# UNDERSTANDING USERS’ ACTION ON DATA ANALYTICS RECOMMENDATIONS

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# Abstract

Current trends indicate that many organizations are making significant investments in Data Analytics (DA) to leverage big data. However, recent studies also indicate that a large percentage of these investments are unsuccessful and that a majority of users do not act upon a data analytics tool's recommendations. This research draws upon the S-O-R framework and the Theory of Planned Behaviour to develop and empirically validate a theoretical model of the factors that influence/hinder a user's concordance with and actions taken with respect to a DA tool's recommendations. The model reflects the nuances of DA tool use within organizations including: (i) technological characteristics, (ii) individual characteristics, (iii) situational characteristics, and (iv) task-related characteristics. In addition, this study investigates the factors that shape a user's perception of the quality of a DA tool's recommendations, while trying to understand how, and to what extent, this perception influences a user's concordance with, and the actions taken in regards to, a DA tool's recommendations. The results of this research confirm that personal concordance and recommendation actionability are positively associated with user action on a DA tool's recommendations. Moreover, perceived risk of action was found to be negatively associated with user actions taken with respect to a DA tool's recommendations. It was also found that DA tool recommendation quality is shaped from intrinsic data quality, contextual data quality, DA tool quality, DA tool recommendation understandability, and analyst competency.

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# Chapter 1

## 1. Introduction

The importance of data-driven decisions cannot be over-emphasized in today's business environment. In the news, media, and academic literature, many scholars and practitioners are talking about the potential effects of Data Analytics (DA) on addressing such a priority. According to a report by Forbes, "the most successful companies have adopted a data-driven culture in which they maximize the use of data by providing necessary training and promoting the sharing of data across all levels of employees and departments" (Gleeson 2017). On these grounds, the current age is referred to as the data analytics era (Henke et al. 2016). The current Information Systems (IS) literature argues that DA tools can empower decision-making processes and enhance organizational decision quality (Chen et al. 2012; Manyika et al. 2011). Among the many factors which have caused the denomination of such a claim, the most prominent is the rapid advancement of many new IT technologies which has facilitated: data generation, broadcast, and storage; the widespread adoption of these technologies among users and organizations; and the enhancement of computational power (Henke et al. 2016). Current studies show that ninety percent of the world's data has been created in the last two years. Moreover, it is expected that by 2020, there will be more than fifty billion devices around the world, creating, collecting, and analyzing data (Gunst 2018). These advancements have paved the way for many Information Technology (IT) companies to develop a variety of DA tools to satisfy their business customers' need to make informed data-driven decisions grounded in various forms of data.

Data Analytics refer to a set of quantitative and qualitative techniques which are used to analyze and examine datasets to provide insights about the available information stored in the datasets. These techniques are used by practitioners to enhance decision quality (Rouse 2019). Generally, there are three different types of data analytics: descriptive, predictive, and prescriptive (Bekker 2017). Descriptive analytics, using data aggregation methods, provides insights about the past. Predictive analytics, relying on statistical modeling techniques, provide insights about the future. Prescriptive analytics, using optimization methods, seek to provide a recommendation for a business solution (Evans and Linder 2012). Prescriptive DA tools have the highest impact on users as these tools generally recommend a course of action by uncovering unknown information stored in datasets to facilitate decision making within organizations (Gubbi et al. 2013). As such, generated DA tool recommendations are grounded in data; users often rely on the proposed recommendations to enhance the quality of their decisions (Ghasemaghaei et al. 2018). In this regard, some IS scholars recently have explored the antecedents of user intentions to use DA tools (Kwon et al. 2014; Riggins and Wamba 2015), while other IS scholars have investigated the conditions under which using DA tools could enhance organizational decision quality (Cao et al. 2015; Sharma et al. 2014). However, to get real value out of investing in DA tools, organizations need to create an organizational environment which facilitates the translation of data-driven decisions into data-driven actions (Kaplan et al. 1996). To date, no studies have identified conditions under which a user will be motivated and assisted in acting upon a DA tool's recommendations. Therefore, having identified this gap, this thesis focuses on this issue and strives to investigate this phenomenon further.

## 1.1. Research Motivation

As discussed above, the availability of many new DA tools has facilitated the analyses of a variety of data, and many organizations have been motivated to implement DA tools to exploit big data to enhance decision quality (Chen et al. 2012; Coulton et al. 2015). Current trends show that investing in DA tools for data leverage has become a priority for many organizations (Weldon 2016). According to a recent report by the International Data Corporation (IDC) (Bertolucci 2015), the size of investment in DA tools by the end of 2016 reached US$103 billion and is expected to reach US$203 billion by 2020. However, according to the same report, only a quarter of respondents in a survey of managers from a group of companies that had already invested in DA tools reported that investments in DA tools were deemed successful.

Another study by Deloite (2013) found that only 25% of organizations that had invested in DA tools reported a significant improvement in their expected outcomes. These findings were confirmed by an additional and more recent study by Dresner Advisory Services (2017) where only 21% of organizations reported somewhat improvement in their expected outcomes from using DA tools, while only 9% reported significant improvements (Nashua 2017). A variety of factors can affect the success of investing in DA tools. For instance, Colas et al. (2014) identified three such factors: data quality, DA tool quality, and analytical skills. Moreover, Ghasemaghaei et al. (2017) argue that a firm's resources are among the crucial factors determining the success of a DA investment.

Further, Akter and Wamba (2016) argue that companies need to consider the challenges associated with using DA recommendations to obtain the benefits. These include "integration of big data from different sources and formats, introducing new 'agile' analytical methods, and machine-learning techniques, and increasing the speed of data processing and analysis." Wu et al. (2016) also claim that DA investment failure is the result of neglecting the necessary conditions that are essential to generate actionable recommendations. If organizations want to reap the benefits of their investments in DA tools, they should create an environment that facilitates acting on the recommendations generated by the DA tools. This refers to a DA user implementing or executing those recommendations.

Interestingly, according to another recent report by Forbes (Columbus 2016), only 41% of business executives do indeed act upon recommendations made by a DA tool. These findings raise the question as to why such a large percentage of DA users do not act on these recommendations. This is an important question to answer, because such inaction negates the value of investing in DA tools, in addition to wasting the efforts put into using them. This study therefore seeks to investigate the conditions under which recommendations generated by a DA tool translates into action by a DA user.

## 1.2. Research Objectives

The objectives of this study are two-fold. The first objective is to investigate the conditions under which a DA user will act on a DA tool's recommendation. Recent surges of investment in DA tools have been reported. Many organizations have either invested or are considering investing in these tools, with the whole purpose to make data-driven decisions that enhance outcomes for organizations (Chen et al. 2012; Coulton et al. 2015). However, according to Kaplan et al. (1996) a right decision is only valuable when it is followed by a series of required actions. Further, making the right decision does not imply the required action would necessarily follow. Therefore, to be more specific, this study seeks to understand the factors that facilitate or hinder a DA user's action on recommendations from a DA tool.

To study this phenomenon, the S-O-R framework (Mehrabian and Russel 1974) is used. In the IS literature, the S-O-R framework has been used to examine IT users' responses and behaviors in regards to employing a given IT system (Peng and Kim 2014; Morrison et al. 2011; Kawaf and Tagg 2012). According to this framework, in this study, the environmental stimulus (i.e., DA recommendation) affects the internal state (i.e., concordance with a DA recommendation) and shapes the external response (i.e., action on a DA recommendation) of the organism (i.e., DA user). Moreover, according to Agency Theory (Alchian and Demsetz 1972; Jensen and Meckling 1976), when one party (the agent) is hired by the other party (the principal) to perform a task, although both parties act rationally, their actions will be based on the self-interests of each. Therefore, such actions could potentially increase the chance of a conflict between the two parties (Eisenhardt 1989). In this study's context, the principal is the DA user, and the agent is the DA tool. Extant literature shows that the principal's compliance with the Agent's recommendations is affected by the principal's concordance with that recommendation (Keil et al. 2000; Wang and Benbasat 2007; Francalanci and Galal 1998; Wang and Benbasat 2009). Therefore, this study argues that the level of the DA user's concordance with a DA tool's recommendation is expected to influence the principal's action on the agent's recommendation.

In line with the above discussion, the first research objective of this study is:

— *To develop and empirically validate a theoretical model of the factors that influence/hinder a DA user's concordance with and action on a DA tool's recommendation.*

According to the S-O-R framework, the environmental stimulus is the origin of the organism's response. In this regard, the S-O-R framework asserts that the positive perception of the nature and characteristics of the stimulus positively affect the organism's internal state and external response. For instance, Wang et al. (2010) found that there is a positive relationship between web aesthetics and online consumers' satisfaction. Wang et al.'s (2011) findings reveal that a web page's aesthetic stimulus positively influences the cognitive, affective, and conative outcomes of online consumers. To prepare a DA tool's recommendation, humans, tools and statistical models should work hand-in-hand to propose a data-driven action (Russom 2011), and the combination of these factors shape the perception of the proposed DA tool's recommendation's quality (Ghasemaghaei et al., 2018). The expectation is that this perception of quality will affect the DA user's concordance with and action on a DA tool's recommendation. Thus, the second research objective of this study is:

— *To investigate what factors shape the DA user's perception of the quality of a DA recommendation, and to what extent, and how this perception influences a DA user's concordance with and action on the DA tool's recommendation.*

## 1.3. Dissertation Contribution and Structure

This study makes two significant contributions to the extant literature. Many organizations are currently making sizable investments in DA tools to leverage big data. However, as explained above, these investments are mostly reported to be unsuccessful, and the majority of business executives who receive DA tools' recommendations do not act upon their recommendations. Therefore, this study's first theoretical contribution is to identify the conditions under which a DA tool's recommendation translates into A DA user's concordance with and action on the recommendation. Second, this study investigates to what extent the perception of DA tool's recommendation quality shapes its concordance with and affects action on such a recommendation, as well as identifying the DA recommendation's characteristics that shape these quality perceptions. Further, by illuminating the factors that affect the successful leveraging of this increasingly critical information technology, this study also promises substantial implications to facilitate the use of DA tools and recommendations by organizations.

The rest of this dissertation is structured as follows: Chapter 2 provides a contextual background of action or lack thereof on DA tools' recommendations: Chapter 3 presents the theoretical background for this research and details the proposed theoretical model and associated hypotheses: Chapter 4 describes the experimental methodology for collecting data to validate the proposed model empirically: Chapter 5 illustrates the preliminary data analyses and the results of statistical tests of the model's hypotheses, and finally, Chapter 6 outlines the study's contributions to both theory and practice, as well as its limitations and avenues for future research.

# Chapter 2: Contextual Background

## 2.1. Action on a Recommendation

Acting on a recommendation generated from a DA tool refers to a DA user actually implementing or executing that recommendation. In this regard, the IS literature has consistently shown a positive relationship between intention and actual use in the context of Information Technology (IT) use (Lin and Lu 2000; Luarn and Lin 2005). Current literature asserts that an IT system's various characteristics will affect its actual adoption and its use (Venkatesh 2000; Brown et al. 2010). According to Brown et al. (2010), several factors affect the ultimate use and adoption of a technology. These factors include technological characteristics of an IT system, as well as the individual and organizational characteristics of an IT user. Although the intention to act is among the factors affecting an IT system (e.g., in the context of this study a DA user), this research argues that intention is a necessary but insufficient condition for a DA user to act upon a DA tool's recommendation. Therefore, to study acting on a DA tool's recommendation, it is necessary to look over the current state of the literature on the intention to use and accept technology.

Most of the current literature on acting on IT systems' recommendations mainly focus on intentions to act on or to comply with such recommendations (Wang and Benbasat 2009; Lowry and Moody 2014; Johnston and Warkentin 2010). For instance, the intention to act has been studied for the online social network (OSN) and the online consumer review literature, where a user of these systems receives a recommendation from a friend or a review writer to either engage in a social relationship or to purchase a product or service (Matook et al. 2015; Garbarino and Strahilevitz 2004; McKnight et al. 2002). In this regard, Matook et al. (2015) assert that OSN users become overwhelmed when seeking a recommendation on these platforms because of the increase in the availability of various information sources. Garbarino and Strahilevitz (2004) have found that the online consumer reviews (i.e., a typical source of online recommendations) from known sources are more acted upon, as opposed to those by a recommender system which is either unknown or less known.

Intention to act has also been studied in the Decision Support Systems (DSS) literature, where a user receives advice from a recommendation agent (Wang and Benbasat 2009; Choi et al. 2011; Wang et al. 2014). A recommendation agent is a software program that considers consumer preferences for a product or service. This software then accordingly provides product or service recommendations to match those preferences (Xiao and Benbasat 2007). In this regard, Wang and Benbasat (2007) have studied the intention to act on a recommendation of an RA system. In their work, a recommendation agent acts as an agent on behalf of its users who are considered the principals. According to Wang and Benbast (2007), agency conflicts exist in this context as well. Information asymmetry takes place when online buyers (the principals) assume that a recommendation agent (the agent) holds more information and is not providing it fully to them. Buyer is therefore not able to accurately assess and verify the quality and integrity of the proposed agent's recommendations (Wang and Benbast 2007). Goal incongruence occurs when an online buyer assumes that the online recommendation agent acts opportunistically to increase the profit of the vendor who owns the online recommendation agent (Wang and Benbasat 2007). Therefore, the buyer is not able to trust the proposed agent's recommendations.

Intention to comply with a recommendation is another construct researched in the current literature. As opposed to the intention to act, the intention to comply with a recommendation has been studied in broader fields such as IS and medicine. In the context of IS, the intention to comply with an IT recommendation is used similarly to the intention to act. In this regard, some of the current studies have focused on complying with a course of action recommended by an IT system such as an online recommender system (Johnston and Warkentin 2012; Wilson et al. 2015). Intention to comply has also been used in the context of complying with organizational system security policies (Putri and Hovav 2014; Al-Omari et al. 2012; Hovav and Putri 2016; Straub 1990; D'Arcy and Hovav 2009; Siponen and Vance 2010; Bulgurcu et al. 2010; Anderson and Agarwal 2010). Intention to comply with a recommendation has also been studied in the medical literature. In this context, compliance with a recommendation has been used to measure the extent to which a patient follows a physician's recommendations on a course of treatment (Laugesen et al. 2015; Kerse et al. 2004; Boeka et al. 2010; Pedro et al. 2013; Vagias et al. 2014; Young and Oppenheimer 2006).

According to the current IS literature, many factors potentially influence a user's intention to act upon an IT recommendation. For instance, Bulgurcu et al. 2010 asserted that information security awareness is the main driver of an employee's intention to act on security protocols. Herath and Rao (2009) also stated that threat appraisal is the most prominent factor affecting an individual's action. Johnston and Warkentin (2010) also support these findings.

Another factor that affects action on a recommendation is concordance. Concordance, a communicational agreement between a recommendation seeker and a recommender, is another factor that influences action on a recommendation (Laugesen et al. 2015; Kerse et al. 2004). Concordance has been widely used in the medical and health literature, emphasizing the agreement between a patient (the recommendation seeker) and a physician (the recommender) on a proposed treatment (Laugesen et al. 2015; Kerse et al. 2004). These studies show that higher levels of concordance are associated with greater chances of the seeker complying with and acting on a recommendation (Laugesen et al. 2015; Kerse et al. 2004; Hausman 2001).

Another factor that might affect intentions to act on a recommendation is trust, an essential predictor of user engagement in any relationship (Jones and George 1998), that plays an additional role on intentions to act on a recommendation (Matook et al. 2015). However, while the most accepted definition trust is the acceptance of and exposure to vulnerability while dealing with another party (Beldad et al. 2010), this social construct lacks a universal denotation (Beldad et al. 2010). Trust as acceptance of and exposure to vulnerability conceptualizes the willingness of a trustor to be vulnerable to the actions and recommendations of a trustee who is going to act on behalf the trustor (Beldad et al. 2010). In our context, a trustor is a DA user, whereas a trustee is a DA system or a DA analyst who is working with a DA system to prepare a recommendation. Generally, a DA recommendation contains a series of unknown future actions. Therefore acting on such recommendations could put actors in a vulnerable situation which requires them to trust the recommender. This type of trust is measured through three different dimensions: competence, benevolence, and integrity (Gillespie and Dietz 2009). Competence measures the ability of a trustee to act reliably and effectively. Benevolence measures the morality of a trustee in the conduction of an action. Finally, integrity measures the completeness of a trustee's actions (Gillespie and Dietz 2009).

According to the current literature, another factor that affects action is perceived risk of action. Perceived risk of action has a long history of research in various fields of management, especially marketing literature (Garbarino and Strahilevitz 2004). Here, perceived risk of action is two-fold: the perception of the likelihood that the proposed action will end up being wrong, and the perception of the seriousness of the consequences of the action being wrong (Kaplan et al.1974; Taylor 1974; Bettman 1973; Lopes 1995; Garbarino and Strahilevitz 2004; Herath and Rao 2009).

Organizational support is one more factor quoted in the literature as affecting an individual's action on an IT recommendation. Organizational support refers to the extent to which a firm supports or dictates a preferred behavior (Putri and Hovav 2014). Current literature asserts that organizational support indicates the probable outcome of a particular action and its consequences (Compeau and Higgins 1995; Putri and Hovav 2014).

Among all the identified antecedents of action on a recommendation, the quality of the recommendation is the most critical factor affecting a user's intentions to act upon it (Wang and Benbast 2009; Todd and Benbasat 1999). According to Wang and Benbasat (2009), higher levels of perceived recommendation quality positively influence a user's intention to utilize the recommender's advice.

The antecedents of intention to act or comply with an IT recommendation mostly belong to one general category of the user's beliefs about the technology. Given the context of this study, which is to understand the conditions under which a DA user will actually act on a DA tool's recommendation, this study argues that intention is a necessary but insufficient condition for a DA user to act upon a DA tool's recommendation. Within an organizational setting, acting on a DA tool's recommendation will depend on a slew of individual and organizational factors that extend beyond the user's beliefs about the technology (i.e., the DA tool) (Matook et al. 2015).

The current literature thus identifies several antecedents of an individual's action on an IT recommendation, including the ones discussed above in addition to others. Table 2.1 summarizes some of these predictors.

| **Table. 2.1. Summary of the Current Literature** | | |
|---|---|---|
| **Antecedents of Action on a Recommendation** | **Definition** | **Literature** |
| **Recommendation Quality** | The quality of a recommendation from a user's perspective (Parasuraman et al. 1988). | Schwartz et al. 2017; Gilkey et al. 2016; Nilashi et al. 2016; Gujral and Chandra 2014; Dong et al. 2013; Kant and Bharadwaj 2012; De Meo et al. 2011;Kim et al. 2010; Moricz et al. 2010; Parasuraman et al. 1988 |
| **Concordance** | Concordance refers to the extent to which an IT user agrees with a proposed IT tool's recommendation (Laugesen et al. 2015) | Barrow et al. 2018; Laugesen et al. 2015; Elmore et al. 2015; Bennett et al. 2014; Wang et al. 2014; Kuhlen et al. 2012; Larget et al. 2010; Kerse et al. 2004; |

| | | |
|---|---|---|
| **Trust** | The willingness of an individual to be vulnerable to the actions of others (Mayer et al. 1995). | Warner-Søderholm et al. 2018; Krot and Lewicka 2012; Palvia 2009; Xie and Peng 2009; McKnight 2005; McKnight et al. 2002; McKnight and Chervany 2001; Mayer et al. 1995 |
| **Risk of Action** | The risk associated with the implementation or execution of a recommended course of action (Lee et al. 2007). | Cummings 2018; Arends et al. 2017; Lachman 2007; Lee et al. 2007; Depoortere et al. 2006; Jung and Reidenberg 2006; De Hoog et al. 2005; Borum et al. 1999 |
| **Organizational support** | The extent to which employees believe that their organization supports their actions (Eisenberger et al. 2002). | Kurtessis et al. 2017; Eisenberger and Stinglhamber 2011; Kossek et al. 2011; Eisenberger et al. 2002; Rhoades and Eisenberger |

| | | |
|---|---|---|
| | | 2002; Eisenberger et al. 2001 |
| **Source Competency** | The ability of a trustee to act reliably and effectively (Gillespie and Dietz 2009). | Bateman and Liang 2016; Riehle 2015; Johnston and Warkentin 2012; Gillespie and Dietz 2009; Paquette 2007 |
| **Information Security Awareness** | The awareness regarding the potential risks associated with acting on an IT system's recommendation (Shaw et al. 2009) | McCormac et al. 2017; McIlwraith 2016; Peltier 2016; Bulgurcu et al. 2010; Shaw et al. 2009; Peltier 2005; Siponen 2000; Thomson and Von Solms 1998 |
| **Organizational Culture** | The underlying beliefs, assumptions, and values of an organization (Needle 2004). | Driskill 2018; Alvesson and Sveningsson 2015; Schein 2010; Needle 2004; Jo Hatch and Schultz 1997; Schein 1990; Barney 1986; Frost et al. 1985 |

## 2.2. DA Tool's Recommendation Quality

The perceived DA tool's recommendation quality assesses the quality of a DA tool's generated recommendation from a DA user's perspective. According to the current IS literature, quality of a recommendation is one of the main factors that can determine the extent to which an IT user accepts the recommendation generated from an IT system (Nilashi et al. 2016). From an IT user's perspective, an IT recommendation of high quality depends on several factors which vary according to the context and field. For instance, in the recommendation agent literature, the value of an IT recommendation is dependent on the recommendation's accuracy in predicting the preferences of the IT user (Chen et al. 2012). According to Komiak and Benbasat (2006), this value enhances user satisfaction. Chen et al. (2012) also claim that the ability to predict an IT user's preferences makes a recommendation of high quality, and can increase the IT user's reliance on the system in the future. This is the result of the IT user's belief that these IT systems offer better decision support; these, in turn, can result in a long-term relationship between the IT system user and the recommender system (Nilashi 2016). However, if the IT system users find such recommendations to be unsuited or biased, a distrustful behavior towards the IT system is established, and this can pose a hugely negative impact on the reliance on the provided recommendations (Nishlashi 2016; Chau et al., 2013).

Varying by domain, accuracy is not perceived to be the only means by which to assess the quality of an IT system recommendation (McNee et al., 2006). If recommendations are only provided based on the IT user's previous behavior, the novelty of such a recommender system falls under question (Nishalashi 2016). For instance, imagine IT users go online to get a movie recommendation. If the suggestions are films they have already seen, this will not help them explore new ones. The literature therefore considers novelty a factor that affects an IT user's perception of a recommendation's quality (Vargas and Castells 2011). It is worth noting that novelty alone does not essentially lead to a better perception of a recommendation quality (Cremonesi et al. 2011; Ekstrand et al. 2014; Said et al. 2013), especially if the IT system's recommendation is far from the IT user's interest and expertise (Nishalashi 2016).

Diversity also affects an IT user's perception of an IT system's recommendation as it denotes to what extent, over time, the recommendations are similar (Bodoff and Ho 2015). On the one hand, the current literature suggests that a balanced variety in the proposed recommendations positively affects how IT users perceive their quality (Ekstrand et al. 2014; Said et al. 2013). On the other hand, being either too similar or too different is also problematic, as users become frustrated over time and regard such recommendations with lower trust (Fleder and Hosanagar 2009).

Current IS literature points to transparency as a factor that shapes recommendation quality perception (Wang and Benbasat 2005; Xiao and Benbasat 2007). Current studies into transparency focus on IT users' perception of the process behind how the recommendations are generated. Not surprisingly, trust is one of the most significant reported factors with regards to shaping recommendation quality (Pu and Chen 2007; Nashilishi 2016). The interplay between trust and transparency are connected by shaping the IT system's recommendation quality such that the higher levels of transparency enhance the trust which itself increases the positive perception of recommendation quality (Pu and Chen 2007).

### 2.2.1. Measurement of DA Recommendation Quality

Considering the current literature, two questions in regards to the context of this study can be raised:

1. To what extent is a DA tool's recommendation different from any other sort of IT system's recommendation?
2. To what extent are the reactions to a DA tool's recommendations different from the reactions to any other recommender system's recommendations?

