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Increasing firm agility through the use of data analytics: The role of fit

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ABSTRACT

Agility, which refers to a dynamic capability within firms to identify and effectively respond to threats and opportunities with speed, is considered as a main business imperative in modern business environments. While there is some evidence that information technology (IT) capabilities can help organizations to be more agile, studies have reported mixed findings regarding such effects. In this study, we identify the conditions under which IT capabilities translate into agility gains. We focus on a specific and critical IT capability, the use of data analytics, which is often leveraged by firms to improve decision making and achieve agility gains. We leverage dynamic capability theory to understand the influence of data analytics use as a lower-order dynamic capability on firm agility as a higher-order dynamic capability. We also draw on the fit perspective to suggest that this impact will only accrue if there is a high degree of fit between several elements that are closely related to the use of data analytics tools within firms including the tools themselves, the users, the firm tasks, and the data. The proposed research model is empirically validated using survey data from 215 senior IT professionals confirming the importance of high levels of fit between data analytics tools and key related elements. The findings provide the understanding of the impacts of data analytics use on firm agility, while also providing guidance to managers on how they could better leverage the use of such technologies. These findings could be more broadly used to inform the effective use of other forms of IT in organizations.

1. Introduction

Agility, which captures a firm's ability to identify and effectively respond to threats and opportunities with speed, is considered as a critical firm dynamic capability in modern business environments [61]. Agile organizations are better positioned to grow their revenue, and extract higher profit margins [16]. Organizations develop agility as a higher-order dynamic capability through the development of appropriate work routines and leveraging lower-order dynamic capabilities (e.g. information technology use) that allow them to enhance, align, and reconfigure their substantive (ordinary) capabilities [66].

Information Technology (IT) use is one key way for firms to enhance their agility [45]. For instance, the use of data analytics tools can help firms to sense changes in the market and through this, improve their response speed and efficacy; i.e., increase their agility [58]. There are mixed findings in the literature regarding the impacts of IT on firm agility [45]. For example, while Tallon [65] and Lu & Ramamurthy [47] found that IT capabilities increase firm agility, Liu et al. [45] and Swafford et al. [64] found that IT capabilities do not increase firm agility. Hence, there may be moderating factors that can explain this inconsistency. Theorizing on and detecting such factors that help IT capabilities translate into firm agility is needed since it has important theoretical and practical implications, on which we elaborate later.

We specifically focus on exploring the impact of data analytics use, an increasingly critical firm IT capability, on firm agility. The use of data analytics refers to the extent and frequency of utilizing such tools. The use of data analytics has become imperative in many organizations; it is a key tool in modern competitive environments [7,14,78]. The importance of these tools stems from their ability to help organizations make better, more informed and often faster decisions (i.e. be more agile) [9,49]. These benefits accrue because firms that appropriately use data analytics have the ability to sense and respond to market changes effectively and efficiently [74]. However, not all companies investing in data analytics increase their agility from their investments in these tools [15]. In a recent report, only 25% of firms reported that the use of analytics has “significantly” improved their organization's outcomes (Deloitte [19]). Hence, it is worthwhile asking what makes some investments in data analytics more fruitful than others. Illuminating the mechanisms that help in mobilizing such large investments to produce gains in firm agility can inform theory and guide business actions.

Given the growth in the use of data analytics and the mixed outcomes it has produced, the main objective of this paper is to understand under which conditions the use of these IT tools would increase firm

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agility. To this end, we rely on Dynamic Capability Theory (DCT) [67] combined with the fit perspective [41]. This synergetic combination, as we argue and show, can shed light on why certain organizations are more agile than others due to the use of data analytics. Particularly, we use DCT to investigate the impact of data analytics use (a lower-order dynamic capability) on firm agility (a higher-order dynamic capability). This is consistent with the prevalent view that IT capabilities are lower-order dynamic capabilities that enable the development of higher-order dynamic capabilities, such as agility [5,45]. In trying to understand why firm IT capabilities do not always increase firm agility, we turn to the fit perspective. According to this perspective, the fit between people and elements of the environment improves organizational outcomes [41]. In the IS literature, the fit perspective is represented by the prominent Task Technology Fit (TTF) theory [31]. Although this theory considers the task-technology and the people-technology fit aspects, most IS research has only considered the task-technology fit aspect (e.g., [46,76]). In this research we return to the original spirit of the TTF theory to include both types of fit and further extend it to also include a third type of fit that we deem particularly important in the case of data analytics - namely the fit between the data analytics tools and the data. Thus, we consider the fit between data analytics tools and: (i) the type/s of "data" to be analyzed through these tools; (ii) the "tasks" that are to be carried out based on the data; and (iii) the "employees" who execute these tasks by using the analytics tools. As the main focus of this article is on the impact of IT capability (here data analytics use) on agility, we focus on the pair-wise fit levels between data analytics tools and each of these three relevant organizational resources.

Towards the above objectives and leveraging the above theories, we propose and empirically validate a research model using survey data collected from 215 senior IT professionals. The findings show that the high levels of fit between data analytics tools, people, tasks, and data is the glue that enables them to work in tandem, and ultimately yield agility gains through the use of data analytics tools. These findings show that not all data analytics initiatives are created equal, and that not all of them will be similarly beneficial. The benefits they provide, we argue and demonstrate, will depend on their fit to relevant elements on the organization.

2. Background and theory

This section provides a review of the literature pertaining to the DCT as well as firm agility and data analytics use. Then the fit perspective is discussed; together with DCT it provides the theoretical basis for our research model.

2.1. Dynamic capability theory

The DCT arises from a resource-based view (RBV) of the firm that argues that firms have specific resources [67]. Resources are "stocks of available factors that are owned or controlled by the firm"([2], p. 35). These can be tangible assets, such as capital, equipment, technology, and/or facilities [39]. They can also be intangible assets, such experiences of employees [70]. Not all resources are equally important for firms. Firm resources that are difficult to imitate, rare, and valuable enable a firm to become more competitive [67]. In the IS literature, the RBV has been used to explain how organizations create value from IT resources (e.g., assets and skills) [13,34,79,80].

Teece et al. [67] argue that a firms' competitive advantage is dependent on their dynamic capabilities. In this theory, the term "dynamic" reflects "the capacity to renew competences so as to achieve congruence with the changing environment" (p. 515). In the context of this study, DCT provides a framework for analyzing whether firm IT capabilities (data analytics use in our case) could be leveraged to increase a firm's agility. Given the growth in the use of data analytics and the mixed outcomes it has produced, this paper focuses on this particular capability, as an instance of IT capabilities. According to Chen et al. [14], DCT is an appropriate lens to understand the impact of data analytics use in firms. Many firms have invested in data analytics but have not still successfully produced positive outcomes [15]. Hence, the moderating mechanisms that govern the translation of firm data analytics use into agility remain unclear.

