualizations can provide rich insight into performance in different market segments, as well as an overview of strategies used and how they perform financially. They argued that such dashboard visualizations built on BDA can track and measure specific campaigns, as well as aggregate customer and product feedback. Thus, dashboards provide a dynamic way of incorporating real-time data and enabling direct comparison between different alternative choices and how they have performed. Nevertheless, de Jong et al. [43] recently suggested the importance of developing a more nuanced understanding of how dashboard visualizations affect decision making at the individual level, and particularly how informational cues present in such dashboards influence the quality of decisions. Because dashboards present information in different formats and with different quality criteria, it is important to understand the core attributes in organizational-based activities and how they influence the decision making quality of the end users.

2.2. The role of dashboard visualizations in decision making

One goal of dashboard visualizations is to create business knowledge to support informed decision making [6,46]. Decision making can be defined as the choice between two or more competing courses of action [47] and can be divided into two parts: the process of making the decision and the result of the decision. For this study, we built on the concept of decision making quality, defined as the perceived satisfaction of a decision by the decision maker [29,48]. This definition corresponds to the later aspect of decision making, which nonetheless is dependent on the process of making an informed decision. Dashboards can enhance the decision making process by engaging human interpretation of information to gain insights [14] and enable the identification of patterns and trends in vast data sets [13,16,49]. More precisely, dashboards can aid the decision making process by increasing understandability [13, 14], presenting data in an effective and efficient manner [50], and reducing information overload [15]. For dashboard visualizations to be helpful, they must align with human cognitive perception and memory abilities [15] and follow design principles that facilitate cognitive access [51]. In other words, visualizations must be both effective and expressive to be perceived as valuable in the decision making process [52].

Although some studies have provided empirical insight into the use of visualizations in dashboards for improving decision making, we still know little about the challenges associated with conveying complex data into simple and actionable visualizations to enhance decision making quality [43,53]. Because dashboards often visualize quantified information, they can augment human understanding which in turn reduces biases [54]. The ability to interpret complex data is increased significantly when individuals move from textual information to visual input, which is thought to be processed more rapidly in the human brain [55]. However, the ineffective design and use of information in dashboards can have the opposite effect, causing decision makers to become overwhelmed and resulting in suboptimal decisions [56]. Human cognitive processing capacity can be affected by both the amount of data and the format in which it is presented [57]. Thus, it is important to consider that decision makers have limited cognitive capacity to absorb particularly complex information presented on dashboards [44]. Consequently, although dashboard visualizations may offer decision makers a useful tool for processing complex information, our knowledge of how the presence of information may affect decision making quality remains limited. In other words, it is important to understand the tipping point at which analytics-based visualizations of complex information become more of a hurdle than an aid.

According to Chan [51], data visualization may contribute to further distancing and deadening of conscience by removing the visibility of real people and events and aestheticizing representations of catastrophes. Specifically, the type and format of information presented in visualizations are critical factors influencing the performance of decision makers, particularly in terms of decision quality [37]. The quality of the decision provides valuable insight into how dashboards affect the decision making process. To improve decision quality, the complexity and uncertainty of the information must be reduced, and the technological capabilities must be designed to enable human abilities [46]. Nevertheless, misformatting of vital information has been found to distract the user from task-relevant information [58], affecting the quality of decisions. Furthermore, the decision time increases when the user utilizes working memory to interpret complex visual cues [47,50]. Thus, there is a need to explore how the IQ of dashboard visualizations influences decision making and through what mechanisms such effects materialize.

2.3. IQ, satisfaction, and task complexity

IQ has long been studied in the IS discipline as an important enabler of the use of a given system [20]. In their seminal work, Wixom and Todd [59] highlighted that IQ has been conceptualized in an intrinsic and contextual view. The authors argue that an intrinsic

conceptualization of IQ offers a rather limited perspective by regarding information as an object that can be assessed in isolation of the context in which it is applied. A context-based conceptualization extends the concept of IQ, suggesting that it is important to consider the value of information in relation to a task being completed. In addition, building on the work of Wang and Strong [20], several studies, including that of Wixom and Todd [59], have argued that a representational perspective on IQ is important, as it reflects the degree to which information presentation effectively facilitates interpretation and understanding.

Building on this stream of research, there is a consensus that IQ can be distilled through a core set of dimensions that jointly capture the different perspective. Thus, in this study we follow the conceptualization of Wixom and Todd [59] who identify the following four dimensions as key aspects of IQ: *accuracy* (reflecting intrinsic quality), *completeness* and *currency* (reflecting contextual quality), and format (reflecting representational quality). These dimensions also are appropriate for understanding the qualities of dashboard visualizations, as they incorporate aspects related to the task and the visual representation of information [60,61].

Wixom and Todd [59], as well as subsequent work have provided detailed definitions for these IQ dimensions. *Format* refers to how well the information is presented [59], the degree to which the provided information is presented in a clear manner [24] and is easy to understand [62]. *Currency* represents the users' perception of the currentness of the information [59]. Al-Mamary et al. [62] found information to be current if the information is provided in a timely manner for the purpose required and sufficiently up to date to address the task at hand. *Completeness* refers to the system's ability to provide all necessary information. It reflects the degree to which the information is available and has sufficient depth and width for the current task [63]. Finally, *accuracy* is defined as the users' perception of the correctness of the information, reflecting how accurate the information is and how many errors it contains [62]. In addition, the accuracy of information can be interpreted as the degree to which information is correct, unambiguous, meaningful, believable, and consistent [63]. With dashboards becoming increasingly more important in organizations, there is a renewed focus on how aspects of IQ as presented in dashboards influence decision making quality [43].

The definition of IQ used here underscores the importance of considering such information within the context and domain in which it is being used. In other words, the quality of information is contingent on how useful it is for completing a given task. Thus, when examining the impact of IQ dimensions on decision making quality, it is important to understand the degree to which such information satisfies the decision maker's requirements for the given task. Prior studies have built on these dimensions and explored how the presented information influences the use in decision making. For instance, Filieri and McLeay examined the role of IQ dimensions in travelers' use of online reviews and found that accuracy and currency are of particular importance, and Setia et al. [64] identified the combination of dimensions as an important enabler for customer service units to improve service. Although several other studies have built on these dimensions individually or at an aggregate level to examine how they influence the use of digital technologies (e.g., mobile website adoption, hospital information systems, e-government services) [65,66], we still do not know how the representation of these dimensions on visual mediums such as dashboard visualizations affects decision making.

This issue is particularly prevalent for organizational decision making, in which the role of dashboards is to reduce perceptions of task complexity and to facilitate the use of important and synthesized data for enhanced decision making [43]. Thus, we draw on the task complexity literature, which forms the theoretical basis for linking information use to decision making tasks [31]. *Task complexity* has been defined as the degree of cognitive load or mental effort required to identify and/or solve a problem [33]. Wood [67] suggested that task complexity is dependent on the information cues that must be processed when performing a task to reach a decision. Thus, information that satisfies the task requirements will reduce the perceived task complexity and lead to improved decision making [68]. As a result, information satisfaction from the decision maker's perspective will contribute to perceptions of decreased task complexity.

We define *information satisfaction* as the user's attitude or feelings toward the overall level of information provided in relation to a given task [59]. Thus, in our theorizing we argue that information satisfaction and task complexity are a set of interdependent mechanisms through which IQ translates into improved decision making quality [69]. Prior studies have noted that to reduce the perception of task complexity, users must obtain information that satisfies their task requirements. Thus, the attributes of information that are important and the corresponding information satisfaction vary according to the task at hand [70]. In effect, there are complex interactions among the IQ attributes provided to decision makers, their level of information satisfaction, and their perception of the complexity of the task [71].

To date, the management literature has failed to keep pace with the development of analytics-based dashboards and their impact on decision making. This is particularly pronounced when considering that dashboard visualization is a medium of information presentation, and that different aspects of IQ can either enhance or undermine decision making. Interestingly, Godfrey Team [72] argued that the discussion in the literature has provided very generic recommendations, such as that dashboards should be kept simple and reliable for decision makers. Thus, there is a need to understand not only which IQ dimensions on dashboard visualizations influence decision making quality, but also how such effects are realized. Although dashboard visualizations are being used at an accelerating rate to aid decision making, we still do not know how the representation of IQ dimensions in visual formats affects the quality of decisions and how such effects are realized. Based on our theorizing, we have developed a conceptual research model, which is presented next.

