

# Problem resolution with business analytics: a task-technology fit perspective

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118

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## Abstract

**Purpose** – The study explores the extent to which business analytics can address business problems using the task-technology fit theory.

**Design/methodology/approach** – The qualitative research approach of pattern matching was adopted for data analysis and 12 semi-structured interviews were conducted. Four propositions derived from the literature on task-technology fit are compared to emerging core themes from the empirical data.

**Findings** – The study establishes the relationships between various forms of fit, arguing that the iterative application of business analytics improves problem understanding and solutions, and contends that both under-fit and over-fit can be acceptable due to the increasing costs of achieving ideal fit and potential unaffected outcomes, respectively. The study demonstrates that managers should appreciate that there may be a distinction between those who create business analytics solutions and those who apply business analytics solutions to solve problems.

**Originality/value** – Extant studies on business analytics have not focused on how the match between business analytics and tasks affects the level to which problems can be addressed that determines business value. This study enriches the literature on business analytics by linking business analytics and business value through problem resolution demonstrated by task-technology fit. To the authors' knowledge, this study might be the first to apply pattern matching to study the fit between technology and tasks.

**Keywords** Problem resolution, Business value, Business analytics, Task-technology fit, Pattern matching

**Paper type** Research paper

## 1. Introduction

The application of business analytics (BA) to address business problems and seize opportunities has led to improvements in firm performance. The recorded performance improvements affirm the relevance and suitability of BA in addressing business needs through task execution (Mikalef *et al.*, 2019; Muller *et al.*, 2018). These performance enhancements encompass benefits like cost reductions, sales growth and increased market share, all attributable to the application of BA (Aydiner *et al.*, 2019; Yasmin *et al.*, 2020; Zhu *et al.*, 2021). While some studies highlight the realization of these benefits (Chen *et al.*, 2021a, b; Conboy *et al.*, 2020; Dong and Yang, 2020), others note that implementations of BA often yield disappointing results (Grover *et al.*, 2018). These inconsistencies can be explained by the extent to which the fit between BA and a task affects problem resolution to realize benefits.

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Prior research on the value of information technologies (IT) suggests that the lack of fit between the technology and task can impact task productivity (Howard and Rose, 2019; Yang *et al.*, 2013). Additionally, BA does not yield benefits without an association with tasks (Kitchens *et al.*, 2018). However, there is a lack of empirically grounded understanding of how the fit between BA and tasks affects the magnitude of benefits realized through business problem resolution.

Therefore, this study seeks to investigate how the alignment between tasks and BA, referred to as task-technology fit (TTF), impacts the extent of these benefits. More specifically, TTF refers to the fit that arises from the interaction of technology features and task requirements (Howard and Rose, 2019; Rai and Selnes, 2019). TTF theory has been selected as a lens that facilitates a deeper understanding of the level of realized benefits (Burton-Jones *et al.*, 2021). Additionally, TTF is appropriate based on its prior application to assess how BA impacts the attainment of the specific benefit of firm agility (Ghasemaghaei *et al.*, 2017).

The fit between task and technology is described in terms of whether a technology has sufficient features to meet task requirements (Howard and Rose, 2019; Yang *et al.*, 2013). Specifically, when a technology does not have enough features to address a task this is referred to as under-fit, while over-fit indicates there are more features in the technology than required for the task, and ideal fit means the technology has exactly the right amount of features for the task (Junglas *et al.*, 2008). To illustrate, an ideal fit between drone characteristics and delivery needs (i.e. task), increases the usefulness of drone delivery services (Koh *et al.*, 2023). Conversely, a lack of ideal fit, exhibited by under-fit or over-fit, would decrease the usefulness of the drone delivery service. When technology cannot entirely address a task, this suggests a potential loss of benefits to an organization.

This paper focuses on BA as a specific technology employed for the analysis of data to improve decision-making (Holsapple *et al.*, 2014). BA is employed in two main ways: addressing known problems and identifying opportunities (Fernandez-Vidal *et al.*, 2022). In this study, tasks are defined as the activities carried out to resolve business problems (D'Ambra and Wilson, 2004). Clear and well-defined tasks have understandable goals that enable the assessment of BA application success in those tasks (Kitchens *et al.*, 2018; Nalchigar and Yu, 2020). When tasks are not well-defined, achieving fit between them and BA can be difficult. Further, even when the task is clear, BA may not be the perfect fit to address that task. This study aims to empirically evaluate the effectiveness of BA in tackling business problems by examining the fit between BA and the tasks it addresses. Hence, we ask the following question: *How does the fit between BA and assigned tasks influence overall business problem-solving capacity?*

In addressing the research question, we conducted semi-structured interviews with data scientists and top executives from various organizations. It is important to note that different organizations employ varying tools and methods for data analysis (Grover *et al.*, 2018). The choice of a diverse group of interviewees aimed to encompass a wide spectrum of BA applications. Pattern matching was employed to discover correspondence between theoretical propositions on TTF and empirical observations (Sinkovics, 2018). The emergent themes derived from the analysis of the semi-structured interview data constitute the empirical observation, while the propositions advanced were grounded on the literature on TTF (Howard and Hair, 2023; Junglas *et al.*, 2008). Pattern matching is suitable for the extant exploratory research that seeks to build on what is already known about TTF while also permitting new insights to emerge from observations.

This study reveals that various forms of fit between BA and tasks significantly impact the extent to which BA effectively addresses business problems. Notably, the iterative application of BA towards the resolution of problems implies a steady progression from under-fit towards ideal fit. The understanding of a problem improves as it is addressed, which results in the improvement of the solution. Under-fit can be acceptable because the

costs of reaching an ideal fit may exponentially increase as progress is made toward that ideal fit. Thus, the match between BA and tasks can be affected by other considerations that extend beyond the characteristics of BA or the task. Over-fit may not affect outcomes and helps to increase the variety of problems that BA can address. However, it is possible that BA is not being applied to problems for which it is suitable. In this respect, this study underscores the intricate interplay between different forms of fit. Moreover, prior research on BA has not delved into how the fit between BA and tasks affects the ability to address problems and, ultimately, determines business value. This study enriches the literature on BA by applying pattern matching to understand how the achievement of business value is affected by problem resolution that occurs through the fit between BA and tasks. To the best of the authors' knowledge, this study may represent the first application of pattern matching to explore the fit between BA and tasks and its impact on business problem-solving capacity.

The rest of the paper is structured as follows. We start by discussing the theory of TTF. This is followed by an overview of BA and its application in the context of TTF to address business problems. We subsequently advance some propositions. Next, we highlight data collection and analysis in the research method section. After that, the findings are presented, followed by theoretical contributions and implications for practice.

## 2. Theoretical background

### 2.1 Task-technology fit

Technology has specific characteristics that make it suitable for addressing business problems. At the same time, users who employ a technology and the task through which the technology is applied also possess unique characteristics. The relationship between the characteristics of the technology, task and user is termed TTF (Chen *et al.*, 2021b; Goodhue and Thompson, 1995; Howard and Rose, 2019; Junglas *et al.*, 2008). TTF can be used to evaluate the efficacy of attaining task outcomes. When a technology has too many or too few features, this may undermine the attainment of task outcomes (Howard and Rose, 2019). It is only when there is a perfect fit between technology features and task characteristics that users obtain the best outcomes from using the technology in the task (Junglas *et al.*, 2008). Therefore, the utilization of a poorly designed technology may not lead to the best outcomes (Goodhue and Thompson, 1995). Here, poorly designed technology refers to having either too many or too few features than necessary to accomplish a task effectively. For instance, BA can lead to an excessive number of insights through visualizations, which are a feature of BA (Saggi and Jain, 2018).

Technology is often designed with specific features, irrespective of how those features can be applied to particular tasks (Gebauer *et al.*, 2010). Typically, technology is designed to accommodate a range of tasks rather than being tailored to a single task (Sein *et al.*, 2011). This design approach results in technology being equipped with numerous features, some of which may be irrelevant to certain tasks. As a result, when technology is applied to various tasks, it can exhibit an excess, shortage or the ideal number of features for each task. This is the essence of TTF. These scenarios can also arise when technology is employed for tasks it was not originally designed for (Gregor and Hevner, 2013).

