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Opinion paper

Unpacking task-technology fit to explore the business value of big data analytics

Givemore Muchenje [a,*], Marko Seppänen [b]

[a] Faculty of Management and Business, Tampere University, FB308 Festia Building, Korkeakoulunkatu 7, 33720, Tampere, Finland
[b] Faculty of Management and Business, Tampere University, Tampere, Finland

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ABSTRACT

Understanding how the application of big data analytics (BDA) generates business value is a persistent challenge in information systems (IS) research. Improving understanding of how BDA realizes business value requires unpacking theories to study the phenomenon. This study unpacks the task-technology fit (TTF) theory toward generating new and improved insights into the business value of BDA. Extant studies on TTF have mainly focused on traditional IT which is different from digital technologies like BDA that are malleable and dynamic. While TTF has primarily focused on how the technology meets task requirements, this study contends that tasks can also be structured to fit the functionality of technology. This study proposes a 2 × 2 matrix framework to explain how BDA and tasks interact. The framework indicates how the reconfigurability of tasks and the editability of BDA impact the fit between tasks and BDA. Future research should explore how the fit between tasks and BDA changes over time.

1. Introduction

Tasks are the activities through which business outcomes are achieved. Technologies are crucial to executing those tasks. The interaction between a task and technology is referred to as task-technology fit (TTF) (Goodhue & Thompson, 1995; Howard & Rose, 2019; Mathieson & Keil, 1998; Teo & Men, 2008). The fit between the task and technology determines whether the technology can be applied to the task. When the technology and task characteristics do not match, users may feel disinclined to use the technology in the task. In this article, we unpack the TTF theory to explore the business value of big data analytics (BDA). TTF signifies a novel approach to understanding BDA's business value in that it focuses on both the task and technology (Jeyaraj, 2022).

While TTF has been used extensively to explore the benefits of using information technologies (IT), there has been limited application of the theory in the context of digital technologies like BDA (Gebauer et al., 2010; Goodhue & Thompson, 1995; Junglas et al., 2008; Zigurs et al., 1999). BDA differs from traditional IT. Traditional IT support the business's day-to-day operations while BDA focuses on analyzing data to extract insights that lead to better decision-making (Gupta & George, 2016). There is a limited understanding of how the nature of BDA affects its fit with tasks. The fit between tasks and technology affects how much business value can be realized from the application of the technology (Junglas et al., 2008). Therefore, it is crucial to understand the nature of this fit. To address the knowledge gap, we unpack TTF with an emphasis on BDA as a digital technology. Unpacking a theory is important when there is a change in the theory's key constructs (Burton-Jones et al., 2021). Technology is a key construct of TTF. A change in technology calls for an exploration of what that change means for the fit between the technology and tasks. Digital technologies possess unique characteristics.

The unique characteristics of digital technologies are their generativity (Avital and Te'eni, 2009; Nambisan et al., 2019; Yoo et al., 2012), embeddedness, and editability (Benbya et al., 2020), self-referentiality and reprogrammability (Yoo et al., 2010), and non-materiality (Baskerville et al., 2020). These characteristics enable digital technologies to be applied to a variety of tasks. BDA includes database technologies such as Hadoop, advanced analytics and visualization applications (Zhu et al., 2021). BDA use aims to support strategic goals, enhance organizational performance, and achieve better decision outcomes (Holsapple et al., 2014). These goals are achieved through tasks, which makes exploring how BDA and tasks fit a crucial research agenda.

The concept of fit arises from the interaction between a task and technology (Goodhue & Thompson, 1995; Howard & Rose, 2019;

* Corresponding author.
E-mail addresses: givemore.muchenje@tuni.fi (G. Muchenje), marko.seppanen@tuni.fi (M. Seppänen).

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Mathieson & Keil, 1998; Teo & Men, 2008). Fit highlights the importance of aligning technology characteristics with task characteristics. The lack of fit between the task and technology is referred to as task-technology misfit (Howard & Rose, 2019). Task-technology misfit means that the technology includes too few or too many features to perform the task. This connotes that there is fit when technology has just the right number of features relative to the requirements of a task. Task characteristics define what is to be achieved and how the desired outcome can be attained (Zigurs & Buckland, 1998). We argue that the fit between tasks and BDA determines the business value of BDA.

This study makes the following contributions to knowledge. We suggest that the fit between BDA and tasks is not necessarily that of bilateral dependence but also unilateral dependence (Teece, 1986). Fit can be in terms of the technology aligning with the requirements of a task. It can also be the unilateral dependence of a task on a technology, that is, the task must conform to the technology (Baskerville, Myers, & Yoo, 2020; Fernandez-Vidal, Gonzalez, Gasco, & Llopis, 2022). This study, therefore, extends the literature on TTF by broadening the understanding of the emergence of fit between tasks and technology. Specifically, explorations of fit should not be limited to the extant understanding of fit as the technology meeting task requirements (Gebauer et al., 2010; Howard & Rose, 2019; Jeyaraj, 2022) but also account for the task conforming to technology characteristics (Fernandez-Vidal et al., 2022). We posit that the editability and generativity of BDA positively affect the level of fit between BDA and tasks. We introduce the concept of dynamic fit which indicates that the fit between BDA and a task can change during the execution of the task. Further, we advance a taxonomy of different ways that BDA and tasks can interact. We propose that the greater the reconfigurability of a task, the greater the achievability of an ideal fit. Building on TTF, this paper extends the literature on the business value of BDA (Kitchens et al., 2018; Lehrer et al., 2018; Muller et al., 2018) by highlighting the importance of achieving ideal fit to maximize this business value (Junglas et al., 2008).