3. Research model

The research model, shown in Fig. 1, is based on the theoretical grounding and corresponding literature overview discussed in Section 2. The research model supports the view that the quality of information presented through dashboard visualizations is critical for enhancing decision making. This is achieved by providing decision makers with information that caters to their requirements, and which enables them to reduce the complexity of tasks. We ground this reasoning in the literature on task complexity and decision making and the IQ literature [31, 59]. Based on the theorizing, it is suggested that perceived task complexity has a central role in affecting decision making quality and that it is affected by the level of information satisfaction and the corresponding attributes of IQ that decision makers are presented with [73, 71]. The four underlying aspects that concern IQ are argued to facilitate information satisfaction (i.e., the perceptions of required data to complete a task) and to reduce the perceived task complexity. We hypothesize that these mechanisms in turn facilitate improved decision making quality. Thus, we propose an indirect effect whereby the satisfaction from information will lead to greater confidence in making accurate and correct decisions, while at the same time the reduction of perceived task complexity will facilitate the sense of comprehension and command over the decision making task, leading to improved quality of decisions.

3.1. Influence of IQ on information satisfaction

The definition of information satisfaction is based on the work of Wixom and Todd [59] and refers to the user's attitude or feelings toward the overall level of information provided in relation to a given task. Several studies have built on this notion and defined information satisfaction as the degree to which users are satisfied with the information they are able to access through a system [74]. Wixom and Todd

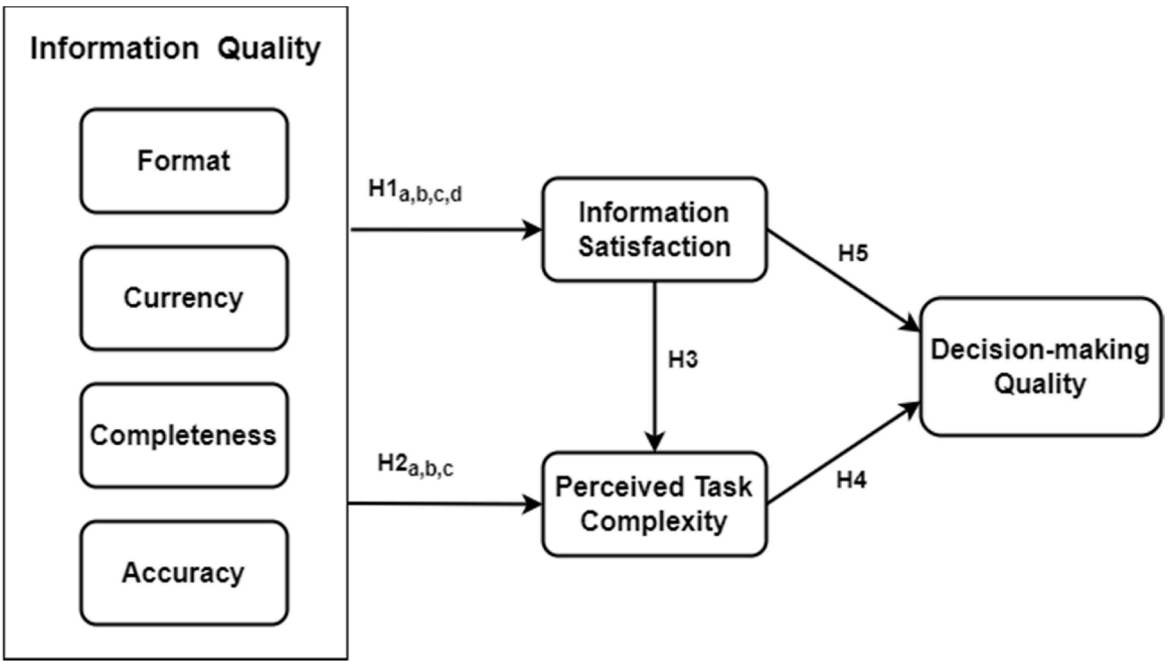

Fig. 1. Research model and hypotheses.

[59] noted that being able to effectively interact with a system is a necessary condition for obtaining useful information from it. Hence, the level of satisfaction that users perceive from their information is dependent on all four dimensions of IQ. In decision making contexts in which analytics-based dashboards are used, the user's perception of how well the information is presented—its *format*—can lead to improved information consumption and easier identification of key information [75]. This is because relevant formatting of complex information through appropriate visualization can solve the problem of information overload [76]. When information is presented in an appropriate format, unconscious processing can assign an appropriate weight to each piece of information and result in greater satisfaction [75]. In addition, because such tasks are dependent on having up-to-date information, the level of up-to-date information (currency) on the dashboard is argued to positively affect overall information satisfaction [29]. Visual cues on dashboards can signify the degree to which the information presented is up to date, such as the recency of the latest data points or other indicators of the latest additions to the graphs and charts present on such dashboards. Because decisions in the organizational context are dependent on constantly changing conditions, it is critical to facilitate continuous update of information and incorporate key cues that are up to date [77]. Information that is outdated is suggested to prompt feelings of dissatisfaction [29], particularly in the business context, where firms need to rely on real-time information to address pressing issues in the business environment [78].

Furthermore, the ability to base a decision on information provided on analytics dashboards requires completeness in terms of having the necessary information to take informed actions [79]. Information completeness, and the corresponding satisfaction from such information, stems from having sufficient breadth, depth, and scope to complete the task at hand [80]. This means that dashboards must include a complete set of informational resources appropriate for helping tackle a task [81]. In the case of organizational operations for which decisions are of high impact, it is important that decision makers have a complete overview of all necessary information to correctly assess a given situation. The presence of such informational cues has been argued to increase decision makers' information satisfaction [82]. Finally, the degree to which users are satisfied by the information they receive with regard to their task has been shown to be contingent on the accuracy of the information provided [83]. Accuracy refers to the sense of correctness of presented information, which can be established in different ways on visual representations, such as cues of origin, sufficient detail, and contextual information to make sense of available visualizations [84]. A distrust of the quality of information provided or a sense that it is not credible will lead to reduced information satisfaction [85]. In organizational settings, the believability of presented information in the form of visual representations is critical to allow decision makers to confidently rely on such information [86].

The foregoing arguments highlight an important and underexplored link between how IQ is represented on dashboard visualizations and the ways in which it affects the satisfaction of decision makers from the visual cues they are given to make a decision. Thus, we argue that due to the nature of decisions made in organizational operations when using dashboards, the accuracy of information is an important aspect of enhancing overall information satisfaction. Based on the above, we propose the following hypothesis:

H1a,b,c,d. Information quality (format, currency, completeness, accuracy) will have a positive effect on information satisfaction.

3.2. IQ and perceived task complexity

Perceived task complexity is a reaction to task characteristics that may be evoked for reasons other than the task characteristics themselves [87]. Perceived task complexity is related to individual differences such as task-domain knowledge and cognitive capacity, as well as objective task features such as difficulty and clarity [88]. In this study, the perceived task complexity is argued to be affected by the reaction to the task characteristics, the information provided, and the perceived fit between the information and the task. Because visual representations in the form of analytics dashboards can enhance the comprehensibility of raw data, they can significantly impact the sense of information overload and ease of interpretation and lead to increased understandability, which are precursors for reducing perceived task complexity. When it comes to dampening perceived task complexity in dashboard visualizations, the dimensions of format, currency, and completeness will influence such perceptions of decision makers. In what follows, we explain how each of these underlying dimensions impacts perceived task complexity. Contrarily, it has been suggested that accuracy does not

have an impact on task complexity, given that the perceived complexity of a task is dependent on the contextual (completeness and currency) and representational (format) aspects of the information provided instead of the intrinsic qualities of the data (accuracy) [21,89]. In other words, task complexity has more to do with the decision maker's perceptions of information rather than the intrinsic qualities of the information itself.