When technology includes more features than necessary for a specific task, users may choose to utilize the relevant features for that task (Fuller and Dennis, 2009). Previous research has thus contended that, to a certain extent, an excess of features may not detrimentally impact outcomes (Yang *et al.*, 2013). This implies that an excessive number of features in technology only starts to negatively affect the achievement of outcomes once a particular threshold is surpassed. Earlier examinations of TTF have primarily concentrated on the use of IT systems for tasks such as scheduling and document approval (Yang *et al.*, 2013), as well as using the

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Internet to locate specific information on webpages (Aljukhadar *et al.*, 2014). In contrast, this study focuses on BA as a technology employed to address a variety of business problems. Since BA only brings value when its use is attached to tasks (Kitchens *et al.*, 2018), TTF is well positioned to provide an understanding of the business value of BA and how the value can be achieved through tasks (Furieux, 2012).

### 2.2 Business analytics and problem resolution

Firms have realized the potential of BA in different applications. BA refers to “the techniques utilized in order to examine, process, discover and expose hidden underlying patterns, interesting relations and other insights concerning the application context under investigation” (Iqbal *et al.*, 2020, p. 1). What insights are considered relevant and how quickly they must be generated is determined by the usage context (Conboy *et al.*, 2020). Nonetheless, the success of organizations is determined by BA’s ability to analyse data intelligently (Shiau *et al.*, 2023). Among the plethora of BA features is the ability to make predictions and prescriptions (Lepeniotti *et al.*, 2020). Other features relate to specific types of BA such as information extraction, text summarization and sentiment analysis within text analytics (Gandomi and Haider, 2015). Additionally, certain features are associated with how BA is applied such as decision modelling, decision-making and decision execution (Saggi and Jain, 2018). The application contexts of BA include manufacturing processes (Popovic *et al.*, 2018), supply chain management (Chen *et al.*, 2015, 2021a, b), customer preference discovery (Kitchens *et al.*, 2018; Zhou *et al.*, 2018) and healthcare (Wang *et al.*, 2018). In each of these contexts, the application of BA may entail starting with *what* and moving toward *how* or starting with *how* and then defining *what* (Fernandez-Vidal *et al.*, 2022). In the former case, an organization identifies inefficiencies or opportunities (what) and then applies BA (how) in addressing them. In the latter case, an organization identifies and understands the capabilities of BA (how) and seeks to identify which aspects of the organization can be improved through those capabilities (what).

The resolution of a problem or capturing of an opportunity, through tasks, represents a benefit to an organization that we categorize as business value. Thus, the extent to which a user takes advantage of the fit between the task and BA determines how much business value is realized. Notwithstanding, tasks can be either well-defined or unclear (Avital and Te’eni, 2009). Well-defined tasks have low ambiguity and are finite. Unclear tasks have high ambiguity and may not have an obvious end. Given the desirability of ideal fit (Junglas *et al.*, 2008), we argue that when the task to be addressed with BA is not clear, achieving an ideal fit in such a scenario can be difficult (Avital and Te’eni, 2009). The fit between BA and a task can only be estimated accurately when the features of BA and the characteristics of the task are clear (Mathieson and Keil, 1998). Therefore, while the material features of BA, such as the capability to conduct predictive analytics are present, there is a requirement for clarity regarding the specific task and its objectives to which BA can be applied (Lehrer *et al.*, 2018). Without this clarity, it becomes challenging to effectively fit BA’s known features with the task at hand. Arguably, the ability of BA to fit a task remains ambiguous if the task itself is not clear. Therefore, the greater the task’s ambiguity, the more challenging it becomes to achieve an ideal fit between BA and the task. In other words, we propose that:

*Proposition 1 (P1).* The more unclear a task, the harder it is to reach an ideal fit between BA and the task.

Ideal fit is associated with the best possible outcomes (Junglas *et al.*, 2008). In this case, BA provides neither more nor fewer features than are required to adequately perform the task (Howard and Rose, 2019). There is a perfect match between the features of BA and the requirements of the task. Indicatively, the ideal fit will result in the best possible problem

resolution. Expressed differently, when BA matches the task at hand, the best possible business value will be realized. For instance, BA use has been associated with a reduction in waste in manufacturing processes (Popovic *et al.*, 2018). When the task is to optimize the manufacturing processes, ideal fit means BA manages to identify ways to achieve this in a way that fulfils all criteria that must be met. In other words, meeting all optimization criteria with BA signifies successful task resolution. Therefore, we assert that:

*Proposition 2 (P2).* The closer to the ideal fit, the more successful the task resolution.

When there is an under-fit, technology does not solve the problem in an ideal manner. Notably, when there are too few features in the technology, it may be hard to perform essential functions of the task (Howard and Rose, 2019). In other words, the features of BA that should coincide or intersect with those of the task are missing or not available in the right amounts (Smith and Mentzer, 2010; Zigurs and Khazanchi, 2008). A salient aspect of realizing business value with BA is to first identify tasks that can be carried out (Kitchens *et al.*, 2018). This means the task precedes the application of BA. Under-fit occurs when it is discovered that BA cannot meet all the requirements of the task. One possible reason for this under-fit is the technical limitations of BA algorithms that may simply not be capable of meeting the complexity of task requirements. Thus, under-fit may result in failed or partial success in task resolution. Therefore, we propose that:

*Proposition 3 (P3).* The greater the under-fit between BA and task, the greater the negative impact on task resolution.

When technology offers an excessive number of features for a task, creating an over-fit, it can detrimentally impact the achievement of outcomes, indicating a failure to address the task adequately (Howard and Hair, 2023; Howard and Rose, 2019). There is a decrease in task productivity due to the excess number of features in the technology (Yang *et al.*, 2013). Hence, we contend that over-fit between BA and the task negatively influences task resolution. BA can be used in the task of improving a product feature based on analysing large volumes of online customer reviews (Zhou *et al.*, 2018). However, BA often generates not only heterogeneous but also conflicting insights that far exceed the requirements for improving the product feature. This makes it difficult to complete the task. Specifically, not all insights can be incorporated into the product feature development. Any attempts to do so may be detrimental. Succinctly, we propose that:

*Proposition 4 (P4).* The greater the over-fit between BA and task, the greater the negative impact on task resolution.

The propositions advanced are summarized in Table 1.

To further illustrate these propositions, we focus on how BA helps in addressing tasks. The features of BA constituting the analytics goal include objectives for description, prediction and

Item	Aspect	Proposition presentation
P1	Problem clarity	The more unclear a task, the harder it is to reach an ideal fit between BA and the task
P2	Ideal fit	The closer to the ideal fit, the more successful the task resolution
P3	Under-fit	The greater the under-fit between BA and task, the greater the negative impact on task resolution
P4	Over-fit	The greater the over-fit between BA and task, the greater the negative impact on task resolution

**Table 1.**  
Propositions on the fit  
between BA and tasks

**Source(s):** Authors' own creation

prescription (Nalchigar and Yu, 2020). The task's features include the question goal, referring to what the business wants to achieve by applying BA. When the question to be addressed is not clear, this makes the task ambiguous thus making it difficult to achieve the fit between the analytics goal and question goal (P1). When there is a fit between BA and the task, it means the analytics goal provides the right insights to address the question goal. In other words, the insights generated from BA are sufficient to address the problem (P2). Under-fit can occur when the question goal demands specific insights from BA that cannot be availed through the analytics goal. As such, this hurts the resolution of the task (P3). Even though the task's question goal may demand the description goal (i.e. descriptive insights), the analytics goal may also include prediction and prescription goals that are not required for the task. The inclusion of these other goals in the insights generated from BA means there is more information provided than is required for the question goal. Consequently, the greater the amount of information provided beyond the task's requirements, the more difficult it can be to address the task (P4).