The current literature describes DA as a "process of exploring data to extract meaningful insights, which can be used to understand and better improve the business performance" (Dykes 2010). Therefore, the primary purpose of a DA tool is to generate value by answering questions such as 'why?' and 'so what?' The primary purpose of other recommender systems – and in general any other IT system – differs from that of a DA tool. DA tools generate their recommendations through a "process of organizing data into informational summaries to either monitor how different areas of a business are performing" or prepare a summary on the available decision options which match the interests of an IT user (Musgrove 2016).

Reactions to a recommendation from a DA tool are also different from those to any other recommender system. According to Wang and Benbasat (2007), a recommendation agent acts as on behalf of its users who are considered the principals. Therefore two different agency conflicts might arise in this context: information asymmetry and goal incongruence. Information asymmetry occurs when online buyers (the principals) assume that a recommendation agent (the agent) holds more information and does not provide the full intended information to them. The buyer is therefore unable to accurately assess and verify the quality and integrity of the proposed agent's recommendations (Wang and Benbast 2007). Goal incongruence occurs when an online buyer assumes that the online recommendation agent acts opportunistically to increase the profit of the vendor who owns the online recommendation agent (Wang and Benbasat 2007). In this case, the buyer is not able to trust the proposed agent's recommendations. All these conflicts arise because the recommender system is not in-house. However, an in-house DA system is composed of "a combination of some processes and tools, including SQL queries, statistical analysis, data mining, fact clustering, and data visualization" (Russom 2011) which would likely result in less conflict between a DA user and a DA tool's recommendation.

That said, it is necessary to define a new measurement scale for a DA tool's recommendation quality, especially as the current literature lacks a solid definition for such a construct, though some scholars have tried to come up with a measurement scale for similar versions. Ghasemaghaei et al. (2018), for instance, recently conceptualized Data Analytics competency. In their work, Data Analytics competency refers to "a firm's ability to effectively deploy Data Analytics-based resources in combination with other related resources and capabilities.” In doing so, they validated the above construct (i.e., Data Analytics competency) and proposed this as a second-order construct made up of “data quality, the bigness of data, analytical skills, domain knowledge, and tools sophistication.” A similar overall approach is used to measure DA recommendation quality in this study.

To this end, the currently available frameworks will be relied on. Accordingly, this study assesses the perceived DA recommendation quality through the lens of the SERVQUAL Framework (Parasuraman et al. 1988). According to this framework, the quality of an IT system will be evaluated based on its physical environment quality, outcome quality, and interaction quality (Brady and Cronin 2001).

Physical environment quality measures IT systems based on design and ambient condition. Outcome quality evaluates an IT system based on its merits in fulfilling a technical task. And finally, interaction quality determines the expertise of an IT system user in performing a required service (Brady and Cronin 2001). Relying on the SERVQUAL framework, a DA tool’s recommendation quality is a second order construct composed of data and DA tool quality which reflects the physical environment quality, DA tool’s recommendation understandability which reflects the outcome quality, and the analyst competency which reflects the interaction quality.

Data quality refers to the quality of the raw information stored in datasets (Detlor et al. 2013). It can be assessed based on different aspects of intrinsic and contextual data characteristics (Wang et al. 1996). According to Tress (2017), intrinsic data characteristics refers to the accuracy and objectivity of data, reflecting the extent to which the data is correct without being partial. Contextual data characteristics indicate the degree to which data corresponds to the task at hand. Some of the dimensions of contextual data characteristics are “value-added, relevancy, timeliness, completeness, appropriate amount of data” (Tress 2017).

An IT system’s functionality (in the context of this study, that of a DA tool) will be evaluated based on its practicality and aesthetics (Brady and Cronin 2001). Additionally, recommendation understandability measures the comprehensiveness of the explanation facility in a DA tool’s recommendation. It therefore indicates the degree to which logical processes and the line of reasoning are outlined in a DA tool’s recommendation (Wang and Benbasat 2009). And finally, analyst competency refers to the perception of a set of competencies, abilities, and skills of the person working on a DA tool and preparing a DA tool’s recommendation (Ghasemaghaei et al. 2016; Draganidis and Mentzas 2006).

Drawing on these understandings, the next chapter will propose and delineate the factors that influence a DA user to concur with and act on a DA tool’s recommendation. The factors that shape the perception of the quality of a DA recommendation will also be explored.

# Chapter 3: Theory Development

As discussed in Chapter 1, this study has two main research objectives. The first is to investigate which factors influence a DA user to concur with and act on a DA tool's recommendation. The second is to explore the factors that shape the perception of the quality of a DA recommendation and to try to establish to what extent this perception influences a DA user to concur with and act on the DA tool's recommendation. As discussed in the following sections, this study draws on the Stimulus-Organism-Response (S-O-R) Framework and the Theory of Planned Behaviour to provide the theoretical foundations of the proposed research model that addresses the research objectives of the current study.

## 3.1. Stimulus-Organism-Response (S-O-R) Framework

The Stimulus-Organism-Response (S-O-R) Framework (Mehrabian and Russell 1974), originated in environmental psychology literature, asserts that external environmental cues serve as stimulus (S) affecting the internal state of an organism (O) which in turn, as a reaction to those environmental cues, brings about a behavioural response (R) (Luqman et al. 2017). According to the S-O-R framework, environmental cues influence the internal state of the organism and emotionally change the perceptions and feelings of the individual (i.e., organism) (Bagozzi, 1986). The prior internal state of an organism (e.g., pleasure, arousal, dominance) also mediates the effects of environmental cues and behavioural responses (Mummalaneni 2005). Therefore, depending on the external environmental stimulus and the current emotional state, the organism generally generates either an approval or avoidance behaviour, which is a reaction to the interaction of the environmental cues and the internal state of the individual (Mehrabian and Russell 1974; Eroglu et al. 2001). Figure 3.1 illustrates the S-O-R framework in the IT systems' use context.

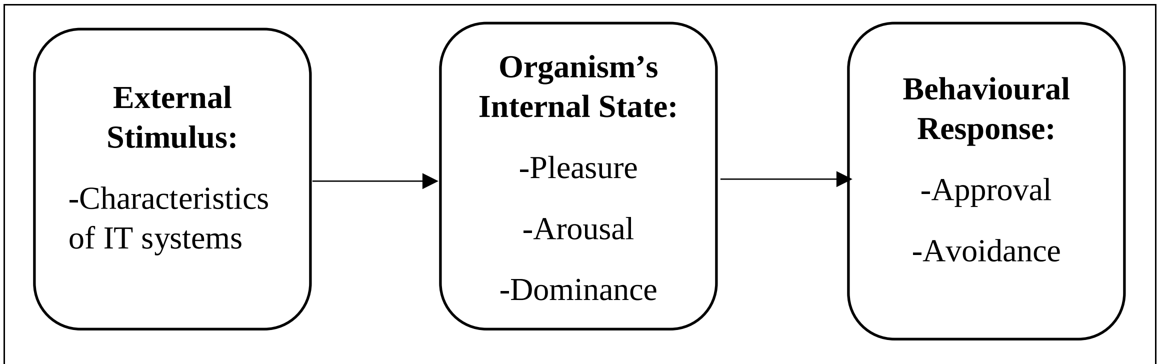


Figure 3.1. S-O-R Framework

With minor modifications, many scholars of various fields have used the S-O-R framework in their studies (Mummalaneni 2005). Many scholars in the IS field have notably drawn on the S-O-R framework to explain the extent to which a website's features (e.g., a recommendation agent) affect the users' internal state and shape their behaviours when using the recommendations from these systems (Benlian 2015). For instance, Peng and Kim (2014) employed this framework in the online shopping environment to determine online shoppers' intentions to purchase or re-purchase from an online recommender system. According to their findings, environmental cues of an online recommender system – such as color, lighting, and layout – affect the perceptions of the users, and determine their behaviours when relying on such a system (Kim and Peng 2014). In a similar context, Animesh et al. (2011) have also employed the S-O-R framework as a theoretical foundation to examine the effect of technological features of online shopping websites (i.e. the characteristics of the virtual artifacts and the environment of a given virtual location) as the environmental stimuli in shaping the behaviours of the participants. Animesh et al. (2011) state that interactivity and sociability affect their user's virtual experiences (i.e., internal state), which in turn enhance a user's intentions to purchase from those sites. In this regard, interactivity relates to the technological environmental stimuli that are generally designed by online shopping website developers, in particular the aesthetic quality or sociability of such sites. Additionally, Williams and Dargel (2004) suggested that the ambient conditions, symbols, and web page architecture, functioning as the environmental stimuli, change the internal state of the users, and shape their behaviours.

Besides the environmental stimulus, the S-O-R framework also posits that the current state of an organism is another significant factor in determining the organism's response. Benlian (2015) argued that the cognitive and affective internal state of a recommender system's user mediates the effect of a recommender system's recommendation transparency (i.e., environmental stimuli) and the degree to which they rely on those recommendations (i.e., behavioural responses).

The S-O-R framework is thus an appropriate overarching framework for the current research for the following reasons:

1. It provides a theoretical justification to investigate the effects of a DA tool's recommendation (i.e., environmental cue) on a DA user's concordance with (i.e., internal state) and action on (i.e., behavioural state) that DA tool's recommendation.
2. It provides a theoretical rationale for studying the factors that shape the perception of a DA's recommendation quality as the user's state of mind resulting from her/his cognitive and affective assessments of the DA tool's recommendation.
3. It allows for the examination of other environmental stimuli in shaping the DA user's perceptions of her/his internal state in relation to a particular behaviour (i.e., concordance with a DA tool's recommendation in this study) and behavioural response (i.e., action on a DA tool's recommendation in this study).

## 3.2. Theory of Planned Behaviour

The Theory of Planned Behaviour (TPB) (Azjen 1985; Azjen 1991) has been used in many different studies in the information systems literature (Mathieson 1991; Taylor and Todd 1995; Harrison et al. 1997; Battacherjee 2000; Song and Zahedi 2001; George 2002; Pavlou 2002; Suh and Han 2003; George 2004; Pavlou and Fygenson 2006; Han et al. 2010; Kautonen et al. 2015; Yadav and Pathak 2016). TPB is an extension of TRA, the Theory of Reasoned Action (Azjen and Fishbein 1980) and differs from TRA because of its ability to deal with volitional behaviours over which individuals lack complete control (George 2004). According to Gary Kielhofner (2008), “volition is one of the three sub-systems that act on human behaviour. Within this model, volition refers to a person's values, interests, and self-efficacy”. In this regard, volitional behaviours refer to actions individuals conduct based on a thorough cognitive decisional process. Figure 3.2 illustrates the TPB and its related constructs and relationships.

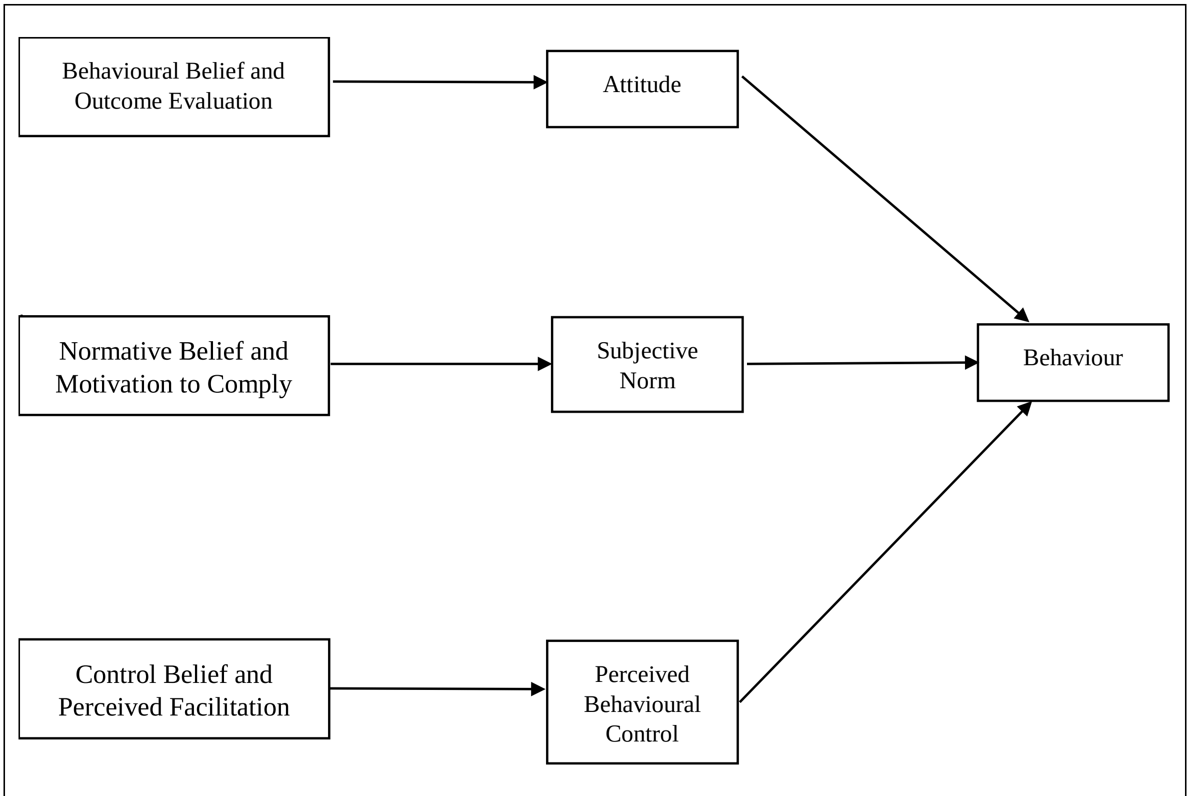


Figure 3.2. Theory of Planned Behaviour[1]

According to TPB, the intention to act determines how individuals respond and behave. Intention to perform is itself stimulated by three factors: (a) attitude toward the

[1] Figure 3.2. is adopted from Mathieson (1991).

behaviour, (b) subjective norms, and (c) perceived behavioural control. Accordingly, attitude toward the behaviour evaluates the user's desire to use an IT system; subjective norms refer to the user's perception of social pressure to perform the behaviour; and perceived behavioural control measures how users perceive their control over performing the behaviour (Azjen 1985; Azjen 1991; Mathieson 1991).

Attitude toward a behaviour is an IT user's positive or negative feeling about the consequences of performing a behaviour. According to TPB, attitude towards the behaviour is determined by behavioural beliefs and outcome evaluations. In this context, behavioural belief refers to the IT system user's perception over the subjective probability of a particular outcome in the case of performing the behaviour, and outcome evaluation reflects the user's assessment of the desirability of the outcome (Mathieson 1991).

As stated earlier, subjective norms refer to "the perceived opinions of the referent others" (Mathieson 1991). A referent refers to those individuals or groups whose opinions are perceived by the IT system user to be important (Azjen 1985; Mathieson 1991). According to TPB, the subjective norm is a function of the products of normative beliefs and motivation to comply. Normative belief reflects the IT system user's perception of a referent's desired behaviour. Motivation to comply also refers to the extent to which the IT system user is interested in complying with the interests of the referent other (Mathieson 1991).

Finally, control beliefs and perceived facilitation predict perceived behavioural control. Control beliefs refer to an IT system user's perception of the availability of required skills, resources, and opportunities to conduct a behavioural response. There are two different types of control beliefs; (a) situational (e.g., having sufficient monetary resources); and (b) personal (e.g., having the ability to use the IT system) (Mathieson 1991). Perceived facilitation denotes an IT system user's assessment of the importance of having resources to achieve a particular outcome (Azjen 1985; Azjen 1991; Mathieson 1991).

The underlying premise of the current study is that concordance with a DA tool's recommendation influences whether a DA user acts on the recommendation. TPB provides a robust theoretical foundation for testing this premise, along with a robust conceptual framework for examining the factors that affect the DA user's action on a DA tool's recommendation. The appropriateness of choosing this theory is described in detail in the following sections.

## 3.3. Research Model and Hypothesis Development

In this study, the S-O-R framework and the TPB are the underlying research framework to support the proposed research model and its related hypothesis. However, Brown et al. (2010) are relied on (2010) for a theoretical lens to justify choosing such constructs.

Acting on a recommendation generated from a DA tool refers to a DA user implementing/executing that recommendation. According to Brown et al. (2010), several factors affect the ultimate technology adoption and use. These factors include the following characteristics: those that are technological, individual, situational, and task-related. Building on the fact that acting on a recommendation is the ultimate expected outcome of the use of a DA tool, it is likely these factors will also affect the DA user's action on the DA tool's recommendation.

The current IS literature has shown that various characteristics of an IT system affect its actual adoption and use (Venkatesh 2000; Brown et al. 2010). In the context of this study, technological characteristics refer to the characteristics of a DA-generated recommendation. To be more precise, this study examines the characteristics of a DA tool's -generated recommendation through its quality. Perceived DA recommendation quality depicts outcome evaluation in the TPB model.

Situational characteristics represent the organizational context in which the technology has been implemented (Brown et al. 2010). These factors have been shown to directly impact the ultimate technology use (Taylor and Todd 1995; Brown et al. 2010). Along these lines, an organization's culture plays an essential role in stimulating users to adopt and use a proposed technology (Windschitl and Sahl 2002). This study examines organizational culture from the perspective of whether its orientation is evidence-based. Organizational evidence-based culture corresponds to the subjective norms in the TPB model. The choice was made because an organization with evidence-based organizational culture would be more likely to encourage its personnel to make decisions based on available evidence (in the context of this study, DA recommendations) (Pfeffer and

Sutton 2006). Organizational concordance with a DA tool's recommendation is another factor (Putri and Hovav 2014; Windschitl and Sahl 2002; Eisenberger et al. 1986) which can stimulate a DA user to act on a DA tool's recommendation. Organizational concordance with a DA recommendation portrays the normative belief in the TPB model.

A recommendation's actionability is the next organizational factor affecting a DA user's action the DA recommendation. Actionability is equivalent to control beliefs in the TPB model. Task-related characteristics describe the complexity and how easy an action can be analyzed (Brown et al. 2010). In this study, the perceived risk of action is portrayed as a task-related characteristic affecting a DA user's action on a DA tool's recommendation. Perceived risk of action corresponds to behavioural belief in the TPB model.

Finally, personal concordance is an individual characteristic that refers to the intention to perform a behaviour within the TPB model.

Table 3.1 summarizes the above discussion.

**Table 3.1. Constructs and Associated Theories**

| Construct | Type of Characteristic | TPB Model | S-O-R Framework |
|---|---|---|---|
| **DA Recommendation Quality** | Technology | Outcome Evaluation | Stimulus |
| **Organizational Evidence-Based Culture** | Situational | Subjective Norm | Stimulus |

| | | | |
|---|---|---|---|
| **Organizational Concordance** | Situational | Normative Belief | Stimulus |
| **Actionability** | Situational | Control Belief | Stimulus |
| **Perceived Risk of Action** | Task-Related | Behavioural Belief | Stimulus |
| **Personal Concordance** | Individual | Intention to perform a behaviour | Internal State |
| **Action on a DA recommendation** | Behaviour | Behaviour | Response |

To fulfill the research objectives outlined earlier, this study draws on the above theoretical foundations to propose the research model (depicted in Figure 3.3) and nine associated hypotheses, detailed below.

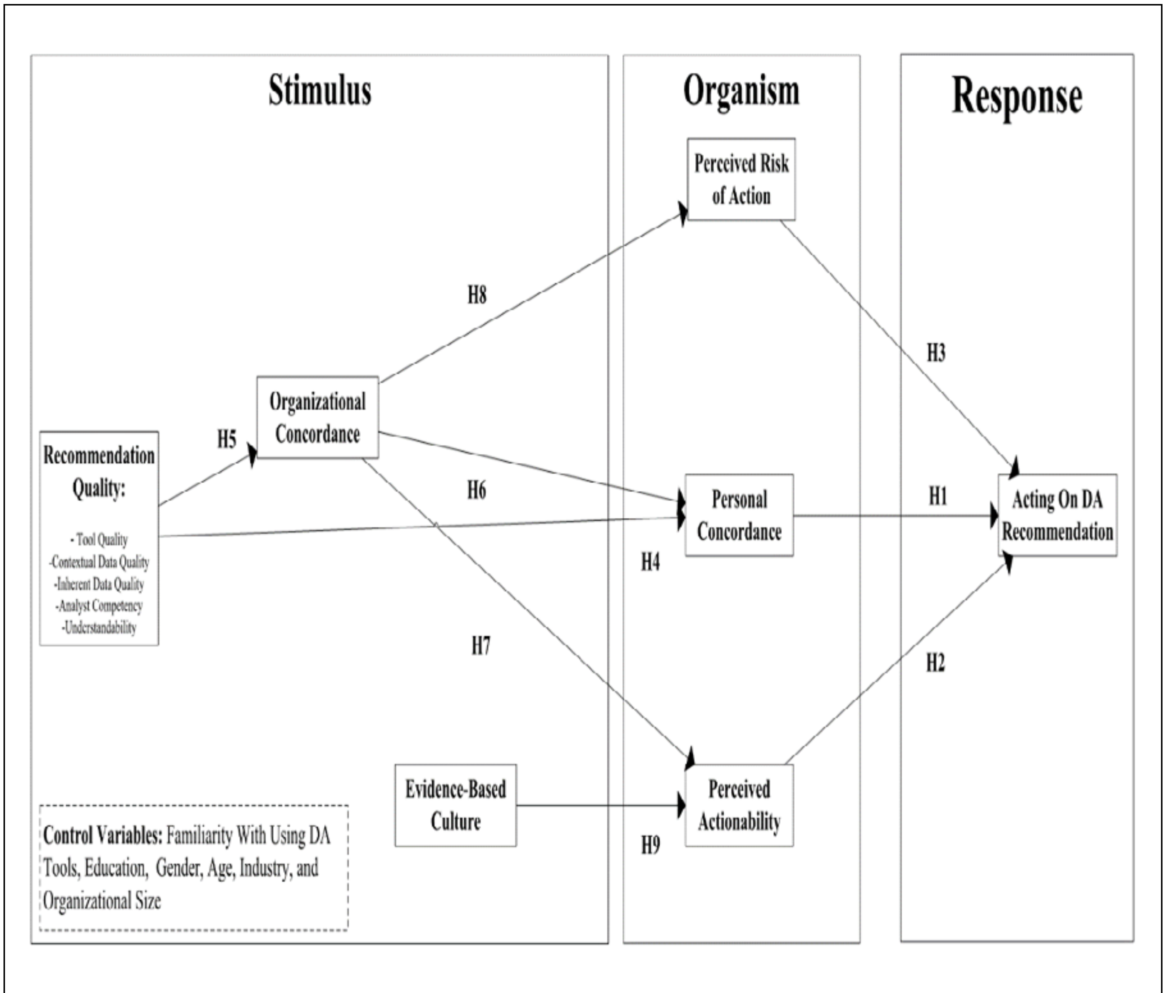


**Figure 3.3. Research Model**

## 3.3.1. Personal Concordance

In the context of this study, personal concordance refers to the extent to which a DA user agrees with a recommendation proposed by a DA tool. As described earlier, personal concordance has been widely used in the medical and health literature to emphasize the agreement between a patient (the principal) and a physician (the agent) on a proposed course of treatment (Laugesen et al. 2015; Kerse et al. 2004). In that literature, concordance refers to a communicational agreement between a principal and an agent (Laugesen et al. 2015; Kerse et al. 2004). Studies show that higher levels of principal-agent concordance are associated with greater chances of principal compliance with the agent's recommendation by acting on or following such a recommendation (Laugesen et al. 2015; Kerse et al. 2004; Hausman 2001).

According to the S-O-R framework (Mehrabian and Russell 1974), the internal state of an organism (in the context of this study, a DA user) will change when it receives an environmental stimulus (i.e., a DA tool's recommendation). The newly-formed internal state could have a negative or positive effect on the organism's current attitude, such that it will either acknowledge or ignore the stimulus. As stated in the S-O-R framework, the newly-shaped internal state drives the organism's behaviour (Peng and Kim 2014; Kawaf and Tagg 2012). In the context of this study, it is expected that when DA users receive DA tools' recommendation, their internal state change to either concordance or disagreement with the recommendation. Applying the S-O-R framework, concordance with an environmental stimulus guides the organism's generated behaviour. Therefore, it could be asserted that the concordance of a DA user with a DA tool's recommendation coordinates the user's next actions when receiving the recommendation.