Perceived task complexity is largely dependent on the ease of understanding the information presented on dashboards, reflecting the clarity and comprehensibility of that information [63]. By choosing a format that corresponds to the conceptual question [47], dashboards can contribute to ease of understanding [90]. Fehrenbacher and Palit [91] suggested that the presentation of information may be more important when the complexity increases, as the need for simplifying the information increases accordingly. Thus, information that is presented in an appropriate, easy to comprehend format likely will lessen the decision maker's perceived complexity of the task at hand [92]. Kyndt et al. [87] also identified the amount of information as an influential factor of perceived task complexity, which is consistent with the close association of task complexity and information amount suggested in information processing theory [88]. A lack of information may increase the perceived complexity of the task, as the user will not have the necessary information to understand the task. In addition, the timeliness of information has been argued to influence the level to which it can be actionable for use in a task [93]. Outdated information is likely to be disregarded, causing more of an informational overload and thus further exacerbating perceptions of task complexity [29]. Nelson et al. [21] also argued that the level of currency influences users' perceptions concerning the degree to which information reflects the current state of the world. Thus, perceptions of task complexity increase when the information provided is not updated, and as a result, cannot be applied.

Additionally, completeness has been demonstrated to have a substantial influence on user information processing in online channels [24]. Increasing task complexity requires the extended use of short-term memory for acquiring and analyzing massive amounts of information [88]. To facilitate information processing, users may have higher expectations for consistently represented and complete information in complex tasks [91]. Therefore, it is reasonable to expect that complete information will reduce the perceived complexity by reducing the cognitive effort required to evaluate information sources and minimize the use of heuristics [94]. When there is a lack of complete information for performing a decision making task, individuals may believe that the issue is increased complexity of the task rather than a lack of in-depth information. Thus, we argue that information completeness operates toward the opposite effect—reducing task complexity. This phenomenon is especially relevant in the context of organizational operations in which decision making tasks are complex by default and thus there is a high need for informational completeness [95]. Based on the foregoing argumentation, we propose the following hypothesis:

H2a,b,c. Information quality (format, currency, completeness) will reduce perceived task complexity.

As a result of perceived information satisfaction through the mechanisms described above, we argue that decision makers will realize a reduction in perceived task complexity when they have found information that satisfies their needs. In tasks that require processing of information to make informed decisions, perceptions of information satisfaction have been argued to reduce the cognitive overload of decision makers [96]. In addition, high-quality information related to the task can enable decision makers to focus on the essential input needed to complete the task, thereby reducing the perceived complexity of the task [97]. One of the key findings on information processing from decision makers is that when faced with a task, the amount and quality of information that decision makers are presented with influence their perception of the complexity of the task [98]. Furthermore, when there is overall satisfaction with the information provided on dashboard visualizations, decision makers will have sufficient input and in an appropriate format to process the requirements of the task at hand [99]. This in turn will lead to a perception of reduced task complexity, because there is sufficient input to correctly tackle the requirements of the task. Therefore, information satisfaction contributes in multiple ways to prompting perceptions of reduced task complexity, both in triggering the cognitive mechanisms of decision makers to more easily complete a given task and in reducing feelings of information insufficiency [100]. From the foregoing, we thus hypothesize the following:

H3. Information satisfaction will reduce perceived task complexity.

3.3. Decision making quality

The quality of the decision provides valuable insight into how the dashboard and visualized information affects the decision making process. Decision quality has been captured in prior studies using both subjective and objective measures. Objective measures evaluate whether the decision was the correct one given a single correct option. On the other hand, subjective measures capture the degree to which respondents have confidence in their choice [48]. In this study, we build on a conceptualization of decision making quality, defined as the perceived quality of a decision made [29,48]. In examining what aspects contribute to improved decision making quality, several studies in different contexts have found a positive and significant relationship between information satisfaction and perceived decision making performance [101,102]. Furthermore, they concluded that satisfied people have greater commitment, engagement, and emotional attachment, leading to better performance and overall higher-quality decisions [103].

These findings underscore the importance of having a strong focus on designing and using analytics-based dashboards. Such dashboards have been shown to be increasingly important for decision makers at different levels within an organization, particularly in organizational settings [104]. In addition, information satisfaction from analytics dashboards entails continued use and familiarization, which has the potential to enhance decision making quality [99]. Within the context of organizational operations, prior studies have also noted that the degree of information satisfaction from decision makers is an important predictor of overall decision making quality [40]. Because organizational operations favor a rational decision making approach, satisfaction from provided information is imperative for making the right choices [40]. In addition, the past few years have seen an increased reliance of decision makers on information provided through analytics-based dashboards, which further highlights the importance of providing information that caters for such requirements [105]. From the foregoing argumentation we hypothesize that:

H4. Information quality will have a positive effect on decision making quality.

One way of achieving improved decision quality is by designing technological capabilities to enhance human capacities [46]. If the user is able to use the dashboard to identify and extract task-relevant information, they have the necessary resources to make an informed decision. Improved decision quality can be achieved by decreasing the complexity and uncertainty of tasks and the information provided to complete them [46]. Greater complexity requires more use of working memory in information processing [47], which may affect decision quality. The results of Davcheva and Benlian [50] demonstrate an increase in time with complex visual cues compared with simple visual cues. Furthermore, Davcheva and Benlian [50] concluded that complex visualization reduces certainty and accuracy and increases the time to make decisions owing to the increased cognitive load. Because increased complexity requires more time for processing the information, it potentially can undermine decision making quality. In addition, there is a long research stream connecting task complexity with decision making

quality [31]. The key finding from such studies is that when decision makers perceive that a task is complex and difficult to solve, so will their perception of the quality of the decision they made [106]. Such perceptions and attitudes toward the quality of selected decision may stem from a feeling of difficulty in selecting among several equally effective alternatives or the absence of any solution which is clearly superior [107]. Thus, when perceptions of task complexity are active in decision makers it is also likely that the quality of decisions that they make will also be reduced. Hence, we hypothesize the following:

H5. Perceived task complexity will reduce decision making quality.

4. Method

This study has explored how the IQ dimensions of analytics dashboards affect users' decision making quality in an organizational context. We took an experiment-based approach by creating four scenarios based on fictional companies with associated decision making tasks and dashboards. Specifically, we developed two sets of four tasks and created mock-up dashboards that users consulted to make a decision. The two sets of four dashboards were chosen to remove any variability from the design and to control for different ways of presenting and formatting information. The research model described in Section 3 was tested empirically via a survey, allowing participants to complete several decision making tasks and evaluating the dashboards based on the constructs in the research model.

4.1. Development of scenarios

The scenarios were based on four fictional tasks of companies in various industries offering different products and services. Each scenario consists of a textual description of what the company does and the participant's simulated role in the company. In addition, each scenario includes an associated decision making task that the participants must complete using the information provided in a dashboard [108]. To ensure that the IQ of the dashboard itself was tested and not just the IQ of one element, the tasks were designed to require the knowledge of several information inputs to be solved correctly. The scenarios as well as the accompanying text were developed in consultation with three industry experts that use such decision making dashboards for their respective tasks in organizational activities. After an initial round of data collection from them, we also consulted online examples of decisions made with the aid of dashboards and developed a first set of scenarios. These scenarios were discussed with the group of experts and after some rounds of revising and refining were finalized. The necessary information for each decision making task created the basis for the visualization to include in the dashboard.

After creating the scenarios, we performed an iterative process of designing the mock-up dashboards in consultation with the group of experts [109]. These dashboards were developed and refined in an iterative process until there was consensus that they presented a sufficiently clear scenario and visualization to serve as a realistic example. For example, if one dashboard had a high level of completeness, the associated dashboard had a lower level of completeness. Our goal was to develop two dashboards for each scenario, each of which emphasized different IQ dimensions. The four scenarios were developed not based on varying degrees of task complexity, but by taking IQ attributes into account during dashboard design. After designing for the different variations of IQ, we also performed a small-scale study with 17 respondents who were asked to evaluate the levels of IQ for the two designs. These respondents were different from those involved in the previous phase. The results were in alignment with the dimensions we selected. Further details regarding the differences in IQ dimensions between the two variations of the two scenarios are presented in Appendix E. After launching this pretest, we also performed a first-phase study with 76 participants, which further verified the differences between the two variations of visualizations.