This article is structured as follows. We next discuss the literature on TTF and BDA. Since TTF does not relate to a specific technology, it is crucial to point out the features of the technology under study. We highlight salient features of BDA. The article then proceeds to explore the business value of BDA in the context of TTF. Propositions are presented to underscore how BDA can realize business value. In the discussion section, we point out the implications of this study. The conclusion spotlights the contributions of this article.

2. Theoretical background

2.1. Task-technology fit

TTF is the extent to which a given technology helps an individual to perform tasks (Goodhue & Thompson, 1995). This earlier study makes the following additional assertions. First, the performance of the individual is moderated by the degree to which the technology fits the task. Second, user characteristics determine how well they use technology. The antecedents of TTF are interactions between the individual, task, and technology. Rephrased, TTF theory states that improved performance in terms of faster or more efficient accomplishment of tasks is a result of the fit between individual abilities, technology functionalities and task requirements (Goodhue, 1995).

TTF has been explored in terms of the fit between group tasks and group support systems (Zigurs & Buckland, 1998). Group support systems enable groups or teams to communicate, interact and share information in problem formulation and resolution. Accordingly, in the context of TTF, tasks exist at the individual and group levels. At the individual level, a task refers to individual actions that generate outputs (Aljukhadar et al., 2014; Goodhue & Thompson, 1995). At the group level, a task relates to how members of a team must work together to achieve stated goals through some process and using given information (Zigurs & Buckland, 1998). We define tasks as the activities that can be performed with BDA to create business value.

The fit between a task and technology refers to how efficiently and effectively a particular task can be performed with a particular technology (Mathieson and Keil, 1998). Fit has been denoted as profile deviation, mediation, moderation, gestalts, covariation and matching (Venkatraman, 1989). These six types of fit have been highlighted in connection with TTF (Howard & Rose, 2019; Teo & Men, 2008; Zigurs & Khazanchi, 2008). These various types of fit have their challenges in the context of TTF. Some of these challenges have been articulated as follows (Howard & Rose, 2019). First, fit as moderation requires the identification of specific characteristics of the task and the technology that interact to determine performance. The challenge with this is that the list of task characteristics and technology characteristics that can be mapped together is colossal. Second, with fit as matching, there is no certainty that performance from a pairing of the task and technology is a consequence of TTF (Howard & Rose, 2019). This study builds on alternative approaches to fit that have been advanced in the literature.

The fit between a task and technology can be an ideal fit, over-fit, or under-fit (Junglas et al., 2008). Ideal fit indicates that there is an exact match between task requirements and technological functionality. Since no technology can exactly match the requirements of a task (Goodhue & Thompson, 1995), ideal fit means that the gap between technological functionalities and task requirements is imperceptible. Over-fit relates to the technology providing more functionality than is required for the task requirements. Under-fit means that the technological functionality falls short of task requirements. Under-fit has also been labeled as "Too Little" to indicate that too few technological features cause users to be unable to perform the task (Howard & Rose, 2019). In the same vein, over-fit has been labeled as "Too Much". To explicate over-fit, we note that when technological features that are irrelevant to a task are entwined with those required to meet task requirements, the application of the relevant features will cause the irrelevant ones to be more than the task's requirements (Soda & Furlotti, 2017). In addition, the features of technology may have been crafted without consideration for the current portfolio of tasks. This means that the application of the technology to the portfolio of tasks may result in over-fit or under-fit.

Before proceeding to the next section on the features of BDA, we highlight some of the criticisms that have been levelled against TTF. First, it has been argued that TTF does not clearly outline what constitutes a task environment (Rai & Selnes, 2019). Specifically, TTF does not account for interdependencies among tasks. The fit between a task and technology is affected by other related tasks that may apply the same technology. As a result, TTF has been redefined as "how well the technology is integrated with the set of interrelated tasks (practices) in a social context" (Rai & Selnes, 2019), p. 2). While organizational tasks tend to have interdependencies, we argue that it is still possible to evaluate how technology fits a particular task.