According to Horne et al. (2008), concordance with a prescribed physician's recommendation is a patient's primary driver to follow the medical advice given. A DA tool's recommendation is very similar; in both cases the prescriber (either a physician or DA tool) suggests a series of actions to be followed by the person who receives the prescription. It is therefore expected that concordance of a DA user with a DA recommendation increases the user's intention to pursue the course of action prescribed. According to the TPB model, a behavioural response is determined by the intention to perform such an action (Azjen 1985). In this regard, TPB suggests that if individuals evaluate the proposed behaviour to be positive, their intention to carry out the recommended actions significantly increases. TPB also indicates that there is a significant positive correlation between an individual's intention to act and the completed action. Therefore, in the context of this study, it could be asserted that there is a higher chance of a DA user following the prescribed actions stated in a proposed DA recommendation when the user concurs with the proposed recommendation.

Hence, it is hypothesised that:

***H1: A higher level of concordance between a DA user and a DA tool's recommendation is positively associated with the DA user action upon the recommendation.***

### 3.3.2. Perceived DA Tool's Recommendation Actionability

Perceived Recommendation Actionability refers to the extent to which a DA user finds a DA tool's recommendation to be actionable considering the available resources, capabilities, and constraints (Shoemaker et al. 2014). Current literature argues that the attitudes of individuals towards the decision options available to them in a given situation are entirely triggered by their desires, beliefs, and values (Steele and Stefánsson 2015; Slovic et al. 1977). When making a decision, individuals form a preferential attitude towards a specific decision alternative to increase the coherence among their other attitudes (Steele and Stefánsson 2015). To keep this coherence, individuals will strive to ensure the decision they make is compatible with their constraints (Simon et al. 2001). In the context of this study, if DA users find the DA tool's recommendation does not contradict their constraints (i.e., is actionable), they will form a coherent positive attitude towards it. According to the TPB model, this judgment is similar to the behavioural beliefs that seem to affect a DA user's personal attitude. According to the S-O-R framework, there is a positive correlation between an organism's attitude and the behavioural responses it generates, especially when the new attitude is in line with the organism's current internal attitude.

Perceived recommendation actionability delineates control beliefs in the TPB model. A control belief is the perception of an IT system user (in the context of this study, a DA user) of the availability of the skills, resources, and opportunities required to conduct a behavioural response. There are two different types of control beliefs; (a) situational (e.g., having enough monetary resources); and (b) personal (e.g., having the ability to use the IT system) (Mathieson 1991). Based on the TPB model, prior to performing a behavioural response, IT system users evaluate whether they have access to both the required monetary resources (i.e., situational control beliefs) such as funds needed and non-monetary resources (i.e., personal control beliefs), such as required personnel. Before pursuing a set of actions prescribed in a DA tool's recommendation, DA users assess whether they access to those necessary resources and also whether prevailing organizational constraints are reflected in the proposed recommendation (Vancouver and Schmitt 1991). If the agent's recommendation is deemed to remain within the user's limitations, the DA user forms a preferential attitude towards it (Steele and Stefánsson 2015) and is more likely to act upon the proposed recommendation (Van Slyke 2007). In this study, if DA users find a DA tool's recommendation to be actionable (i.e., in line with their organizational constraints), they are more likely to act on the DA tool's recommendation.

Hence, it is hypothesised that:

***H2: Higher perceived DA recommendation actionability is positively associated with a DA user acting upon the recommendation.***

## 3.3.3. Perceived Risk of Action

Perceived risk of action refers to the risk associated with the implementation or execution of a recommended course of action (i.e., a DA tool's recommendation) (Lee et al. 2007).

There are different classifications of the risks associated with an action in the current literature. For instance, Bettmen (1973) classifies the perceived risk of action into five general categories, risks that are functional, physical, financial, social, and psychological. However, Roselius (1971) categorizes the risks associated with a course of action into losses related to time, hazards, ego, and money.

Studies have evaluated perceived risk of action based on two factors: (1) the perceived uncertainties associated with taking a recommended course of action and (2) the seriousness of the outcome expected as the result of the action (Lee et al. 2007; Garbarino and Strahilevitz 2004; Kaplan et al. 1974; Taylor 1974; Bettman 1973; Bauer and Cox 1967). Uncertainty refers to the potential threats when taking a recommended course of action may incur adverse consequences, whereas the seriousness of the outcome portrays the consequences that might arise from taking such an action.

Perceived risk of action is similar to behavioural belief in the TPB model and refers to how the IT system user (i.e., the DA user) perceives the subjective probability of a particular outcome if the behaviour is performed. Based on the extant literature, behavioural beliefs could have either a positive or a negative effect on how an IT system user follows the recommendations of an IT system. For instance, there is a lower chance of IT system users (i.e., DA users) following the recommendations of an IT System (i.e., a DA tool's recommendation) if they form a negative belief about the adverse outcomes of relying on the recommendation (Wang et al. 2016). These beliefs are to be considered the internal state of the IT system user (i.e., the DA user).

Applying to S-O-R, the main driver of DA users' behaviour of are their internal behavioural status. If DA users perceive an action outlined in a DA tools' recommendation to be risky, there is a higher chance that they will not follow it. Prior studies have confirmed this claim (Smith 2015; Berry and Ryan 2013; Rezakhani 2012; Taxman and Marlowe 2006). According to the extant literature, when risk is involved, individuals tend to either avoid the action or manage the risk associated with it, as opposed to taking action (Garbarino and Strahilevitz 2004).

Hence, it is hypothesised that:

***H3: Higher perceived risk of action on a DA tool's recommendation is negatively associated with a DA user acting upon the recommendation.***

## 3.3.4. Perceived Recommendation Quality

Perceived DA Recommendation Quality assesses the quality of a DA-generated recommendation from a DA user's perspective. This recommendation quality can be assessed through the lens of the SERVQUAL Framework (Parasuraman et al. 1988) where the quality of an IT system is evaluated based on qualities related to its physical environment, outcome, and interaction (Brady and Cronin 2001). Physical environment quality measures an IT system based on its design and ambient conditions. Outcome quality evaluates an IT system based on its merits in fulfilling a technical task. And finally, interaction quality determines an IT system user's expertise in performing a required service (Brady and Cronin 2001). Relying on the SERVQUAL framework, a DA tool's recommendation quality is a second order construct composed of data quality, DA tool quality, perceived DA recommendation understandability, and analyst competency. In this regard, data and DA tool quality reflect the physical environment quality. The perceived understandability of a DA recommendation indicates the outcome quality. And, analyst competency demonstrates the interaction quality.

Data quality refers to the quality of raw information stored in datasets (Detlor et al. 2013). This can be assessed based on different aspects of intrinsic data characteristics and contextual data characteristics (Wang et al. 1996). According to Tress (2017), inherent data characteristics are defined as the accuracy and objectivity of data, impartially reflecting the extent to which the data is correct. Contextual data characteristics indicate the degree to which data corresponds to the task at hand. Some of the dimensions of contextual data characteristics are "value-added, relevancy, timeliness, completeness, and the appropriate amount of data" (Tress 2017). Current literature argues that an IT system's service quality (in the context of this study, DA recommendation quality) will be affected by these aspects of data stored in a dataset (Lycett 2013). Therefore, it is expected that a higher perception of data quality increases the user's perception of the DA recommendation quality.

An IT system's functionality (i.e., a DA tool, in the context of this study) will be evaluated based on its practicality and aesthetics (Brady and Cronin 2001). Studies argue that a higher perception of an IT system's functionality and aesthetics increases the perception of the quality of its recommendations (Huang et al. 2012; Kim et al. 2010).

Therefore, it is expected that a higher perception of a DA tool's functionality (i.e., DA tool's quality) enhances the understandability of its recommendation quality.

Perceived DA recommendation understandability measures the comprehensiveness of the explanation facility in a DA tool's recommendation. DA recommendation understandability indicates the degree to which logical processes and the line of reasoning are outlined in a DA tool's recommendation (Wang and Benbasat 2009). Extant literature shows that the more comprehensively a recommendation is outlined and justified, the higher the chance an IT user will perceive the recommendation to be of high quality (Gediki et al. 2014; Aman and Liikkanen 2010; Wang and Benbasat 2007). Therefore, it is expected that a higher perception of the understandability of a DA tool's recommendation increases the perception of its quality.

And finally, analyst competency refers to the perception of a set of competencies, abilities, and skills of the person who is working on a DA tool to prepare a DA recommendation (Ghasemaghaei et al. 2016; Draganidis and Mentzas 2006). Like any other IT system, a DA tool requires a technical expert to generate valuable insights (Ghasemaghaei et al. 2016). This person could be different potentially from the DA user who is receiving the DA recommendation. Having the appropriate level of expertise or confidence in an analyst's skill increases the DA user's ultimate perception of the recommendation (Wong 2012). All these positive perceptions enhance the understanding of the DA tool's recommendation's quality.

According to the TPB Model, perceived outcome evaluation is one of the variables that determines the attitude towards a behaviour (i.e., a DA user's concordance with a DA tool's recommendation). Outcome evaluation reflects an IT user's (i.e., a DA user's) assessment of the desirability of the outcome (Mathieson 1991). According to Sadeghi and Farokhian (2011), perceived service quality (i.e., perceived recommendation quality in this case) is the most prominent determinant of an IT user's assessment of outcome. Therefore, it is expected that the perceived DA tool's recommendation quality is the most critical factor in determining a DA user's attitude towards that recommendation.

By applying to the S-O-R framework, external stimulus affects and changes the internal state of an organism. According to Mehrabian and Russell (1974), the extent of change is dependent on the individual's current state. If individuals find the attitude change to be positive, they will be less resistance towards accepting the new behaviour. In the context of this study, a DA tool's recommendation is perceived to be an external stimulus. There is therefore a higher chance of concordance with such a stimulus if the DA user perceives the DA tool's recommendation to be of high quality.

Hence, it is hypothesised that:

***H4: A higher level of perceived DA recommendation quality is positively associated with the concordance between a DA user and the DA tool's recommendation.***

### 3.3.5. Organizational Concordance

Organizational concordance refers to the extent to which DA users perceive that their organization agrees with a DA tool's recommendation. This perception is generated by assessing their organization's legal, moral, and financial support that is provided for a DA tool's recommendation (Eisenberger et al. 1986).

Organizational support is part of the normative beliefs in the TPB model. Normative belief reflects the perception of the IT system user (i.e., a DA user), the perception of the referent (i.e., the organization), and perception of the potential performance of the desired behaviour (i.e., a DA tool's recommendation). Generally, firms are looking to enhance their performance (Hughes and Morgan 2007; Howes et al. 2000) and are therefore, more willing to support activities that help them achieve this goal (Howes et al. 2000; Eisenberger et al. 1986). In this regard, it could be asserted that if a DA tool's recommendation is perceived to be of high quality, it is more likely that DA users perceive that their organization concurs with the DA tool's recommendation.

Hence, it is hypothesised that:

***H5: A higher level of DA recommendation quality is positively associated with the concordance between a DA user's organization and a DA tool's recommendations.***

The current literature argues that there is a positive correlation between the positive perception of employees of the organizational support and concordance with a recommendation (i.e., a DA tool's recommendation) and the reciprocal contributions of employees in the form of compliance behaviour with such a recommendation (Bell and Menguc 2002; Mooran et al. 1998; Shore and Wayne 1993; Wayne et al. 1997). For instance, Beidas et al. (2018) have shown that organizational concordance is the primary determinant of behavioural health service delivery among physicians in a hospital.

According to social exchange theory, an employee's opinions about her/his organization are formed by the reciprocal relationship between the employee and the organization (Eisenberger et al. 1997). The norm of reciprocity requires the employee to respond positively to the desires of the employer. Therefore, employees tend to respect their Organizational desires and needs when taking actions (Eisenberger et al. 1997; Rousseau 1990).

The above assertion is in line with the theoretical perspective of this study. According to the TPB model, organizational concordance corresponds to normative beliefs, whereas personal concordance corresponds to attitude – which in turn is expected to affect the intention to perform a behaviour. As stated in the TPB model, normative belief is one of the main determinants of the intention to act. Therefore, it is expected that if DA users perceive that their organization concurs with the actions prescribed in a DA tool's recommendation, they will become more willing to concur with such a recommendation.

Hence, it is hypothesised that:

***H6: A higher level of perceived organizational concordance with a DA tool's recommendation is positively associated with a DA user's concordance with the recommendation.***

The perception of organizational concordance correlates to the normative beliefs in the TPB model. Normative beliefs reflect the IT system user's (i.e., a DA user's) perception of a referent's perception of the potential performance of the desired behaviour. This perception is affected by the user's perception of having access to sufficient financial and personnel resources to execute a DA tool's recommendation; this is perceived DA tool's recommendation actionability.

The current literature argues that organizational concordance and support are among the most critical factors predicting the success of an IT project (Pinto and Selvin 1987). Indeed, current literature perceives organizational concordance as the continued commitment of an organization towards the implementation and execution of an IT system's recommendation (Asnawi et al. 2014). Continued commitment includes the allocation of adequate financial and nonfinancial resources, such as personnel, time, and sufficient managerial support, for the implementation and execution of the course of action indicated in an IT recommendation (i.e., a DA tool's recommendation) (Abdel Aziz and Rizkallah 2015). The consistency theory (Lecky 1961) suggests that people tend towards consistent behaviours over time. Therefore, it is expected that if an organization is in concordance with a DA tool's recommendation, it will provide sufficient financial and nonfinancial resources needed for the implementation and execution of the recommendation.

Hence, it is hypothesised that:

***H7: A higher level of organizational concordance with a DA tool's recommendation is positively associated with the perceived recommendation actionability of such a DA tool's recommendation.***

Employees are supposed to follow their organization's overall strategies and guidelines (Beer and Eisenstat 2000). One of the major guidelines that may or may not be officially stated is failure tolerance (Abdel Aziz and Rizkallah 2015). This refers to informing employees (i.e., DA users) that, although the organization is looking for success, it is committed to accepting potential failures, tolerating potential losses and remaining open to failing to benefit from opportunities (Baumgartner 2010; Coffman 2006). Current literature argues that employees of organizations with higher failure-tolerance are more willing to take risky actions (Clifford 1991; Clifford 198). Like any proposed recommendation (Irikura et al. 2005), that proposed by a DA tool is associated with a set of uncertainties. Organizational concordance with such a recommendation signals to DA users that the organization acknowledges such associated uncertainties (Boland and Lehmann 2010). If DA users finds that their organization is in accordance with a DA tool's recommendation and are willing to take on risk – rather than impose them on the DA user – they will feel more secure in acting on that recommendation. Therefore, It is expected that the organizational concordance with a DA tool's recommendation would lessen the perceived risk of action on a DA tool's recommendation.

Hence, it is hypothesised that:

***H8: A higher level of perceived organizational concordance with a DA tool's recommendation is negatively associated with the perceived risk of action on such a DA tool's recommendation.***

## 3.3.6. Evidence-Based Organizational Culture

Evidence-based organizational culture refers to a working environment that encourages its personnel to follow a systematic approach in making informed decisions based on available evidence (Pfeffer and Sutton 2006). An evidence-based culture creates an environment in which the person making decisions becomes more vigilant in sensing the changes in environmental cues and evidence while becoming less affected by misrepresented evidence (Potworowski and Green 2012). Organizational cultures that favour evidence-based decision-making are more likely to facilitate the conditions required for the implementation and execution of evidence-based decisions (Bernal et al. 2009; Schneider et al. 1998). In line with the current theoretical perspective of this study and applying the S-O-R framework, this kind of organizational culture is a stimulus that facilitates the required conditions for acting on a DA tool's recommendation. Therefore, an organization with an evidence-based culture would be more willing to prepare the necessary resources for its employees to act on the DA tool's recommendations.

Hence, it is hypothesised that:

***H9: An evidence-based organizational culture is positively associated with the perceived recommendation actionability of a DA tool's recommendation.***

# Chapter 4: Research Methodology

Before any data collection occurred, an ethics protocol for data collection was approved by the ethics research board at McMaster University.

The hypotheses proposed in this study were tested using a cross-sectional survey and the survey instrument tested before the actual data collection with a pilot study involving 50 participants.

Once the pilot survey process was complete, before participating in this study, participants were asked to declare whether they were using any types of DA tools in their organizations. They were then asked to reflect back on a recent decision they had to make at work for which they used a DA tool or asked someone else to complete such an analysis for them. Subsequently, they were invited to complete a survey that measured the constructs in the proposed research model, which included responding to a question on whether they acted on the DA recommendation they had received.

## 4.1. Measures

To ensure content validity, all measurement scales were selected from the existing literature, although the scales were slightly adapted to reflect the context of this study. Details of all these are included in Appendix A and described briefly below:

- The measure of acting upon a DA recommendation was made using a 5-item reflective scale, adapted from McKnight et al. (2002, where the items achieved a

Cronbach's Alpha (α) reliability score of 0.92. The items were slightly modified to reflect the context of this study.

- Perceived Individual Concordance was measured using a 3-item reflective scale adapted from Coote et al. (2004). In that paper, the items achieved a Cronbach's Alpha (α) reliability score of 0.82. The items were again slightly modified to reflect the context of this study.
- Perceived Organizational Concordance was measured using a 3-item reflective scale, adapted from Coote et al. (2004). In that paper, the items achieved a Cronbach's Alpha (α) reliability score of 0.82. The items were slightly modified to reflect the context of this study.
- Perceived Actionability was measured using a 3-item formative scale, adapted from Shoemaker et al. (2014). The items were also slightly modified to reflect the context of this study.
- Perceived Personal Risk of Action was measured using a 5-item formative scale adapted from Corbitt et al. (2003). The items were slightly modified to reflect the context of this study.
- Perceived Evidence-Based Organizational Culture was measured using a 5-item formative scale adapted from Cao et al. (2015). The items were slightly modified to reflect the context of this study.

Relying on the SERVQUAL framework (Parasuraman et al. 1988), DA recommendation quality was modeled as a second-order formative construct, formed by the following first-order constructs: Perceived Intrinsic Data Quality, Perceived Contextual Data Quality, Perceived DA Tool Quality, Perceived DA Recommendation Understandability, and Perceived Data Analyst Competency. In this regard, the following measurement scales were used, selected from the extant literature.

- Perceived Intrinsic Data Quality was measured using a 4-item formative scale adapted from Wang and Strong (1996). The items were slightly modified to reflect the context of this study.
- Perceived Contextual Data Quality was measured using a 5-item formative scale adapted from Wang and Strong (1996). The items were slightly modified to reflect the context of this study.
- Perceived DA Tool Quality was measured using a 5-item formative scale adapted from Nilashi et al. (2016). The items were slightly modified to reflect the context of this study.
- Perceived DA Recommendation Understandability was measured using a 3-item reflective scale adapted from Ye and Johnson (1995). In that paper, the items achieved a Cronbach's Alpha (α) reliability score of 0.86. The items were slightly modified to reflect the context of this study.
- Perceived Data Analyst Competency was measured using a 4-item reflective scale adapted from McKnight et al. (2002). In that paper, the items achieved a Cronbach's Alpha (α) reliability score of 0.96. The items were slightly modified to reflect the context of this study.

## 4.2. Other Questions Included in the Study

The survey used in this study included five open-ended questions to gain deeper insights into participants' perceptions regarding the constructs employed in the research model that affected the DA user's action on a DA tool's recommendation. The purpose of these open-ended questions was to allow a deeper understanding of the experiences of DA users and why they did or did not end up acting on the DA recommendations they generated or received. These questions were as follows:

- In your opinion, what are the most critical factors affecting the quality of data used by DA tools to make their recommendations?
- In your opinion, what are the characteristics of a DA tool's recommendation that are necessary for you to deem it as a high-quality recommendation?
- In your opinion, what are the most important factors necessary for you to act upon a DA tool's recommendation?
- In your opinion, does your organization have an evidence-based culture? Please explain why or why not?
- In your opinion, does your risk tolerance affect your decision to act upon a DA tool's recommendation? Please explain why or why not?

The survey also included questions related to five control variables to explore the potential impacts on the proposed relations in the research model. These variables included familiarity with using DA tools, education, gender, age, industry, and the size of the organization they worked for.

The first control variable considered for this study was familiarity with using DA tools. According to the Current IS literature, participants' familiarity with using an IT system could impact the perception regarding the usefulness of the IT system (Arnold et al. 2006; Wang and Benbasat 2009). Current studies indicate that education is positively related to using IT technologies (Igbaria and Parasuraman 1989; Harrison and Rainer Jr 1992; Nadkarni and Gupta 2007). Therefore, education was included as one of the control variables in this study. Kim and Son (2009) also suggest that gender and age are among essential control variables in using an IT system, and these were added to the survey. Additionally, Fauzi (2009) indicates that industry details should also be considered when participants are asked to portray their perceptions in using an IT system. Finally, Zhao and Balagué (2015) found that organizational size also affects an IT user's reliance on IT recommendations. Therefore, this study also controlled industry and organizational size.

## 4.3. Participants and Sample Size

The participants of this study were recruited through a market research firm, and were middle managers who recently received a DA recommendation. This sampling choice was made because the context of this study is to understand the conditions under which a DA user concurs with and acts on a DA tool's recommendation. An invitation letter to participate was sent by the market research firm via email. In return for taking part, participants received a point-based incentive (redeemable for various prizes) for their assistance in the study.

A series of recommendations from the extant literature was consulted to determine the required number of participants. Based on the Gefen et al. (2000) recommendations, the minimum sample size to use the Partial Least Square (PLS-SEM) technique is 10 times the number of items used to measure the construct, with the highest number of items in the research model or the highest number of paths going into a construct. In the proposed model, the highest number of items among all the scales was five, thus, the required sample size was 50 participants. However, based on recommendations from Roldán and Sánchez-Franco (2012), 110 participants are required for sufficient statistical power of 0.80 to detect a medium effect size (f= .25). As a final point, to control the potential outliers and spoiled surveys, 300 samples were targeted, and ultimately, 299 samples were collected.

## 4.4. Pilot Study

Prior to the actual data collection, a pilot study was conducted to examine the clarity of the instructions and questionnaire. The pilot study included 50 participants, middle managers, who were also recruited by the market research firm. Participants were asked to reflect back on a recent decision they have had to make at work for which they used a DA tool or asked someone else to complete such an analysis for them. They were first asked to respond to the measurement scale questions. Participants were then asked to provide their comments on the open-ended questions. The pilot study did not result in any changes in the measurement instrument. Therefore, they were included in the final dataset. It is noteworthy that the McMaster Research Ethics Board's approval was secured before any data collection.

## 4.5. Data Collection Procedure

Participants progressed through the data collection as follows:

1. Participants were first asked to read the consent letter (Appendix B) and agree to participate in the study.
2. Next, participants were asked to declare whether they are using any types of DA tools in their organizations, as illustrated in Figure 4.1.