### 3. Research method

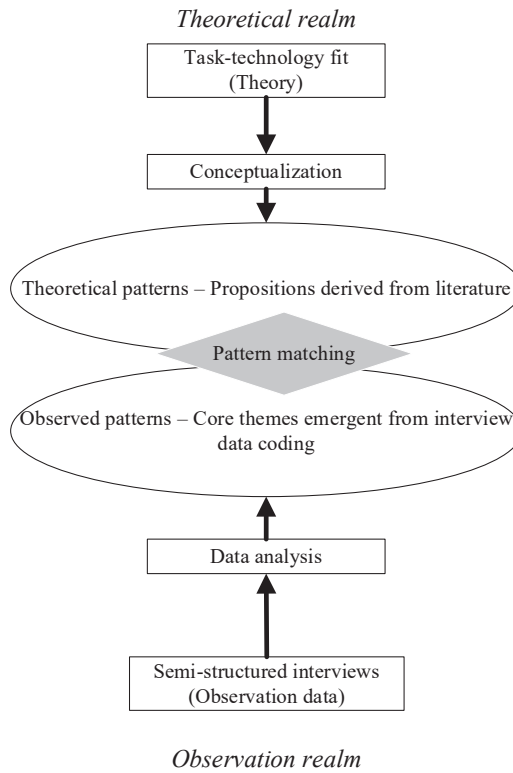
#### 3.1 Pattern matching

This study aims to develop theory using pattern matching, which entails comparing predicted theoretical patterns with observed empirical patterns (Sinkovics, 2018). The theoretical patterns are derived through explanatory theory construction, involving the formulation of preliminary explanations for what might be observed empirically. These preliminary explanations can be articulated as propositions or hypotheses. In the context of this study, we propose the preliminary explanation that the fit between BA and tasks influences task resolution, subsequently impacting the business value derived from BA. As part of constructing the explanatory theory in the theoretical realm of pattern matching, we present four propositions (refer to Table 1).

The observation realm of pattern matching consists of data construction theory and observation theory. Data construction theory describes the relevant raw data and how it should be collected. This data construction theory is highlighted in the subsequent section on data collection. Observation theory includes the construction of a framework that details how convincing inferences can be advanced from the data. The data analysis section, highlighting the coding of data, corresponds to observation theory. An illustration of the pattern matching process is provided in Figure 1.

We chose to employ pattern matching for two primary reasons. Firstly, it is well-suited for exploratory research, and secondly, the patterns presented in explanatory theory construction (i.e. propositions) serve as guiding principles for exploration and may evolve during the study (Sinkovics, 2018). The use of pattern matching enables this study to benefit partially from deductive and inductive approaches without being affected by the challenges each approach entails. Deduction involves deriving observations based on established rules and explanations as premises, while induction moves from specific observations and explanations to infer general rules (Mantere and Ketokivi, 2013). The inductive part of the observation realm, as depicted in Figure 1, benefits from "the ability of qualitative data to offer insight into complex social processes that quantitative data cannot easily reveal" (Eisenhardt and Graebner, 2007, p. 26). The theoretical realm, as shown in Figure 1, includes aspects of deduction in the formulation of propositions. Even though premises in deduction can be empirically falsified, they are not revised. This is not the case with pattern matching in which the initial arguments can be revised (Sinkovics, 2018). The reconciliation of theoretical patterns (i.e. propositions) and observed patterns leads to a theory of the fit between BA and tasks.

We chose to use semi-structured interviews for collecting data within the observation realm of pattern matching because the utilization of BA varies considerably across different



**Figure 1.**  
Pattern matching

**Source(s):** Adapted from Sinkovics (2018)

domains and business contexts (Grover *et al.*, 2018). Consequently, semi-structured interviews offer the opportunity to delve into the intricate relationship between business problems and BA, and how their fit influences the resolution of those business problems. Essentially, this study aims to gain insight into how the fit between tasks and BA manifests in various situations. Of particular interest are the diverse business problems that BA addresses, which can differ significantly between individuals and organizations.

Since data collection in the observation realm is informed by the theoretical realm, the second rationale for using semi-structured interviews comes from the TTF theory, which is fundamentally based on the effective usage of BA by users to accomplish their objectives (Burton-Jones and Grange, 2013). In the TTF literature, the assessment of the fit between a task and technology has typically been evaluated from the user’s perspective (Howard and Hair, 2023; Howard and Rose, 2019; Junglas *et al.*, 2008). Consequently, a qualitative research methodology employing semi-structured interviews, highlighting users’ perspectives of BA within specific contexts, was deemed apt for assessing the fit between BA and tasks.

### 3.2 Data collection

We collected data through semi-structured interviews. Interviews are regarded as one way to generate data that relies on the interviewees’ valid knowledge and their ability to express such

knowledge appropriately (Goldkuhl, 2019). We employed purposeful sampling, involving the use of pre-determined criteria, to select interviewees (Matavire and Brown, 2013). These criteria included the appropriateness of the interviewees' work roles and the extent of BA application within their respective companies. Specifically, we sought interviewees with roles such as data scientists who actively applied BA to address business problems, acknowledging that work roles may vary across organizations. We conveyed the study's nature in the consent forms provided to interview partners and, in the initial stages of the interviews, gathered information about their work roles and the business problems they addressed with BA. These steps facilitated the assessment of the interviewee's suitability for the study.

In addition to IT service providers, interviews were also conducted with representatives from other business sectors. We evaluated the extent of BA application by referencing information available on the companies' websites, which detailed the nature of problems addressed with BA. For IT service providers, we were particularly interested in their provision of BA solutions across a range of industries, contributing to the diversity and depth of this study. Stated differently, these IT service providers were selected because they were using BA to address different business problems in diverse industries like manufacturing, mining and retail. BA solutions encompass the generation of insights through data analysis and their application to tackle specific problems (Nalchigar and Yu, 2020). A guideline for the interview questions is included in Appendix. The interviews, conducted in English, took place from March to June 2023, with an average duration of approximately 50 min. The interview participants were all based in Finland. This made engagement easier with the authors who are also based in the same country. Consent forms were signed by the interviewees, granting permission to record the interviews, which were then transcribed using Microsoft Teams. Table 2 below provides further details regarding the interviews. It is

No	Interviewee job title	Years with company in current role	Sector	Interview duration (in minutes)	Interview date (month in 2023)
A1	Project Manager	1	Engineering	36	March
A2	People Lead, Data and Analytics	5	Healthcare	43	March
A3	Chief Data Officer	1.5	Healthcare	44	March
A4	Global Owner of Business Intelligence Solutions	2	Engineering	58	March
A5	Data Scientist	1	Technology	46	March
A6	Chief Business Officer	2	IT Service Provider	66	March
A7	Vice President, Integration	2	IT Service Provider	44	April
A8	Data Strategy Lead	2	IT Service Provider	58	April
A9	Vice President	1	IT Service Provider	42	April
A10	Data Scientist	2	IT Service Provider	62	May
A11	Managing Director	10	IT Service Provider	58	May
A12	Partner	10	IT Service Provider	47	June

Source(s): Authors' own creation

Table 2.  
Interviewee details



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important to note that this study considers the time interviewees had spent in their present roles within their current companies, regardless of their overall professional experience.

### *3.3 Data analysis process*

The data analysis relates to the observation realm, as illustrated in [Figure 1](#). We were guided in conducting the data analysis by the analytical move of asking questions ([Grodal et al., 2021](#)). The question we kept in mind in the analysis of each interviewee's responses is: "How is BA being applied to address problems in this context?". The analysis of the data yielded first-order categories. Second-order categories were generated using the data analysis move of merging categories ([Grodal et al., 2021](#)) and ensuring category viability ([Lo et al., 2020](#)). Category viability is achieved by grouping similar entities and differentiating those that are dissimilar. The following questions, following the analytical move of asking questions, further helped to generate second-order categories from the first-order categories. Is BA addressing the business problem successfully? How is the nature of the problem affecting how it is addressed with BA? These questions broadened the analytical scope, providing room for the identification of new emerging categories that extended beyond the initial categorization. Subsequently, the authors engaged in discussions and reached a consensus on framing the emerging themes derived from the data analysis.

## **4. Findings**

In this section, we begin by outlining the coding process and showcasing selected interview quotes. Subsequently, we delve into the description of the four central themes that surfaced. Finally, we assess the alignment between these four core themes within the observation realm and the corresponding propositions in the theoretical realm.