To simplify, we present an example of the process of creating dashboards for one scenario. However, the process was similar for all scenarios and was performed for every scenario. The process began by creating several different graphical and textual representations of the data, with each representation emphasizing different dimensions of IQ. The next step was to create a dashboard by combining one representation of each information type in one view [110]. Finally, a second version of the dashboard was created by adjusting details or changing the representation of the information representation. We describe each scenario next, and provide a full description of each scenario and decision making task in Appendix A.

4.1.1. Example scenario

The first scenario is based on a company selling trucks (motor vehicles) to other businesses through a B2B channel. The participant's task is to use the results of a market study to recommend the best location for opening a new service location. Four location options are displayed on a map in the dashboard (Appendix A), and the participant is informed that an optimal location has a significant number of potential customers and as little direct competition as possible. This information must be obtained from other charts included in the dashboard and used to evaluate each of the four locations. The two dashboard versions belonging to the scenario differ only in the color palettes used, related to the IQ dimension *format*. The colors used are adopted from the study of Bartram et al. [111] on how different color properties and the combination of colors in palettes contribute to various affective interpretations of visualizations. The color palettes used in the dashboards are created by combining the six colors chosen as "best" (according to the results of [111]) in the categories *calm* and *playful*. The six colors chosen for the playful palette also were included in the palettes perceived as both exciting and positive [111].

4.1.2. Design tools

The dashboards were created using Figma, a web-based graphics editing and user interface design application [112]. Figma provides the user with a blank canvas, and each element is created by combining basic elements, such as lines, shapes, and text, into more complex constructions. Figma was chosen because of its ability to create realistic-looking dashboards without the need for an actual dataset. Additionally, it allows the user to freely change any parts of the design, an essential feature for emphasizing different IQ dimensions. In addition, Tableau was used to create more complex graphical representations, such as map-based charts. Because Tableau requires datasets to create charts, mock data were created using Mockaroo, a free data mocking library [113]. The mock data set was customized to fit the formats required by the desired charts in Tableau and the measures needed in the relevant scenarios (Fig. 2).

4.1.3. Validity pretests

A small usability test was conducted to ensure the quality and usability of the dashboards. The usability test design follows the principles developed by the Nielsen Norman Group [114]. To obtain relevant results, the testing context had to be as similar as possible to the actual context. Because participants in the planned survey would not have the opportunity to ask questions, the participants in the usability test were not provided with additional information or guidance during the whole test session. Each scenario was presented in a textual format to replicate the actual context and to avoid influencing the participants by subconsciously emphasizing important information. The participants ($n = 12$) were presented with the goal of the user testing and how it would be conducted and asked to narrate their activities and thoughts while completing the task. After each scenario, the participants provided feedback on their experience and raised any questions they might have. The researcher did not answer the questions, to avoid influencing the results for the following scenarios. During the test, the lead researcher

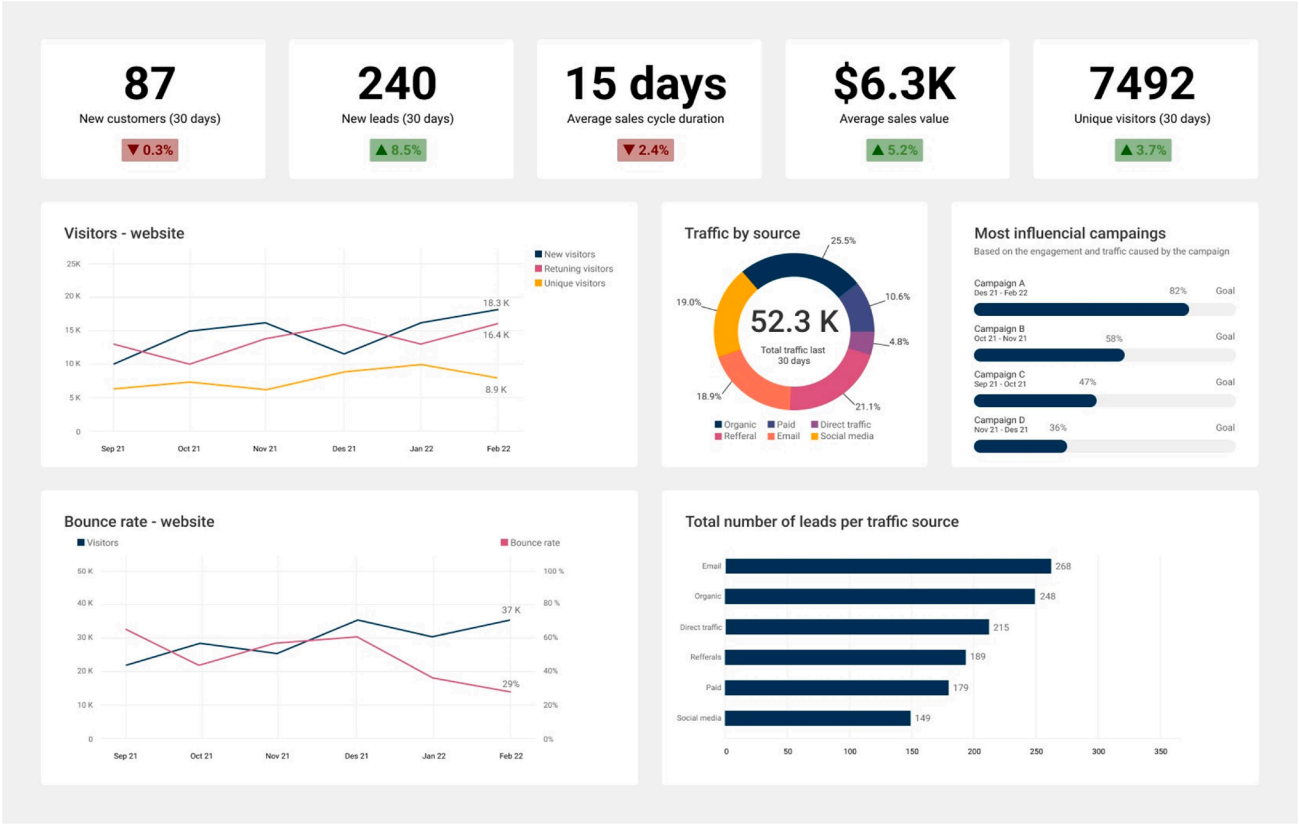

Fig. 2. Example mock-up dashboard - Version A of the dashboard belonging to scenario 4.

only wrote down the feedback given and observations made. If further clarification was needed, it was discussed with the participant after completing all scenarios. Each participant was presented with four scenarios and one dashboard per scenario. The dashboard versions given to the participants were alternated to avoid bias in the results. Minor adjustments were made to the scenarios and dashboards based on the feedback from the usability testing

4.2. Survey design

To empirically test the research model and to capture the beliefs and opinions of participants in the experiment, a survey-based study was conducted during their interaction with the scenarios and mock-up dashboards.

4.2.1. Survey approach

This study used a questionnaire-based survey with two sets of identical questionnaires to generate the quantitative data. The questionnaires were designed using the Alchemer survey tool.[1] The questionnaire begins with an introduction to the study's purpose, how the participant's information would be used, and the structure of the questionnaire. The questionnaire had no time limit; however, some tasks were timed. First, the participant was asked to provide demographic data: age, education, employment status, and industry. Next was a section on the participant's previous experience with marketing, business, and dashboards. These questions are a combination of numerical input and preselected items with the opportunity to provide a short answer if none of the options matched. The rest of the study is based on the scenarios described in Section 4.1 with the associated tasks and dashboards. Each scenario contains a textual description, an explanation of chosen terms, and a decision making task. The participant can navigate forward after confirming that they have read and understood the task. The next page provides the same information and a dashboard containing all the necessary information to address the given task. The participant addresses the task by deciding among the 2 to 4 provided options. Additionally, participants were informed that the timer starts when they enter the page. After addressing the task, participant is informed that the timer has stopped and is asked to evaluate the provided information and their own performance. The questionnaires consist of four scenarios with decision making tasks, and each section is structured as explained above. The two questionnaires are structured similarly and differ only in which version of the dashboard is included for each scenario.