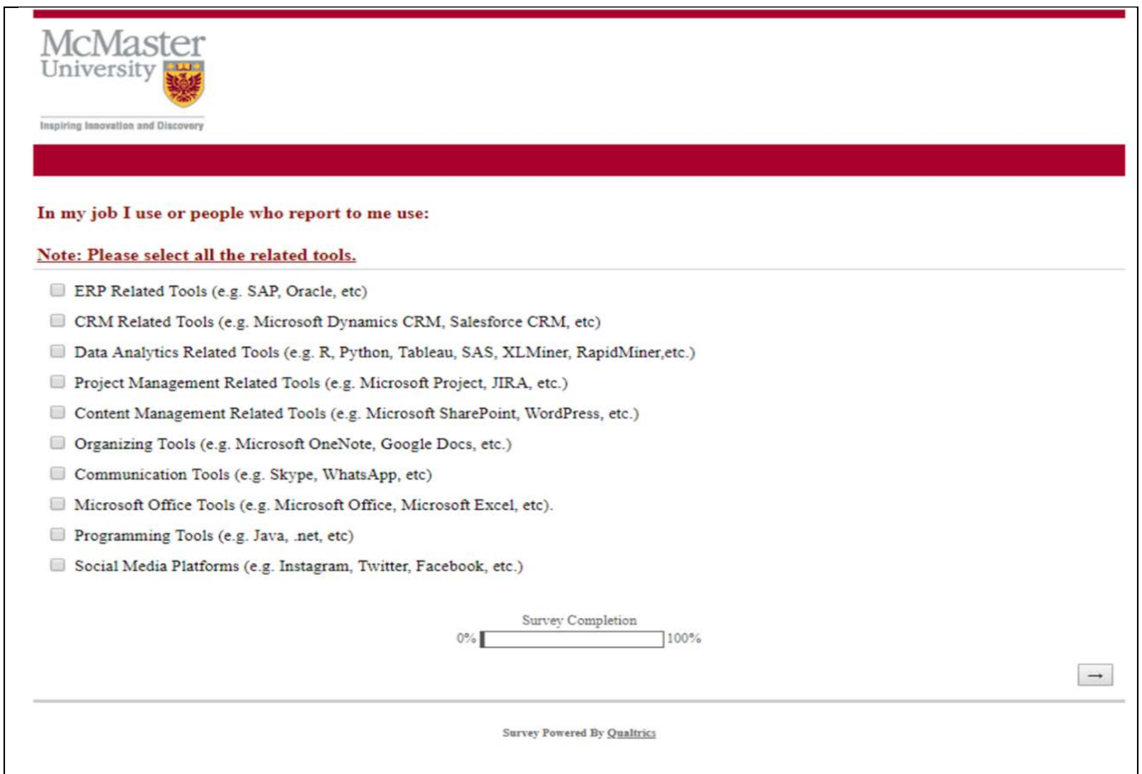


**Figure 4.1. Filtering Question**

3. If they were not using any DA tools, they were not eligible for the study and were thanked for their time. Figure 4.2 illustrates the message.

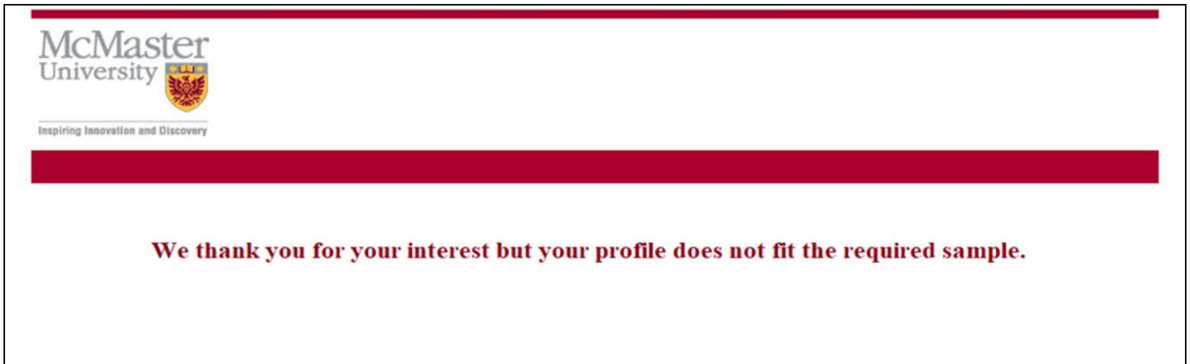


**Figure 4.2. Filtering Out Message**

4. In the next step, as shown in Figure 4.3, the participants were asked to reflect back on a recent decision they had to make at work for which they used a DA tool or asked someone else to complete such an analysis for them.

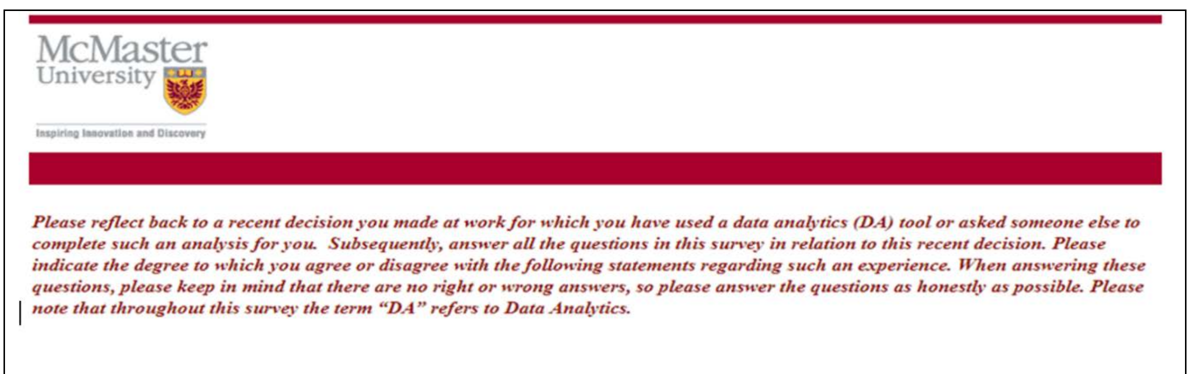


**Figure 4.3. Participation Announcement**

5. Participants were asked to fill out a questionnaire that included the measures of all the constructs in the research model as well as the control variables and open-ended questions.
6. Finally, participants were debriefed (Appendix D) and thanked for their participation.

## 4.6. Model Validation

To answer the main research questions, and to validate the research model, structural equation modeling (SEM) was employed. SEM is a form of causal modeling techniques to impute and validate the proposed relationships in a research model (Hancock 2003) by combining a measurement model (i.e., confirmatory factor analysis) and a structural model (i.e., relationships between constructs of interest) (Meyers et al. 2006). As the proposed research is exploratory in nature, the Partial Least Square (PLS-SEM) technique was more suited over other SEM techniques (Chin et al. 2003; Gefen et al. 2000). Another reason to support the choice of PLS-SEM was that this technique does not make any distributional assumptions regarding the data (Chin et al. 2003; Venkatesh and Agarwal 2006). To that end, SamrtPLS 3.0 was used for the two main purposes of data analysis and model validation. The evaluation of the research model followed a two-step process: (1) measurement model; and (2) the structural model.

Below is a summary of the analyses performed. The measurement model was evaluated by assessing the reliability and validity of the measures used to represent the model's constructs (Chin 2010). As the proposed research model contains reflective, formative, and second-order formative constructs, various steps were conducted to evaluate the measurement model. Table 4.1 illustrates the tests performed to assess the reflective constructs in the proposed research Model.

**Table 4.1. Summary of Test- Measurement Model**

| Analysis | Test | Note |
|---|---|---|
| Reliability of Measurement Instruments | Cronbach's alpha | Acceptance criterion: Value > 0.70 (Nunnally and Bernstein 1994) |
| | Composite reliability | Acceptance criterion: Value > 0.60 (Bagozzi and Yi 1988) |
| Convergent and Discriminant Validity | Item cross-loading | Acceptance criterion: The loading on the corresponding construct (i.e., theoretical construct) should be larger than loading on other constructs by at least 0.10 (Chin 2010; Gefen and Straub 2005) |
| | Fornell-Larcker Criterion | Acceptance criterion: The square root of the Average Variance Extracted (AVE) of a construct must be larger than the correlation between that construct and any other construct in the model (Barclay et al. 1995) |
| Multicollinearity | Bivariate Correlations | Acceptance criteria:<br>- Bivariate correlations greater than 0.8 can indicate traces of multicollinearity (Meyers et al. 2006) |
| | VIF | - Variance Inflation Factors (VIFs) greater than 3.3 may indicate potential multicollinearity issues (Petter et al. 2007) |

To test the formative constructs in the measurement model, the steps suggested by Hair et al. (2011) were followed. According to Hair et al. (2011), using the bootstrapping technique (i.e., with the minimum bootstrap sample of 5000), each indicator's weight (i.e., relative importance) and loading (i.e., absolute importance) should be assessed for its significance. It is worth noting that the number of cases should be equal to the total number of cases in the original sample. The next step was to check the significance of the indicators. In this regard, as suggested by Hair et al. (2011), the critical t-values for a two-tailed test are as follows:

- 1.65 (significance level = 10 %)
- 1.96 (significance level = 5 %)
- and 2.58 (significance level = 1 %)

If the indicator weight is significant, it could be asserted that there is sufficient empirical support to keep it in. However, if both the weight and loadings were not significant, unless there was theoretical support for keeping the indicator, it should be removed. Moreover, for formative constructs, multicollinearity tests are similar to those in reflective constructs (Hair et al. 2011).

The next step in validating the formative constructs was to examine to what extent the formative measurements were correlated. In this regard, the Variance Inflation Factor (VIF) statistic was used (Petter et al. 2007).

Finally, to evaluate the measurement properties of the second-order formative construct (i.e., DA tool's recommendation quality), a two-step analysis was conducted (Bagozzi and Fornell 1982). The first step was similar to the one used to validate the first-order formative constructs. Each first-order construct shaping the second-order formative construct was assessed by its weights and loading to ensure its significance. And the second step was to calculate a weighted sum of the first-order indicators. This indicator was calculated by multiplying items values by PLS weights for each first-order indicator. Finally, a composite index on the weighted sum of the first-order indicators was created for the second-order construct (Diamantopoulos and Winklhofer 2001). In the end, the VIF statistics was used to test the extent to which the formative constructs were correlated (Petter et al. 2007).

After examining the appropriateness of the measurement model, the structural model was evaluated to determine whether the proposed research model is supported by the data collected (Chin 2010). Table 4.2 provides a summary of the analyses performed.

**Table 4.2. Summary of Test- Structural Model**

| Analysis | Calculation | Note |
|---|---|---|
| Path Coefficients Significance | Obtained from SmartPLS | A bootstrap approach was employed to evaluate the significance of path coefficients (Chin 1998) |
| R2 for Endogenous | Obtained from SmartPLS | Although no specific acceptable threshold value has been set for R2, a large enough R2 values to achieve |

| | | |
|---|---|---|
| Variables | | Adequate explanatory power is sought-after (Gefen et al. 2000; Urbach and Ahlemann 2010) |
| Effect Sizes | Obtained from SmartPLS | The magnitude of the effect sizes of each path was evaluated following these values:<br><br>$f2$ small (.02), $f2$ medium (.15), and $f2$ large (.35) (Chin 2010) |
| Goodness of Fit (GoF) index | $GOF = \sqrt{\overline{Communality} \times \overline{R^2}}$ | Absolute GoF can be used to assess the PLS model regarding overall (both measurement and structural levels) prediction performance<br><br>The suggested baseline values of $GoF_{small}$ (.10), $GoF_{medium}$ (.25), and $GoF_{large}$ (.36) were used to evaluate the fit of the model (Tenenhaus et al. 2005; Wetzels et al. 2009) |

Follwing this, a series of additional post-hoc analyses were conducted to evaluate the effects of control variables that were used in the study (i.e., familiarity with using DA tools, education, gender, age, industry, and organizational size).

The next chapter includes details regarding the data analyses performed in this dissertation as well as the results obtained.

# Chapter 5: Data Analysis and Results

The previous chapter provided a summary of the procedures and methods used to collect and analyse the data in this study. This chapter outlines the employed procedures and results in detail. Section 5.1 describes the preliminary data analysis. Section 5.2 discusses the validation of the measurement model. This chapter ends with Section 5.3 which describes the structural model analyses.

## 5.1. Preliminary Data Analysis

To examine the correctness of the data to be used in this study, a series of preliminary data analyses were conducted, with the valid responses examined first, the outliers and missing values were next. Finally, the demographics and backgrounds of the participants were checked.

### 5.1.1. Data Screening

To sort out the valid responses, two-step screening method was employed. In the first step, a "quality control" question was included at the end of the survey (see Appendix A). Participants were asked to select a specific response which indicated to what extent they had paid attention to the questions in the survey. The responses of those participants who did not choose the proper answer were removed from the acceptable response dataset. Responses were also screened based on the time participants spent filling out the survey, and the responses of those participants who spent less than five minutes were discarded.

As a result, and by employing the above data screening procedures, 24 responses (i.e., 22 in the first step and 2 in the second step) were excluded from the dataset of this study.

### 5.1.2. Outliers and Missing Values

According to Myers et al. (2006), outliers are those "cases with extreme or unusual values on a single variable (univariate) or a combination of variables (multivariate)." To calculate them, composite scores were first calculated for each construct in the proposed research model. Then box plots were used to identify the outliers and as a result, 35 were identified. As suggested by Myers et al. (2006), outliers should be removed from the research pool if the researcher cannot justify them. Therefore, these outliers were removed from the dataset. Table 5.1 represents the summary of the detected univariate outliers. Separate box plots for the individual constructs are available in Appendix E.

**Table 5.1. Univariate Outliers**

| Construct | Outlier Case ID | Number of Outliers | Number of New Outliers |
|---|---|---|---|
| Action on a DA Tool's Recommendation | 44,45,74,75,137, 233,243, 264,270 | 9 | 9 |
| Personal Concordance | 68,84,131,188,258, 74,233,270 | 8 | 5 |
| Actionability | 19, 68,74,137,233,270 | 6 | 1 |
| Perceived Risk of Action | None | 0 | 0 |
| Organizational Concordance | 65,66,70,113,192, 68,74,75,188,233,270 | 11 | 5 |
| Evidence-Based Organizational Culture | 80,110,141,144,170,262, 74,233 | 8 | 6 |
| Recommendation Quality | 68,74,233,270 | 4 | 0 |
| Recommendation Understandability | 77,106,253, 19,68,74,233,264,270 | 9 | 3 |
| Inherent Data Quality | 127, 74,233,258,262 | 5 | 1 |
| Contextual Data Quality | 58,81, 68,74,233,258,270 | 7 | 2 |
| DA Tool Quality | 124,198, 74,233,262 | 5 | 2 |
| Data Analyst Competency | 71, 58,68,74,80,233 | 6 | 1 |
| | | **Total** | **35** |

*Numbers indicate the responses.*
*Gray numbers are instances which have already been excluded.*

To check the multivariate outliers, a Mahalanobis distance analysis was employed. Mahalanobis distance refers to “the multivariate ‘distance’ between each case and the group multivariate mean (known as the centroid)” (Meyers et al. 2006). According to Meyers et al. (2006), Mahalanobis distance assesses each case with the chi-square distribution (alpha level = 0.001). If a case reaches this threshold, it should be considered a multivariate outlier. As a result of this assessment, five new multivariate outliers were identified and removed from the dataset. Therefore, 235 usable cases remained in the acceptable responses’ dataset. For the final step in the data screening process, the missing values in the dataset were tracked down. The assessment showed there were no missing values in the final acceptable responses’ dataset.

### 5.1.3. Demographics

Besides the questions related to the constructs in the proposed research model, the questionnaire used in this study also included a series of demographic related questions. The results showed that out of 235 participants, 80 (34%) were female, and 155 (66%) participants were male. Also, the results revealed that the age of most of the participants ranged from 31-50. Table 5.2 illustrates the specific age distribution.

| Table 5.2. Distribution of Participants by Age | | |
|---|---|---|
| **Age Group** | **Frequency** | **Percentage** |
| 21-30 | 22 | 9.3% |
| 31-40 | 85 | 36.1% |
| 41-50 | 59 | 25% |
| 51-60 | 49 | 20.7% |
| Larger than or equal to 61 | 21 | 8.9% |

Participants were asked questions regarding the control variables of this study (i.e., education, organizational size, the extent of DA use, and familiarity with DA tools). The results of the responses are discussed below.

As shown in Table 5.3, the majority of the participants (i.e., 93.2 %) in this study were university degree holders. To be more precise, 44.3% of the participants held a bachelor's degree, 40% held a master's degree, and almost 9% of the participants had a Ph.D.

| Table 5.3. Distribution of Participants by Education | | |
|---|---|---|
| **Category of Education** | **Frequency** | **Percentage** |
| High School | 6 | 2.5% |
| College Diploma | 10 | 4.3% |
| Bachelor's Degree | 104 | 44.3% |
| Master's Degree | 94 | 40% |
| PhD | 21 | 8.9% |

The results were exciting in regards to the organizational size of the participants of this study. Data Analytics tools are expensive (Pickup 2015); it is therefore expected that, as opposed to SMEs (i.e., Small and Medium Size Enterprises), large firms invest more in implementing DA tools. The results showed that the majority of participants (i.e., 53.6%) in this study were working in organizations with more than 1000 employees. Table 5.4 illustrates the distribution of the participants of this study by organizational size in more detail.

| Table 5.4. Distribution of Participants by Organisational Size | | |
|---|---|---|
| **Number of Employees** | **Frequency** | **Percentage** |
| Lower than 100 | 25 | 10.7% |
| 101-500 | 44 | 18.7% |
| 501-1000 | 40 | 17% |
| 1001-5000 | 52 | 22.1% |
| More than 5000 | 74 | 31.5% |

As expected and controlled for, the majority of the participants in this study used DA tools often or almost always (i.e., 86%). Table 5.5 summarizes the results.

| Table 5.5. The Extent of DA Use | | |
|---|---|---|
| **Frequency of DA Use** | **Frequency** | **Percentage** |
| Almost Always | 87 | 37% |
| Often | 115 | 49% |
| Sometimes | 32 | 13.6% |
| Not Much | 1 | 0.4% |
| Not At All | 0 | 0% |

Finally, as shown in Table 5.6, a good majority of the participants (i.e., 66%) in this study were extremely familiar or very familiar with DA tools.

**Table 5.6. Familiarity with DA Tools**

| The Extent of Familiarity | Frequency | Percentage |
|---|---|---|
| Extremely Familiar | 69 | 29.4% |
| Very Familiar | 86 | 36.6% |
| Moderately Familiar | 73 | 31% |
| Slightly Familiar | 7 | 3% |
| Not Familiar | 0 | 0% |

## 5.2. Measurement Model

Before validating the research model, the measurement model should be verified. In this regard, construct reliability and validity should be evaluated for each construct in the proposed research model. There were three different types of constructs in this study: reflective, formative, and second-order formative construct, with reliability and validity tests varying by construct type. This section provides detailed reliability and validity analyses for the different kinds of construct this study employed.

## 5.2.1. Reflective Constructs

This section provides a detailed description of a set of techniques employed to validate the measurement model of the reflective constructs in the proposed research model.

### 5.2.1.1. Reliability Analysis

Reliability refers to the extent to which the items in the measurement scale are consistent in measuring the variable (e.g., acting on a DA tool's recommendation). (Pedhazur and Schmelkin 1991; Straub et al. 2004). Current literature suggests two different techniques to test the reliability of a measurement scale: Cronbach's alpha (Cronbach 1951) and composite reliability. Both Cronbach's alpha and composite reliability measure the internal consistency among the items of a measurement scale (Raykov 1997). According to the current literature, the minimum accepted range for Cronbach's alpha is $\alpha$ greater than 0.7 (Kline 2000; Nunnally 1978). Also, composite reliability higher than 0.6 is acceptable (Bagozzi and Yi 1988). As such, the statistical analysis software SPSS 22 was employed to calculate Cronbach's alpha.

The software SmartPLS 3.0 measures the composite reliability of the measurement scales of the reflective constructs in this study's proposed research model. As shown in Table 5.7, the measurement scales in this study are reliable as they meet the above criteria.

| Table 5.7. Reliability Statistics | | |
|---|---|---|
| **Construct** | **Cronbach's alpha** | **Composite Reliability** |
| Acting on a DA tool's recommendation | 0.936 | 0.952 |
| Personal Concordance | 0.857 | 0.913 |
| Organizational Concordance | 0.877 | 0.924 |
| Recommendation Understandability | 0.878 | 0.925 |
| Analyst Competency | 0.891 | 0.925 |

#### 5.2.1.2. Validity Analysis

Construct validity ensures that measurement items of a construct are closely correlated (i.e., convergent validity). It also distinguishes among constructs in the proposed research model (i.e., discriminant validity) (Pedhazur and Schmelkin 1991; Straub et al. 2004). Generally, convergent and discriminant validity is used to determine if the measurement items load on their latent construct more than any other related construct in the proposed research model (Gefen and Straub 2005). Two different techniques are used to measure the different types of construct validity: cross-loading analysis and Fornell-Larcker analysis (Fornell and Larcker 1981; Urbach and Ahlemann 2010).

Cross-loading analysis ensures that the loading of the items of a construct is greater by at least 0.1 than any other constructs (Chin 1998; Gefen and Straub 2005; Urbach and Ahlemann 2010). In this study, to calculate the cross-loadings of the items of the reflective constructs in the proposed research model, SmartPLS 3.0 was employed. Table 5.8 represents the result.

**Table 5.8. Items Loadings and Cross-loadings of Measures**

| Construct | Item | Acting | Per. Con. | Org. Con. | Understand. | Analyst Com. |
|---|---|---|---|---|---|---|
| Acting on a DA Tool's Recommendation | act1 | **0.819** | 0.529 | 0.557 | 0.581 | 0.421 |
| | act2 | **0.919** | 0.52 | 0.532 | 0.657 | 0.383 |
| | act3 | **0.917** | 0.51 | 0.465 | 0.658 | 0.364 |
| | act4 | **0.911** | 0.51 | 0.471 | 0.648 | 0.393 |
| | act5 | **0.899** | 0.534 | 0.504 | 0.653 | 0.341 |
| Personal Concordance | conp1 | 0.53 | **0.873** | 0.741 | 0.604 | 0.506 |
| | conp2 | 0.501 | **0.876** | 0.718 | 0.531 | 0.48 |
| | conp3 | 0.509 | **0.897** | 0.743 | 0.526 | 0.513 |
| Organizational Concordance | cono1 | 0.536 | 0.716 | **0.883** | 0.573 | 0.484 |
| | cono2 | 0.458 | 0.77 | **0.909** | 0.553 | 0.534 |
| | cono3 | 0.528 | 0.751 | **0.897** | 0.55 | 0.57 |
| Recommendation | und1 | 0.644 | 0.563 | 0.561 | **0.924** | 0.489 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Understandability | und2 | 0.677 | 0.55 | 0.561 | **0.898** | 0.429 |
| | und3 | 0.606 | 0.577 | 0.555 | **0.867** | 0.455 |
| Analyst Competency | anc1 | 0.356 | 0.476 | 0.517 | 0.416 | **0.837** |
| | anc2 | 0.452 | 0.525 | 0.561 | 0.544 | **0.882** |
| | anc3 | 0.331 | 0.469 | 0.481 | 0.396 | **0.876** |
| | anc4 | 0.33 | 0.496 | 0.493 | 0.41 | **0.878** |

As shown in Table 5.8, all the items had more substantial loadings on their pertinent construct compared to their loadings on the other constructs at least by a difference of 0.13 which satisfies the requirement of magnitude difference of 0.1. All the constructs had higher loadings with their related items than the other items. The results confirm adequate construct validity (Hair et al. 2010; Meyers et al. 2006; Straub et al. 2004).

The Fornell-Larcker criterion (Fornell and Larcker 1981) was employed for the second analysis. This criterion checks whether a construct shares more variance with its measurement items than with any other construct. In this regard, the Average Variance Extracted (AVE) of each construct should be higher than the factor's largest correlation with any other factor (Gefen and Straub 2005; Lehmann 1988; Urbach and Ahlemann 2010). In this study, SmartPLS 3.0 was used to compute the AVEs and correlations for the four factors. As shown in Table 5.9, the results confirmed the adequate construct validity for all the constructs.

| Table 5.9. Factors' Correlations and Square Roots of AVE for Discriminant Validity | | | | | |
|---|---|---|---|---|---|
| | **Acting** | **Per. Con.** | **Org. Con.** | **Understand.** | **Analyst Comp.** |
| Acting | **0.893** | | | | |
| Personal Concordance | 0.582 | **0.882** | | | |
| Organizational Concordance | 0.566 | 0.832 | **0.896** | | |
| Recom. Understandability | 0.716 | 0.628 | 0.623 | **0.897** | |
| Analyst Competency | 0.425 | 0.567 | 0.592 | 0.511 | **0.868** |

## 5.2.2. Formative Constructs

As stated in Chapter 4, each indicator's weight (i.e., relative importance) and loading (i.e., absolute importance) should be assessed for its significance using the bootstrapping technique (i.e., with the minimum bootstrap sample of 5000) to test the measurement model for formative constructs. The indicators that were not significant were dropped. Table 5.10 represents the results.