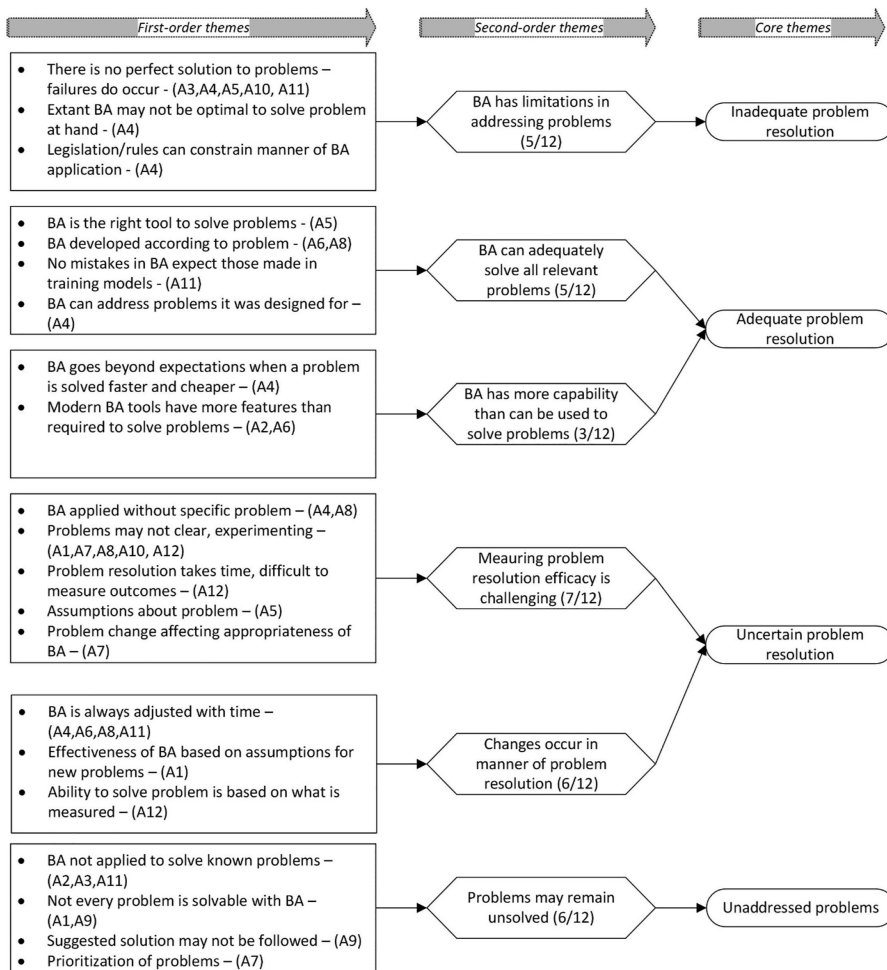
### *4.1 Coding process and selected interview quotes*

The coding process was sequential, progressing from first-order themes to second-order themes and finally the core themes. This is shown in [Figure 2](#). The first-order themes are descriptive and emerged directly from the analysis of interview quotes.

The second-order themes indicate a merging of first-order themes into superordinate themes ([Grodal et al., 2021](#)). Further, the core themes are an aggregation of the second-order themes. For the second-order themes, the number in brackets (e.g. 6/12) is the number of interviewees reflected in this theme as a fraction of the total interviewees. In [Table 3](#), we show the supporting first-order interview quotes for each specific theme. The BA context column indicates to what purpose BA was being applied.

### *4.2 Description of four core themes*

*4.2.1 Inadequate problem resolution.* The application of BA may produce results that are lower than those expected. Lower-than-expected results can be recognized based on the problem definition. Interviewees who worked in IT service provision companies indicated that problem definitions included not only what needed to be done but also what constitutes success or failure in addressing that problem. When it comes to creating potential solutions using proof of concept, the interviewees encountered challenges with data quality. Data quality issues are an inherent problem that is associated with BA ([Jones, 2019](#)). The BA solution is limited by the quality of available data and thus improves as more data becomes available. As one interviewee pointed out:



Source(s): Authors' own creation

Figure 2. Categories in data analysis

We created a proof of concept to show that this would work but we cannot guarantee accuracy because of the data quality issues. If we made certain changes and started collecting the data we needed, then the model can become much more useful than how it is currently. With the proof of concept, we tried to get as far as possible with the data we had. At the same time, we advised them on what would be needed in the future. (A10)

The reason BA cannot reach an accuracy of 100% can be attributed to data quality issues (A11). Due to inaccuracies, certain aspects of a problem remain unsolved. When the target was for BA to help in achieving a 100% advertising conversion rate, it was accepted that it would always fail in certain ways (A5). The question then becomes to what extent a “failed” solution is acceptable. Visualization through reporting is an important part of BA. An adequate solution would involve these visualizations containing all the relevant information for everyone’s needs. However, the reporting that was provided failed to meet the needs of all users (A3).

Second-order theme	BA context	Supporting first-order quotation
BA has limitations in addressing problems	Customer engagement	<i>“One of the metrics of course is the success rate. What is the success rate? Do we reach the success rate? In practical cases where we have implemented this, the customers accept that we cannot reach 100% and it’s not necessary to reach 100% because the last 10% is so costly to reach and there would still be mistakes which means it cannot be done.” (A11)</i>
	Forecasting	<i>“We also realized that this is the limit to which we can go in terms of accuracy because there is a data quality issue, but we can try and develop a model, similar model for another forecasting thing that is needed by them. So that way even though they were satisfied in the sense that they knew that there is an inherent problem with the data they have, and there is nothing we can do with it now.” (A10)</i>
BA can adequately solve all relevant problems	Customer acquisition (advertising conversion)	<i>“In manufacturing, we had a lot of issues with the tools because the pipeline was not stable and we could not get the data for some days because it did not load . . . but now in X[A5’s current company], that side of tooling is already done, and we do not need to worry about that . . . that is exactly what I need.” (A5)</i>
	Equipment monitoring	<i>“We do all the calculations and present the data to the people as actions. We tell them you need to fix this elevator and then the next one is this. It [business analytics] gives you the decisions already made, and this is the most profitable way to take action.” (A4)</i>
BA has more capability than can be used to solve problems	Warehouse optimization	<i>“You need to know what is fit and proper for your business context. If you think about modern tools, they have more features than you will ever use. The tools are not the bottleneck, that I can assure you.” (A6)</i>
	Predictive equipment maintenance	<i>“In business analytics, we just match the technology side with what is being asked. On the technology side, going beyond expectations means that we can do it faster and cheaper. If we can do stuff more cost-efficiently, it means that we can do more stuff than what was expected.” (A4)</i>
Measuring problem resolution efficacy is challenging	Identifying opportunities	<i>“In many cases, the client organization has an idea that they want to do better, and they might even have selected the area where they want to be better but then they don’t have a tangible idea of what being better looks like.” (A8)</i>
	Business process improvement	<i>“Some customers have a clearer reason for what kind of data they need and how they want to automate their processes. For other customers, we do a lot of consulting to help them to strengthen their vision and identify their needs.” (A7)</i>

**Table 3.**  
Coding themes and  
supporting quotes

(continued)

Second-order theme	BA context	Supporting first-order quotation
Changes occur in the manner of problem resolution	Logistics optimization	<i>“If you understand the baseline, it’s much easier to improve. But many times, those KPIs [key performance indicators] are not defined in the beginning phase, and that of course makes it quite hard to understand the return on investment on these topics [BA’s use to solve problems] if you don’t measure the starting point. You usually get results on the things you can measure.” (A12)</i>
	Operational efficiency	<i>“It is not uncommon that the solution that they thought of in the beginning is not the solution that solves the core problem. It is just a patch. If you keep on focusing on those, you will end up having just a very complex and confusing set of tools that are not really helping the user and are most likely not used.” (A8)</i>
Problems may remain unsolved	Simulation of production	<i>“You must always be very clear about what you are solving or what process you are talking about. When you have these analytic tools there is also the risk of having a lot of different kinds of visualizations and metrics that nobody understands. Which of these 50 metrics is the most important? In my mind, analytics is a tool that cannot solve everything.” (A1)</i>
	Equipment usage optimization	<i>“For miners, it is always about productivity, so we don’t need to fix anything that’s not broken. If the cost of collecting the data and doing activities intelligently with it is too expensive, then it’s more viable not to do anything and do things in the old way.” (A9)</i>

Source(s): Authors’ own creation

Table 3.