The following three challenges of TTF have been noted (Furneaux, 2012). First, it can be difficult to clarify the demands of a task. This is because tasks can be complex (Campbell, 1988; Haerem et al., 2015). Complexity arises from the fact that tasks can be linked with multiple desired outcomes or there can be multiple ways of arriving at the task's desired outcome. Complexity increases if for each of the multiple outcomes of the task there are multiple paths to arrive at it. Building on this complexity aspect, tasks have been classified into simple, problem, decision, judgment, and fuzzy (Zigurs & Buckland, 1998). Simple tasks have a single desired outcome and a single solution. The demands of simple tasks may be easy to clarify. Problem tasks are associated with finding the best solution from multiple possible solutions to achieve a single well-defined outcome. Decision tasks are associated with finding a solution that satisfies multiple outcomes. Judgment tasks exhibit uncertainty regarding the solution. Fuzzy tasks are perhaps the most difficult to clarify. They are not focused and potentially involve multiple solutions and multiple outcomes as well as uncertainty about achieving those outcomes. We note that these task aspects can make it difficult to come up with a list of technological functionalities that fits them.

However, BDA can be adaptively altered to fit the demands of some of these complex tasks (Benbya et al., 2020).

The second challenge connected with TTF is that establishing the capabilities of an information system is difficult. The features of the technology can be dynamic, especially in consideration of the reprogrammability of digital technologies (Yoo et al., 2010). Rather than consider the editability of BDA as an impediment, we regard it as possibly leading to the notion of dynamic fit. Dynamic fit here refers to the possibility of the fit between the task and technology changing during the execution of the task. This is logical if we assume that users can decide to pursue an alternative path to achieving the same task outcomes with the same technological functionalities. This reasoning anchors on the type of task that is involved. Fuzzy tasks may require changing the way the features of the technology are used to realize outcomes.

The third challenge associated with TTF is ascertaining whether the capabilities of the technology match the characteristics of a task (Furneaux, 2012). Prior research has primarily relied on self-reported measures to assess the fit between the task and technology (Goodhue & Thompson, 1995; Goodhue, 1995; Howard & Rose, 2019). We suggest that matching BDA to tasks can be a process involving incremental adjustments to BDA until an ideal fit is attained. This suggestion is contra to the assertion that technology will not be used if it does not offer sufficient advantage (Dishaw & Strong, 1999). We posit that a technology such as BDA that is editable and reprogrammable can still be used even though there may be an initial under-fit with tasks. In this study, we contextualize TTF by removing the construct of user characteristics and focusing on BDA and tasks (Hong et al., 2014). This contextualization is salient when highlighting how BDA can be applied to tasks that do not entail user involvement (Leonardi, 2011). We proceed to highlight the characteristics of BDA in connection with TTF.

2.2. Big data analytics

BDA is the process of extracting insights from the analysis of diverse and high volume fast-moving data (Gandomi & Haider, 2015). The effectiveness of BDA is measured by the ability to deliver insights when and where they are needed throughout the different levels of an organization (Chen et al., 2015). Indicatively, the analysis of data with BDA aims to "create actionable insights for sustained value delivery, measuring performance and establishing competitive advantages" (Wamba et al., 2015), p. 235). Even though BDA is often explored through its three analytics categories of descriptive, predictive, and prescriptive, we do not emphasize these distinctions (Lepenioti et al., 2020). Building on this prior literature, we define BDA as the extraction of actionable insights from diverse, high volume, and fast-growing data to create business value through the execution of tasks. BDA is used as a decision system and decision support system (Clarke, 2016). As a decision system, the inferences from BDA are extremely influential in decision-making. This is the case with the automation of decision applications. When BDA is used as a decision support system, the insights that it generates are evaluated by humans before being applied.

The focus of BDA is not merely on advanced reporting or visualization of extant data to extract better insights but on linking explanatory variables to business outcomes (Baesens et al., 2016). BDA is valuable when linked to specific business goals. The application of BDA does not automatically lead to better decisions and improvements in business value (Muller et al., 2016). Consequently, we highlight the emergence of business value through tasks. Insights are useful when generated with a focus on what potential actions can be taken with them (Kitchens et al., 2018). The fit between BDA and the task to which BDA is applied can be defined as that of predefined profiles since such a fit is independent of the use context (Gebauer et al., 2010). In that case, BDA is expected to meet the exact requirements of the task.

We posit that the fit between a task and technology can exist at different levels. BDA has an acontextual fit with tasks in the process of insights generation. This means that insights are generated with a target of exactly fitting specific tasks. The next level is that of contextual fit and involves the actual deployment of the generated insights in tasks. This is the level that we focus on in this study. When the insights are deployed in the task, that is when a discovery will be made whether BDA has an ideal fit, over-fit or under-fit with the task. For instance, the insights may fall short of the requirements of the task that needs to be accomplished.

BDA falls under the broad category of technologies that are referred to as 'digital'. The unique characteristics that differentiate digital technologies from other technologies are reprogrammability, homogenization of data and self-referentiality (Yoo et al., 2010). Reprogrammability relates to the ability of digital technology to be altered which enables such technologies to meet the requirements of different tasks. Homogenization of data relates to the ability of digital technologies to uniformly tackle various forms of data that relate to tasks. Self-reference means that those tasks whose requirements can be fulfilled with digital technologies essentially possess aspects that can be represented in digital form. As a digital technology, BDA can be modified or updated continuously and systematically (Kallinikos et al., 2013).