4.2.2. Survey instrument

All constructs used are derived from prior literature in which they were empirically validated. Each construct included in the questionnaire, except for the demographic questions, decision time, and decision accuracy, were formulated as statements measured using a 5-point Likert scale: strongly disagree, disagree, neutral, agree, and strongly agree. This section presents the items used to measure the construct; a list of all items is provided in Appendix B.

Information quality refers to the user's perception of the quality of the system's output, which in this study included the information given in the task description and through the dashboard. Information quality consists of four broad dimensions: *completeness, accuracy, format*, and *currency*. These dimensions are adopted from Wixom and Todd [59] due to their extensive use, representativeness, and relevance to the context of this study. Completeness (COM) refers to the system's ability to provide all necessary information [59] and how well it aids the user in making a decision. Information format (FOR) comprises all factors related to how the information is presented. Information accuracy (ACC) refers to how correct [59], unambiguous, and error-free [63] the user

[1] https://www.alchemer.com/

perceives the information to be [59]. Finally, information is current (CUR) if provided in time for the necessary purpose and sufficiently updated to solve the current task [62]. The dimensions are measured separately using items from the study of Wixom and Todd [59].

Information satisfaction (INS) refers to the user's attitude or feelings toward the overall level of information provided in relation to a given task [59]. The constructs used to measure information satisfaction are adopted from Wixom and Todd [59] and comprise two items to measure the degree to which the participant is satisfied with the information received to solve the problem at hand.

Perceived task complexity (PTC) refers to the user's perceived fit between the information provided and the task and the reaction to both the task characteristics and the information. Perceived task complexity is dependent on individual differences [88] and includes the reaction to the task characteristics that may be evoked by factors other than the task itself. The items used to measure perceived task complexity were adopted from the study of Kyndt et al. [87] and measure the participant's difficulty in understanding and solving the task.

Decision making quality (DMQ) refers to the participant's perceived quality of their decision, measured using six items adopted from the study of Jarupathirun and Zahedi [48].

4.2.3. Survey participants

Participants for the experiment were recruited through a series of qualifying criteria, including good knowledge of organizational operations and a relevant education. Two sets of questionnaires with the corresponding two variations of four sets of dashboards, were distributed through Amazon Mechanical Turk (MTurk) in February 2023. The survey had a total of 597 respondents, 301 from version A and 296 from version B. Seventy-four surveys were completed only partially and were subsequently removed from the final dataset. In total, the records of 524 participants were included in the analysis. As shown in Table 1, the greatest proportion of respondents were between 22 and 34 years old (40.64 %), followed by 35 to 44 (35.26 %) and 45 to 54 (18.7 %).

The four scenarios (Appendix A) were presented in randomized order following a Latin square design approach so that all variations appeared to respondents. In this way, the sequence of the four different scenarios and the corresponding questions was randomized, so that all possible variations appeared. For instance, one respondent could be instructed to complete tasks, 3, 4, 2, and 1 in that order, whereas another respondent could be instructed to complete tasks 2, 4, 1, and 2. This was done to control for fatigue in responses that could have been greater in the last scenario. This was done to control for any unintended systematic variations during the design [115]. Most respondents had a college degree, either a master's (31.67 %) or a bachelor's (56.67 %). Furthermore, the vast majority of respondents had experience with the use of dashboards in their professional environments (74.23 %), while a smaller percentage of the sample had used them during their studies (20.8 %).

As shown in Table 1, the predominant employment status was full-time employed, 74.61 % of the total sample. Concerning the participant's industry, almost one-half of the respondents worked in the technology sector (48.7 %), followed by the service industry (16.3 %), health (7.2 %), and banking and finance (6.8 %). The remaining 21 % reported working in a variety of different industries, including education, retail, entertainment, construction, and manufacturing. The greatest proportion of the respondents had experience with dashboards from either school (20.8 %), work (74.23 %), or personal use (4.77 %). Only 0.19 % had never made or used a dashboard before.

Table 1
Descriptive statistics about the sample.

Factor	Sample Version A (n = 269)	Sample Version B (n = 255)	Sample Total (n = 524)	Proportion
Age				
22–34	102	111	213	40.64 %
35–44	97	93	190	35.26 %
45–54	55	43	98	18.70 %
55 or older	15	8	23	4.38 %
Education level	3	4	7	1.33 %
10 years of school				
12–13 years of school	13	19	32	6.11 %
Bachelor	163	134	297	56.67 %
Master	85	91	166	31.67 %
PhD	5	7	12	2.29 %
Employment status				
Employed full-time	202	189	391	74.61 %
Employed part-time	37	38	75	14.31 %
Freelance/contract employee	3	6	9	1.71 %
Self-Employed	24	16	40	7.63 %
Other	3	6	9	1.71 %
Experience with dashboards				
School	57	52	109	20.80 %
Work	197	192	389	74.23 %
Personal	15	10	25	4.77 %
Have not made or used a dashboard	0	1	1	0.19 %

5. Analysis

5.1. Data analysis approach

A PLS-SEM analysis was applied to assess the validity and reliability of the research model, using SmartPLS3 software to conduct all necessary analyses. PLS-SEM was considered an appropriate methodology for this study, as the path model includes multiple formatively measured constructs, and the method is often used in organizational research for estimating complex relationships between constructs [116,117]. Hair et al. [118] listed two requirements for achieving an appropriate sample size for PLS-SEM analysis: (1) the sample size should be ten times larger than the highest number of formative indicators used to measure one construct, and (2) the sample size should be ten times larger than the highest number of structural paths in the structural model aimed at a particular latent construct. This study would meet these requirements if the sample size exceeded (1) 80 and (2) 50 participants. The study had 304 entries of data reflecting the four different scenario-based decision tasks of each respondent, which significantly exceeded both requirements. Finally, because this research aimed to develop a theory, PLS-SEM is considered an appropriate predictive tool [118].

5.2. Measurement model

The measurement model represents the relationships between the observed data and the latent variables. The model must be examined to evaluate the results of PLS-SEM before the structural model can be assessed [119]. The measurement model contains only first-order reflective constructs, and the same assessment criteria were used to evaluate each construct. Tests of reliability, convergent validity, and discriminant validity were conducted on each latent construct. Reliability was evaluated on both an item level and a construct level. The construct-to-item loading was examined to assess the indicator reliability. Acceptable item reliability is achieved with loadings above 0.70 [119]. The cross-loadings are provided in Appendix C. At the construct level, the internal consistency reliability is assessed by examining the Composite Reliability (CR) and Cronbach Alpha (CA) values, both of which should be above the threshold of 0.70 [120]. CR differs from CA, as the items are weighted based on each construct indicator's individual loading [119], while CA assumes that all factors have the same loading. Thus, CA can be viewed as the lower bound and CR as the upper bound for internal consistency. The convergent validity of each construct is assessed by checking whether the average variance extracted (AVE) is

above the lower limit of 0.50 [121]. All values were above the threshold, indicating sufficient convergent validity (Table 2).

Three methods were used to establish discriminant validity. First, using the Fornell–Larcker criterion [122], discriminant validity was established if the square root of AVE was higher than the correlation with any other latent construct. This criterion ensures that the constructs better explain the variance of their own indicators than the variance of other latent constructs. The second method tested whether the outer loadings of each indicator were greater than the correlation with any other construct. Finally, discriminant validity was assessed using the Heterotrait–Monotrait (HTMT) ratio of the correlations proposed by Henseler et al. [123] as a better indicator of discriminant validity. The HTMT is defined as the average of the indicator correlations across constructs relative to the average of the indicator correlations within the same construct. All values were below the threshold of 0.90 [119] (Appendix D).

5.3. Structural model

Having established the validity and reliability of constructs and items, the next step in our analysis was to examine the properties of the structural model. Fig. 3 summarizes the structural model from the PLS analysis and includes the coefficient of determination (R^2) and the standardized path coefficients (β). The coefficient of determination measures the variance explained in each of the endogenous variables [119] and is used to verify the structural model. Its value ranges from 0 to 1, with greater values indicating higher explanatory power [119]. The values of the path coefficient range between -1 and 1 and describe the strength of the (positive or negative) relationship among constructs [124]. The significance of the PLS analysis results (t-statistics) is determined by performing a bootstrap analysis in SmartPLS3 with 5000 subsamples. A two-tailed test was used with a 95 % confidence level, meaning that significance is ensured if $p < 0.05$. The significance level of the path coefficients is denoted by asterisks in the structural model.