*4.2.2 Adequate problem resolution.* Effective problem resolution is achieved when the predetermined success metrics for those problems are met. The presence of clearly defined and well-known success metrics signifies a high degree of precision in problem definitions. It is important to note that BA does not typically exist in advance but is tailored specifically to address a particular problem. Consequently, the entire BA process aligns with the unique demands of that problem. Features may be continually integrated or developed within BA until all the specific requirements of the problem are satisfied. In explaining how business problems are tackled with BA, one interviewee articulated the following perspective:

You need to know first what you are trying to achieve. What are your business objectives? Then, you need to define what information you need to run your business efficiently. You need to know what data you need for that. How do you combine the data? What are the data products you need? (A6)

The above suggests a backward movement from a business problem and objectives that are associated with the resolution of that problem toward the acquisition of the data ingredients required to solve those problems. BA then connotes a forward progression from the data and its analysis to achieving the business objectives. BA can also be inherently adequate in solving problems when the problem involves the discovery of something. In discovering things, the problem is the lack of understanding of what is happening. These are the types of problems that are unclear, ambiguous and open-ended (Avital and Te’eni, 2009). The

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ambiguity emanates from the fact that whatever is discovered (or not discovered) may be considered a solution. This is highlighted by the following assertion:

Let's say someone wants to understand at the grassroots level what is happening. How are my projects? Why is this one doing badly? Analytics can go to a very low level. But it can be at a big level too. For management, we need to be able to produce accurate trends so that they understand where the company is going and what actions to take. I call this the reporting part of business analytics. (A4)

*4.2.3 Uncertain problem resolution.* The resolution of business problems with BA is not always a straightforward process. A lot of experimentation is involved. In the case of consulting companies, the main source of uncertainty highlighted by the interviewees is that these companies' clients struggled to clearly outline the nature of the problems they were facing. This meant that the consulting company, as a solution provider, also faced challenges in crafting an appropriate BA solution. Thus, the first step made in addressing problems with BA was to understand the problems. As highlighted by the interviewees, what was often considered a problem turned out to be merely a symptom of the underlying issue. Additionally, the BA solution that the clients sought was sometimes not the actual solution required to solve the problem. On the role of experimenting in problem resolution with BA, one interviewee expressed this as follows:

It is really about experimenting, having a hypothesis and then experimenting and analysing the data and gathering different data together and figuring out if you can find enough information to back up your hypothesis or prove your hypothesis wrong. (A8)

When the problems are known, there are still challenges or uncertainties around the resolution of such problems. Parameters that extend beyond understanding the problem are especially difficult to deal with. The problem may not contain all the relevant information, and such information may potentially be unknowable. In this regard, assumptions are made about the aspects of the problem that are not known (A5).

Problem resolution often presents uncertainty, particularly when initial performance indicators to gauge the success of BA implementation are lacking. The first step is defining these performance indicators. Establishing performance or success metrics plays a pivotal role in assessing the effectiveness of problem resolution (A12). It is worth noting that success metrics can take the form of service level agreements (A6), which may pertain to the implementation of a BA solution rather than its actual effectiveness. Even though service level agreements are connected to the results of problem-solving, not all of these outcomes can be quantified. When business problem resolution involves qualitative values that are challenging to measure, the overall assessment of the BA solution's effectiveness becomes a complex endeavour. This notion was succinctly expressed as follows:

We have created a solution [BA solution] for joint surgery. The solution analyses the risk to the patient based on data. We need to know how much human suffering there is after the surgery. So, it is not always about the quantitative side. (A6)

*4.2.4 Unaddressed problems.* Not all problems amenable to BA intervention find resolution, as indicated by the interviewees who raised concerns about their feasibility. What becomes evident is the imperative to efficiently streamline and prioritize problem-solving, particularly for those issues deemed significant (A3). Significance, in this context, encompasses both the return on investment associated with applying BA to tackle the problem and the urgency with which the issue requires attention. This prioritization process inevitably results in the non-resolution of certain problems. The urgency of addressing these problems was underscored in the following manner:

We recommend a solution for the customer and build a road map for them. We advise that they focus on certain areas in the short term and that means we need to build these things. In the mid-term, we need to build these things, and these are the main topics for the long term. (A7)

While the BA solution might require application at a specific time, it may not necessarily be administered as recommended, and in some cases, it may not be applied at all. Predictive maintenance may suggest that machinery be taken offline for minor repairs to avoid major problems. However, the fact that the machinery is still functional means that the planned maintenance may be ignored (A9). Literature has emphasized that machinery can continue functioning despite its deteriorated state, even though this increases the risk of major failures (March and Scudder, 2019).

#### 4.3 Matching theoretical and observed patterns

In this section, we discuss the match between theoretical patterns and observed patterns. This is shown in Table 4. The term “no pattern” means either the theoretical or observed pattern did not have a corresponding pattern. Pattern correspondence reflects the match between patterns. For each theoretical pattern, a corresponding observed pattern that aligns with it was found. The observed pattern of uncertainty in problem resolution suggests that the lack of problem clarity can make it hard to match specific problems and BA. The ability of BA to solve problems improves when the problems are clear. Thus, proposition P1 is supported.

BA is an adequate tool for solving problems because it is often developed according to the nature of the problem. Empirical observations reveal that BA often offers more features than necessary for problem resolution (refer to Figure 2). In these instances, the application of BA demonstrated a positive track record in successfully resolving problems, thus reinforcing the support for proposition P2. Nevertheless, given the contextual nature of BA use, some interviewees also noted instances where BA falls short in addressing business problems within their specific domains. More precisely, interviewees acknowledged that not all problems have perfect, foolproof solutions and therefore, the application of BA may not always result in a comprehensive problem resolution. Consequently, these observations provide further support for proposition P3.

While interviewees acknowledged the presence of more features in BA than is strictly necessary to address problems, this stance does not support proposition P4. Notably, interviewees did not emphasize any adverse consequences associated with over-fit. On the contrary, they perceived over-fit as affording flexibility in problem-solving, allowing for diverse approaches or the resolution of different problems. Essentially, over-fit results in the thorough resolution of problems, ensuring that all the necessary features for problem-solving are present in BA, even if some extra features remain unused (Soda and Furlotti, 2017). Despite BA being a tool designed for problem-solving, the observations highlight instances where problems remained unresolved. The concept of “fit” is inherently linked to technology utilization (Goodhue and Thompson, 1995). However, these observations suggest that the utilization (or non-utilization) of BA may be influenced by factors extending beyond fit.

Theoretical pattern	Observed pattern (core theme)	Pattern correspondence
P1 (Problem clarity)	Uncertain problem resolution	Matched
P2 (Ideal fit)	Adequate problem resolution	Matched
P3 (Under-fit)	Inadequate problem resolution	Matched
P4 (Over-fit)	No pattern	No observations made
No pattern	Unaddressed problems	No theoretical grounding

Source(s): Authors' own creation

**Table 4.**  
Matching propositions  
with observations

## 5. Discussion

This study's empirical findings highlight the effectiveness of BA in solving business problems. Specifically, the study has explored the manifestation of different types of fit concerning how BA addresses those business problems to realize business value. The findings highlight the influence of task clarity in establishing fit between BA and the task. Moreover, the study depicts how the resolution of business problems with BA may extend beyond the notion of fit. In other words, business problems may remain unaddressed despite the existence of ideal fit between BA and tasks. We now present the theoretical and practical implications of the study.

### 5.1 Theoretical contributions

This study presents three notable contributions. Firstly, this study enriches the literature on the realization of business value using BA (Dong and Yang, 2020; Kitchens *et al.*, 2018; Nalchigar and Yu, 2020). This prior literature focuses primarily on how BA can address business problems without paying attention to the extent to which BA is suitable for addressing those business problems. In other words, there is an implicit assumption within the literature that BA is suitable for addressing business problems. Using the theoretical lens of TTF, this study suggests fit as a dimension that should be considered in the application of BA. Specifically, this study suggests that BA can also experience under-fit when applied to task resolution. Consequently, TTF offers a valuable approach for assessing the effectiveness of BA application, highlighting that the realization of business value from BA does not necessarily imply a perfect fit for the task.

Secondly, this study makes a valuable contribution to the existing literature on TTF. While TTF is commonly perceived as a static point or a state of equilibrium, this study sheds light on the potential dynamics in the state of fit (Howard and Rose, 2019; Rai and Selnes, 2019; Yang *et al.*, 2013). The empirical findings from this study reveal that the understanding of tasks tends to improve as they are resolved, indicating a progressive enhancement in the fit between BA and tasks, including a reduction in the degree of under-fit, as tasks are addressed. This suggests that it may not be a prerequisite for a business problem to be initially well-defined before applying BA. The requirement of problem clarity has been emphasized as crucial for attaining business value from BA (Kitchens *et al.*, 2018). Previous research on how TTF evolves has primarily focused on how technology's appropriation improves for recurring tasks (Fuller and Dennis, 2009). Consequently, this study introduces an alternative perspective, highlighting how the task itself evolves, resulting in changes in fit over time, even though the technology remains unchanged.