**Table 5.10. Outer Weights and T-Values on Formative Constructs**

| Construct | Item | Weight | T-Value | Keep |
|---|---|---|---|---|
| **Recommendation Actionability** | Actab1 | 0.568 | 8.547 | Yes |
| | Actab2 | 0.312 | 3.3561 | Yes |
| | Actab3 | 0.250 | 2.902 | Yes |
| **Perceived Risk of Action** | PRA1 | 0.747 | 1.659 | Yes |
| | PRA2 | 1.016 | 2.287 | Yes |
| | **PRA3** | **0.027** | **0.092** | **No** |
| | **PRA4** | **-0.085** | **0.225** | **No** |
| | PRA5 | -1.242 | 2.716 | Yes |
| **Perceived Tool Quality** | TQ1 | 0.266 | 4.960 | Yes |
| | TQ2 | 0.143 | 2.233 | Yes |
| | TQ3 | 0.135 | 2.257 | Yes |
| | TQ4 | 0.181 | 4.109 | Yes |
| | TQ5 | 0.173 | 3.341 | Yes |
| | TQ6 | 0.124 | 2.219 | Yes |
| | TQ7 | 0.224 | 3.3796 | Yes |
| **Inherent Data Quality** | IDQ1 | 0.426 | 8.761 | Yes |
| | IDQ2 | 0.266 | 4.973 | Yes |
| | IDQ3 | 0.167 | 2.997 | Yes |
| | IDQ4 | 0347 | 5.328 | Yes |

| | | | | |
|---|---|---|---|---|
| **Contextual Data Quality** | CQ1 | 0.392 | 6.394 | Yes |
| | CDQ2 | 0.329 | 5.298 | Yes |
| | CDQ3 | 0.124 | 2.054 | Yes |
| | **CDQ4** | **0.061** | **0.947** | **No** |
| | CDQ5 | 0.321 | 4.500 | Yes |
| **Evidence-Based Culture** | **EC1** | **0.065** | **0.332** | **No** |
| | EC2 | 0.336 | 1.653 | Yes |
| | EC3 | 0.374 | 1.796 | Yes |
| | EC4 | 0.335 | 1.651 | Yes |
| | **EC5** | **0.040** | **0.184** | **No** |

As shown in Table 5.10, five indicators (i.e., PRA3, PRA4, CDQ4, EC1, and EC5) did not meet the requisites to remain in the measurement model. Therefore, they were removed from the model.

### 5.2.3. Second-Order Formative Construct

As stated in Chapter 4, the first step in evaluating a second-order formative construct is to check the significance level of the correlations between the first order constructs shaping the second-order one. Those first-order constructs that do not have a significant relationship with recommendation quality should be removed. However, as shown in Table 5.10, all of the relationships between first-order constructs and recommendation quality were significant. As a result, all of them were kept in the model. The results are shown in Table 5.11.

**Table 5.11. Second Order Formative Construct**

| Relationship | Weight | T-Value | Keep |
|---|---|---|---|
| RU → RQ | 0.167 | 13.215 | Yes |
| TQ → RQ | 0.367 | 18.256 | Yes |
| IDQ→ RQ | 0.204 | 14.145 | Yes |
| CDQ → RQ | 0.205 | 15.768 | Yes |
| AC→ RQ | 0.123 | 16.146 | Yes |

*RQ stands for recommendation quality; RU stands for recommendation understandability; TQ stands for tool quality; IDQ stands for inherent data quality; CDQ stands for contextual data quality; AC stands for analyst competency*

Next, a weighted sum of the first-order indicators was calculated. This indicator is calculated by multiplying the value of items by PLS weights for each first-order indicator. The next step is to create a composite index for the second-order construct (Diamantopoulos and Winklhofer 2001). A composite index value for the DA tool's recommendation quality was generated and the result of these analyses indicated that the second-order formative construct (i.e., recommendation quality) was working properly.

### 5.2.4. Multicollinearity Analysis

Multicollinearity portrays the extent to which other constructs will explain a construct in the model (Hair et al. 2010). It becomes problematic when there is a high correlation among predictor variables that could lead to an unreliable estimate of regression coefficients (Allison 2012). Bivariate correlations and the Variance Inflation Factor (VIF) were calculated to test multicollinearity (Meyers et al. 2006). According to the current literature, the maximum accepted range for bivariate correlations is 0.8 (Meyers et al. 2006) and VIF should also be less than 5 (Hair et al. 2011; Ringle et al. 2015). The results of the analysis show that bivariate correlations were less than 0.8 and all the VIF values were less than 5. Therefore, it can be asserted that the result of this study will not suffer from any multicollinearity related issue.

### 5.2.5. Common Method Bias

To inspect the Common Method Bias (CMB), two different techniques were employed: the Harman’s one-factor test and the marker variable technique (Lindell and Whitney 2001). For Harman’s one-factor test, the unrotated solution to the principal component analysis (PCA) revealed several factors. However, none of those factors explained the majority of the variance. Therefore, the results of this test proposed a low probability of a substantive common method variance component in the data.

The marker variable technique was also used to examine any potential common method bias. According to Malhotra et al. (2006), the marker variable should be an unrelated continuous variable. Therefore age was selected as a proper construct. To assess the CMB, according to Malhotra et al. (2006), the correlation between a theoretically unrelated construct (here in this study perceived risk of action was used) and the marker variable measured. This value (0.03) was considered the method variance and was parcelled out from the other correlations. The next step was to rerun the analysis. The results did not show any significant difference between the original correlations and the adjusted ones.

After conducting both Harman's one-factor and marker variable tests, it was concluded that common method bias does not exist in the data and is thus unlikely to affect the findings of this study.

## 5.3. Structural Model

Having validated the measurement model, the next step in the data analysis was to test the structural model. To do so, the empirical evidence was examined to check whether they supported the theoretical hypotheses in the proposed research model. To that end, Structural Equation Modeling using SmartPLS 3.0 was employed to evaluate the proposed hypotheses and the significance of the path coefficients.

### 5.3.1. Hypotheses Testing

The results, shown in Figure 5.1 and Table 5.12, indicate that the data supported all the hypothesised relationships. As shown, personal concordance ($\beta$=0.206; $\rho$<0.05) and recommendation actionability ($\beta$=0.578; $\rho$<0.001) positively and significantly influenced acting on a DA tool's recommendation, supporting $H_1$ and $H_2$ respectively. Moreover, the perceived risk of action was found to have a significant negative correlation with acting on a DA tools recommendation (β=-0.123; ρ<0.05), supporting $H_3$. The results supported the hypothesized relationships of recommendation quality on personal concordance (β=0.243; ρ<0.01), as well as on organizational concordance (β=0.726; ρ<0.001). Thus $H_4$ and $H_5$ were supported. The results indicated that organizational concordance positively and significantly correlated with personal concordance (β=0.656; ρ<0.001), providing support for $H_6$. The results also showed that both organizational concordance (β=0.487; ρ<0.001) and an organization with an evidence-based culture (β=0.261; ρ<0.01) positively correlated to recommendation actionability, supporting $H_7$ and $H_9$. Finally, organizational concordance negatively influenced the perceived risk of action (β=-0.243; ρ<0.01), providing support for $H_8$.

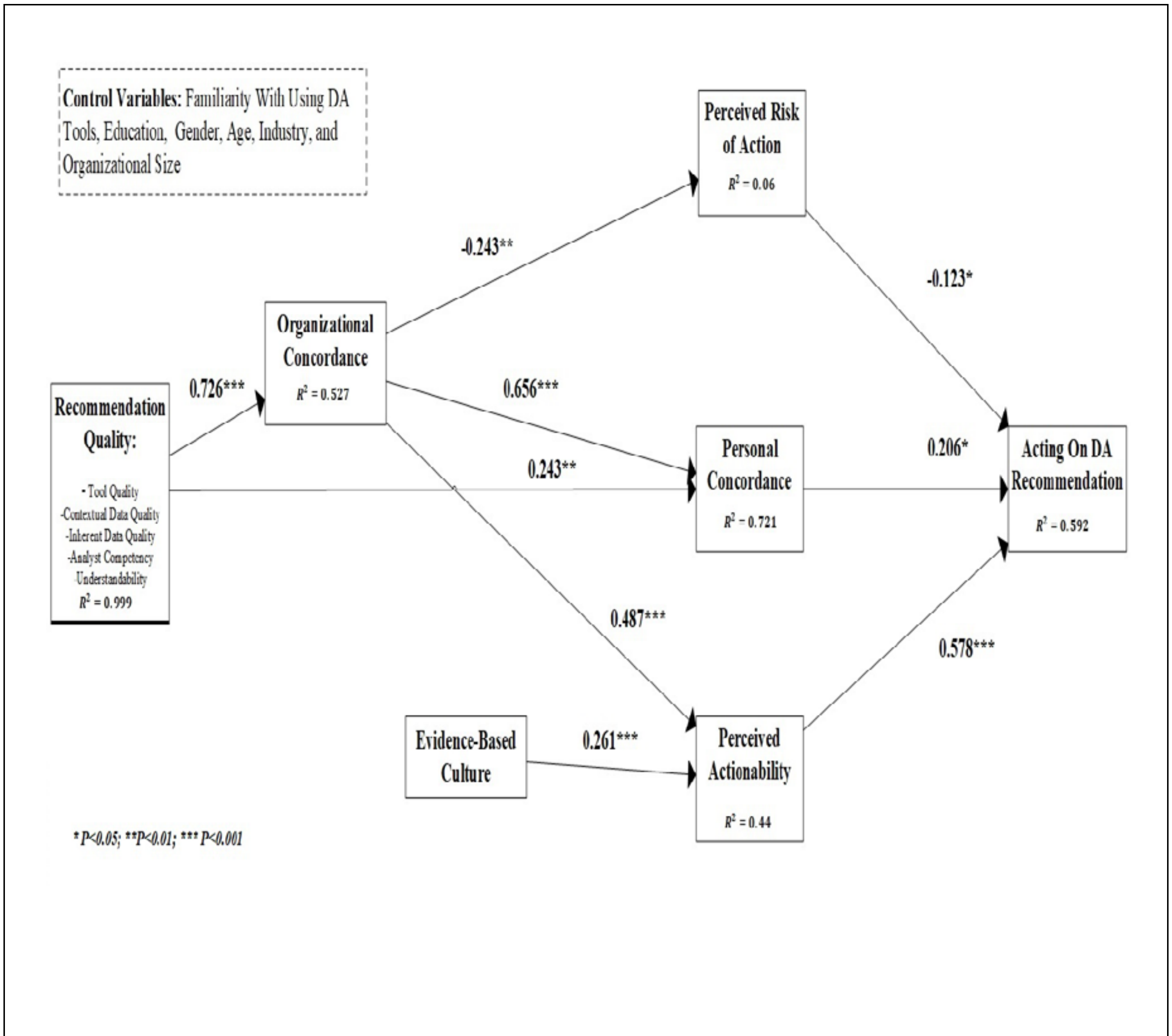


**Figure 5.1. PLS Model Results**

| Table 5.12. Validation of Study Hypotheses | | | | |
|---|---|---|---|---|
| **Hypothesis** | **Path coefficient** | **t-statistic** | **Significance** | **Supported?** |
| P.Con→ Acting | 0.206 | 2.094 | 0.05 | **Yes** |
| Actionability → Acting | 0.578 | 6.864 | 0.000 | **Yes** |
| PRA → Acting | -0.123 | 2.040 | 0.05 | **Yes** |
| RQ→ P.Con | 0.243 | 3.002 | 0.01 | **Yes** |
| RQ → O.Con | 0.726 | 16.334 | 0.000 | **Yes** |
| O.Con→ P.Con | 0.656 | 8.649 | 0.000 | **Yes** |
| O.Con → Actionability | 0.457 | 5.460 | 0.000 | **Yes** |
| O.Con → PRA | -0.243 | 2.729 | 0.01 | **Yes** |
| E-Cul → PRA | 0.261 | 3.204 | 0.000 | **Yes** |

### 5.3.2. Analysis of R-Squared

The coefficient of determination values (i.e., $R^2$) of the endogenous constructs in the research model were also examined. $R^2$ describes the variance of the dependent construct explained by the independent constructs (Gefen et al. 2000). According to Falk and

Miller (1992), the minimum value for $R^2$ of all the endogenous constructs in the research model should not be less than 0.10 in Social Sciences' research. This statement asserts that at least 10 % of an endogenous construct should be explained by its direct exogenous constructs. Moreover, Chin (1998) also provided a spectrum to evaluate $R^2$. Accordingly, any $R^2$ value above 0.670 is considered as substantial. $R^2$ values around 0.333 are deemed moderate. Any values of less than 0.190 are viewed as weak (Urbach and Ahlemann 2010). Table 5.13 illustrates the evaluated $R^2$ of all the endogenous constructs in this study.

**Table 5.13. R Squared**

| Construct | $R^2$ | Conclusion |
|---|---|---|
| Acting on a DA tool's Recommendation | 0.592 | Moderate Explanation |
| Personal Concordance | 0.721 | Substantial Explanation |
| Organizational Concordance | 0.527 | Moderate Explanation |
| Actionability | 0.440 | Moderate Explanation |
| Perceived Risk of Action | 0.060 | Weak Explanation |

As shown in Table 5.13, acting on a DA tool's recommendation and personal concordance with a DA tool's recommendation has been explained to a great extent (i.e., the first objective of this study). Organizational concordance and recommendation actionability were moderately explained. However, the value of $R^2$ for the perceived risk of action was very low. This is not deemed problematic because the perceived risk of action was not an independent variable in the research model, and only one variable (i.e., organizational concordance) was predicting it in the research model.

### 5.3.3. Analysis of Effect Sizes

Effect size ($f^2$) is used as a proxy to determine the impact of an independent construct on a dependent one (Cohen 1988). To be specific, effect size allows a researcher to figure out to what extent an independent variable affects a dependent one. According to the current literature, effect sizes are categorized into three distinct categories: small (values around 0.02), medium (values around 0.15), and large (values around or larger than 0.35) (Roldán and Sánchez-Franco 2012). To evaluate the effect size of the hypothesized relationships in this study, SmartPLS 3.0 was used. The results are illustrated in Table 5.14.

**Table 5.14. Effect Sizes**

| Relation | $f^2$ | Effect Size |
|---|---|---|
| Personal Concordance → Act | 0.066 | Small |
| Actionability → Act | 0.49 | Large |

| | | |
|---|---|---|
| Perceived Risk of Action → Act | 0.033 | Small |
| Recommendation Quality → Personal Concordance | 0.1 | Small |
| Recommendation Quality → Organizational Concordance | 1.113 | Large |
| Organizational Concordance → Personal Concordance | 0.729 | Large |
| Organizational Concordance → Actionability | 0.304 | Medium |
| Organizational Concordance → Perceived Risk of Action | 0.063 | Small |
| Evidence-Based Culture → Actionability | 0.088 | Small |

### 5.3.4. The Goodness of Fit of the Research Model

The goodness of fit (GoF) index is a metric which evaluates to what extent the model fits the data. The GoF index is defined as the “geometric mean of the average communality and average $R^2$for all endogenous constructs” (Akter et al. 2011). The following equation calculates the GoF.

$$GOF = \sqrt{\frac{\sum_n AVE_n}{n} - \frac{\sum_m R_m^2}{m}}$$

In the above equation, n represents the number of reflective constructs in the research model and m represents the number of endogenous constructs. According to current literature, the threshold for GoF is a value larger than 0.36. The GoF for this study was 0.54, which far exceeds the suggested threshold of 0.36 and thus indicates good performance of the model (Wetzels et al. 2009). Therefore, it can be concluded that the model is performing well, and data fits well with it.

## 5.4. Post-Hoc Analyses

In this section, the results of a series of post-hoc analyses (i.e., analysis of the impacts of the control variables and saturated model analysis) are presented.

### 5.4.1. Analysis of the Impacts of Control Variables

As discussed earlier, besides the constructs in the proposed research model, several control variables were added to the questionnaire. These variables were controlled and analyzed for potential impact on the endogenous constructs in the proposed research model. In total, this study controlled for six different variables: participants' familiarity with DA tools, frequency of DA tool use, age, gender, education, and organizational size.

To analyze the effect of these control variables on the main endogenous variables of this study (i.e., acting on a DA tool's recommendation and personal concordance with such a DA tool's recommendation), each was added one at a time to the model, linking to the endogenous constructs. To test the significance and strength of their effects, SmartPLS 3.0 was employed. The results are depicted in Table 5.15.

**Table 5.15. Results on Control Variable Analysis**

| Control Variable | Endogenous Variable | Path Coefficient | P-Value | Significance |
|---|---|---|---|---|
| Familiarity with DA tools | Action | 0.093 | 0.045 | **Significant** |
| | Personal Concordance | 0.061 | 0.081 | **Marginal** |
| Frequency of DA tool use | Action | 0.046 | 0.180 | n.s. |
| | Personal Concordance | -0.010 | 0.767 | n.s. |
| Organizational Size | Action | 0.005 | 0.917 | n.s. |
| | Personal Concordance | 0.001 | 0.968 | n.s. |
| Age | Action | -0.024 | 0.527 | n.s. |
| | Personal Concordance | 0.016 | 0.614 | n.s. |

| | | | | |
|---|---|---|---|---|
| Gender | Action | -0.002 | 0.972 | n.s. |
| | Personal Concordance | -0.005 | 0.894 | n.s. |
| Education | Action | -0.001 | 0.994 | n.s. |
| | Personal Concordance | -0.027 | 0.406 | n.s. |

Interestingly, as illustrated in the above table, familiarity with DA tools was significantly influenced by acting on a DA tool's recommendation. Familiarity with DA tools while not significantly affecting personal concordance at the $p<0.05$ level, was found to moderately correlate with personal concordance at the $p<0.10$ level. This is referred to as 'marginal' significance (i.e., $0.10 < p < 0.05$). Recently, the notion of marginal significance has appeared in the IS literature (Dimoka and Davis, 2008; Hong and Pavlou, 2010; Dimoka et al., 2012). Hence, it could be concluded that familiarity with DA tools correlates with both action on a DA tool's recommendation and personal concordance with such a DA tool's recommendation. This is an interesting finding that adds value to the findings of this research and enhances our understanding as to why people do not act on a DA tool's recommendation. As shown in Table 5.15, the rest of the control variables do not influence acting on DA tools' recommendations or personal concordance with such DA tools' recommendations.

### 5.4.2. Saturated Model Analysis

Saturated model analysis was used to explore any probable non-hypothesized relationships among the constructs in the proposed research model. To this end, a new model containing all the possible links among the constructs was created. Then, using SmartPLS 3.0, a path analysis was performed. Results of this analysis are represented in Table 5.16.

**Table 5.16. Saturated Model Analysis Results**

| Relation | Path Coefficient | P-Value | Validation |
|---|---|---|---|
| OC → Act | 0.014 | 0.906 | Rejected |
| RQ → Act | 0.100 | 0.317 | Rejected |
| EC → Act | -0.031 | 0.630 | Rejected |
| Actionability → PC | 0.066 | 0.368 | Rejected |

| | | | |
|---|---|---|---|
| PRA → PC | -0.028 | 0.595 | Rejected |
| EC→ PC | -0.120 | 0.060 | Rejected |
| **Actionability → PRA** | **-0.349** | **0.007** | **Accepted** |
| **RQ → PRA** | **-0.281** | **0.018** | **Accepted** |
| EC → PRA | -0.151 | 0.146 | Rejected |
| **RQ → Actionability** | **0.458** | **0.000** | **Accepted** |
| EC → OC | 0.095 | 0.272 | Rejected |
| **RQ → EC** | **0.654** | **0.000** | **Accepted** |

*Act stands for acting on a DA tool's recommendation; OC stands organizational concordance; RQ stands for recommendation quality; EC stands for evidenced-based organizational culture; PC stands for personal concordance; PRA stands for the perceived risk of action.*

As shown in Table 5.16, among the non-hypothesized relationships, four were significant. The first one was the effect of actionability on perceived risk ($\beta$=-0.349; $\rho$<0.01). As shown, higher levels of actionability reduce perceived risk of action. This finding implies that if DA users find a DA recommendation to be actionable (e.g., they have access to enough resources to execute the action), they will feel more confident in acting on such a DA tool's recommendation.

It was also found that a higher perception of recommendation quality is negatively associated with the perception of risk of action ($\beta$= -0.281; $\rho<0.05$). Again, this finding is in line with the current literature on risk and action: according to Jaeger et al. (2013), "risk is the mark of a new consciousness, a way of looking at a world of technological and environmental uncertainty." Perceiving a recommendation to be of high quality is associated with a lower perception of related uncertainties and is thus expected to reduce the risk of action (Jaeger et al. 2013).

It was also found that higher levels of perception of recommendation quality are positively correlated with recommendation actionability ($\beta$=0.458; $\rho<0.001$). This could be because a good DA tool's recommendation should consider the constraints of its user. Finally, it was found that recommendation quality is positively correlated with the perception of the evidence-based culture of an organization ($\beta$=0.654; $\rho<0.001$). Although, there is no justification in the literature for this relationship, however, this relationship makes sense when viewed in the reverse direction (i.e., an evidence-based organizational culture is positively correlated with DA recommendation quality). From this perspective, one would expect that organizations with an evidence based caulture would strive to ensure that all the elements that comprise higher DA recommendations' quality are in place in order to support evedince-based decsion making.

# Chapter 6

## 6.1. Discussion

Recent studies on big data analytics indicate that investments in DA tools have increased dramatically. According to a recent report, it is expected that the amount of investment in DA tools will reach US$200 billion dollars by 2020 (Bertolucci 2015). According to Columbus (2017), DA tools adoption among the organizations interviewed by Forbes has increased from 17% in 2015 to 53% in 2017. These findings show a drastic increase in the number of organizations that adopt DA tools to support organizational decisions. However, recent reports also indicate that among organizations that adopted DA tools, only 37% reported them to be successful in their initiatives (Newgenapps 2018). It has also been found that only 41% of the business executives who are either using DA tools or receiving recommendations generated from a DA tool will act on those recommendations (Columbus 2017).

These findings raise the question as to why are such a large percentage of DA users not acting on DA tools' recommendations? It is an important question to address because inaction negates the value of investing in DA tools, in addition to wasting the efforts put into using them. To the best of my knowledge, no study to date has investigated the conditions under which a DA tool's recommendation translates into action by a DA user, and this research was conducted to examine that phenomenon.

To that end, this study had two primary research objectives:

- To develop and empirically validate a theoretical model of the factors that influence/hinder a DA user's concordance with and action on a DA tool's recommendation.
- To investigate what factors shape the DA user's perception of the quality of a DA recommendation, and to what extent, and how this perception influences a DA user's concordance with and action on the DA tool's recommendation.