2.2. Agility as a firm dynamic capability

Agility has emerged as a critical firm capability in today's hypercompetitive business environment [36,58]. It refers to the firm's ability to sense and quickly respond to changes in the environment which often involves reconfiguring firm resources [58].

Dynamic capabilities are different from substantive capabilities (e.g., operational routines) [25] in that dynamic capabilities describe how firms reconfigure and integrate their resources to respond to environmental changes [5]. As such, dynamic capabilities help firms to sense and respond to opportunities they may have or threats they may face [66]. Since agility embodies these aspects, and is used for creating and changing other capabilities, it is considered as a dynamic capability [58].

Grant [32] and more recently Ayabakan et al. [5] describe a hierarchical structure of capabilities within firms where lower-order capabilities lead to higher-order ones. Higher-order capabilities create firm differential advantage because they are truly valuable, and rare. From that perspective, it is argued that organizations develop agility as a higher-order dynamic capability through the development of their work routines and leveraging lower-order dynamic capabilities (e.g. information technology use) that allow them to align, enhance, and reconfigure other capabilities and resources [66].

2.3. Data analytics usage as a firm dynamic capability

In this study, data analytics use refers to the extent and frequency of employing such tools within organizations. Data analytics refer to information technologies and processes that support reporting, statistical analyses and data mining [14]. These tools have three main categories: descriptive (i.e., understanding what happened in the past), predictive (i.e., understanding what will happen in the future), and prescriptive (i.e., used to simulate outcomes of possible actions) [18,78]. Data analytics use has become a critical IT capability for firms in recent times with the advent of "Big Data" (i.e., data that is high in volume, velocity and variety) [5,15,35] and the growing need for better, more informed and faster decisions [7,37,81].

Analyzing data in a timely manner enables firms to gain insights from their environments and to better sense changes in their markets [1,58,78]. Firms that are able to collect data that is high in terms of volume, variety, and velocity, and effectively apply powerful analytical tools to such data are in a better position to make complex decisions in a more timely manner (i.e. are more agile) [10,14,29]. Thus, data analytics use could be viewed as a lower order dynamic capability that is critical to achieving firm agility (a higher-order firm capability) [14,45].

2.4. The fit perspective

The notion of fit emerged from contingency theory, which argues that organizational outcomes (e.g. agility, competitiveness, etc.) are the consequences of the level of fit between two or more factors (e.g. employee skill sets, information technology resources, etc.) [31]. Consequently, organizational studies that are grounded in fit theory have considered the extent to which "the congruence between two conceptually distinct constructs" [24] impacts the outcomes for individuals or firms [40].

Venkatraman [72] conceptualized fit in six ways: as *mediation*, as *gestalts*, as *moderation*, as *matching* as *co-variation*, and as *profile deviation*. In the matching perspective, fit refers to the match between two relevant factors [72]. Given the nature of the current study (e.g., focusing on the match between the tools and the data), fit as matching was deemed to be the most suitable perspective for capturing the fit between analytical tools and key firm relevant elements (i.e., tasks, data, people). An example of measuring fit from a fit as matching perspective can be found in the TTF line of research. TTF is defined as the extent to which the capabilities of a technology matches: (i) the abilities of the individual who performing a task using that technology; and (ii) the task itself [31,68].

In this study, as explained earlier, we extend the traditional focus of the IS literature on task-technology fit and focus on the pair-wise facets of fit between three types of resources, all of which are presumed to be highly relevant for the ability of data analytics use to generate agility gains: Task-Technology (T-T) fit, Person-Technology (P-T) fit, and Data-Technology (D-T) fit (technology refers to data analytics tools).

T-T fit has been a common focus in IS research (e.g., [43,46,76]) where a single construct (TTF) directly measures the fit between the technological tools and the requirements of the tasks that individuals have to perform [6]. Although many studies have used TTF (e.g., [30, 77]), the widespread investments in the use of data analytics increases the urgency for IT researchers to develop a deeper and broader understanding of the fit of the technologies to other relevant elements, beyond task. From a practical perspective, until we better understand the phenomenon of fit and ensure its presence when using new IT, achieving organizational benefits from the use of such systems (e.g., data analytics) is likely to continue to be difficult and unpredictable [62]. From a theoretical perspective, our argument is that the concept of fit and its critical role are underspecified in the data analytics literature. Our research addresses this critical gap by developing an expanded theoretical understanding of fit, including the fit between data analytics tools with key related firm elements (i.e., data, people, tasks) which is then leveraged to understand under what circumstances data analytics use will translate into agility gains.

Studies using the fit perspective and its narrow TTF conceptualization have shown that the extent to which technological tools employed by firms are aligned with organizational tasks can improve organizational outcomes [40]. This fit facet can be relevant to data analytics as well, since data analytics tools that are not amenable to required organizational tasks (e.g., projecting changes in demand, finding new market segments) will require user time and effort to adapt to the task at hand, may produce suboptimal task outcomes, and some users may even bypass such less fitting data analytics solutions in order to avoid the hassle and still deliver on the task (e.g., they may use a panel of salespeople rather than the system to project demand in a new market). Hence, when T-T fit is low, it may slow users down, lead to suboptimal decisions, system use can be time consuming and frustrating, and lead users to find ways to tweak the system or deal with the task without the system [38].

The fit perspective as well as the original TTF conceptualization also presumes that there should be fit between technology characteristics, and individual abilities, which considers the match between the preferences and the abilities of employees and the technological tools given to them [52]. When users have no proper training regarding the use of the analytics tools allocated to them or just dread their use (e.g., when they have low self-efficacy or get stressed about their use), it will take them longer to execute needed analyses, they may postpone or avoid conducting needed analyses, and may commit mistakes in carrying out the task.