Prior research has pointed out that BA is malleable (Benbya *et al.*, 2020; Yoo *et al.*, 2012). Saliiently, this would indicate that the state of under-fit should not be persistent. In essence, changes to BA should lead to the addition or alteration of features such that under-fit is eliminated. However, this study notes that under-fit can be persistent because users tend to accept that technology may not meet the entire demands of a task. Interpreted otherwise, ideal fit is not always attainable.

Thirdly, qualitative research can be guided by the principle of theoretical engagement, which suggests that the researcher should "offer theoretical abstractions resulting from the analysis/interpretation of the data" (Sarker *et al.*, 2013, p. xiii). Grounding on the empirical data, we offer the theoretical abstraction that the existence of over-fit between BA and tasks can be difficult to observe. This can be attributed to users of BA appropriating only those aspects of the technology that are relevant to the task. In other words, features of BA that are extraneous to task requirements may not necessarily be considered a liability. Contrary to indications from prior literature that over-fit may be detrimental to the resolution of business problems (Junglas *et al.*, 2008), the observations made in this study suggest that over-fit may

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not hurt problem resolution. Rather, over-fit was perceived as increasing the variety of problems that can be addressed by BA. In the case of IT consulting companies, the existence of more features in BA than those required to solve problems meant the same BA solution could be applied to different problems.

### *5.2 Implications for practice*

This study has four key practical implications. Firstly, solving business problems through BA is often an iterative process, where the understanding of the problem improves as it is addressed. This implies that the initial stages of implementing a BA solution offer a learning opportunity. Consequently, these early stages might exhibit characteristics of under-fit. This initial under-fit can serve as a tool for assessing whether the current solution should be continued or if an entirely new one is needed. By emphasizing these aspects, we aim to raise awareness among managers that the problems suitable for BA application may not always be clear from the outset. The lack of problem clarity should not be seen as a deterrent. Moreover, BA can be adapted to address problems differently, allowing for flexibility in problem-solving approaches.

Secondly, the study highlights some factors that contribute to the lack of task clarity. For instance, the interviewees indicated that there is often no baseline to measure the success of problem resolution, and the expected outcome from solving the problem is often unclear. They also highlighted that problems typically lack pre-defined technological solutions, with BA being perceived as merely one potential technological solution. Addressing these concerns about problem clarity can enable managers to enhance the fit between BA and tasks, thereby improving the effectiveness of problem-solving with BA.

Thirdly, the extent to which organizations promote BA is a crucial factor in determining its effectiveness in problem-solving. Key users play a pivotal role in fostering the use of BA. Managers should recognize that a distinction may exist between those who create BA solutions and those who apply these solutions to tackle problems. Therefore, the effective use of BA is contingent upon users being aware of its potential as a solution. Furthermore, it is imperative to avoid addressing symptoms rather than the underlying issues. What is perceived as a problem may just be a symptom of the actual problem. Additionally, business problems evolve, meaning that a BA solution which was previously an ideal fit for a task may become an under-fit.

Finally, a deep understanding of TTF can empower managers to enhance the magnitude of business value derived from BA. This study offers valuable insights in this context. The pursuit of improved business value necessitates the mitigation of both under-fit and over-fit scenarios. Without consideration of TTF, managers may remain unaware of whether they are maximizing the potential business value from their BA applications. Suboptimal applications of BA can still yield positive outcomes. As TTF encompasses both the task and technology dimensions (Jeyaraj, 2022), its comprehension urges managers to address both aspects, rather than focusing solely on one at the expense of the other. To be more precise, enhancing business value may entail the elimination of inefficiencies within both BA and the associated tasks.

### *5.3 Limitations and future research directions*

This study has some limitations. First, purposeful sampling for interviewees creates an obvious limitation that needs to be recognized. However, this explorative study benefited from well-informed interviewees, and we reached saturation with this number of interviews. In addition, the emergent core themes are sufficiently broad and cover an extensive range of BA applications. However, the interviewees are all based in Finland. This may have limited the variety of perspectives on how BA can be applied.



Second, we focused on applications of BA in different organizations. The context-specific nature of BA (Grover *et al.*, 2018) means the match between BA and tasks may not be replicable across different applications. However, the core themes were generated from the merging of specific categories and may be useful in explicating the overall nature of the match between BA and tasks. Further, the core themes demonstrate category viability through distinctiveness among categories (Lo *et al.*, 2020).

While we have not found evidence of the negative impact of over-fit on task outcomes, previous studies have indicated its existence (Junglas *et al.*, 2008). We suggest that future empirical research tackle the specific contexts under which the application of BA to tasks does not generate positive outcomes. While business value is often perceived as a positive value, the focus on over-fit may highlight novel insights on the possibility of negative business value. This study has highlighted the idea of unaddressed problems as a core theme. One reason why BA may not be applied is the costs associated with the execution of specific tasks. Another reason may be that tasks that are not time critical may be ignored. Despite the existence of a potentially ideal fit, future research could tackle the question: When is the application of BA to solve problems not desirable?

## 6. Conclusion

Business problems are resolved successfully when there is an ideal fit between BA and the tasks to which it is applied. However, such a match may not always be possible. Thus, this study sought to explore problem resolution with BA using a TTF perspective. The results showed that the problems to which BA can be applied may not be clear. Further, it may not be possible to achieve perfect problem clarity because the understanding of problems tends to improve as the problems are solved. At the same time, the shortcomings of BA also become apparent when it is applied to specific problems.

While the theoretical arguments posited in prior studies on the impact of under-fit and over-fit on task outcomes were supported, this study did not find supporting evidence for over-fit. The empirical argument for over-fit is that BA always contains more features than are required. Hence, it is up to the user to select the features they intend to use. Thus, over-fit is not detrimental to task outcomes. Overall, this study has pointed out the importance of achieving an ideal fit between BA and tasks. However, there may still be some challenges in realizing value from BA as highlighted by the existence of under-fit between BA and tasks.

## References

- Aljukhadar, M., Senecal, S. and Nantel, J. (2014), "Is more always better? Investigating the task-technology fit theory in an online user context", *Information and Management*, Vol. 51 No. 4, pp. 391-397, doi: [10.1016/j.im.2013.10.003](https://doi.org/10.1016/j.im.2013.10.003).
- Avital, M. and Te'eni, D. (2009), "From generative fit to generative capacity: exploring an emerging dimension of information systems design and task performance", *Information Systems Journal*, Vol. 19 No. 4, pp. 345-367, doi: [10.1111/j.1365-2575.2007.00291.x](https://doi.org/10.1111/j.1365-2575.2007.00291.x).
- Aydiner, A.S., Tatoglu, E., Bayraktar, E., Zaim, S. and Delen, D. (2019), "Business analytics and firm performance: the mediating role of business process performance", *Journal of Business Research*, Vol. 96, pp. 228-237, doi: [10.1016/j.jbusres.2018.11.028](https://doi.org/10.1016/j.jbusres.2018.11.028).
- Benbya, H., Nan, N., Tanriverdi, H. and Yoo, Y. (2020), "Complexity and information systems research in the emerging digital world", *MIS Quarterly*, Vol. 44 No. 1, pp. 1-17, doi: [10.25300/MISQ/2020/13304](https://doi.org/10.25300/MISQ/2020/13304).
- Burton-Jones, A. and Grange, C. (2013), "From use to effective use: a representation theory perspective", *Information Systems Research*, Vol. 24 No. 3, pp. 632-658, doi: [10.1287/isre.1120.0444](https://doi.org/10.1287/isre.1120.0444).