As presented in Fig. 3, out of the ten hypotheses, nine were empirically supported. Format is found to have a positive and significant effect on information satisfaction ($\beta = 0.402$, $t = 12.567$, $p < 0.001$), as well as currency ($\beta = 0.311$, $t = 9.258$, $p < 0.001$) and completeness ($\beta = 0.341$, $t = 10.418$, $p < 0.001$). Nevertheless, there was no significant effect on the relationship between accuracy and information satisfaction ($\beta = 0.071$, $t = 1.428$, $p > 0.05$). When examining the relationship between IQ dimensions and perceive task complexity, our results indicate that all hypotheses are supported, with format (β = -0.278, t = 9.375, $p < 0.001$), completeness (β = -0.388, $t = 11.058$, $p < 0.001$), and accuracy (β = -0.289, t = 7.218, $p < 0.001$) exerting negative and significant effects. Furthermore, our analysis indicates that information satisfaction also has a significant effect on perceived task complexity (β = -0.374, t = 10.735, $p < 0.001$), which highlights the fact that when users are presented with information that satisfy their needs, the corresponding tasks also are perceived as easier. Finally, decision making quality is found to be affected by information satisfaction (β = 0.412, t = 14.721, $p < 0.001$), while the effect of perceived task complexity is found to be significant but to a lesser extent (β = -0.153, t ==2.985, $p < 0.01$).

The structural model explains 64.9 % of variance in information satisfaction (R^2 = 0.649), 40.6 % for perceived task complexity (R^2= 0.406), and 47.7 % for decision making quality (R^2= 0.477). These coefficients of determination represent moderate to substantial predictive power (Table 3).

The model is assessed in terms of the effect size f^2, which indicates an exogenous constructs contribution to an endogenous latent variable R^2. Since all values are above the threshold of either 0.15 or 0.35, we can assume that they have moderate to large effect sizes. In addition, the outcome variable of decision making quality was controlled for using several variables, including age of respondent, experience using dashboards, and sex. We found no evidence of a statistically significant control variable. In addition, we performed an analysis of the full model using only the first presented scenario vs the only the last scenario to control for the presence of fatigue. Comparing the two models revealed no statistically significant difference between the paths, demonstrating that fatigue did not have any influence on outcomes and reported values.

5.4. Test for mediation

We used a bootstrapping approach to examine whether the effect of IQ dimensions on decision making quality (DMC) is mediated through the constructs of information satisfaction (IS) and perceived task complexity (PTC). This bootstrapping method is a nonparametric resampling procedure that enforces no assumptions on normality of sampling distribution [125,126]. Following the recommendations of Hair Jr et al., (2016), we first confirmed that the mediated paths (IQ → ISA → DMC and IQ → PTC → DMC) were significant. We examined the indirect effects involved in the proposed research model by including a relationship between the predictor variables of IQ and DMC [127]. We found that three of the four paths were nonsignificant and that one path—format—had only partial significance for DMC ($\beta = 0.0135$, $t = 2.125$, $p < 0.05$). These results suggest a partial mediation between IQ dimensions and DMC, with IQ affecting DMC through information satisfaction and perceived task complexity (Table 4).

Since there are multiple mediators and paths in this indirect effect, a multiple mediation analysis can be used to clarify the effect of each variable. To test for the mediation paths, we used the bootstrapping procedure in PLS and calculated the standard error of each mediation effect. We then calculated the t-statistic for each mediation path by dividing the effect of the indirect path (i.e., the product of each indirect path) by the standard error of mediation effects. This way of calculating the significance of indirect paths facilitates the nonimposition of any distributional assumptions of the indirect effects. In addition, it allows for calculation of the entire indirect effect simultaneously in the presence of multiple mediating effects rather than isolating part of the structural model. Because the indirect effects were found to be significant while the direct effects included only one effect that was significant, we can conclude that information satisfaction and perceived task

Table 2
Assessment of reliability, convergent, and discriminant validity of reflective constructs.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Format	**0.772**						
(2) Currency	0.321	**0.752**					
(3) Completness	0.289	0.548	**0.745**				
(4) Accuracy	0.367	0.378	0.478	**0.796**			
(5) Perceived task complexity	0.278	0.243	0.367	0.401	**0.723**		
(6) Information satisfaction	0.302	0.233	0.322	0.389	0.287	**0.831**	
(7) Decision making quality	0.367	0.387	0.304	0.399	0.321	0.342	**0.720**
Mean	3.85	3.84	3.91	3.86	2.83	3.88	3.69
Standard deviation	0.86	0.83	0.86	0.91	1.22	0.89	0.96
AVE	0.597	0.567	0.555	0.634	0.524	0.691	0.518
Cronbach's alpha	0.787	0.681	0.767	0.644	0.691	0.687	0.847
Composite reliability	0.747	0.724	0.797	0.776	0.688	0.870	0.866

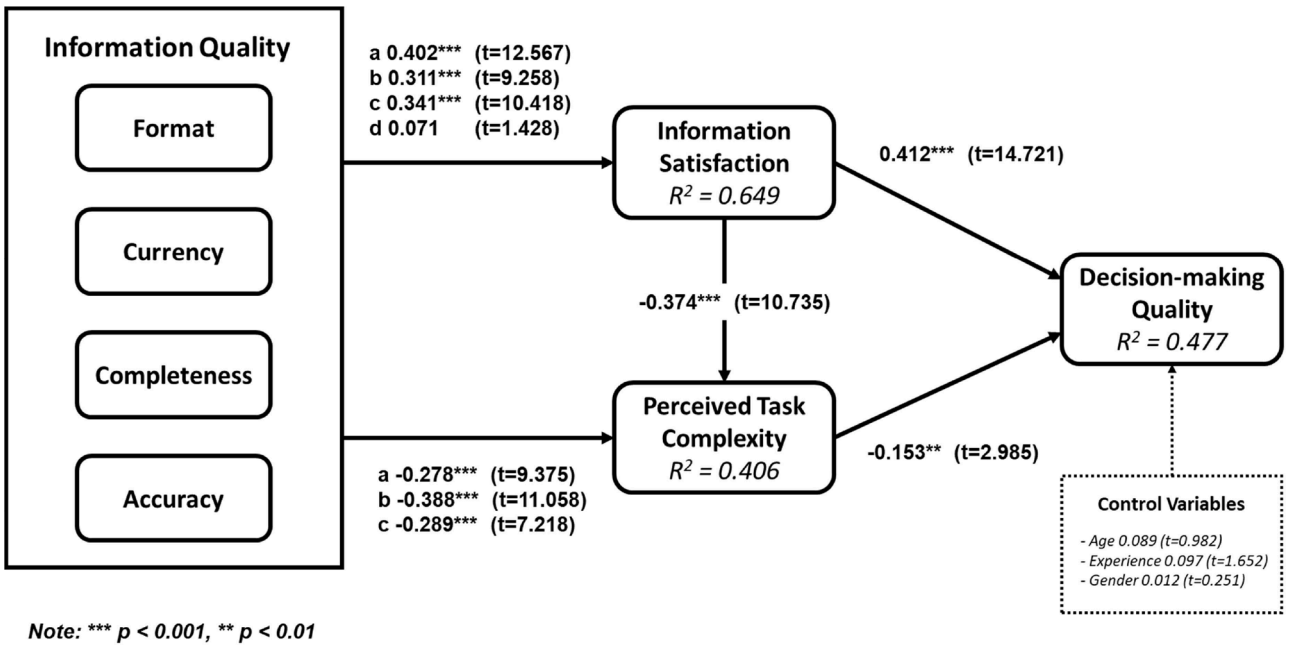

Fig. 3. Estimated relationships of structural model.

Table 3
Summaries of hypotheses with effect sizes.