3. Realizing business value through tasks

In this section, we depict the interaction between BDA and tasks in the form of a framework. Both tasks and technology have static and dynamic aspects. Static tasks are well-articulated, finite and have low ambiguity (Avital & Te'eni, 2009). Such tasks are either simple or problem tasks and have clear desired outcomes (Zigurs & Buckland, 1998). Tasks can be dynamic in the sense that their execution paths can be altered. Dynamic tasks can be unclear and ambiguous (Avital & Te'eni, 2009). The lack of clarity can stem from changes in the task requirements or alterations to expected task outcomes during the execution of the task. BDA is static when its application to tasks is based on the extant capabilities of the technology. This means that the extant BDA functionality is sufficient to meet the requirements of tasks. BDA is dynamic when it must be altered to meet the requirements of specific tasks. In Fig. 1 below we show the interactions between the task and technology (BDA) along the static and dynamic dimensions in the format of a 2 × 2 matrix. Each quadrant is then elaborated in separate subsections.

3.1. Stable interaction

We refer to *stable interaction* as the emergence of an ideal fit between the task and technology. In other words, BDA is expected to produce known business value when applied to known tasks. Material agency (Leonardi, 2011) and routinization (Winter, 2003) constitute the basis of ideal fit. Material agency refers to the capacity of BDA to act on tasks without human intervention. Automation of decision-making exhibits

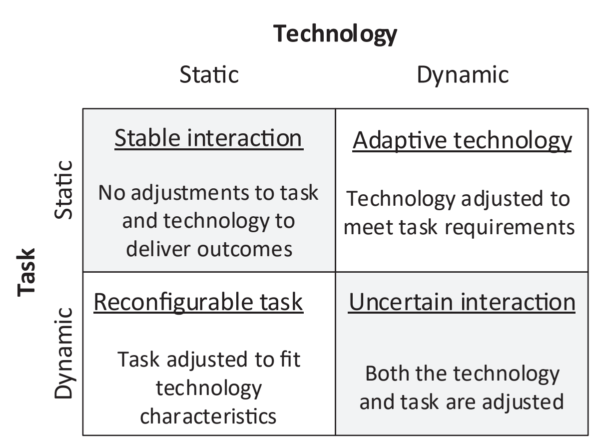

Fig. 1. Conceptual model of task-technology fit.

the material agency of BDA (Clarke, 2016). The material agency of BDA has been demonstrated in service innovation (Lehrer et al., 2018). The service innovation can entail providing content that is automatically tailored to the user according to their behavior in online channels. Routines are learned, patterned, and repetitious actions that aim to achieve specific objectives (Winter, 2003). A pattern indicates how the interaction between BDA and tasks becomes a solution that addresses a problem in a particular context (Zigurs & Khazanchi, 2008). Business problems that are addressed with BDA through tasks underline the business value of BDA.

While it is possible that over-fit can be persistent when it does not have adverse effects on expected outcomes, we do not see how under-fit can become part of the 'stable interaction' between BDA and tasks. We indicate that ad hoc use of BDA in tasks is not likely to result in an ideal fit. Solving problems in an ad hoc manner helps to respond to unpredictable changes in the business environment (Winter, 2003). However, ad hoc use of BDA also impairs the ability to accurately sense and respond to customer needs (Kitchens et al., 2018). Patterns do not normally develop and there are typically no repetitions with ad hoc problem-solving.

Stable interaction is grounded in the tool view of technology (Orlikowski & Iacono, 2001). The tool view posits that technology is designed to perform certain tasks. As a tool, BDA brings about performance benefits based on its defining characteristic of analysing data to generate insights that are relevant to addressing pre-articulated problems through tasks. This means that a problem is identified for solving, and then BDA is applied in tasks that constitute the problem-solving process (Hippel & Krogh, 2016). Stated differently, BDA is a technical solution for harnessing identified opportunities or efficiency issues (Fernandez-Vidal et al., 2022).

The positive effect that BDA has on operational efficiency and the attainment of favorable outcomes can be construed as a sign of an ideal fit between BDA and tasks (Aljukhadar et al., 2014). Tasks involving manufacturing operations are examples of tasks that have clearly defined objectives (Popovic et al., 2018). In these manufacturing operations, BDA aims to enhance manufacturing performance by maximizing equipment uptime. The task involved here is of ensuring that the manufacturing equipment continues to function. This has clear operational efficiency measures in the form of uptime which constitutes the goal of the task. In Fig. 1 we present *stable interaction* as an optimum state in achieving business value with BDA. However, the path to achieving an ideal fit can require first addressing under-fit or over-fit by changing the task or technology. We expect that routinization should involve the elimination of under-fit or over-fit. Building on the discussion in this section, we put forward the following propositions.