Although TTF has been used in many previous studies, we argue that its use has been limited in three ways. First, its use has focused on direct effects of fit on firm outcomes (e.g., [43,46,76]). As such, it does not consider the possibility that fit can moderate the effect of firm capabilities on firm outcomes, beyond its direct effect. Assessing the moderating impact of fit on the influence of an IT capability on firm outcomes is important because previous studies have reported mixed findings regarding the effects of IT capabilities (here data analytics use) on firm outcomes (here agility); the levels of fit among IT and key related elements may explain this inconsistency. Second, the common practice in IS research is to employ TTF theory by focusing only on T-T fit when other dimensions of fit may be relevant. Given the context of this study, we include the people-technology perspective originally introduced in Goodhue & Thompson [31] but not mostly utilized in the IS literature and we further expand the TTF perspective to add “D-T fit” as another fit dimension. This fit dimension stems from the notion that not all data analytics tools can equally cater to all types and sources of data; and with the growing breadth of data types and sources in organizations this fit dimension may also matter. It specifically considers the congruence between the data analytics tools and the data they should process. This fit facet is deemed to be important since a tool may or may not be able to support a quick and accurate analysis of data with certain properties or structures. For instance, even when TTF facets are high in the context of predictive modeling (e.g., people are trained well in the use of the technology, and the technology has all the relevant algorithms built in), when a tool cannot easily access or process relevant data (e.g., when it is stored in a format it cannot easily read), the analysis will be time consuming and in some cases infeasible or inaccurate, which may affect task performance and the gains obtained from using the tool. We hence argue that the fit between different analytical tools and the data fed to them can too play a critical role in improving organizational outcomes from the use of data analytics. Finally, TTF focuses on a single scale to measure the fit between technology and relevant firm elements. Thus, in this study, we consider T-T fit, P-T fit, and D-T fit as separate constructs to explore the moderating impact of each on the main relation in our research model.

3. Research model and hypotheses

According to DCT, in order to be more agile, firms need to improve their capabilities to address changes in their environment [45]. The research model in Fig. 1 integrates the DCT with the Fit perspective discussed above to explain how the use of data analytics could lead to firm agility.

The definitions of the constructs in the model, which are all at the organizational level, are shown in Table 1. Next, the hypotheses with appropriate support are developed.

Organizational agility is often conceptualized as being comprised of two facets: operational adjustment agility, and market capitalizing agility [47]. As defined in Table 1, *Operational adjustment agility* focuses on internal processes and the extent to which they can be quickly be adapted to changes in an organization's external environment (Sambamurthy et al. [60]. *Market capitalizing agility*, refers to a dynamic entrepreneurial mindset in setting strategic direction, and decision making under uncertainty (Sambamurthy et al. [60]. Both facets of agility focus on a continuous change; market capitalizing agility emphasizes on entrepreneurial mindset, while operational agility focuses on speedy implementation [47].

Data analytics use could enhance firm agility because it can help organizations to better and more quickly understand their markets, make timely business decisions and rapidly leverage opportunities by effectively analyzing data [15]. For example, real-time access to global information helps firms to collect, analyze, and disseminate information relating to changes in competitors' actions, customer needs, and technology developments [47]. More specifically, the use of data analytics which caters to decision making speed and quality can increase market capitalizing agility because it increases a firm's ability to respond to changes by improving services/products to address changing consumers' needs in a timely fashion. Moreover, the use of data analytics can increase operational adjustment agility because it can help with the optimization and calibration of business processes within organizations allowing them to enhance their ability to quickly respond to changes in their environment in the right way, using optimal decisions, and at lower costs relative to their competitors.

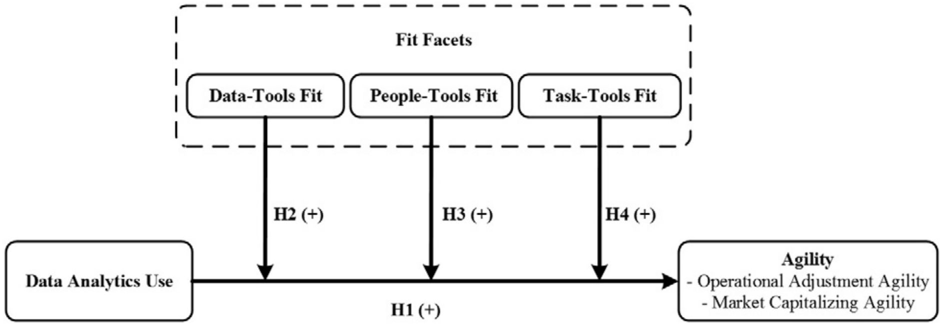

Fig. 1. Research model.

Based on the DCT, the use of data analytics can be viewed as a firm information processing capability that enhances their decision making abilities especially under uncertainty (Chen et al., [14]). This is consistent with IT business value research, according to which firm agility is a higher-order capability that stems from a combination of lower-order capabilities [33,75]. Accordingly, studies increasingly consider IT capabilities (e.g., data analytics use) as lower-order capabilities that enable higher-order capabilities at the organizational level, such as agility [5,60]. Synthesizing these views, data analytics use can enable firms to quickly sense and interpret business challenges and opportunities, and hence help firms respond faster and become more agile. Hence,

H1. Data analytics use will increase firm agility.

According to the fit perspective, we argue that in order for data analytics use effects to accrue, there should be a good match between these tools and other key related elements including data, tasks, and employees. In this study, the matching perspective of fit has been applied which, as discussed earlier, conceptualizes fit as a theoretically defined match between two relevant organizational factors [72]. Thus, in our context, the stronger the match between data analytics tools and key relevant firm elements, the higher the chances that the use of such tools will result in firm agility. Hence, at higher levels of fit between data analytics tools, tasks, people, and data, firms are more likely to respond to threats and opportunities in a more timely manner (i.e., become more agile) through the use of data analytics. Each fit facet can contribute to strengthening or weakening the effect of using data analytics on agility as explained in more detail below.

3.1. Data-tools fit

Modern technologies can produce various types of data in different formats [61]. Recently, there have been great improvements in the tools available to handle such data [49]. However, there is a complex relationship between analytical tools and data [55]. Data analytics tools should be able to fulfill the data analyses needs of users by making it easy to retrieve relevant data and execute the needed analyses. In this regard the choice of the right analytics tools for the type of data at hand is important in enabling firms to take advantage of the different types of data available to them [82]. For example, data analytics tools that are geared towards analyzing structured data may not be suited for analyzing unstructured data. Along these lines and according to the D-T fit perspective, high levels of fit along this dimension allow the organization to analyze all relevant data relatively quickly and effectively. In so doing, they are able to obtain faster, more precise and data-informed decisions related to both improving services/products and optimization of business processes which makes them more agile through the use of data analytics. In contrast, when this fit facet is low it may take analysts more time to find a way to analyze the target data and in many cases they may simply postpone or avoid this task. In other words, they will invest more time in forcing the system to work with less fitting data or avoid making decisions, rather than quickly running the needed analyses. All of these conditions would lead to less agility due to the use of data analytics than would be possible with a higher D-T fit. Hence,

H2. The fit between data analytic tools and data moderates the effect of data analytics use on firm agility, such that the effect is stronger with higher levels of fit.