Relationship	Beta coefficient	Confidence interval	F^2 value	Effect size
H1a. Format → Information satisfaction	0.402***	[0.312, 0.465]	0.312	Large
H1b. Currency → Information satisfaction	0.311***	[0.246, 0.351]	0.175	Medium
H1c. Completeness → Information satisfaction	0.341***	[0.278, 0.380]	0.192	Medium
H1d. Accuracy → Information satisfaction	0.071	[0.008, 0.134]	0.034	n.s
H2a. Format → Perceived task complexity	-0.278***	[-0.314, -0.222]	0.140	Medium
H2b. Currency → Perceived task complexity	-0.388***	[-0.454, -0.328]	0.211	Medium
H2c. Completeness → Perceived task complexity	-0.289***	[-0.341, -0.217]	0.152	Medium
H3. Information satisfaction → Perceived task complexity	-0.374***	[-0.431, -0.302]	0.206	Medium
H4. Information satisfaction → Decision making quality	0.412***	[0.329, 0.475]	0.333	Large
H5. Perceived task complexity → Decision making quality	-0.153**	[-0.194, -0.087]	0.007	Medium

Table 4
Structural paths and effects.

Structural path	Effect	Bias-corrected 95 % confidence interval	Variance account for (VAF)
a1xb1	0.112	[0.084–0.134]	0.487
a2xb1	0.082	[0.057–0.105]	0.412
a3xb1	0.085	[0.045–0.113]	0.429
a4xb1	0.063	[0.034–0.092]	0.354
a1xb1xb2	0.042	[0.026–0.064]	0.289
a2xb1xb2	0.033	[0.021–0.045]	0.245
a3xb1xb2	0.034	[0.022–0.047]	0.264
a4xb1xb2	0.018	[0.011–0.024]	0.135
a1xb2	0.077	[0.059–0.086]	0.342
a2xb2	0.068	[0.052–0.081]	0.310
a3xb2	0.056	[0.042–0.071]	0.278
Total indirect effect	**0.670**	**[0.548–0.723]**	**1.245**

Note: a1xb1: Format → Information satisfaction → Decision making quality; a2xb1: Currency → Information satisfaction → Decision making quality; a3xb1: Completeness → Information satisfaction → Decision making quality; a4xb1: Accuracy → Information satisfaction → Decision making quality; a1xb1xb2: Format → Information satisfaction→ Perceived task complexity → Decision making quality; a2xb1xb2: Currency → Information satisfaction→ Perceived task complexity → Decision making quality; a3xb1xb2: Completeness → Information satisfaction→ Perceived task complexity → Decision making quality; a4xb1xb2: Accuracy → Information satisfaction→ Perceived task complexity → Decision making quality; a1xb2: Format → Information satisfaction→ Perceived task complexity → Decision making quality; a2xb2: Currency → Information satisfaction→ Perceived task complexity → Decision making quality; a3xb2: Completeness → Information satisfaction→ Perceived task complexity → Decision making quality.

complexity partially mediate the effect of IQ on DMC.

5.5. Test of robustness

To examine the robustness of our proposed model, we complemented our analysis with a test of robustness to examine alternative relationships and conceptual models according to suggested guidelines [128, 127,129]. Specficially, we estimated an alternative robustness model with no relationship between information satisfaction and perceived task complexity. This model did not demonstrate a good overall robustness, highlighting the importance of the relationship as we have in the baseline model. Having established the robustness of our model, we argue that in the main research model, it is the overall satisfaction of information that will lead to the perception of reduced task complexity. Satistically, because our proposed research model does not have a statistically worse overall fit for the estimation model compared to the overall fit of the etimated alterntive model, we can conclude that the alternative model is not preferable to the main model. In addition, we estimated a model in which the two mediating variables of information satisfaction and perceived task complexity freely correlated (i.e., there is no stated relationship between the two variables in the model), as well as a model in which the two constructs jointly form a second-order construct. These models yielded similar results as the proposed model.

Thus, we can conclude that the results of the robustness test add to the credibility of our main research model.

Finally, we included an alternative variable (perceived ease of task) as a sole mediator to the existing model instead of the current mediators. This showed a good overall model fit, confirming the robustness of the model.

6. Discussion

This study contributes to our understanding of how dashboard visualizations influence decision quality in an organizational context. To date, there is a lack of studies that empirically examine how individual IQ dimensions affect decision making quality when using dashboards. As most information in the organizational context is now presented in a visual format via dashboard analytics, it is important to understand how the visual cues and their respective quality dimensions affect those making decisions. Furthermore, we still lack an understanding of how such information when presented in a visual format influences perceptions of the decision maker concerning overall information satisfaction and task performance. We argue that information satisfaction and perceived task performance are important mechanisms that mediate the effect of IQ dimensions on decision making quality. Furthermore, much of the prior work did not examine how visualizations affect decision making in actual tasks, meaning that the question of what quality dimensions are important is detached from the context of their use. To assess this shortcoming in the literature, in the present study we proposed and assessed a scenario-based decision model by applying four dimensions of IQ to determine their influence on decision quality through the mediation of information satisfaction and perceived task complexity. By developing two sets of mock-up dashboards and dividing users into two groups, we investigated how users respond to the different aspects of IQ and how this influences their perceived decision making quality. Based on our results, we draw the following research and practical implications.

This research contributes an empirical foundation to the theoretical framework on decision making with visualization in organizational tasks. Through a survey with 524 respondents, we found that several dimensions of IQ have an impact on the user's perspective concerning information satisfaction. In other words, the format, currency, and completeness affect the satisfaction of users with the information they received when exposed to decision making tasks in an organizational setting. These empirical findings support the notion that completeness acts as an important antecedent of information satisfaction [59] and underscore the importance of providing comprehensive, relevant, and meaningful information in visualizations.

Information format was found to be another influential dimension of IQ. This finding is in line with the claim that visual presentation of information affects the user [38] and can facilitate cognitive access [51]. It also underscores the importance of presenting the information in an understandable and concise matter. Finally, the study found a significant effect of information currency on information satisfaction [130]. In relation to the nonsignificant effect of accuracy, this can be attributed to the fact that respondents were questioned about a fictitious scenario; in real-life situations, decision makers who are alert and attentive to detail will focus on the accuracy of information provided. In addition, because this was a realistic but not real scenario, the respondents might not have had the capacity to effectively discern accurate information. Cheung et al. [131] suggested that accuracy is related to the confirmation or disconfirmation of information. If a user encounters parts of information they know are factual, they are more inclined to assume that the information as a whole is accurate [131]. Because the information that the participants were to evaluate was based on fictitious scenarios, a participant's lack of ability might have affected the results to confirm information with previous knowledge or additional sources. Additionally, accuracy might have been evaluated based on how the dashboard displays information. For example, if a participant had to assume data values based on graphs, they are unable to confirm their assumptions, which may have affected the perception of accuracy. Ahn and Sura [63] suggested that when accuracy is difficult to achieve, users search for information completeness, which may explain why information completeness was found to have a highly significant effect. On the other hand, this finding also highlights some of the dangers of using dashboards to based decisions on, as through familiarity and continued use decision makers might become less sensitive to cross-validating information they are presented with on the dashboards.

In terms of perceived task complexity, it is striking to find that all the three hypothesized relationships are found to be significant and negative. This finding highlights that perceptions of how complex a decision making task is, are heavily dependent on the quality of information that is provided and how this information is presented. To the best of our knowledge this is one of the first studies that has examined the effect of individual IQ dimensions and their relationship with perceptions of task complexity for organizational operations. While the study of Arguello et al., [132] highlighted the importance of IQ in relation to perceived task complexity on visual representations, the authors did not delve into the individual dimensions and their effects. Our results show that format, currency, and completeness exert a negative effect, which translates to reduction of perceived task complexity. This result also highlights how important it is to understand not only what information is important for decision makers for complex tasks, but also how this information should be provided and presented. Similarly, we find that information satisfaction inversely affects perceived task complexity. This shows that there are both direct and indirect effects of IQ dimensions on perception of task complexity. Thus, the combined results provide some interesting future avenues on how to develop analytics-based dashboards that can alleviate perceived complexity and result in less technology-induced stress for users.