P1a: The higher the level of routinization the greater the possibility of achieving an ideal fit.

P1b: The higher the ad hoc *interaction of tasks and BDA, the lower the possibility of achieving an ideal fit.*

3.2. Adaptive technology

TTF is grounded on the premise that the technology that fits task requirements will be used (Dishaw & Strong, 1999; Junglas et al., 2008). This implies that there may be persistence in the use of technologies in those tasks in which there is an ideal fit. The assumption behind this argument is that technologies are fixed, at least relative to the execution of tasks. For digital technologies like BDA, a defining characteristic is generativity (Yoo et al., 2012). Generativity means that digital technologies are dynamic and malleable. It is this generativity that enables BDA to deal with tasks that are unclear and ambiguous (Avital & Te'eni, 2009). We propose that because of this generativity, any lack of fit between BDA and tasks may not be persistent.

To demonstrate, BDA can be understood in terms of the predictions that it generates and tasks as activities that use these predictions. Fit can be estimated when both technology characteristics and task characteristics are known (Mathieson & Keil, 1998). What is known is the ability of BDA to generate predictions, and what tasks can use those predictions (Kitchens et al., 2018). Within BDA, the final stage in predictive modeling is the use of the model. Such a model generates predictions or classifications for a new set of observations (Shmueli & Koppius, 2011). The predictive model can be treated as a feature of BDA that is aligned to tasks. Correct predictions beyond the requirements of tasks indicate over-fit. Incorrect predictions show an under-fit. There is a cost associated with each incorrect prediction which infers a loss of business value (Kitchens et al., 2018). The malleability of BDA is in ensuring not only that the predictive model fits the task but updating such a model to enhance its fitness for the task.

BDA is editable which makes it pliable to fit different types of tasks (Kallinikos et al., 2013). We assert that the ability of BDA to meet task requirements is determined by the extent to which BDA can be edited to match those task requirements. The fit between the task and technology is thus governed by the limits of that editability. The ability to customize BDA for specific applications ensures the fit between BDA and tasks (Ransbotham & Kiron, 2017). Another way of looking at this is to view BDA as an assemblage of practices and technologies denoting "how things get done when it comes to operating on evidence – with goals of increasing understanding, making predictions, generating new valuable knowledge" (Holsapple et al., 2014), p. 134). We argue that BDA can be adapted to meet the requirements of tasks, that is, BDA enables things to be accomplished. Unlike traditional IT that may not be easily reconfigured, the reprogrammability of BDA can eliminate under-fit with those tasks. Reprogrammability demonstrates how the flexibility of technologies helps to meet flexible tasks (Leonardi, 2011). Further, reprogrammability increases the portfolio of tasks to which BDA can be applied. We proffer the proposition below that underscores how the changes that can be made to BDA can help to reduce under-fit with tasks.

P2*: When the technology must meet task requirements, the fit between the task and technology is dependent on the extent to which the technology is malleable such that the greater the malleability of the technology the lower the possibility of under-fit.*

3.3. Reconfigurable tasks

Based on the features of BDA, tasks can be crafted. Such tasks fit the capabilities of BDA. This is akin to the solution presenting itself before the problem (Hippel & Krogh, 2016). Reflectively, BDA is not only carried out to evaluate solutions for extant business problems but also leads to the discovery of observations and patterns that were not envisioned before the analysis of data (Chen et al., 2021). The new unanticipated insights present an opportunity to craft tasks to realize business value from them. BDA use has been classified into optimizing and learning (Chen et al., 2021). In optimization, BDA is used in the identification of solutions for established objectives. The use of BDA in learning entails the identification of opportunities. This has connotations of evaluating what else technology can be used for based on its features (Fernandez-Vidal et al., 2022). The tasks that will be crafted to realize the discovered opportunities must fit the features of BDA.

While insights may be discovered automatically from the analysis of data (Agarwal & Dhar, 2014), the question is whether organizations make investments in BDA with the hope of discovering useful insights at some point without a focus on specific pre-identified business problems. The structuring of tasks according to emergent opportunities can be regarded as a by-product of how BDA was meant to be used. BDA use leads to the discovery of insights into previously hidden patterns and unknown correlations in the data (Chen et al., 2015). An example of a task that fits BDA is customer service interaction (Lehrer et al., 2018). In these customer service interactions, BDA provides insights that trigger the structuring of the task of meeting the needs of the customer. BDA can also make recommendations for action, which allows the task of service provision to be structured according to those recommendations.

The depiction of TTF is that it is the functionality of the technology that must fit the task (Junglas et al., 2008). Based on reconfigurable tasks, we argue that the task can also fit the technology. The argument comes down to whether it is the task or technology that is controlling the interaction between them. The concept of unilateral dependence has been advanced to highlight how one resource can control the nature of the interaction among the resources (Teece, 1986). In Fig. 1, we depict the task as being reconfigurable when it has unilateral dependence on technology. Building on the dependency of tasks on BDA, we put forward the proposition below.