3.2. People-tools fit

Based on the fit perspective, there should be a good fit between individuals' competencies and their job requirements [23]. When employees have the required skills to fulfill their job tasks (including the use of analytical tools), they are more likely to perform at a higher level and the results of their work are improved [6,83]. The P-T fit perspective builds on this notion and argues that there should be a good fit between the abilities of the users of technology and the technologies they use. High fit of the employees with the technology would decrease

Table 1
Construct definitions.

Construct	Definition
Fit	"[T]he congruence, match, agreement, or similarity between two conceptually distinct constructs" ([24], p. 51). In our context we focus on the extent of congruence between data analytics tools and other relevant organizational elements (people, data, tasks).
Data analytics use	The use of "new generation of technologies and architectures, designed to economically extract value from very large volumes of a wide variety of data by enabling high-velocity capture, discovery, and/or analysis [of such data]" ([26], p. 9).
Agility	The speed and ease with which organizations can respond to threats and opportunities in the business environment [65]. In this study we treat organizational agility as combination of operational adjustment agility, and market capitalizing agility representing inward and outward agility dimensions respectively: (i) Operational adjustment agility is defined as "the ability of firms' business processes to accomplish speed, accuracy, and cost economy in the exploitation of opportunities for innovation and competitive action." ([60], p. 245). (ii) Market capitalizing agility is defined as a "firm's ability to quickly respond to and capitalize on changes through continuously monitoring and quickly improving product/service to address customers' needs" ([47], p. 933).

the gap between their abilities/values and the environmental demands [6]. Such a fit would allow employees to take full advantage of data analytics tools to enhance their understanding of the changing market and customer demands as well as the performance of their internal business process in relation to the same. This enhanced understanding is then reflected in their ability to respond to such changes better and faster (i.e. become more agile). In contrast, when this fit facet is low, employees may postpone or avoid the task with which they have difficulties, take longer time to execute it while learning "on the go", or even make errors while executing tasks resulting in wrong decisions or having to repeat tasks. All of these conditions would lead to less agility due to the use of data analytics than would be possible with a higher P-T fit. Hence,

H3. The fit between data analytic tools and people capabilities moderates the effect of data analytics use on firm agility, such that the effect is stronger with higher levels of fit.

3.3. Tasks-tools fit

As per the fit perspective, there should be a good match between a firm's task requirements and the mechanisms used to support the execution of such tasks [50]. In the context of this study, firm tasks being undertaken should match the analytical mechanism afforded by the technology [52]. This enhances the firm's ability to act faster and improve firm outcomes [27]. This is the case since the right IT can provide the information required for completing organizational tasks (both firm internal processes and product/services improvement) faster, and assist users with making faster and better decisions [40,69]; this should result in improved agility. For instance, a data analytics tool that can run a needed classification model or produce a needed report with a few clicks can contribute to agility more than a tool that requires months of programming for doing the same tasks. As such, when this fit facet is low, employees may waste time trying to execute a task using data analytics that are inappropriate for that task or may even get the wrong results resulting in wrong decisions or having to repeat tasks. All of these conditions would lead to less agility due to the use of data analytics than would be possible with a higher T-T fit. Hence,

H4. The fit between data analytic tools and tasks moderates the effect of data analytics use on firm agility, such that the effect is stronger with higher levels of fit.

4. Methodology

The hypothesized associations were tested using a survey of the most senior IT professionals in organizations of different sizes and industries. Our participants had titles such as *Chief Information Officer*, *Chief Technology Officer*, and *Vice President of IT*. This sampling choice was made since senior IT professionals' opinions should reasonably and meaningfully reflect the organizational-level business-related and technology-related constructs in our model [12].

4.1. Participants and incentives

A national market research firm administered the survey to senior IT professionals whose roles within firms were verified. Only senior IT professionals of firms that reported on using data analytics tools were allowed to take the survey. This data collection approach has been shown to be valid and reliable in IS research (e.g., [28,63]). Participants were incentivized by a chance to win 1 of the 5 monthly $1000 prizes that were awarded by the research firm. Using this approach, a total of 215 valid questionnaires was retained. The minimum sample size required to detect a medium effect size at a power of 0.80 and alpha of 0.05 would be 102 cases [59]. Thus, our sample satisfies the sample size requirements for the proposed research model.

Table 2
Descriptive statistics, correlation matrix, and AVEs of constructs.

	Mn	SD	AA	CA	DAU	DT	PT	TT
AA	4.29	1.21	**0.82**					
CA	4.32	1.23	0.70**	**0.79**				
DAU	3.42	1.23	0.17**	0.16**	**0.95**			
DT	4.14	1.24	0.57**	0.59**	0.31**	**0.83**		
PT	4.05	1.36	0.55**	0.58**	0.28**	0.78**	**0.90**	
TT	4.02	1.38	0.48**	0.59**	0.31**	0.70**	0.68**	**0.91**

Note: Mn: mean; SD: standard deviation.
D-T: Data-Tools fit; T-T: Tasks-Tools fit; P-T: People-Tools fit; DAU: Data Analytics Use; AA: Adjustment Agility; CA: Capitalizing Agility Note: All measures (except DAU) were based on seven-point Likert scales ranging from "strongly disagree" (1) to "strongly agree"(7). DAU was based on Likert scales ranging from "not much" to "very often".

4.2. Measures

The study adapted previously validated instruments; all items referred to the organization to which the respondents belonged (see items and sources in Appendix A). Perceived agility was measured as a second order formative construct considering both operational adjustment agility and market capitalizing agility as first order constructs using three-item reflective scales for each from Lu & Ramamurthy [47]. Perceived data-tools fit, people-tools fit, and tasks-tools fit were each measured using a three-item reflective scale from Vogel & Feldman [73]. Data analytics use was measured as a reflective construct using a two-item scale adapted from Venkatesh et al. [71].

Four potentially relevant control variables were included in the survey. First, we included firm size, operationalized with number of employees, because larger firms may have access to more resources [16]. Second, we accounted for the nature of data (data "bigness") because the nature of data an organization deals with can influence the ways organizations work with and derive value from data analytics. Third, we included firm industry because the need for agility may not be the same for firms in different industries. Finally, the type of the analytical tools used within firms was included because depending on the type of tools, the depth of analysis could vary in firms.

5. Data analysis and results

5.1. Sample

The sample consisted of 215 North American senior IT professionals representing firms that use data analytics to different degrees. The average age of participants was 44.2 years; and 141 (59%) of them were

Table 3
Loading and cross loading of measures.