According to the current literature, concordance with a recommendation is the primary driving force for an individual to act on such a recommendation. In line with the existing literature, the findings of this study confirmed that higher levels of personal concordance with a DA tool's recommendation is positively correlated with action on such a DA tool's recommendation ($\beta$=0.206; $\rho$<0.05). This was also supported by participants' comments on the related open-ended question. Some examples are provided below:

> *"must have confidence in underlying data and aggregated recommendation."*
>
> *"I need to agree with the recommendation and make sure to know that the source is of high quality and has a near perfect error free backgrounds."*

According to the TPB model, before performing a behavioural response based on a DA tool's recommendation, DA users evaluate whether they have access to both the required monetary resources –such as funds needed and non-monetary resources such as personnel required. Having access to these resources dictates the actionability of such a recommendation. In line with the current literature, the results showed that actionability of a DA tool's recommendation positively influences a DA user to act on such a recommendation ($\beta$=0.578; $\rho$<0.001). This finding was also supported by participants' comments on the related open-ended question. Some examples are provided below:

> *"I have to have the necessary resources to act on the recommendation."*

> *"budgetary resources, time and people to implement."*

> *"Having actionable items listed out as a recommendation."*

Current literature suggests that the perceived risk of action reduces the chance of pursuing an IT recommendation. In line with the existing literature, the findings of this study showed that a higher perception of risk in acting on a DA tool's recommendation is negatively associated with a DA user's action ($\beta$= -0.123; $\rho$<0.05). This finding was also supported by participants' comments on the related open-ended question. Some examples are provided below:

> *"If the tool's recommendation puts the organization at significant financial, legal or other risk we would probably be averse to accepting it without additional specifics."*

> *". Risk tolerance informs all decisions in my practice area. Affects volume of data or degree of certainty required."*

According to the Social Exchange theory, employees' opinions about their workplaces are formed by the reciprocal relationship between the employee and the organization (Eisenberger et al. 1997). Therefore, it was expected that the perception of organizational concordance with a DA tool's recommendation could positively influence the DA user's concordance with such a recommendation. The results of this study confirmed the hypothesised relationship ($\beta$=0.656; $\rho$<0.001).

Current literature defines organizational concordance as the continued commitment of an organization towards the implementation and execution of a DA tool's recommendation (Asnawi et al. 2014). The continued commitment includes the allocation of adequate financial and nonfinancial resources for the implementation and execution of the course of action indicated in a DA tool's recommendation) (Abdel Aziz and Rizkallah 2015). Therefore, it was hypothesized that organizational concordance with a DA tool's recommendation is positively correlated with recommendation actionability. The findings of this study confirmed the hypothesised relationship ($\beta$=0.487; $\rho$<0.001). Moreover, in line with the current literature, it confirmed that organizational concordance reduces the perceived risk of action on a DA tool's recommendation ($\beta$= -0.243; $\rho$<0.01).

Current literature suggests that if an organization favours evidence-based decision-making, it is more likely to facilitate the conditions required for the implementation and execution of evidence-based decisions (Bernal et al. 2009). Therefore, it was expected that, if an organization has an evidence-based culture, it is more willing to prepare the necessary resources for its employees to act on a DA tool's recommendations. The findings of this study confirmed this hypothesis ($\beta$=0.261; $\rho$<0.01).

To address the second objective of this study, recommendation quality was conceptualized and validated as a second-order construct. The first order constructs shaping recommendation quality were: recommendation understandability, tool quality, inherent data quality, contextual data quality, and analyst competency. In line with the second objective of this study, the effect of recommendation quality was tested on personal and organizational concordance.

According to the TPB model, one of the variables which determine the attitude towards a behaviour is perceived outcome evaluation. Outcome evaluation is a DA user's assessment of the desirability of the outcome (Mathieson 1991). According to Sadeghi and Farokhian (2011), perceived service quality (i.e., corresponding to perceived recommendation quality in this study) is the most prominent determinant of an IT user's assessment of the outcome. Therefore, it was hypothesised that recommendation quality positively affects both personal and organizational concordance with a recommendation. The results of this study confirmed that recommendation quality does positively influence both personal concordance ($\beta$=0.243; $\rho$<0.01) and organizational concordance ($\beta$=0.726; $\rho$<0.001) with a DA tool's recommendation.

This study also controlled for a series of factors including familiarity with DA tools, the frequency of DA tool use, organizational size, age, gender, and education. Interestingly, it was found that familiarity with DA tools significantly influenced a DA user's action on a DA tool's recommendation ($\beta$=0.093; $\rho$<0.05). It was also found that familiarity with DA tools moderately influenced personal concordance with a recommendation ($\beta$= 0.061; $\rho$<0.1).

Finally, DSS is an umbrella term encompassing any system that supports a user with making decisions. Such systems typically rely on data and algorithms to process this data resulting in an output that could help a user make a more informed decision. From that perspective, a DA tool could be considered a DSS. Having said that, there are several reasons to warrant developing a theoretical model for users' action on DA recommendations in this study. First, as organizations are facing huge amounts of data (Big Data), they are increasingly relying on DA tools to make sense of this data to improve their decision making. DA tools have been hyped with a lot of associated expectations. That is the main reason why many organizations are now investing or considering investing a vast amount of money in DA tools. According to Bertolucci (2015), the size of investment in DA tools is expected to reach 203 billion US dollars by 2020. However, recent studies indicate that although organizations are making huge investments in DA tools, users do not take the required actions to follow the DA tools' recommendations. This negates the value of making such investments. Therefore, this study was conducted to gain a better understanding of this phenomenon. Second, to the best of my knowledge, only a few numbers of studies have examined user action on recommender systems in the context of an eCommerce experiment. The context of shopping online is very different from the context of using DA tools in organizations. Therefore, the generalizability of the findings of the eCommerce study in our context is questionable. Third, this study contributes by developing and validating a second-order construct measuring DA tools' recommendation quality. Finally, the current study surveyed actual users of DA tools regarding an actual decision that they had to make for which they solicited a recommendation from a DA tool. Thus, this study expands the current state of literature by focusing on action on a recommendation and conceptualizing and validating the concept of recommendation quality.

## 6.2. Contributions to Theory

This study pursued two main research objectives. The first objective was to identify the factors affecting a DA user to concur with and act on a DA tools' recommendations. To that end, the current research studied the effects of a series of factors on whether a DA user acts upon a DA tool's recommendation and the interrelations among these factors. The second objective was to conceptualize and validate the concept of DA tool recommendation quality. Having pursued the above objectives, the current study makes significant theoretical contributions.

First, to the best of my knowledge, this is the first study that has conceptualized and validated the concept of DA tool's recommendation quality as a second-order construct composed of recommendation understandability, tool quality, inherent data quality, contextual data quality, and analyst competency. It was found that tool quality and analyst competency were the most important factors that shaped the perception of recommendation quality. Therefore, these findings advance the current literature on Data Analytics by conceptualizing and validating this construct.

Second, this research identified DA tool's recommendation Actionability as the most critical factor affecting action on a DA tool's recommendation. This finding enhances the current literature on Data Analytics: current literature argues that prior to pursuing a set of actions prescribed in a DA tool's recommendation, DA users assess whether they have access to the necessary resources to implement a recommendation, and also whether prevailing organizational constraints are reflected in the proposed recommendation (Vancouver and Schmitt 1991). In this regard, the findings of this study showed that if DAs users find a DA recommendation to be actionable (i.e., in line with their organizational financial and non-financial constraints), they will be more likely to act on this DA recommendation.

Third, this study also makes theoretical contributions to evidence-based management literature. According to the results of the current research, the presence of an evidence-based culture increases the actionability of a recommendation such that if an organization has an evidence-based culture, it is more likely that it will provide the resources required to make it possible for DA users to act on DA tools' recommendations.

Fourth, this study also examined the impact of DA users' concordance with the recommendation on whether they will act on the recommendation. It was demonstrated that the more DA users concur with a DA tool's recommendation, the more likely they are to act upon that recommendation, and the more familiar DA users are with a DA tool, the higher the chances of their concordance with and action on that DA tool's recommendations. This specific finding enhances the current literature on Data Analytics by identifying the impact of familiarity with DA tools on concordance with and action on DA tools' recommendations.

Finally, this study provides another theoretical contribution with regards to risk management. The findings showed that the perceived risk of action DA users exhibit reduces the chances of their action on a DA tool. It was also found that organizational concordance, actionability, and recommendation quality can significantly reduce a DA user's risk perception, which could in turn result in higher chances of a DA user's action on a DA tool's recommendation.

## 6.3. Contributions to Practice

This research also offers significant practical contributions. A series of factors affecting a DA user's action on a DA tool's recommendation were identified and by using these, organizations can now understand why their employees do or do not act on a DA tool's recommendation. The findings of this study can help companies that are adopting DA tools to prepare an environment in which more DA users will act on DA tools' recommendations.

The first major practical contribution of this study was to identify actionability as the most prominent factor affecting a DA user's action on a DA tool's recommendation. As stated earlier, actionability refers to the extent to which a DA user has access to the required monetary and non-monetary resources to act on a DA tool's recommendation. Therefore, if organizations that have either invested or want to invest in DA tools wish to increase their DA users' action on the tools' recommendations, they should provide the required resources for such actions to take place.

Second, this study also found that familiarity with DA tools also affect a DA user's action on a DA tool's recommendation. Therefore, organizations should think about providing the required training for their DA users to help them become more familiar with the DA tools.

Third, this study also figured the factors that shape DA users' perceptions of recommendation quality. In this regard, organizations should be more cautious in selecting proper and high-quality DA tools. As shown in the results, having a high-quality DA tool could enhance the chances of a DA user's concordance with the DA tool's recommendations, which in turn could result in higher chances of action. Another finding of this study was that having competent data analysts increases the perception of recommendation quality. Thus, companies should provide more training to improve the proficiency of their data analysts in using DA tools. Acquiring high-quality data will also affect the perception of recommendation quality, so if organizations are thinking about investing in DA tools, they should also consider ways to acquire high-quality data from both internal and external resources.

Fourth, the next significant practical contribution of this study was in understanding the effect of the perceived risk of action in reducing the chances of action on a DA tool's recommendation. Three significant factors were shown to affect the perceived risk of action including recommendation quality, organizational concordance, and actionability. Two of these factors are related to organizational factors (i.e., concordance and actionability). It is therefore vital that companies give their employees full support to reduce the perception of risk of action.

Finally, as another practical contribution of this study, it was found that an organization with an evidenced-based culture is more likely to secure the required resources for its DA users to act on DA tools' recommendations and it is highly recommended that businesses develop an evidence-based managerial

## 6.4. Limitations and Future Research

The significance and contributions of the current research notwithstanding, there are several limitations which offer various avenues for future studies. First, participants of this study were only selected among North American middle and top-level managers. Taking into account the probable influences of culture on users' attitude toward IT use (DA tools, to be more specific), extra caution should be exercised in generalizing the findings of this study to DA users in other geographical regions. To that end, further research with different subject demographics and geographical region is essential before generalizing the results of this study to other regions.

Second, prior to participating in this study, participants were asked to reflect on a recent decision they had made for which they received a DA tool's recommendation. Asking such a question from participants can potentially introduce recall bias (Coughlin 1990). Recall bias in social science studies reflects "a systematic error caused by differences in the accuracy or completeness of the recollections retrieved ("recalled") by study participants regarding events or experiences from the past". In this regard, current research shows that 20% of details are irretrievable (Bradburn et al. 1987) and recall bias could potentially affect the judgment of the participants. Future studies could employ other types of controls to avoid this problem.

Third, this study employed only a quantitative research methodology. The results of this study verified the effectiveness of the proposed methodology by confirming the proposed hypotheses. However, among the collected data, the participation rate in open-ended questions of this study was low. The analysis showed that only 146 participants responded to the open-ended questions. Among which only 101 contained usable answers (e.g., some participants entered N/A or just pushed the keyboard to enter some blank characters). The initial content analysis of the results showed that many of these responses (i.e., 94 instances) only contained one sentence or less. In this regard, the results did not provide any insights beyond the factors, reflected in the research model of this study. However, this could be a potential limitation of the current study, which could be addressed in future studies. In this regard, future studies could use some incentives to encourage their participants to provide better feedback to open-ended questions. This limitation could also be mitigated by incorporating or other types of qualitative methods (e.g., interviews) to gain more in-depth insights regarding DA users' experiences.

Fourth, this study did not control for the type of decision for which a DA recommendation was solisted. As a manager's action on a DA recomemndtaion could be influenced by the complexity or strategicness of the decsion at hand, future research should explore the influence of this factor.

Finally, this study only considered some possible factors that could affect acting upon a DA recommendation. Although they accounted for a significant proportion of the variance in the data (i.e., 59.2%), these factors are not exhaustive and, as such, future research could examine the effect of others in this regard.

The saturated model analysis results showed that the perceived risk of action requires more attention. This result showed that recommendation actionability and recommendation quality reduced the perception of risk of action. Moreover, having these two none hypothesized relationships increased the $R^2$ value of the perceived risk of action from 0.06 to 0.134. As it has been confirmed by the results, the perception of risk is among the factors affecting a user's action on a DA tool's recommendation. Therefore, future studies can focus more on this concept.

Moreover, the control factor analysis results also showed that familiarity with DA tools affects a user's action on and concordance with a DA tool's recommendation. This finding revealed that the over time as users become more familiar with DA tools, their concordance with and action on DA tools' recommendations increase. Therefore, future research can study this concept more in detail.

Also, there are a variety of other factors which could potentially correlate with action on a DA tool's recommendation, such as the type of task at hand. Current literature shows that task complexity correlates with users' intention to use an IT system. Therefore, it would be useful if future studies on action on DA tools' recommendation were to take this construct into account. Another potential factor could be the level of strategicness of the decision at hand. There is a gap in the current literature in regards to the level of strategicness of the decision in perusing an IT systems' recommendation. Finally, another potential construct is the type of user who is using the DA tool. Current literature showed that personality types affect users' intentions to use an IT system. Therefore, this is an important concept which needs to be considered in future studies.

## 6.5. Concluding Remarks

This study aimed at fulfilling two main research objectives: (1) develop and empirically validate a theoretical model of the factors that influence/hinder a DA user's concordance with and action on a DA tool's recommendation; and (2) investigate what factors shape the perception of the quality of a DA recommendation, and to what extent, and how this perception influences a DA user to concur with and act on the DA tool's recommendation.

In pursuing these objectives, this study addressed a gap in the current literature as to why the majority of DA users do not act on DA tools' recommendations. A series of factors affecting a DA user's action on a DA tool's recommendation were proposed, selected among technological, individual, situational and task-related factors that rely on two theoretical frameworks: the S-O-R framework and the Theory of Planned Behavior.

To validate the hypothesised relationships, this study employed a quantitative method approach. Data were collected from 235 middle and top-level managers among those who are using DA tools in North America. Results showed that all of the hypothesised relationships were confirmed. The findings also demonstrated the appropriateness of both the research model and method in understanding the factors that can affect a DA user's action on a DA tool's recommendation. This appears to be the first study to identify the factors that affect a DA user's action on a DA tool's recommendation. It is also the first study that conceptualized and validated the notion of DA tool's recommendation quality and can thus serve as a solid theoretical foundation for future studies in this context, in addition to making significant contributions to practice.

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# APPENDIX A. Survey Questions

**The following questions will be asked from participants.**

*Prior to answering the questions in this survey, please reflect back to a recent decision you made at work for which you have used a data analytics tool or asked someone else to complete such an analysis for you. Subsequently, answer all questions in relation to this recent decision. Please indicate the degree to which you agree or disagree with the following statements regarding such an experience. When answering these questions, please keep in mind that there are no right or wrong answers, so please answer the questions as honestly as possible.*

| Construct | Item | Strongly Disagree | Disagree | Somewhat Disagree | Neither Agree or Disagree | Somewhat Agree | Agree | Strongly Agree | Prefer not to answer |
|---|---|---|---|---|---|---|---|---|---|
| Acting on Data Analytics Recommendation | The DA recommendation provided to me was fully executed. | | | | | | | | |
| | The DA recommendation provided to me was completely implemented. | | | | | | | | |
| | My final action completely reflected the DA recommendation provided to me. | | | | | | | | |
| | My final action fully integrated the DA recommendation provided to me. | | | | | | | | |
| | I acted fully on the DA recommendation provided to me. | | | | | | | | |
| Personal Concordance | I fully agreed with the DA recommendation provided to me. | | | | | | | | |
| | I felt that my personal decision-making **values** were consistent with the DA recommendation provided to me. | | | | | | | | |
| | I felt that my personal decision-making **goals** were consistent with the DA recommendation provided to me. | | | | | | | | |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Organisational Concordance | My organization fully agreed with the DA recommendation provided to me. | | | | | | | | |
| | I felt that my organizational decision-making **values** were consistent with the DA recommendation provided to me. | | | | | | | | |
| | I felt that my organizational decision-making **goals** were consistent with the DA recommendation provided to me. | | | | | | | | |
| Perceived Recommendation Actionability | The DA recommendation provided to me was clear. | | | | | | | | |
| | I had access to the **required financial resources** to act on the DA recommendation provided to me. | | | | | | | | |
| | I had access to the **required non-financial resources** (e.g., human resources) to act on the DA recommendation provided to me. | | | | | | | | |
| Evidence-Based Organizational Culture | In my organization, we have an explicit culture that encourages evidenced-based decision making. | | | | | | | | |
| | In my organization, we have explicit organizational strategies that support and guide evidenced-based decision making. | | | | | | | | |
| | In my organization, we have explicit policies/rules that support and guide evidenced-based decision making. | | | | | | | | |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Evidence-Based Organizational Culture | In my organization, we have an explicit culture that encourages evidenced-based decision making. | | | | | | | | |
| | In my organization, we have explicit organizational strategies that support and guide evidenced-based decision making. | | | | | | | | |
| | In my organization, we have explicit policies/rules that support and guide evidenced-based decision making. | | | | | | | | |
| | In my organization, we have a well-defined organizational structure that enables evidenced-based decision making. | | | | | | | | |
| | In my organization, evidence-based decision making is integrated in our business processes. | | | | | | | | |
| Personal Risk of Action | Acting on the DA recommendation provided to me could have affected my career negatively. | | | | | | | | |
| | Acting on the DA recommendation provided to me could have caused my sub-ordinates to think less highly of me. | | | | | | | | |
| | Acting on the DA recommendation could have led to a time loss for me. | | | | | | | | |
| | Acting on the DA recommendation could have posed financial losses to me. | | | | | | | | |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | The data used by the DA tool was unbiased (unprejudiced) and impartial. | | | | | | | | |
| | The data used by the DA tool was trustworthy or highly regarded in terms of its source or content. | | | | | | | | |
| Perceived Contextual Data Quality | The data used by the DA tool was applicable for the task at hand. | | | | | | | | |
| | The data used by the DA tool was appropriately up-to date for the task at hand. | | | | | | | | |
| | The data used by the DA tool had sufficient breadth, depth, and scope for the task at hand. | | | | | | | | |
| | The data used by the DA tool had enough quantity for the task at hand. | | | | | | | | |
| | The data used by the DA tool had enough variability for the task at hand. | | | | | | | | |
| Perceived Data Analytics Tool Quality | The DA tool I used provides accurate recommendations. | | | | | | | | |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Perceived Data Analytics Tool Quality | The DA tool I used provides accurate recommendations. | | | | | | | | |
| | The DA tool I used provides believable recommendations. | | | | | | | | |
| | The DA tool I used provides timely recommendations. | | | | | | | | |
| | The DA tool I used provides relevant recommendations. | | | | | | | | |
| | The DA tool I used provides easy to understand recommendations. | | | | | | | | |
| | The DA tool I used provides recommendations at the right level of detail | | | | | | | | |
| | The DA tool I used provides recommendations in an appropriate format. | | | | | | | | |
| Perceived Recommendation Understandability | The line of reasoning was described in the DA recommendation provided to me. | | | | | | | | |
| | The DA recommendation provided to me was justified. | | | | | | | | |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Perceived Understandability Recommendation | The line of reasoning was described in the DA recommendation provided to me. | | | | | | | | |
| | The DA recommendation provided to me was justified. | | | | | | | | |
| | The problem solving strategy was described in the DA recommendation provided to me. | | | | | | | | |

*The data analyst in the following series of questions refers to the person who carried out the DA analysis. If you carried out the analysis yourself, please answer these questions in relation to your own abilities.*

| Construct | Item | Strongly Disagree | Disagree | Somewhat Disagree | Neither Agree or Disagree | Somewhat Agree | Agree | Strongly Agree | Prefer not to answer |
|---|---|---|---|---|---|---|---|---|---|
| Perceived Data Analyst Competency | 1. Data analysts were competent and effective in providing the DA recommendations. | | | | | | | | |
| | 2. Data analysts performed their role of providing the DA recommendations very well. | | | | | | | | |
| | 3. Data analysts were capable and proficient in working on DA tools. | | | | | | | | |
| | 4. Data analysts were very knowledgeable about DA analytics. | | | | | | | | |

**Open-Ended Questions:**

*When considering the use of DA tools in your organization:*

- In your opinion, what are the most critical factors affecting the quality of data used in DA tools to make their recommendations?
- In your opinion, what are the characteristics of DA tool's recommendation that are necessary for you to deem it as a high quality recommendation?
- In your opinion, what are the most important factors necessary for you to act upon a DA tool's recommendation?
- In your opinion, does your organization have an evidence based culture? Please explain why or why not?
- In your opinion, does your risk tolerance affect your decision to act upon a DA tool's recommendation? Please explain why or why not?

***Please feel free to answer the following questions:***

Which of the following best describes your role in your organization?

- Upper management
- Middle management
- Junior management
- Administrative staff
- Support staff
- Trained professional
- Skilled labor
- Consultant
- Temporary employee
- Researcher
- Self-employed/partner
- Other: Please specify
- Prefer not to answer

Please indicate the number of employees that report to you, directly or indirectly

- 0 employee
- 1 employee
- 2-3 employees
- 4-5 employees
- 6-9 employees
- 10-49 employees
- 50-99 employees
- 100-499 employees
- 500-999 employees
- 1000 or more employees
- Prefer not to answer

Which department of your organization are you currently employed in?

- Accounting
- Administration
- Customer service
- Human resource
- Inventory
- IT
- Management
- Manufacturing
- Marketing and Sales
- Procurement
- Quality assurance
- Research and Development
- Other: Please specify
- Prefer not to answer

Please indicate <u>how often</u> you use data analytics tools in your work. This refers to the frequency of your using data analytics tools.

- Not at all
- Not much
- Sometimes
- Quite often
- Often
- Almost always
- Always
- Prefer not to answer

Please indicate to <u>what extent</u> you use data analytics tools in your work. This refers to how extensively you utilize data analytics tools in your work.

- Not at all
- To a very small extent
- To a small extent
- To a moderate extent
- To a fairly great extent
- To a great extent
- To a very great extent
- Prefer not to answer

Please indicate the precentage of time you spend on the use of data analytics in your work.

- Never
- Rarely, in less than 10% of the time
- Occasionally, in about 30% of the time
- Sometimes, in about 50% of the time
- Frequently, in about 70% of the time
- Usually, in about 90% of the time
- Almost all the time
- Prefer not to answer

How familiar are you with data analytics tools?

- o Not at all
- o To a very small extent
- o To a small extent
- o To a moderate extent
- o To a fairly great extent
- o To a great extent
- o To a very great extent
- o Prefer not to answer

which of the following describes your gender?

- o Female
- o Male
- o Transgender Female
- o Transgender Male
- o Other…
- o Prefer not to answer

which age group do you blong to?

- o 20-30
- o 31-40
- o 41-50
- o 51-60
- o 61-70
- o >71
- o Prefer not to answer

what is you highest level of education?

- o High school
- o College diploma
- o Bachelor's degree
- o Master's degree
- o Ph.D. degree
- o Other
- o Prefer not to answer

Which of the following describes the number of employees in your organization?

- o <100
- o 100-500
- o 501-1000
- o 1001-5000
- o More than 5001
- o Prefer not to answer

Which of the following categories best describes the industry of the organization work in (regardless of your actual position)?

- Agriculture, Forestry, Fishing and Hunting
- Utilities
- Computer and Electronics Manufacturing
- Wholesale
- Transportaiton and Warehoousing
- Software
- Broadcasting
- Other Information Industry
- Real Estate, Rental and Leasing
- Primary/Secondary (K-12) Education
- Health Care and Social Assistance
- Hotel and Food Services
- Legal Services
- Homemaker
- Religious
- Mining
- Construction
- Other Manufacturing
- Retail
- Publishing
- Telecommunicataion
- Information Services and Data Processing
- Finance and Insurance
- College, University and Adult Education
- Other Education Industry
- Arts, Entertainment, and Recreation
- Government and Public Administration
- Military
- Other Industry: Please specify ….
- Prefer not to answer

How many years have you worked at your current organization?

- …..Years
- Prefer not to answer

How many years of working experience do you have in total?