P3: When tasks are based on technology, the fit between the task and technology is dependent on the extent to which the task can be structured or reconfigured such that the greater the reconfigurability of the task the greater the achievability of an ideal fit.

3.4. Uncertain interaction

When the business environment changes, business value can be maintained by changing BDA (adaptive technology) or changing the task (reconfiguring tasks). BDA is expected to have a greater impact on operational efficiency in industrial environments that are characterized by low dynamism than when the industry dynamism is high (Zhu et al., 2021). The connotation of this is that the greater the changes in the industry environment, the greater the need to adjust BDA or tasks to realize or maintain business value. New BDA competencies may be required to adapt to a dynamic business environment (Kitchens et al., 2018). We assert that ideal fit is not a guarantee for maintaining or enhancing business value in a dynamic environment. The business environment's dynamism can cause an ideal fit to produce outcomes that are obsolete or insufficient for the needs of the business. When both tasks and BDA are simultaneously altered to respond to changes in the business environment, there arises the possibility of an under-fit or over-fit emerging. We characterize the concurrent changing of a task and technology as *uncertain interaction* because it can be difficult to accurately determine a priori the kind of fit that will emerge from that interaction.

Fit is sometimes approached from a contingency perspective (Zigurs & Khazanchi, 2008). The contingency perspective has two salient aspects that apply to *uncertain interaction* (Donaldson, 2006). First, fit can expand into misfit that prompts a cycle of changes to attain fit. In the context of TTF, misfit means under-fit or over-fit. This indicates that changes to the task and technology can disrupt ideal fit which prompts the need for further changes in the task and technology to correct the emergent under-fit or over-fit. Second, it is possible to move from one level of ideal fit to a new level of ideal fit. Attainment of ideal fit does not connote that the task and technology may not be altered. We posit that both the task and technology may be altered without affecting the extant ideal fit between them. Business value is created with BDA through optimization mechanisms and experimentation (Grover et al., 2018). Optimization involves changing both BDA and tasks until an ideal fit is achieved. Experiments that innovate products and services can entail changing BDA and tasks until desired outcomes are attained. What we suggest here is that BDA and tasks can have an ideal fit and produce low business value. Changes to both BDA and tasks can lead to a different level of ideal fit that produces greater business value.

The effect of changes to tasks and BDA on fit can be traced back to the initial condition of fit. From a contingency perspective, there may be cycles between under-fit, ideal fit and over-fit where the resultant fit is governed by the extent of the changes. For instance, from an initial condition of under-fit, changes to tasks and BDA can lead to ideal fit or even over-fit. What we propose with *uncertain interaction* is that when both the task and technology are simultaneously altered, the nature of their fit may become very dynamic. Changing both the task and BDA makes sense when we consider the bilateral dependence between them (Teece, 1986). Bilateral dependence refers to the mutual dependence between the task and BDA. Location-based services that use BDA ensure that customers are provided with services when and where they need such services (Baesens et al., 2016). There is a mutual dependence between BDA and the task of providing location-based services. We contend that when the strength of the bilateral dependence between a task and BDA is low, a change in the task, BDA, or both, may not change the nature of the fit between them very much. In other words, such changes may cause little variations in business value. Anchoring on the ongoing discussion, we advance the following proposition.

P4: The greater the strength of the bilateral dependence between a task and BDA, the greater the dynamism of fit when the task or BDA changes.

4. Discussion

In this study, we indicated that TTF needs to be unpacked to explore the interaction between digital technologies like BDA and tasks. Unpacking theory is important to ensure that the theory can be revised to explore new phenomena (Burton-Jones et al., 2021). We noted that the use of TTF has so far largely focused on IT and not digital technologies. BDA is a primary digital technology (Gong & Ribiere, 2021). We highlighted that digital technologies exhibit unique characteristics such as malleability and generativity that differentiate them from traditional IT (Yoo et al., 2012). Building on the nature of digital technologies, we pointed out that TTF has so far partially captured the nature of the relationship between tasks and technologies. The extant focus of TTF is on how technology fits the requirements of tasks. However, digital technologies have the power to shape tasks (Baskerville et al., 2020). We extended TTF to cover the possibility of tasks having to fit the functionality of technology.

This study explored the business value of BDA through the fit between BDA and tasks. We focused mainly on BDA as an antecedent in TTF. We are aware that such contextual research is always partial in scope in that it does not cover all facets of a phenomenon (Avgerou, 2019). Since the TFF antecedent of user capabilities was not the aspect of interest in this study, we did not dwell on it. Contextual research tends to focus on only specific aspects of a phenomenon (Hong et al., 2014). In focusing on BDA and tasks, we pointed out how material agency and routinization are crucial to maintaining an ideal fit. Excluding user capabilities from the discussion of TTF does not suggest that such user capabilities play a minor role in TTF. Nevertheless, material agency demonstrates how tasks can be accomplished with BDA without user intervention.