	AA	CA	U	D-T	P-T	T-T
Adjustment Agility (AA1)	**0.894**	0.624	0.098	0.500	0.456	0.414
Adjustment Agility (AA2)	**0.926**	0.652	0.174	0.539	0.529	0.459
Adjustment Agility (AA3)	**0.897**	0.652	0.056	0.520	0.520	0.453
Capitalizing Agility (CA1)	0.676	**0.866**	0.049	0.584	0.569	0.487
Capitalizing Agility (CA2)	0.622	**0.904**	0.234	0.514	0.499	0.564
Capitalizing Agility (CA3)	0.594	**0.893**	0.155	0.482	0.491	0.528
Use 1 (U1)	0.141	0.173	**0.981**	0.318	0.294	0.325
Use 2 (U2)	0.092	0.151	**0.970**	0.299	0.258	0.286
Data-Tools Fit (D-T1)	0.542	0.567	0.395	**0.883**	0.737	0.675
Data-Tools Fit (D-T2)	0.465	0.520	0.269	**0.932**	0.740	0.650
Data-Tools Fit (D-T3)	0.556	0.530	0.200	**0.924**	0.717	0.614
People-Tools Fit (P-T1)	0.528	0.570	0.267	0.713	**0.944**	0.652
People-Tools Fit (P-T2)	0.545	0.575	0.240	0.714	**0.951**	0.651
People-Tools Fit (P-T3)	0.493	0.504	0.303	0.732	**0.938**	0.638
Task-Tools Fit (T-T1)	0.478	0.577	0.299	0.676	0.676	**0.945**
Task-Tools Fit (T-T2)	0.466	0.560	0.310	0.648	0.618	**0.956**
Task-Tools Fit (T-T3)	0.453	0.564	0.294	0.708	0.669	**0.965**

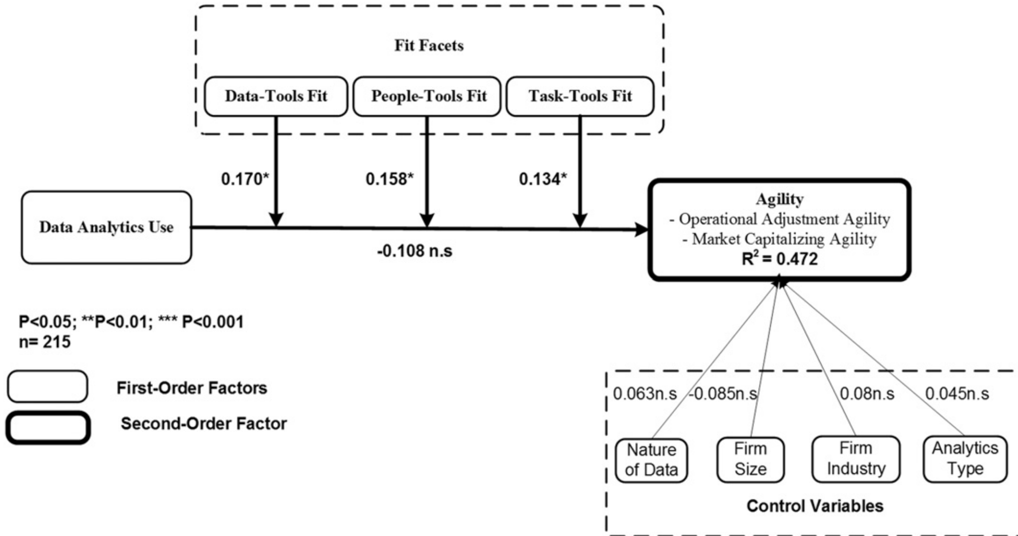

Fig. 2. Results of research model.

males. They worked in firms with different sizes including <50 employees (36%), 50–500 employees (19%) and >500 employees (45%). Regarding industry type, 23% of participants worked in manufacturing firms, 51% worked in services firms, 12% worked in financial firms, and 14% worked in utility firms. In these organizations, analytics use ranged from "not much" to "very often", with a median response of "quite often".

5.2. Measurement model

Construct validity and reliability were first assessed by generating descriptive statistics, the correlation matrix, and Average Variance Extracted (AVE) scores (see Table 2). In this table, the diagonal elements are the square roots of AVE scores and the off-diagonal numbers show the correlation between variables. All square roots of the AVE were larger than the correlation between that construct and any other construct. This supports discriminant validity [17]. All Cronbach alpha scores for reflective constructs and construct loadings exceeded the 0.7 threshold. As Table 3 shows, all indicators loaded most highly on their own theoretically assigned construct, and at a minimum threshold of 0.70. Gefen and Straub (2005) suggest that "loadings of the measurement items on their assigned latent variables should be an order of magnitude larger than any other loading" (p. 93) and the difference should be at least 0.10. As shown in Table 3, this criterion was also met.

Additional preliminary analyses were performed for assessing the validity of the second-order construct (i.e. agility), as well as the potential effects of common method bias. These analyses are described in Appendix B; they indicate that the second-order construct was valid and that there is a low chance of a common method variance component in our data. Hence, estimating the structural model was deemed appropriate.

5.3. Structural model

SmartPLS version 3.0 [57] with bootstrapping employing 500 resamples was used for assessing significance levels. Results are depicted in Fig. 2. Somewhat surprisingly, the results showed that the use of data analytics tools (at average levels of fit) does *not* significantly influence agility ($\beta = -0.108$; ns), not providing sufficient support to H1. However, the fit facets between analytical tools, data, people, and tasks were found to significantly moderate the relation between data analytics use and agility. The moderating effect of data-tools fit on the relation between data analytics use and agility was significant ($\beta = 0.170$; $p < 0.05$), supporting H2; the moderating effect of people-tools fit on the relation between data analytics use and agility was significant ($\beta = 0.158$; $p < 0.05$), supporting H3; and the moderating effect of tasks-tools fit on the relation between data analytics use and agility was also significant ($\beta = 0.134$; $p < 0.05$)[1], supporting H4[2]. Taken together, these results suggest that at average levels of fit, data analytics use does not make firms more agile; and that it may only result in higher firm agility when the fit between the data analytics tools and each of the related factors of data, people and tasks is high. This is explored further in the next section.

5.4. Interaction plot for the impact of fit on data analytics use-agility

The significance of the interaction terms in the structural model implies that the fit between analytical tools, data, people, and tasks influence the impact of the use of data analytics on firm agility. In order to further examine these effects, the Interaction software package[3] was used to more deeply understand these moderating effects. The resulting plots are shown in Fig. 3a, b, c where the implied path coefficients and their two-tailed level of significance are shown next to the regression lines. The plots suggest that at the mean level of fit between data analytics tools, data (Fig. 3a), people (Fig. 3b), and tasks (Fig. 3c) there is no significant impact of data analytics use on firm agility. At levels of fit below the sample mean, a negative relation between data analytics use and firm agility is observed. However, as the fit between data analytics tools, data, people and tasks increases, we see a positive relation between the use of data analytics and agility which becomes significant only at higher levels of fit.