- Burton-Jones, A., Butler, B.S., Scott, S.V. and Xu, S.X. (2021), "Next-generation information systems theorizing: a call to action", *MIS Quarterly*, Vol. 45 No. 1, pp. 301-314, doi: [10.25300/MISQ/2021/15434](https://doi.org/10.25300/MISQ/2021/15434).
- Chen, D.Q., Preston, D.S. and Swink, M. (2015), "How the use of big data analytics affects value creation in supply chain management", *Journal of Management Information Systems*, Vol. 32 No. 4, pp. 4-39, doi: [10.1080/07421222.2015.1138364](https://doi.org/10.1080/07421222.2015.1138364).
- Chen, D.Q., Preston, D.S. and Swink, M. (2021a), "How big data analytics affects supply chain decision-making: an empirical analysis", *Journal of the Association for Information Systems*, Vol. 22 No. 5, pp. 1224-1244, doi: [10.17705/1jais.00713](https://doi.org/10.17705/1jais.00713).
- Chen, L., Zheng, B., Liu, H. and Deng, M. (2021b), "Three-way interaction effect of social media usage, perceived task interdependence and perceived participative leadership on employee creativity", *Internet Research*, Vol. 31 No. 2, pp. 457-478, doi: [10.1108/INTR-02-2020-0104](https://doi.org/10.1108/INTR-02-2020-0104).
- Conboy, K., Dennehy, D. and O'Connor, M. (2020), "'Big time': an examination of temporal complexity and business value in analytics", *Information and Management*, Vol. 57 No. 1, 103077, doi: [10.1016/j.im.2018.05.010](https://doi.org/10.1016/j.im.2018.05.010).
- Dong, J.Q. and Yang, C.H. (2020), "Business value of big data analytics: a systems-theoretic approach and empirical test", *Information and Management*, Vol. 57 No. 1, 103124, doi: [10.1016/j.im.2018.11.001](https://doi.org/10.1016/j.im.2018.11.001).
- D'Ambra, J. and Wilson, C.S. (2004), "Explaining perceived performance of the World Wide Web : uncertainty and the task-technology fit model", *Internet Research*, Vol. 14 No. 4, pp. 294-310, doi: [10.1108/10662240410555315](https://doi.org/10.1108/10662240410555315).
- Eisenhardt, K.M. and Graebner, M.E. (2007), "Theory building from cases: opportunities and challenges", *Academy of Management Journal*, Vol. 50 No. 1, pp. 25-32, doi: [10.5465/AMJ.2007.24160888](https://doi.org/10.5465/AMJ.2007.24160888).
- Fernandez-Vidal, J., Gonzalez, R., Gasco, J. and Llopis, J. (2022), "Digitalization and corporate transformation: the case of European oil and gas firms", *Technological Forecasting and Social Change*, Vol. 174 January, 121293, doi: [10.1016/j.techfore.2021.121293](https://doi.org/10.1016/j.techfore.2021.121293).
- Fuller, R.M. and Dennis, A.R. (2009), "Does fit matter? The impact of task-technology fit and appropriation on team performance in repeated tasks", *Information Systems Research*, Vol. 20 No. 1, pp. 2-17, doi: [10.1287/isre.1070.0167](https://doi.org/10.1287/isre.1070.0167).
- Furneaux, B. (2012), "Task-technology fit theory: a survey and synopsis of the literature", in Dwivedi, Y.K., Wade, M.R. and Schneberger, S.L. (Eds), *Information Systems Theory: Explaining and Predicting Our Digital Society*, Springer, Vol. 1, pp. 87-106, doi: [10.1007/978-1-4419-6108-2\\_5](https://doi.org/10.1007/978-1-4419-6108-2_5).
- Gandomi, A. and Haider, M. (2015), "Beyond the hype: big data concepts, methods, and analytics", *International Journal of Information Management*, Vol. 35 No. 2, pp. 137-144, doi: [10.1016/j.ijinfomgt.2014.10.007](https://doi.org/10.1016/j.ijinfomgt.2014.10.007).
- Gebauer, J., Shaw, M.J. and Gribbins, M.L. (2010), "Task-technology fit for mobile information systems", *Journal of Information Technology*, Vol. 25 No. 3, pp. 259-272, doi: [10.1057/jit.2010.10](https://doi.org/10.1057/jit.2010.10).
- Ghasemaghaei, M., Hassanein, K. and Turel, O. (2017), "Increasing firm agility through the use of data analytics: the role of fit", *Decision Support Systems*, Vol. 101, pp. 95-105, doi: [10.1016/j.dss.2017.06.004](https://doi.org/10.1016/j.dss.2017.06.004).
- Goldkuhl, G. (2019), "The generation of qualitative data in information systems research: the diversity of empirical research methods", *Communications of the Association for Information Systems*, Vol. 44, pp. 572-599, doi: [10.17705/1CAIS.04428](https://doi.org/10.17705/1CAIS.04428).
- Goodhue, D.L. and Thompson, R.L. (1995), "Task-technology fit and individual performance", *MIS Quarterly*, Vol. 19 No. 2, pp. 213-236, doi: [10.2307/249689](https://doi.org/10.2307/249689).
- Gregor, S. and Hevner, A.R. (2013), "Positioning and presenting design science research for maximum impact", *MIS Quarterly*, Vol. 37 No. 2, pp. 337-355, doi: [10.2753/MIS0742-122240302](https://doi.org/10.2753/MIS0742-122240302).

- Grodal, S., Anteby, M. and Holm, A.L. (2021), "Achieving rigor in qualitative analysis: the role of active categorization in theory building", *Academy of Management Review*, Vol. 46 No. 3, pp. 591-612, doi: [10.5465/amr.2018.0482](https://doi.org/10.5465/amr.2018.0482).
- Grover, V., Chiang, R.H.L., Liang, T.P. and Zhang, D. (2018), "Creating strategic business value from big data analytics: a research framework", *Journal of Management Information Systems*, Vol. 35 No. 2, pp. 388-423, doi: [10.1080/07421222.2018.1451951](https://doi.org/10.1080/07421222.2018.1451951).
- Holsapple, C., Lee-post, A. and Pakath, R. (2014), "A unified foundation for business analytics", *Decision Support Systems*, Vol. 64, pp. 130-141, doi: [10.1016/j.dss.2014.05.013](https://doi.org/10.1016/j.dss.2014.05.013).
- Howard, M.C. and Hair, J.F. (2023), "Integrating the expanded task-technology fit theory and the technology acceptance model: a multi-wave empirical analysis", *Association for Information Systems Transactions on Human-Computer Interaction*, Vol. 15 No. 1, pp. 83-110, doi: [10.17705/1thci.00084](https://doi.org/10.17705/1thci.00084).
- Howard, M.C. and Rose, J.C. (2019), "Refining and extending task-technology fit theory: creation of two task-technology fit scales and empirical clarification of the construct", *Information and Management*, Vol. 56 No. 6, 103134, doi: [10.1016/j.im.2018.12.002](https://doi.org/10.1016/j.im.2018.12.002).
- Iqbal, R., Doctor, F., More, B., Mahmud, S. and Yousuf, U. (2020), "Big data analytics: computational intelligence techniques and application areas", *Technological Forecasting and Social Change*, Vol. 153, 119253, doi: [10.1016/j.techfore.2018.03.024](https://doi.org/10.1016/j.techfore.2018.03.024).
- Jeyaraj, A. (2022), "A meta-regression of task-technology fit in information systems research", *International Journal of Information Management*, Vol. 65 August, 102493, doi: [10.1016/j.ijinfomgt.2022.102493](https://doi.org/10.1016/j.ijinfomgt.2022.102493).
- Jones, M. (2019), "What we talk about when we talk about (big) data", *Journal of Strategic Information Systems*, Vol. 28 No. 1, pp. 3-16, doi: [10.1016/j.jsis.2018.10.005](https://doi.org/10.1016/j.jsis.2018.10.005).
- Junglas, I., Abraham, C. and Watson, R.T. (2008), "Task-technology fit for mobile locatable information systems", *Decision Support Systems*, Vol. 45 No. 4, pp. 1046-1057, doi: [10.1016/j.dss.2008.02.007](https://doi.org/10.1016/j.dss.2008.02.007).
- Kitchens, B., Dobolyi, D., Li, J. and Abbasi, A. (2018), "Advanced customer analytics: strategic value through integration of relationship-oriented big data", *Journal of Management Information Systems*, Vol. 35 No. 2, pp. 540-574, doi: [10.1080/07421222.2018.1451957](https://doi.org/10.1080/07421222.2018.1451957).
- Koh, L.Y., Lee, J.Y., Wang, X. and Yuen, K.F. (2023), "Urban drone adoption: addressing technological, privacy and task-technology fit concerns", *Technology in Society*, Vol. 72, 102203, doi: [10.1016/j.techsoc.2023.102203](https://doi.org/10.1016/j.techsoc.2023.102203).
- Lehrer, C., Wieneke, A., Brocke, J., Jung, R. and Seidel, S. (2018), "How big data analytics enables service innovation: materiality, affordance, and the individualization of service", *Journal of Management Information Systems*, Vol. 35 No. 2, pp. 424-460, doi: [10.1080/07421222.2018.1451953](https://doi.org/10.1080/07421222.2018.1451953).
- Lepenioti, K., Bousdekis, A., Apostolou, D. and Mentzas, G. (2020), "Prescriptive analytics: literature review and research challenges", *International Journal of Information Management*, Vol. 50 February, pp. 57-70, doi: [10.1016/j.ijinfomgt.2019.04.003](https://doi.org/10.1016/j.ijinfomgt.2019.04.003).
- Lo, J.Y., Fiss, P.C., Rhee, E.Y. and Kennedy, M.T. (2020), "Category viability: balanced levels of coherence and distinctiveness", *Academy of Management Review*, Vol. 45 No. 1, pp. 85-108, doi: [10.5465/amr.2017.0011](https://doi.org/10.5465/amr.2017.0011).
- Mantere, S. and Ketokivi, M. (2013), "Reasoning in organization science", *Academy of Management Review*, Vol. 38 No. 1, pp. 70-89, doi: [10.5465/amr.2011.0188](https://doi.org/10.5465/amr.2011.0188).
- March, S.T. and Scudder, G.D. (2019), "Predictive maintenance: strategic use of IT in manufacturing organizations", *Information Systems Frontiers*, Vol. 21 No. 2, pp. 327-341, doi: [10.1007/s10796-017-9749-z](https://doi.org/10.1007/s10796-017-9749-z).
- Matavire, R. and Brown, I. (2013), "Profiling grounded theory approaches in information systems research", *European Journal of Information Systems*, Vol. 22 No. 1, pp. 119-129, doi: [10.1057/ejis.2011.35](https://doi.org/10.1057/ejis.2011.35).