Further, the study makes an important contribution to the decision making literature in the organizational context by providing empirical evidence of the positive effect of information satisfaction on decision making quality. The path coefficients demonstrate that information satisfaction was the construct with the greatest impact on decision making quality, whereas perceived task complexity had an inverse and less significant effect. These results suggest that information satisfaction is a necessary construct/condition to consider in future studies in the field of analytics-based dashboards and decision making with visualizations. This is particularly true because it has a negative effect on perceptions of task complexity, which in turn has a significant influence on decision making quality. This research contributes to the decision making literature by explaining the influence of IQ on organizational decisions through the mediation of information satisfaction and task complexity and provides a model suitable for assessing and explaining the effect of IQ in data visualizations. The research implications of these findings, as well as the novel approach of examining such effects though simulated experiments using scenarios, provide future researchers with insight into how they can gain more insight into the use and design of critical decision making tools. In addition, the significance of IQ in dashboard representations also leads to discussions of how it can be achieved, particularly when faced with real decision making tasks at the organizational level.

6.1. Implications for research

Through its methodology and results, this study provides some novel contributions to ongoing research on use of analytics-based dashboards for decision making. To the best of our knowledge, this is one of the first studies to examine the individual dimensions of IQ, presented through visual cues such as those in dashboards, in an indirect relationship with decision making quality within the organizational context. Our study was prompted by the convergence of analytics-based visualizations, decision making, and operations in contemporary organizations and the need to better understand how such digital technologies are used in

practice. Thus, we explored the mechanisms by which each IQ dimension affects the mediating constructs of information satisfaction and perceived task complexity. Such insights can help us better understand the nature of visual representations of information and task command.

Certain types and ways of presenting information can have important ramifications for the usefulness of dashboards and analytics visualizations, and our study opens a discussion of how these cues can influence important mediating conditions. Compared to prior studies, our present results highlight the important role of currency, in contrast to prior studies, such as that of Nelson et al. [21]. As noted by those authors, however, our findings can be attributed to the fact that they emerged from a realistic scenario in which participants were actively trying to solve a business problem. In such circumstances, currency is important, and the significance of the attribute increases because it is used in a direct way by participants. This finding confirms the assumption of Nelson et al. [21] concerning the contexts in which currency would be an important attribute of IQ.

Second, we highlight how perceived task complexity can be influenced by visual informational cues and highlight the importance of this construct in influencing decision making quality. While research on task complexity has been active since the early 80′s, in the past few years there has been less interest in this state, especially in relation to decision making tasks. Nevertheless, we argue that the crucial importance of understanding how decision makers use information from dashboards to address their tasks calls for a more thorough reexamintion of this literature. In our experiment, we were able to simulate decision making tasks within the organizational context, which provided respondents with a realistic measure of task complexity. One of the challenges in studying task complexity is that it is quite ephemeral in respondents' consciousness and is best captured during or shortly after a given task [92]. In our scenario-based approach using visual representations of dashboards, respondents were better able to reflect on how they experience the complexity of the task, which allowed us to examine aspects that affected it (IQ and satisfaction) or were affected by it (decision making quality). Thus, it is important that future research extends the notion of perceived task complexity in scenario-based tasks, especially in understanding how visually presented information can help reduce such states in different contexts.

Finally, our study has some important implications for the use of analytics-based visualizations in the organizational context. A disproportionate number of studies have examined the impact of analytics and visualizations at the organizational level, yet, as our study shows, it is important to develop a more nuanced understanding of how such digital technologies are used by key decision makers. The context of organizational operations is a particularly relevant and important one, given the many high-stake decisions that need to be made on an everyday basis that have significant consequences for organizations. Thus, it is important to understand if and how they can be useful for the people that are using them, and how the design and representation of key information may possibly affect important outcomes. Thus, we adopted a more micro-level examination of the use of such technologies in relation to important organizational outcomes. In this direction, studies that extend our results can examine how different contexts influence outcomes or even incorporate aspects that go beyond the quality of information, such as aesthetics. This is particularly relevant in the age of AI, where factual information is combined with recommendations and suggestions based on complex analytics methods. Such an environment can yield some interesting insights and provide the opportunity to theorize about how decision making is affected by full or partial delegation of responsibility to algorithms. Furthermore, we provide a theoretical extension of the notion of IQ that consider the notion not as textual data points, but as visual cues. As more and more raw data get converted into visualizations, it is important to examine how this conversation is measured within the IQ dimensions of prior studies. In this empirical study, we sought to explore such effects by directly capturing perceptions of IQ of respondents that emerge from their experience and interactions with the dashboard visualizations they have been presented with.

6.2. Implications for practice

The findings of this study present several interesting implications for practice, which provide valuable insights for analysts in general and within the organizational domain. By establishing how IQ affects decision making quality through mediation, this study can help data analysts develop and design beneficial dashboards to improve the ease of informed decision making. The study adds value to companies by providing evidence that dashboards can serve as an aid in improving decision making quality when they are designed appropriately and keeping IQ in mind. Specifically, our results provide evidence that focusing on the IQ of dashboards can reduce the effort required by the user during the decision making process. In addition, the study provides evidence that perceived information satisfaction is an important state, suggesting that the user's evaluation of using a system is an essential factor to assess. Thus, analysts should strive to produce dashboards that require little effort to use by ensuring that the information is complete and provided in an appropriate format. Companies can benefit from reducing the effort required for decision making, as the time saved can be allocated to other activities [59].

This study also provides a model for assessing how IQ affects perceived task performance and decision making quality. Practitioners (such as data analysts or marketing specialists) can use this model and the empirical approach to assess their current dashboards. Furthermore, it can be used in testing to identify improvements that could enhance decision quality. Our results regarding IQ suggest that users believe it is important that the information in the dashboard adds value to the decision making process. For key decision makers in organizations to make informed decisions, their aids must provide comprehensive, relevant, and unambiguous information in a well-organized and understandable format, supporting human abilities [46].

To enhance the benefits of using BDA and visualizations, companies should strive to establish an understanding of how the aspects of each IQ dimension affect their decision making process. Such understanding can be fostered by including decision makers in usability testing. To ensure consistency in their dashboards, companies could establish design principles based on the insights gathered in internal studies using the model provided in this study.

6.3. Limitations and future work

Despite the contribution of this study, it is not without some limitations. First, although we strived to recruit participants knowledgeable about organizational activities through a relevant educational background or experience, not all were actively working in the domain. Future research can extend this type of study by building on a sample of practitioners within a specific domain to have a more representative sample and uniform tasks. Second, although we controlled for some mediating conditions that might explain the influence of IQ dimensions on decision making quality, future research could incorporate additional variables that expand more on task characteristics and how IQ influences them. Doing so can provide a deeper understanding of the mechanisms through which they enable decision makers to deliver high-quality actions. Further, some variables had slightly lower than typical Cronbach alpha values, which might be related to the sample. These do not pose a large risk, since they are very only marginally below 0.7, but future studies may want to reassess the items used and perhaps expand them. Third, respondents self-reported their decision making quality, and it would have been beneficial to have a third party assess the quality of their decisions. Because in this case responses were based on categorical choices, this was not possible, but it could be implemented in a scenario in which respondents justify a decision based on the available data.

Fourth, we did not control for the complexity of each task, which

could an interesting point for further research. As perceived task complexity increases, different attributes of IQ may have a more important or less important role.

In addition to the aforementioned suggestion mentioned above, there are still unexplored areas that could be interesting for future research. A particularly interesting topic would be a comparison of our present results with a similar study using interactive dashboards. By allowing users to interact with the dashboard freely, how it affects the user's perception of IQ and wheteher it changes which dimensions they find important could be assessed. To further investigate the effects of IQ on perceived complexity, future studies could include aspects that would create more variance in the perceived complexity, for example, by varying the difficulty level of the tasks or of the visual elements. Additionally, including the time needed to read and understand the task information in the calculation might provide a different image of how complexity is affected or affects other constructs in the model.

CRediT authorship contribution statement

Sara Hjelle: Writing – original draft, Visualization, Software, Project administration, Methodology, Investigation, Conceptualization. **Patrick Mikalef:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Conceptualization. **Najwa Altwaijry:** Writing – review & editing, Validation, Supervision, Resources, Methodology, Investigation. **Vinit Parida:** Writing – review & editing, Supervision, Project administration, Methodology.

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Supplementary materials

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