6. Post hoc analyses

6.1. Control variable effects

We examined whether the impact of control variables (i.e., nature of data, firm size, industry type, analytical tools type[4]) on dependent

[1] Effect size [17] was calculated to further understand the relative impact of the different types of fit. The results showed that the effect sizes of the three fit types on are similar.

[2] Results also show that the moderating effect of overall fit on the relationship between data analytics use and firm agility was significant ($\beta = 0.161$; $p < 0.01$).

[3] See www.danielsoper.com.

[4] Nature of data was coded as a continuous variable focusing on the volume, variety, and velocity of data. Firm size was coded as a dummy variable (i.e., 1 for <50 employees, 2 for between 50 and 500 employees, and 3 for >500 employees); industry type was coded as a dummy variable (i.e., 1: manufacturing firms; 2: services firms; 3: financial firms; 4 utility firms). Analytical tools type was coded as a dummy variable representing the use of descriptive analytical tools, predictive analytical tools, prescriptive analytical tools, and their combinations in organizations.

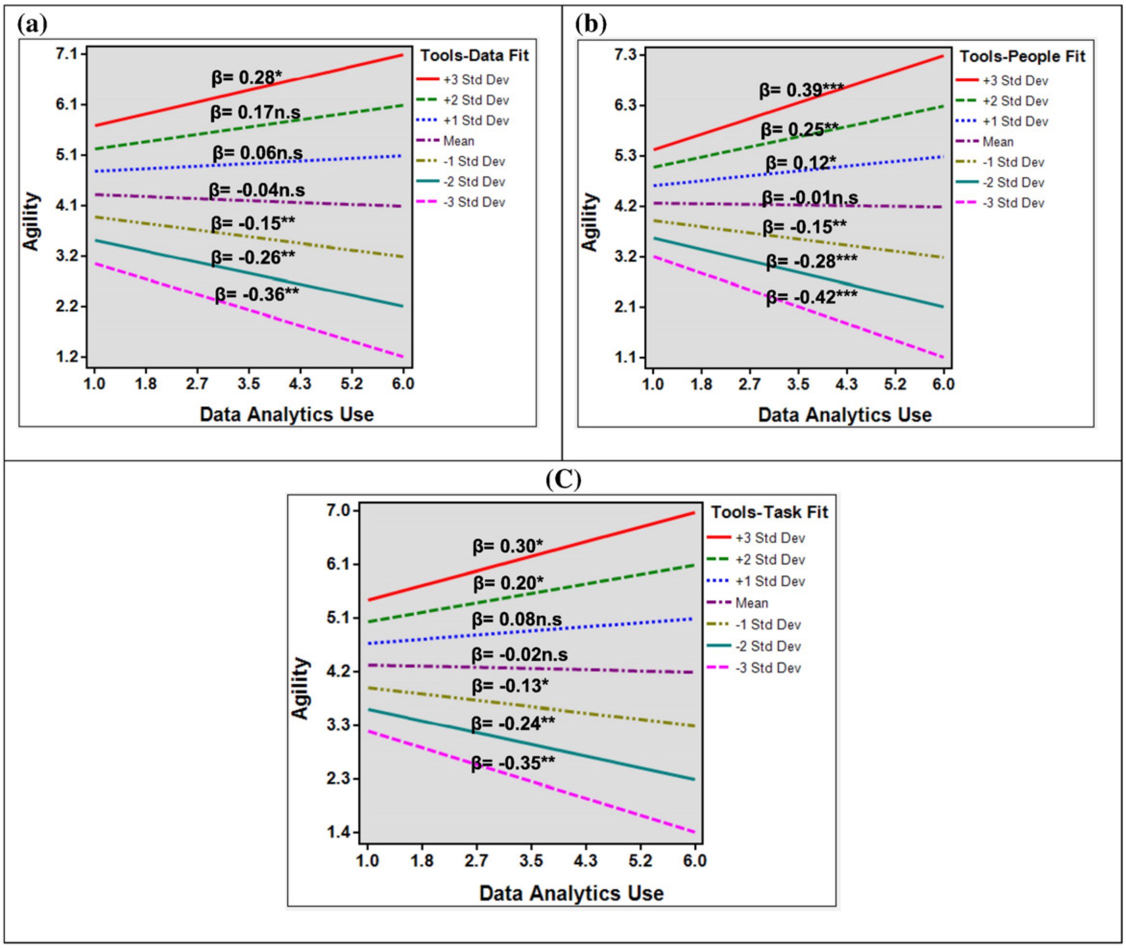

Fig. 3. Interaction plots.

variables was significant. Fig. 2 shows that the nature of data (i.e. volume, variety, and velocity of data) is not significantly associated with agility (β = 0.063; ns). Likewise, firm size did not significantly influence firm agility (β = −0.085; ns). Similarly, industry type did not significantly influence firm agility (β = 0.08; ns). Finally, analytical tools type was also not significantly associated firm agility (β = 0.061; ns).

6.2. Data analytics use and fit combinations analysis

We next classified the organizations in the sample based on their level of utilization of data analytics and the degree of fit[5] between their data analytics tools and key related firm elements using median splits; this produced four quadrants explained in Table 4. The mean and standard deviation of firm agility were calculated for companies in each quadrant (Table 5). As can be seen in Table 5, only 67 companies out of our sample of 215 fell in the fourth Quadrant of Table 4 (high data analytics use and high fit). These numbers demonstrate that most companies, even though invested in analytics to various extents, are not in a position to realize the full benefits of data analytics use. ANOVA analyses (see results in Table 6) were also carried out to assess whether the observed differences in agility for companies that fall in the different quadrants were significant.

As expected, companies in the fourth Quadrant (high data analytics use, and high fit) had the highest agility (mean = 5.12) compared to companies in the other three quadrants. Moreover, the agility for firms in this quadrant was significantly higher than for companies in Quadrants 1 and 2 but not for companies that fell in Quadrant 3. This indicates that having high fit is more important than having high data analytics use without fit. Interestingly, companies that are in the second quadrant (high data analytics use, low fit) had the lowest agility (mean = 3.3) compared to all other quadrants ($p < 0.05$). This again highlights the importance of fit towards realizing agility gains in organizations; one possible explanation for this is that using data analytics tools can actually hurt agility if there is low fit of the tools and key related elements. In such situations employees may put a lot of effort into using these tools while other companies produce the same analyses and reports without much effort (when fit is high). In contrast to Quadrants 1 and 3, companies in Quadrant 2 heavily used data analytics but due to the low fit facets, this use could backfire and result in lower agility. This reaffirms the findings from Fig. 3 where companies with low fit were found to exhibit a negative significant relation between data analytics use and agility.