- Mathieson, K. and Keil, M. (1998), "Beyond the interface: ease of use and task/technology fit", *Information and Management*, Vol. 34 No. 4, pp. 221-230, doi: [10.1016/S0378-7206\(98\)00058-5](https://doi.org/10.1016/S0378-7206(98)00058-5).
- Mikalef, P., Boura, M., Lekakos, G. and Krogstie, J. (2019), "Big data analytics and firm performance: findings from a mixed-method approach", *Journal of Business Research*, Vol. 98, pp. 261-276, doi: [10.1016/j.jbusres.2019.01.044](https://doi.org/10.1016/j.jbusres.2019.01.044).
- Muller, O., Fay, M. and vom Brocke, J. (2018), "The effect of big data and analytics on firm performance: an econometric analysis considering industry characteristics", *Journal of Management Information Systems*, Vol. 35 No. 2, pp. 488-509, doi: [10.1080/07421222.2018.1451955](https://doi.org/10.1080/07421222.2018.1451955).
- Nalchigar, S. and Yu, E. (2020), "Designing business analytics solutions: a model-driven approach", *Business and Information Systems Engineering*, Vol. 62 No. 1, pp. 61-75, doi: [10.1007/s12599-018-0555-z](https://doi.org/10.1007/s12599-018-0555-z).
- Popovic, A., Hackney, R., Tassabehji, R. and Castelli, M. (2018), "The impact of big data analytics on firms' high value business performance", *Information Systems Frontiers*, Vol. 20 No. 2, pp. 209-222, doi: [10.1007/s10796-016-9720-4](https://doi.org/10.1007/s10796-016-9720-4).
- Rai, R.S. and Selnes, F. (2019), "Conceptualizing task-technology fit and the effect on adoption – a case study of a digital textbook service", *Information and Management*, Vol. 56 No. 8, 103161, doi: [10.1016/j.im.2019.04.004](https://doi.org/10.1016/j.im.2019.04.004).
- Saggi, M.K. and Jain, S. (2018), "A survey towards an integration of big data analytics to big insights for value-creation", *Information Processing and Management*, Vol. 54 No. 5, pp. 758-790, doi: [10.1016/j.ipm.2018.01.010](https://doi.org/10.1016/j.ipm.2018.01.010).
- Sarker, S., Xiao, X. and Beaulieu, T. (2013), "Qualitative studies in information systems: a critical review and some guiding principles", *MIS Quarterly*, Vol. 37 No. 4, pp. III-xviii.
- Sein, M.K., Henfridsson, O., Purao, S., Rossi, M. and Lindgren, R. (2011), "Action design research", *MIS Quarterly*, Vol. 35 No. 1, pp. 37-56, doi: [10.2307/23043488](https://doi.org/10.2307/23043488).
- Shiau, W.-L., Chen, H., Wang, Z. and Dwivedi, Y.K. (2023), "Exploring core knowledge in business intelligence research", *Internet Research*, Vol. 33 No. 3, pp. 1179-1201, doi: [10.1108/INTR-04-2021-0231](https://doi.org/10.1108/INTR-04-2021-0231).
- Sinkovics, N. (2018), "Pattern matching in qualitative analysis", in Cunliffe, A., Grandy, G. and Cassell, C. (Eds), *The SAGE Handbook of Qualitative Business and Management Research Methods: Methods and Challenges*, SAGE Publications, doi: [10.4135/9781526430236.n28](https://doi.org/10.4135/9781526430236.n28).
- Smith, C.D. and Mentzer, J.T. (2010), "Forecasting task-technology fit: the influence of individuals, systems and procedures on forecast performance", *International Journal of Forecasting*, Vol. 26 No. 1, pp. 144-161, doi: [10.1016/j.ijforecast.2009.05.014](https://doi.org/10.1016/j.ijforecast.2009.05.014).
- Soda, G. and Furlotti, M. (2017), "Bringing tasks back in: an organizational theory of resource complementarity and partner selection", *Journal of Management*, Vol. 43 No. 2, pp. 348-375, doi: [10.1177/0149206314535435](https://doi.org/10.1177/0149206314535435).
- Wang, Y., Kung, L., Yu, W., Wang, C. and Cegielski, C.G. (2018), "An integrated big data analytics-enabled transformation model: application to health care", *Information and Management*, Vol. 55 No. 1, pp. 64-79, doi: [10.1016/j.im.2017.04.001](https://doi.org/10.1016/j.im.2017.04.001).
- Yang, H.-D., Kang, S., Oh, W. and Kim, M. (2013), "Are all fits created equal? A nonlinear perspective on task-technology fit", *Journal of the Association for Information Systems*, Vol. 14 No. 12, pp. 694-721, doi: [10.17705/1jais.00349](https://doi.org/10.17705/1jais.00349).
- Yasmin, M., Tatoglu, E., Kilic, H.S., Zaim, S. and Delen, D. (2020), "Big data analytics capabilities and firm performance: an integrated MCDM approach", *Journal of Business Research*, Vol. 114 February, pp. 1-15, doi: [10.1016/j.jbusres.2020.03.028](https://doi.org/10.1016/j.jbusres.2020.03.028).
- Yoo, Y., Boland, R.J., Lyytinen, K. and Majchrzak, A. (2012), "Organizing for innovation in the digitized world", *Organization Science*, Vol. 23 No. 5, pp. 1398-1408, doi: [10.1287/orsc.1120.0771](https://doi.org/10.1287/orsc.1120.0771).

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- Zhou, S., Qiao, Z., Du, Q., Wang, G.A., Fan, W. and Yan, X. (2018), "Measuring customer agility from online reviews using big data text analytics", *Journal of Management Information Systems*, Vol. 35 No. 2, pp. 510-539, doi: [10.1080/07421222.2018.1451956](https://doi.org/10.1080/07421222.2018.1451956).
- Zhu, S., Dong, T. and Luo, X.(R.) (2021), "A longitudinal study of the actual value of big data and analytics: the role of industry environment", *International Journal of Information Management*, Vol. 60, 102389, doi: [10.1016/j.ijinfomgt.2021.102389](https://doi.org/10.1016/j.ijinfomgt.2021.102389).
- Zigurs, I. and Khazanchi, D. (2008), "From profiles to patterns: a new view of task- technology fit", *Information Systems Management*, Vol. 25 No. 1, pp. 8-13, doi: [10.1080/10580530701777107](https://doi.org/10.1080/10580530701777107).

## Appendix

### Interview guide

The interview questions followed the guide below. We specifically focused on how successful the application of BA was in solving business problems.

### Introduction

- (1) What is your current role and for how long have you been in this role?
- (2) What are your responsibilities in this role?

### Business analytics and problem-solving

- (1) What is your understanding of BA?
- (2) What analytics tools or methods does the BA team use? (Provide examples.)
- (3) What business problems do you solve with BA?
- (4) To what extent are BA techniques appropriate for solving those business problems?
- (5) How do you evaluate the effectiveness of BA in solving business problems?
- (6) Are there any specific problems that analytics is unable to solve? Give examples.
- (7) What changes can be made to improve the ability of BA to solve business problems?

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