The literature on TTF is not clear about whether the fit between a task and technology should be evaluated at the point when the technology meets the requirements to execute the task, or when the task outcome is achieved. Fit is projected as how well technology meets the requirements of a task (Pagani, 2006). This emphasizes the appropriateness of technology for performing the task and not necessarily achieving the task outcome. However, other studies emphasize fit in terms of achieving task outcomes (Aljukhadar et al., 2014; Teo & Men, 2008). Emphasizing the achievement of task outcomes aligns with the definition of fit as "the congruence between a technology and a task, that is, the extent to which a particular task can be performed effectively and efficiently with a particular technology" (Mathieson & Keil, 1998), p. 222). Effectiveness entails the completion of tasks as well as the achievement of goals (Rai and Selnes, 2019). The business value of BDA is based on the achievement of task outcomes.

We raised the concept of dynamic fit to highlight how the fit between tasks and BDA is subject to change. TTF has been criticized for not addressing change over time (Fuller & Dennis, 2009). Hinging on BDA as an adaptive technology, we have argued that the nature of fit can change over time. It is logical to assume that technology undergoes improvements at some point which affects the nature of fit. Technology changes may be desirable to respond to changes in the business environment. Since under-fit and over-fit are undesirable because they generate business value that is lower than the ideal fit, achieving an ideal fit is paramount (Junglas et al., 2008). From a contingency perspective, dynamic fit can entail transitions between under-fit, ideal fit and over-fit with the duration of under-fit and over-fit possibly being short. The assumption for the shortness of the duration of under-fit and over-fit is that these two types of fit are likely to be transitory phases toward ideal fit.

We argued in this study that the reconfigurability of tasks and editability of BDA control the nature of the fit between them, and consequently, business value. BDA is flexible in that it can be reconfigured to do new things (Leonardi, 2011). We have not addressed what happens when the limits of task reconfigurability and BDA malleability are reached and what that means for fit. We assume that reaching such limits defines the upper bound of the business value that can be realized when applying BDA to a specific task. The contingency perspective assumes that an ideal fit can shift from one level to another (Donaldson, 2006). Hence, limits to the reconfigurability of a task and editability of BDA should also coincide with the highest level of ideal fit between the task and BDA.

4.1. Implications for practice

We have highlighted the following aspects that determine the extent of the business value that can be generated from BDA in the context of TTF. First is the extent to which BDA fits the requirements of tasks. Dependence of the task's accomplishment on the technology means that the task is constrained or enabled by the features that are available in the technology (Fuller & Dennis, 2009). Even so, tasks define the resources that are required to accomplish them (Furlotti & Soda, 2018). In this view, the way tasks are structured determines the business value that can be realized from BDA. The challenge in defining task requirements is that for some tasks these requirements are not clear (Furneaux, 2012). For instance, defining tasks related to reducing the amount of marketing for customers that are likely to churn may be difficult until the technology, that is BDA, has indicated the nature of such customers that are likely to churn (Kitchens et al., 2018). As a solution, tasks may be flexibly defined, or tasks can be re-defined according to how contextual factors unfold.

The pre-definition of a task without consideration of the capabilities of technology can be problematic. The crafting of the task may not contain all relevant requirements and contextual information with the result being a failure when technology is applied to the real-world task (Hippel & Krogh, 2016). This leads to the second determinant of the business value of BDA under TTF. Namely, the extent to which tasks can be structured to fit the capabilities of BDA determines the business value that can be generated. The conundrum for practice in this would be how to accurately ascertain the capabilities of BDA independent of tasks (Furneaux, 2012). Nevertheless, practice should note that BDA only generates value when tasks are carefully created to fit its capabilities. As an example of predictive process analytics, BDA predicts future conditions of business processes (Krumeich et al., 2016). These predictions of the future conditions of processes can be used to come up with prescriptions that forecast how processes get executed. In this case, we suggest that business value only gets realized when tasks that are associated with these processes are created to fit these predictions and prescriptions.

A compromise in the determination of business value around TTF would be to pre-define tasks considering the capabilities of technology. The expectation, in this case, is that the technology is an ideal fit for the task. Pre-defining tasks this way can be based on a historical application of technology in tasks or historically known capabilities of the technologies. The challenge remains that there is no guarantee that the known technological capabilities are a match for the defined task characteristics (Furneaux, 2012). Additionally, such an approach would be self-limiting in that it does not define tasks beyond the known capabilities of technology. Further, it does not make sense to broadly define tasks beyond the capabilities of technology when it is apparent that there is likely to be an under-fit. Tasks differ in terms of their complexity (Campbell, 1988; Haerem et al., 2015), type (Zigurs & Buckland, 1998) and goals (Avital & Te'eni, 2009). Practice may need to consider these various aspects to achieve an ideal fit between tasks and BDA.