7. Discussion

Although many firms have enhanced their IT capabilities to increase agility [45], empirical studies have reported mixed findings about the effects of firm IT capabilities on agility [64]. Along this line, several reports show that not all companies investing in data analytics (as an increasingly critical firm IT capability) experience agility gains from their investments. Hence, there is a need to understand the conditions under

[5] Given our finding that the three types of fit explored are equally important in impacting the relation between a data analytics use and agility, the analyses reported in this subsection rely on an overall second order fit measure that combines the three types of fit.

Table 4
Four quadrants of the data analytics use-fit combinations.

		Fit	
		Low	**High**
Data analytics use	**High**	**Quadrant 2** • High level of data analytics use, but not having enough fit between such tools and key related firm elements • Sub-optimal impacts of data analytics use on firm agility. • Data analytics as a resource is not being properly utilized leading to a waste of this resource and a lost opportunity to capitalize on it.	**Quadrant 4** • High level of using data analytics and the fit between such tools and key related firm elements. • Proper utilization of data analytics tools is likely to lead to firm agility. • The right conditions for reaping high benefits from using data analytics are there.
	Low	**Quadrant 1** • Low level of using data analytics and level of fit between such tools and key related firm elements is also low. • Unlikely to realize any improvements in organizational agility. • Leveraging the investment in data analytics resources is minimal.	**Quadrant 3** • High level of fit between data analytics tools and key firm elements exists, but these tools are underutilized. • Firm agility may not increase. • Investments in data analytics tools as well as in increasing fit with key related elements in the organization are not being properly leveraged leading to a waste of these investments and a lost opportunity to capitalize on them.

which investments in IT in general and data analytics use in particular could lead to positive organizational outcomes such as agility; this is what this study sought to do. In this study, we address this objective by relying on the fit perspectives and the DCT of the firm. In so doing we advance the literature by integrating these two distinct theoretical perspectives for uncovering the mechanisms that influence when data analytics use can enhance firm agility. The DCT explains whether the use of data analytics improves firm agility while the fit perspective explains under what conditions data analytics use will lead to higher firm agility.

Our findings reveal that while data analytics may be a valuable resource for organizations, by itself at average levels of fit, it does not generate agility. In addition, the results of the moderating effects of the fit between analytical tools, data, people, and tasks on the relation between data analytics use and firm agility provide unique insights. Specifically, results show that when there is a low levels of fit (lower than the mean of our sample) between analytical tools, data, people, and tasks, data analytics use can hurt firm agility. However, as the fit facets increase, we start seeing a positive relation between the use of data analytics and agility; this association becomes significant only at higher levels of fit. Hence, when fit is low, the use of analytics stands to undermine the agility of firms, and when fit is high the use of data analytics tools is likely to be fruitful in terms of increasing agility. Thus, one of the novel contributions of this study to theory is this theoretical integration which allows explaining how the fit between resources related to data analytics is critical to obtaining firm agility gains through the use of data analytics. Further, the results from ANOVA tests comparing the agility in organizations that fell into the different quadrants of Table 4 in terms of their utilization of data analytics and the degree of fit they exhibit for these tools with key related firm elements provide a clear indication of how fit is critical in terms of leveraging data analytics use within organizations.

In essence, our findings imply that the often-taken emphasis on the mere use of analytics is somewhat hype, and proper calibration of organizational resources related to data analytics tools is critical for improving organizational agility through the use of data analytics. These findings also relate to and can inform the technology adoption literature, which started pointing to differences between use and meaningful or effective use of IT [11]. In our case this meaningful and effective use entails the use of analytical tools that fit the tasks, people and data in the organization; only then the use improves firm outcomes.

From a theoretical perspective, we leveraged and integrated DCT and the fit perspective to develop and empirically validate a model to study the conditions under which a dynamic IT capability (e.g. data analytics) would lead to higher agility. In so doing, we leveraged the fit and TTF perspectives. In the IS literature, the fit perspective is represented by the prominent TTF theory [31]. Although this theory considers the task-technology and the people-technology fits, most IS research has only considered the task-technology fit and mainly focused on its direct effects on firm outcomes without considering the possibility of its moderating effects (e.g., [46,76]). In this research we return to the original spirit of the TTF perspective to include both types of fit (i.e. T-T and P-T). Furthermore, given the context of this study and modern IT that uses a variety of data types, we proposed a new fit perspective namely, the 'Data-Technology fit'. In our case, it accounted for the congruence between the analytical tools and the data that need to be analyzed. This is an important fit dimension to add to the mix because the variety of data types and the large volumes of data in modern organizations make it challenging to find tools that perfectly fit and can analyze such data. Our results show that this new fit dimension is as important as the others, at least in the examined context. Finally, we assessed the

Table 5
Descriptive statistics with means and standard deviations (SD) of agility for companies in the four quadrants of Table 4.

Quadrant	Number of firms	Agility	
		Mean	SD
1 (low DA use, low fit)	82	3.84	0.88
2 (high DA use, low fit)	30	3.3	1.13
3 (low DA use, high fit)	36	4.7	0.81
4 (high DA use, high fit)	67	5.12	0.86

DA: data analytics use.

Table 6
ANOVA results: agility comparison for companies in the four quadrants of Table 4.

Quadrants	Multiple comparisons	Agility	
		Mean difference	Sig.
1	2	0.54[a]	**0.03**
	3	−0.85[a]	**0.00**
	4	−1.27[a]	**0.00**
2	3	−1.39[a]	**0.00**
	4	−1.81[a]	**0.00**
3	4	−0.41	0.16

1: low data analytics use, low fit; 2: high data analytics use, low fit; 3: low data analytics use, high fit; 4: high data analytics use, high fit.
[a] The mean difference is significant at the 0.05 level.

moderating impact of fit between data analytics tools and the above key relevant firm elements on the influence of data analytics use on firm agility to explain the mixed results of previous findings of this relationship. This broader fit perspective can be applied to other information systems as well. As such, this study can help researchers to better conceptualize and understand the importance of fit between different organizational elements associated with data analytics use in particular and other information technologies in general.

From a practical perspective, our findings clearly show that the impact of the data-tools fit, people-tools fit, and tasks-tools fit on the relationship between data analytics use and firm agility is equally important and thus managers should ensure the fit between data analytics tools with all these key relevant firm elements (i.e., data, tasks, people) in order to increase firm agility when using data analytics. Towards that end, firms should employ thorough selection processes when acquiring data analytics tools to ensure that the selected tools will most closely match their data, people and tasks. They could also redesign their tasks to take better advantage of available analytical tools. Moreover, if the fit is low, managers may be better off avoiding the use of data analytics as using them under low fit conditions may be more taxing than beneficial. In addition, managers could initiate training programs or recruit appropriate individuals to improve the people-tools fit [27]. When employees have the abilities needed to fulfill their job demands, the results of their work are improved [6]. A greater fit of the employees with analytical tools allows employees to take full advantage of such tools to gain a better and faster understanding of the firm environment. Without optimizing these various fits, the implementation of analytical tools may not be fully leveraged or may even be harmful, at least from an agility standpoint.