- …..Years
- Prefer not to answer

Which of the following describes the annual sales revenue of your organization?

- Less than $ 1 million
- $ 1 million - $ 5 million
- $ 5 million – $ 10 million
- $ 10 million - $ 20 million
- $ 20 million- $ 50 million
- $ 50 million - $ 100 million
- $ 100 million - $ 500 million

- $ 500 million – $ 1 billion
- More than $ 1 billion
- Prefer not to answer

# APPENDIX B. Consent Form

**LETTER OF INFORMATION / CONSENT**

**A Study about Data Analytics Tools' Use in Organizations**

| **Student Investigator:** | **Faculty Supervisor:** |
|---|---|
| Seyed Pouyan Eslami | Dr. Khaled Hassanein |
| Department of Business | Department of Business |
| McMaster University | McMaster University |
| Hamilton, Ontario, Canada | Hamilton, Ontario, Canada |
| **(905) 525-9140 ext.26385** | **(905) 525-9140 ext. 23956** |
| E-mail: eslamisp@mcmaster.ca | E-mail: hassank@mcmaster.ca |

**Purpose of the Study:** We are conducting this study as a part of a Ph.D. dissertation that aims to find out how Data Analytics Users react to Data Analytic tools' recommendations. This research will result in guidelines for design of data analytics tools' recommendation.

**Procedures involved in the Research:** This study will last approximately 30 minutes. If you volunteer to participate in this study, you will be asked to complete an online questionnaire. To answer these questions, please reflect back to a recent decision you made at work for which you have used a data analytics tool or asked someone else to complete such an analysis for you. Moreover, you will also be asked to fill out a set of open-ended questions regarding your recent experience in dealing with such a data analytics tool's recommendation. At the end and after completing the questionnaire, you will be asked to respond to open-ended questions to gather basic background information about your experience.

**Potential Harms, Risks or Discomforts:** It is not likely that there will be any harms or discomforts from your participation in this research. Please note that you do not need to answer questions that you do not want to answer or that make you feel uncomfortable. You can also stop taking part in the study (withdraw) at any time.

**Potential Benefits:** Result of this study will help researchers and practitioners understand the conditions under which an organizational decision maker will act on a data analytics tool's recommendation.

**Compensation:** You will be compensated by Research Now as outlined in Research Now's compensation policy. You must complete the survey before you can enter your e-mail address into the sweepstakes. Please note that you are still eligible for compensation if you elect not to answer some of the questions in the survey. Please visit https://www.researchnow.com/termsandconditions/ for further information about the compensation process.

**Confidentiality:** The survey is anonymous. All information collected from you will be kept secure and in strict confidence. Only the researchers named above will have access to the data, which will be stored securely. Participants will not be identified individually in any reports or analyses resulting from this study.

**Participation and Withdrawal:** Your participation in this study is voluntary. If you decide to be part of the study, consequences to you and none of your survey responses will be collected or stored. You will not be eligible for compensation, if you decide to withdraw.

**Information about the Study Results:** We expect to have this study completed by approximately summer 2018. The results of the study will be posted on the MacSphere website (McMaster University Libraries Institutional Repository): https://macsphere.mcmaster.ca/

**Questions about the Study:** If you have questions or need more information about the study itself, please contact me at:

*E-mail:*eslamisp@mcmaster.ca
*Or*
*Telephone:* (905) 525-9140 ext. 26385

This study has been reviewed by the McMaster University Research Ethics Board and received ethics clearance.

If you have concerns or questions about your rights as a participant or about the way the study is conducted, please contact:

McMaster Research Ethics Secretariat
Telephone: (905) 525-9140 ext. 23142
C/o Research Office for Administrative Development and Support
E-mail: ethicsoffice@mcmaster.ca

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**CONSENT**

I understand the information provided for the study “Data Analytics Tool’s Recommendation” as described herein. My questions have been answered to my satisfaction, and by clicking on the “Yes” button below, I agree to participate in this study. I understand that if I agree to participate in this study, I may withdraw from the study at any time.

Yes "I agree to participate."

No "I do not agree to participate."

# APPENDIX C- Instructions

**A Study about Data Analytics Tools' Use in Organizations**

**Student Investigator:**
Seyed Pouyan Eslami
Department of Business
McMaster University
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**(905) 525-9140 ext.26385**
E-mail: eslamisp@mcmaster.ca

**Faculty Supervisor:**
Dr. Khaled Hassanein
Department of Business
McMaster University
Hamilton, Ontario, Canada
**(905) 525-9140 ext. 23956**
E-mail: hassank@mcmaster.ca

**Purpose of the Study:** We are conducting this study as a part of a Ph.D. dissertation that aims to find out how Data Analytics Users react to Data Analytic tools' recommendations. This research will result in guidelines for data analytics use within organizations.

Data Analytics (DA) is the process of examining large data sets in order to uncover patterns, associations, and other useful information to help organizations make more informed business decisions.

In this study you will be asked to complete an online questionnaire. To answer these questions, please reflect back to a recent decision you made at work for which you used a data analytics tool or asked someone else to complete such an analysis for you. Moreover, you will also be asked to fill out a set of open-ended questions regarding your recent experience in dealing with such a data analytics tool's recommendation.

Next

# APPENDIX D- Debriefing letter

**Data Analytics Tools' Use in Organizations**


**Student Investigator:**
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**Faculty Supervisor:**
Dr. Khaled Hassanein
Department of Business
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Hamilton, Ontario, Canada
**(905) 525-9140 ext. 23956**
E-mail: hassank@mcmaster.ca


Thank you for taking this survey. Your time and effort are much appreciated. Your answers are a valuable part of this research.

This study seeks to investigate the factors that influence a data analytics user's concordance with and action on a DA tool's recommendations. Current trends indicate that many organizations are making significant investments in Data Analytics tools to leverage big data. However, recent studies also indicate that a large percentage of these investments are unsuccessful and that a majority of data analytics users do not act upon data analytics tools' recommendations. This research seeks to explain the factors that influence users' action on the recommendations of DA tools within organizations including (i) recommendation characteristics; (ii) user characteristics; and (iii) organizational characteristics.

Please note that "This survey is anonymous. All information collected from you will be kept secure and in strict confidence. Only the researchers named above will have access to the data, which will be stored securely. Participants will not be identified individually in any reports or analyses resulting from this study". In addition, please also note that your participation in this study is completely anonymous as no identifiable information has been collected.

If you have any questions or concerns about this study, its purpose or procedures, please feel free to contact the researchers, Seyed Pouyan Eslami (eslamisp@mcmaster.ca) and/or Dr. Khaled Hassanein (hassank@mcmaster.ca).

**THANK YOU AGAIN FOR YOUR PARTICIPATION.**

**POST-DEBRIEFING CONSENT**

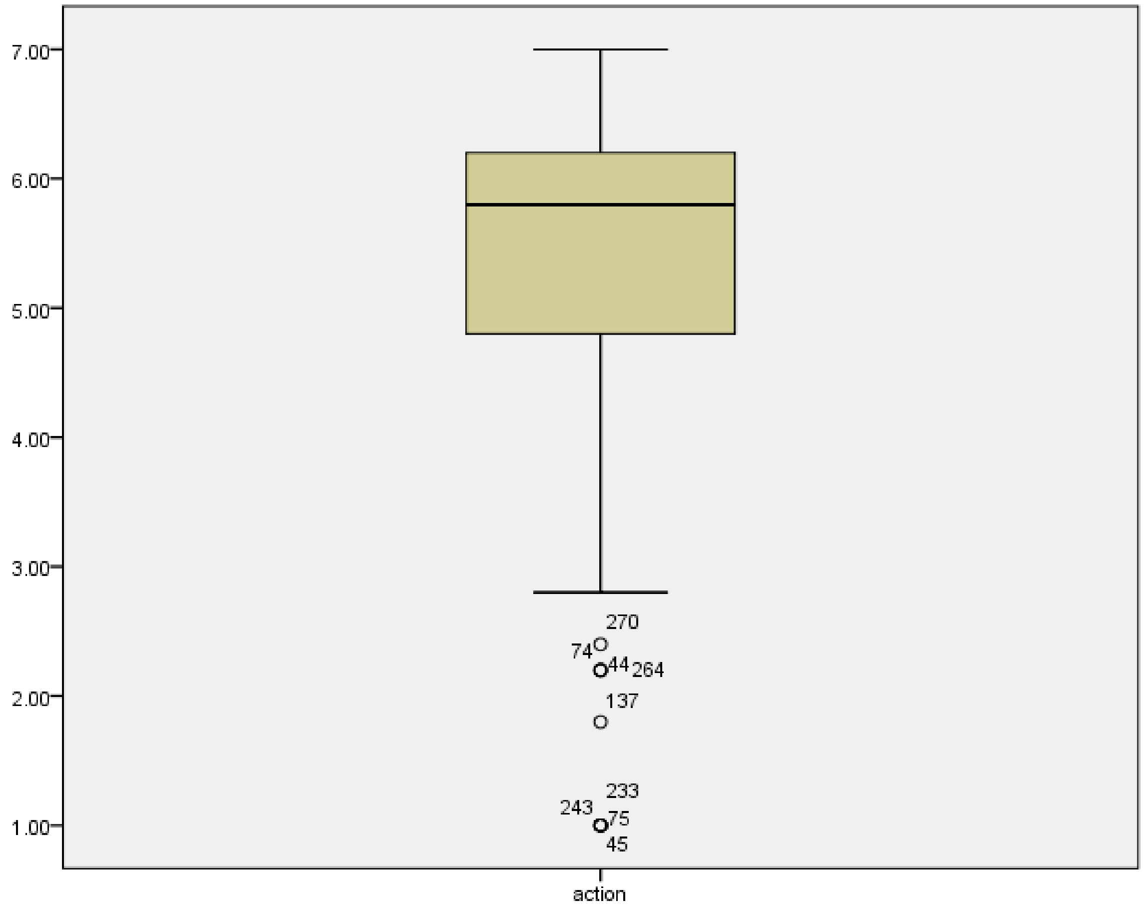
I have been debriefed about the research project entitled “Data Analytics Tools’ Use in Organizations” and I have had an opportunity to read the debriefing information provided. I agree to allow the data collected during my participation in this research project to be used, understanding that I am doing so voluntarily and that confidentiality and anonymity will be maintained.

Yes "I DO want my data to be included in this study."

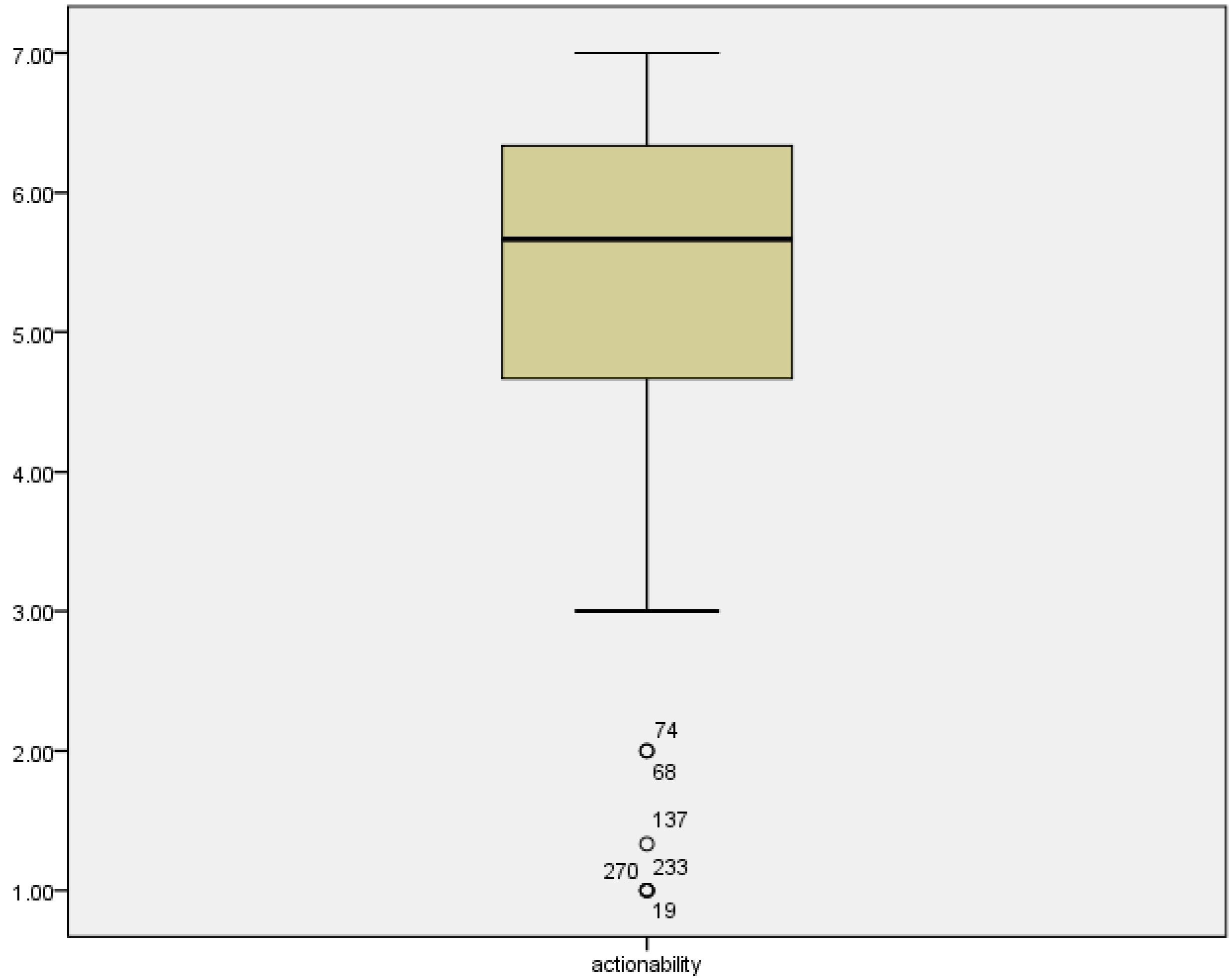
No "I DO NOT want my data to be included in this study."