Lastly, it is interesting to consider that the concept of fit is dynamic. Tools that were perfect fit at the point of selection may not remain highly congruent with data, tasks and people if the needed analyses and the types of data change over time. Hence, fit assessments should be performed *periodically*, and not just at the point of selection. Appropriate steps for improving fit can be taken later on if gaps between the elements (tools, people, data, tasks) emerge. For instance, organizations can consider changing or upgrading the tools, providing training, or purchasing data transformation software packages as a means to improve the discussed fit facets. This will help organizations avoid the pitfalls of assuming that fit is stable and that if a through selection process was applied then the provided tools will be good indefinitely. Given the pace of change in the business environment, this assumption can be wrong and perhaps could have led to the large number of companies in our sample that report low fit and fail to generate agility gains from their use of analytics tools.

As with any research, several limitations should be pointed out in this study. First, we only surveyed senior IT professionals. While this can produce common source bias ([28]; Rausch, Lai et al. [56]), senior IT professionals are the key persons who are particularly knowledgeable about the use of data analytics within their firms and its impact on organizational outcomes. This concern is also somewhat offset by the fact that our sample included respondents from a variety of industries and organization sizes. Future studies should still consider participants from different levels of firms, which may provide additional insights into the use of data analytics. Second, the study was conducted among North American senior IT professionals. Given potential impacts of culture on user perceptions regarding information technology, future research should replicate this research in other cultures. Third, it is worth noting that DCT and agility are primarily relevant in turbulent environments [65]. Although the environment in most industries nowadays is somewhat turbulent [3] and our results showed that industry type did not significantly change the relations in our model, we did not specifically measure the level of changes in firms' environments. Future research can account for possible effects of the degree of turbulence in the firm's environment on the hypothesized model. Fourth, the measures of the three types of fit were rather static in nature. Since fit may change over time, future research can apply longitudinal designs to account for fit dynamics. Fifth, this study focused on a single IT (i.e. data analytics). Future studies could examine the applicability of our findings to other types of IT. Finally, firm agility can be affected by factors other than data analytics use and fit. Hence, the impact of other factors on firm agility warrants future research.

8. Conclusion

This study addressed an important gap in the literature regarding when an IT capability (here, data analytics use) can improve firm outcomes (here, agility) and the resultant anomaly that a significant proportion of firms investing in analytics fail to see gains from their investments. We used DCT to explain the impact of data analytics use on firm agility and leveraged a broad fit perspective to explain when and how this effect accrues. The results showed that for organizations to realize agility through their data analytics use, there should be high levels of fit between analytical tools, data, employees' capabilities, and firm tasks. The results of this study suggest that the effective use of data analytics tools requires the possibly continuous fine tuning of various associated resources; and only when these resources work in tandem, can organizations reap the agility benefits of their investments in data analytics.

Appendix A. Survey items and constructs

Table A1 Measurement items of the variables.

Construct names	Measurement items (7-point scale)	Resources
Agility	7-point Likert scales ranging from “strongly disagree” to “strongly agree”: Operational adjustment agility • My organization can better meet demands for rapid-response, such as special customer requests whenever such demands arise. • My organization can more quickly scale up or scale down production/service levels to support fluctuations in demand from the market. • Whenever there is a disruption in supply my organization can more quickly make the necessary alternative arrangements and internal adjustments. Market capitalizing agility • My organization is quick to make and implement appropriate decisions in the face of market/customer-changes. • My organization constantly looks for ways to reinvent/reengineer to better serve the market place. • My organization treats market-related changes and apparent chaos as opportunities to capitalize quickly.	Lu & Ramamurthy [47]

(continued on next page)

(*continued*)

Table A1 Measurement items of the variables.

Construct names	Measurement items (7-point scale)	Resources
Fit	7-point Likert scales ranging from "strongly disagree" to "strongly agree": Data-tools fit • In my organization there is a good fit between the analytical tools we have access to and the data we process. • The present analytical tools my organization has access to fulfill our data analysis needs. • The analytical tools that my organization currently has access to provide pretty much everything that we need to analyze our data properly. People-tools fit • In my organization, there is a good fit between what our analytical tools can do and our employee capabilities. • The present analytical tools we have access to can be effectively utilized by my organization employees. • The capabilities of our employees allow them to take advantage of the analytical tools that my organization currently has access to. Tasks-tools fit • There is a good fit between the capabilities of the analytical tools we have access to and the tasks that my organization is charged with. • The present analytical tools we have access to help my organization accomplish its tasks. • The analytical tools we have access to provide good support for carrying out my organization's tasks.	Vogel & Feldman [73]
Data analytics use	• Please indicate to what extent does your organization use the data analytics tools? • Please indicate how often does your organization use the data analytics tools?	Venkatesh et al. [71]

Appendix B. Second-order construct assessment

To evaluate the measurement properties for the second-order formative construct (i.e., agility), we followed the formulation suggested by Bagozzi & Fornell [8]. We first multiplied item values by their PLS weights and then we summed them up for each first-order indicator. Then, based on a weighted sum of the first-order indicators, the second-order variables were assessed by creating composite indices [21]. The composite index values were then used as the measures for agility. We also used the Variance Inflation Factor (VIF) statistic to examine whether the formative measures are correlated too highly [53]. The VIF values of agility constructs were below the stringent threshold value 3.3 [20]. Thus, our measures do not have a multicollinearity problem.

B.1. Common method bias assessment

To assess the presence of Common Method Bias (CMB) the Harman's one factor test was carried out. The unrotated solution to the principal component analysis (PCA) suggested several factors none of which explains the majority of variance suggesting a low likelihood of a substantive common method variance component in our data. We also applied the marker variable technique to further test for CMB [44]. A marker variable (Need) was implemented in the research model that was theoretically unrelated to at least one other variable in the study (Agility). CMB can be examined based on the correlation between the theoretically unrelated variable and the marker variable [48]. This value (0.009) was assumed as the method variance, was parceled out from the other correlations, and the analysis was rerun. The results indicate no significant difference between the adjusted ones and the original correlation estimates. Given the results of the market variable test and the Harman's one factor test, we conclude that common method bias is not substantial in our data and, therefore, is not likely contaminating the results.

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