## APPENDIX E- Outliers

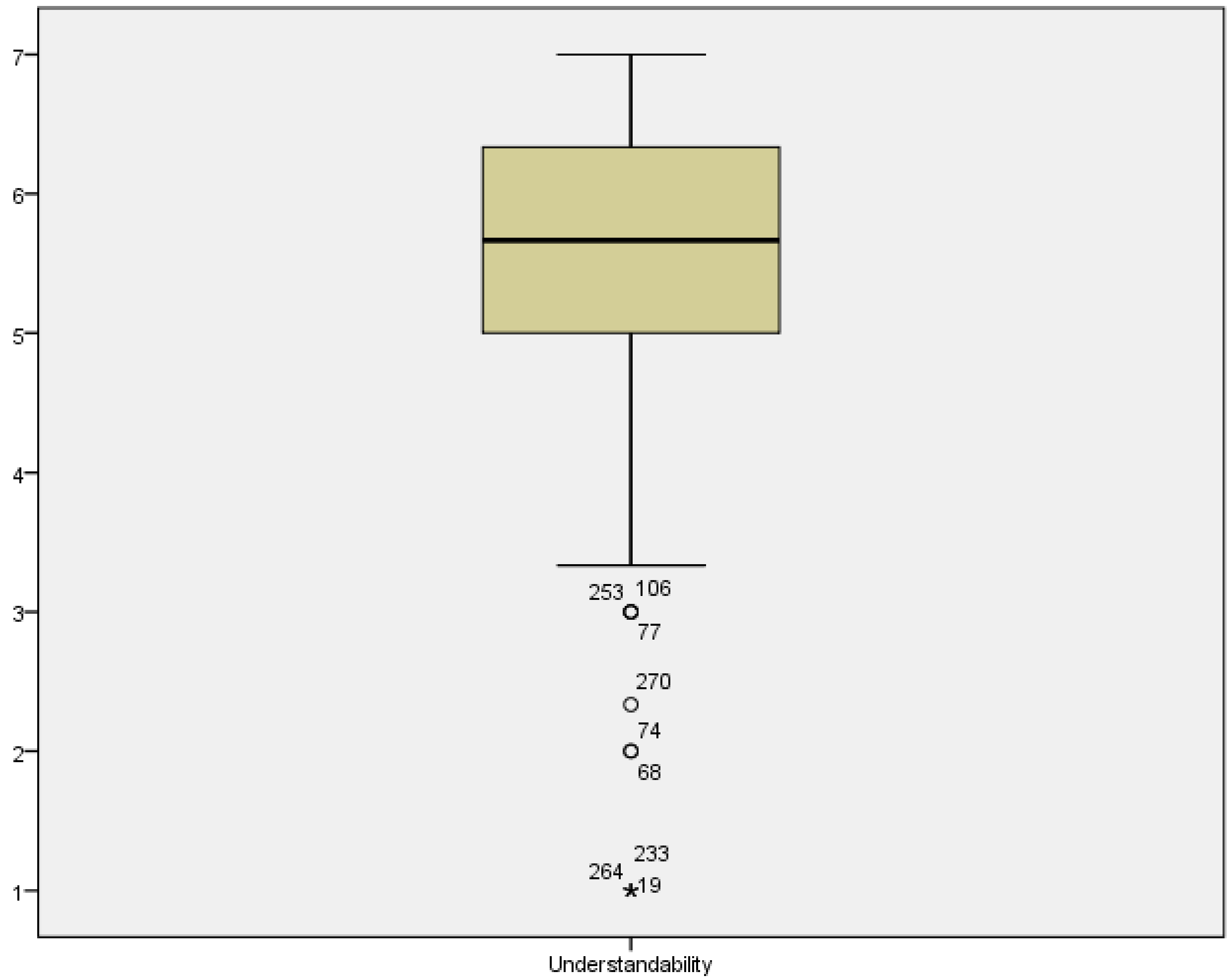
Acting On DA Tool's Recommendation



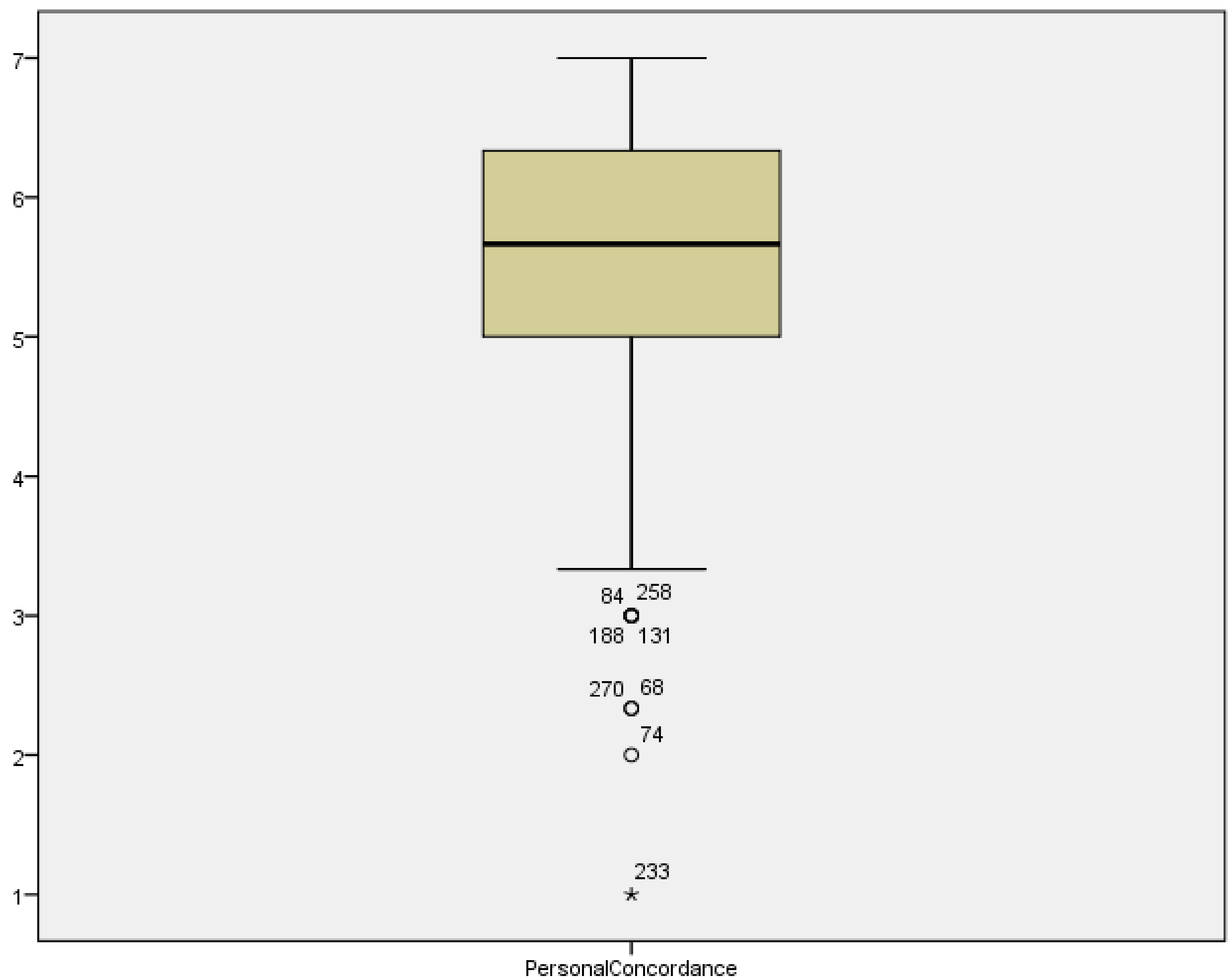
Actionability



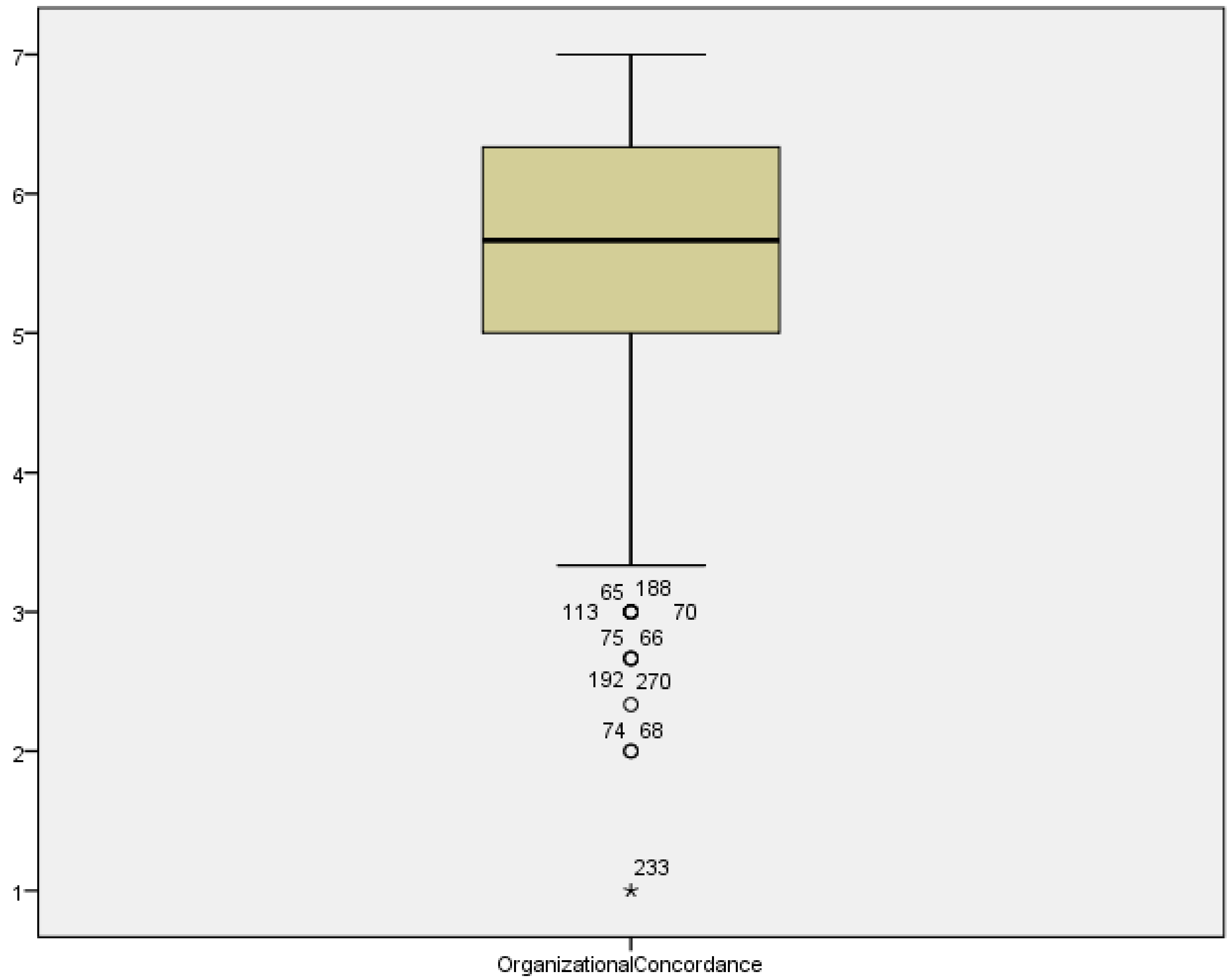
Recommendation Understandability



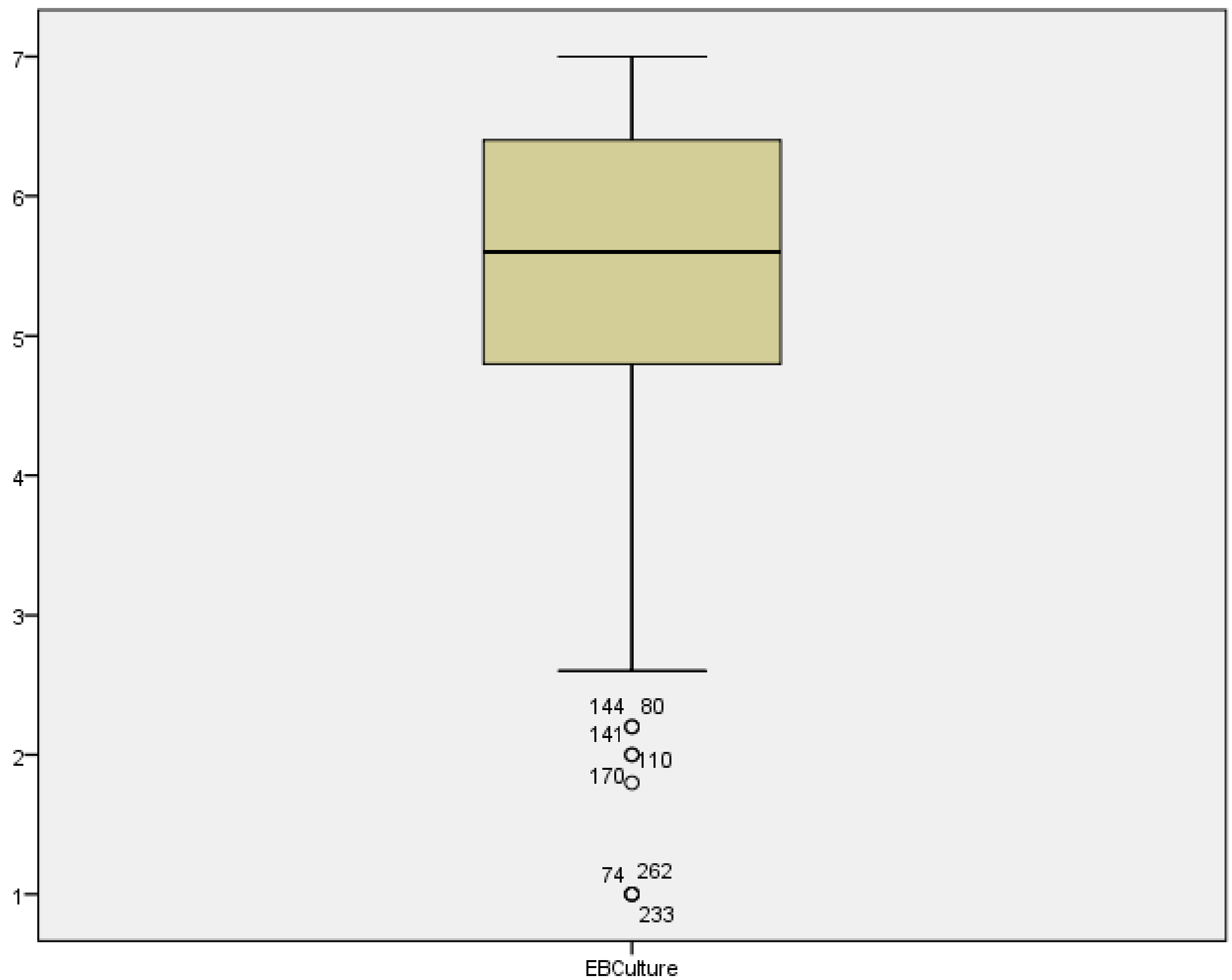
Personal Concordance



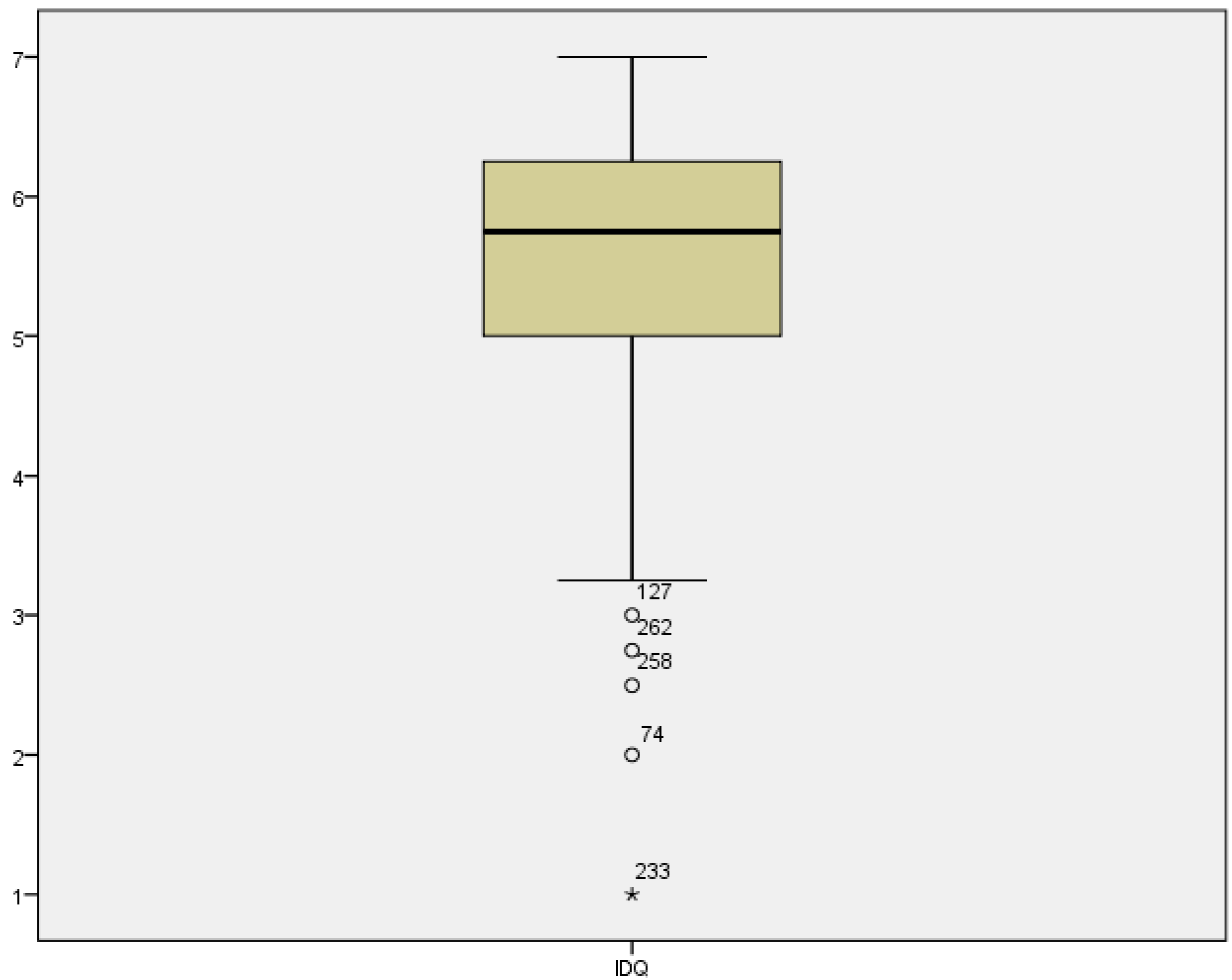
Organizational Concordance



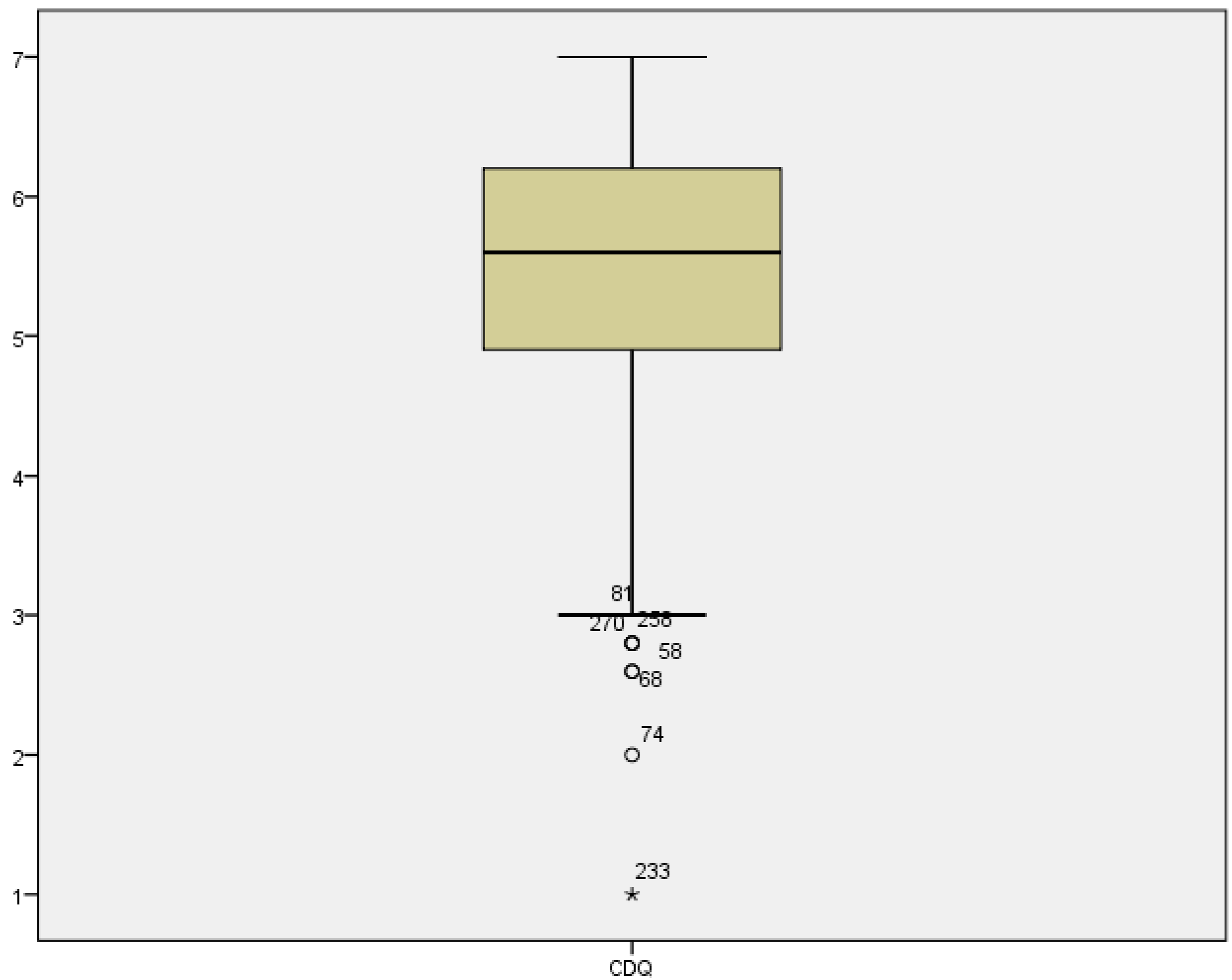
Evidence-Based Culture



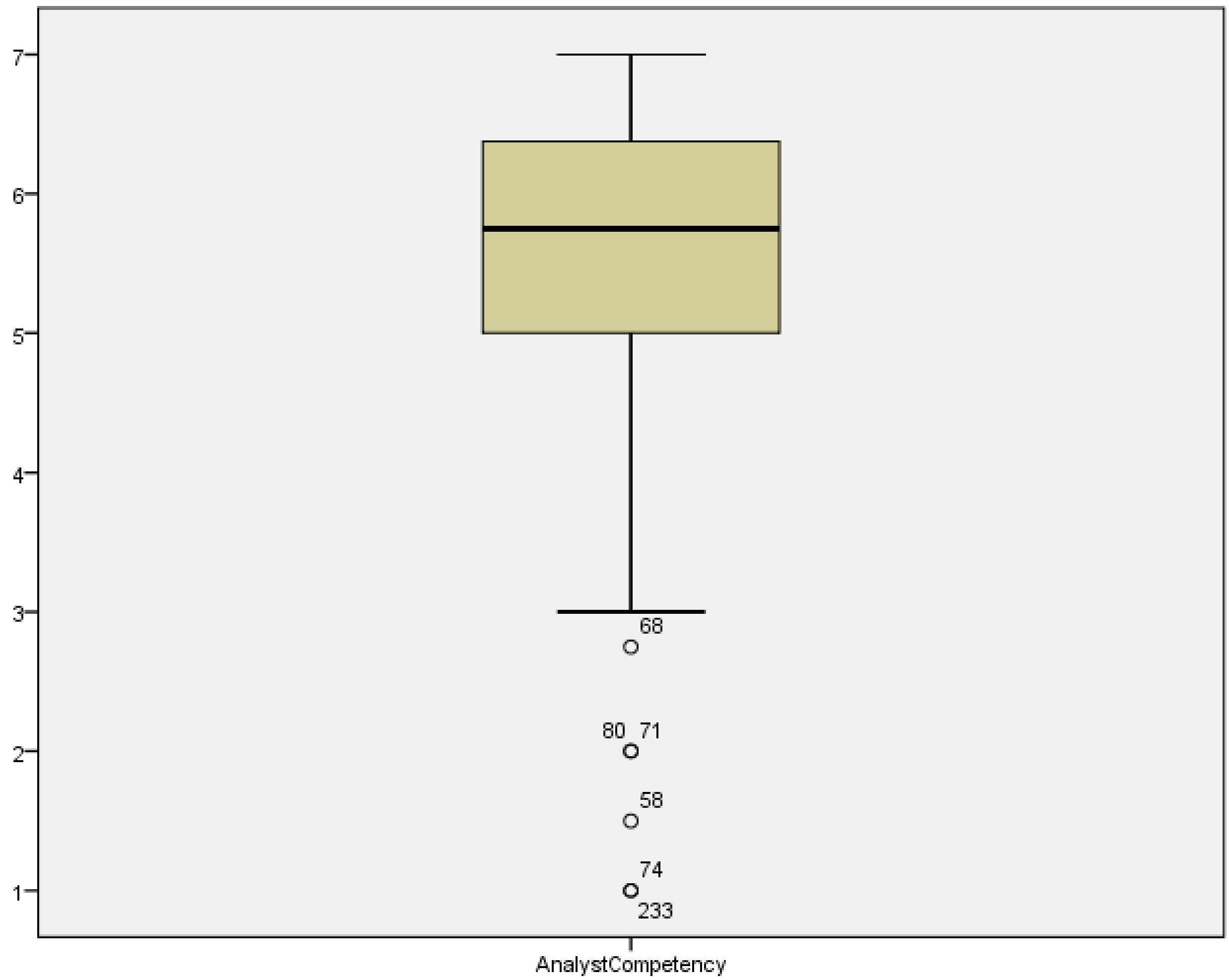
Intrinsic Data Quality



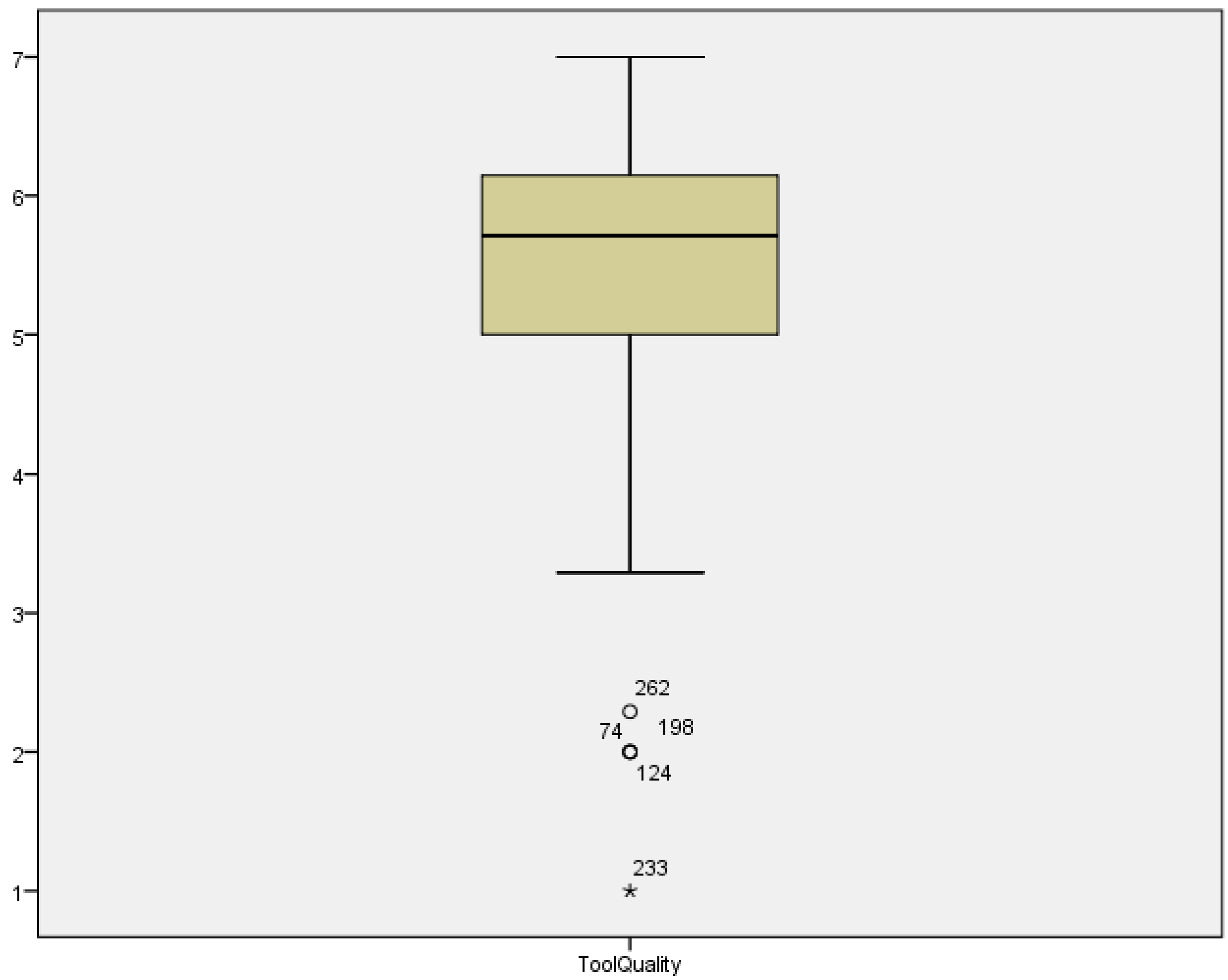
Contextual Data Quality



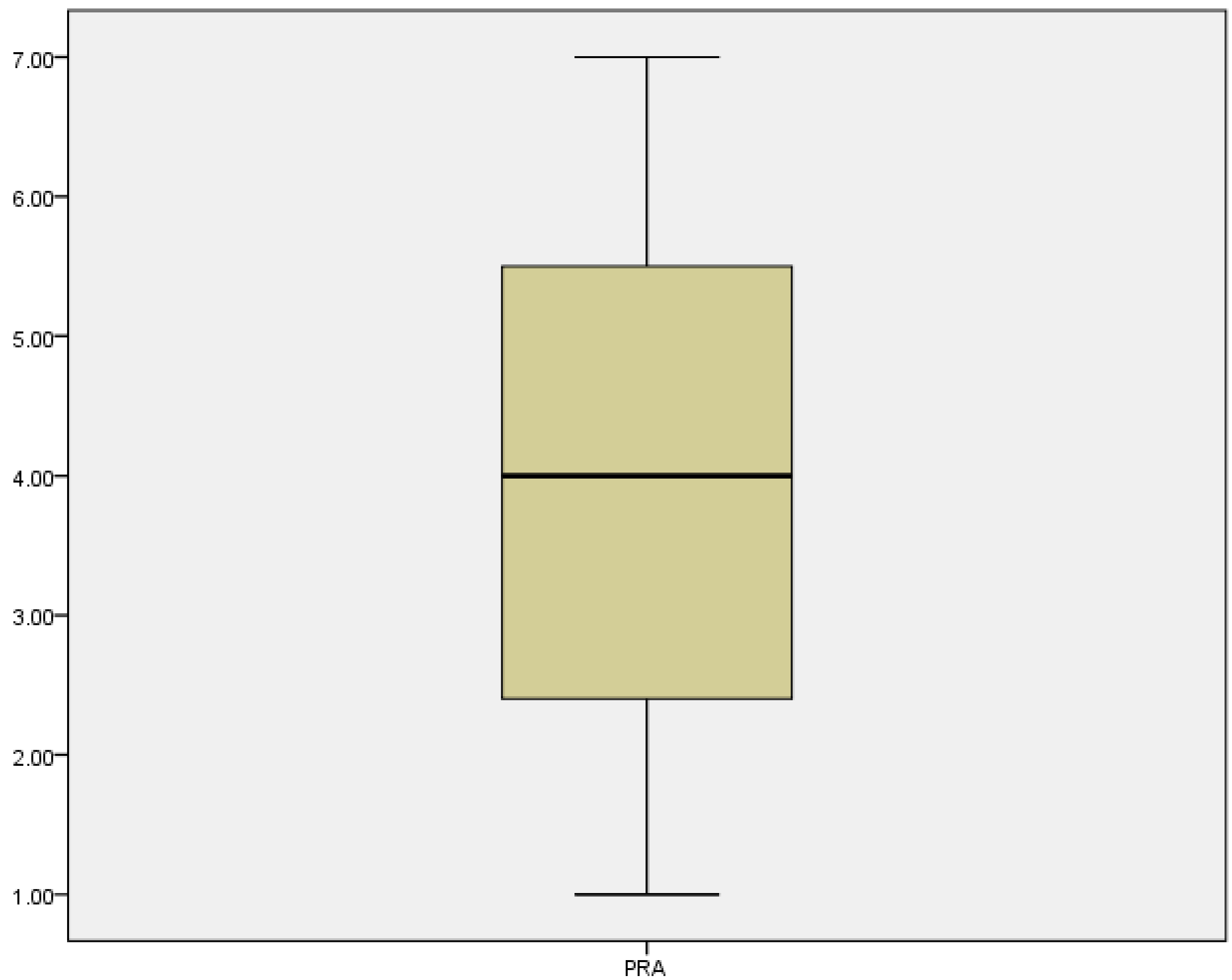
Analyst Competency



DA Tool Quality



Perceived Risk of Action



Recommendation Quality