4.2. Implications for research

The literature on TTF has mainly focused on how technologies can be used to meet the requirements of tasks (Howard & Rose, 2019; Rai & Selnes, 2019). This study highlights the need to consider the increasing role of technologies in shaping the world around us (Baskerville et al., 2020). That is, tasks can be crafted according to the characteristics of BDA. When tasks are crafted according to the technology, it is pertinent to delve deeper into the characteristics of the technology since such characteristics become the determinant of how business value can be realized. BDA falls under the category of digital technologies. The characteristics of these digital technologies such as their editability alter the nature of their fit with tasks (Benbya et al., 2020). Hence, this study indicates the importance of matching specific technology characteristics to task requirements. As an extension to the literature on TTF, this study emphasizes the role of tasks' reconfigurability and technology editability as key determinants of ideal fit.

The literature on the business value of BDA addresses the question of how business value can be realized (Kitchens et al., 2018; Wamba et al., 2015). While the questions relating to how and why phenomena occur are crucial, this study implicates the need to go beyond such questions (Volkoff & Strong, 2013). Business value can be realized with BDA, but the question of *what* business value also requires theoretical consideration. In the context of fit, *what* business value relates to whether such business value represents the highest level that can be achieved (Junglas et al., 2008). This study calls on research on business value to consider both questions of *how* and *what* business value is achieved.

This study has discussed how the fit between the task and technology can be analyzed as a problem-solving process (Hippel & Krogh, 2016). Problem-solving is inherent in the conceptualization of tasks. However, problem-solving also connotes that the solution can present itself before the problem. This means BDA can be treated as a solution available to be associated with tasks that are crafted later. Additionally, we indicated that fit can be explained through unilateral and bilateral dependence between BDA and tasks (Teece, 1986). Unilateral dependence indicates that tasks can be dependent on BDA. Conversely, BDA use can be dependent on task characteristics. Bilateral dependence signifies that tasks and BDA can be inextricably bound together. Further, we pointed out that fit can be understood from a contingency perspective (Donaldson, 2006; Zigurs & Khazanchi, 2008). The contingency perspective reinforces the idea that fit is not necessarily fixed. Rather, there can be cycles between under-fit, ideal fit and over-fit in the execution of a task or possibly, in various instances of the task. In bringing out these aspects, we assert that research can explore TTF according to its purpose (problem-solving), nature (dependence), and transition (contingency).

4.3. Future research directions

The concept of fit assumes that once there is a fit between technology and task, that fit remains the same during the duration of the task. Such a view does not account for the possibility that fit may change during the execution of a task. While there can be an ideal fit between the technology and task at the commencement of the task execution, variabilities in the context may result in a lack of fit as the execution of the task progresses. Future research may need to tackle the nature of this dynamic fit to understand how it affects the generation of business value from the application of BDA in tasks.

The notion of over-fit requires further exploration. Precisely, there is a need to understand whether over-fit is avoidable. Prior research has pointed out that when features of a technology that are relevant to a task are intertwined with those that are irrelevant to the task, then the application of the relevant features causes the irrelevant ones to be over-fit (Soda & Furlotti, 2017). The extra nonrequired but helpful features of technology may nonetheless be useful for other tasks (Howard & Rose, 2019). Future research should explore scenarios where over-fit can be desirable. When a technology presents more features than are required for a task, this can be an opportunity to broaden the scope of the task to utilize those features.

In Fig. 1, "adaptive technology" denotes that BDA can be modified. The extent to which BDA can be altered affects the nature of fit. Future research can address the question of whether there are limits to the editability of BDA that affect its fit with tasks. We highlighted the importance of task reconfiguration in achieving an ideal fit. Future research should explore the extent and limitations of task reconfiguration in the context of TTF. While we emphasized the importance of ideal fit, exploring the contexts where the ideal fit between BDA and tasks may be undesirable may be crucial.

5. Conclusion

TTF offers a novel and robust explication of the business value that can be generated from the application of technologies. The theory is generalizable to all situations where technology is applied to tasks. We noted that the nature of technologies has significantly changed since the theory was advanced. Great changes like the emergence of digital technologies, and the deep impact such technologies have on business problems, calls for unpacking theories or even the development of new theories. This study sought to advance understanding of how BDA generates business value by unpacking TTF. We chose to focus on TTF since it links technologies and tasks. The TTF theory indicates that the business value of BDA is realized when BDA is used to meet the requirements of tasks. This connotes that the business value of a technology is not entirely dependent on the technology, but also on the nature of the tasks to which it is applied. Thus, a potentially great technology that is not applied to the right tasks may not be very valuable to an organization. We argued that fit is also paramount when tasks are structured to align with the functionality of technology.

This study presented four propositions to emphasize the nature of the fit between tasks and BDA. Even though we argued that the editability of BDA can increase the possibility of achieving an ideal fit, there is a need to further explore the limits of this editability. There is the possibility that tasks may have requirements that extend beyond the capabilities of BDA. When tasks' requirements extend beyond the capabilities of BDA, it means that when BDA is applied to those tasks there is a high possibility of under-fit. While tasks can be reconfigured to match the characteristics of BDA, there can be a limit to the extent to which the tasks can be reconfigured. These are areas that future research should explore to improve understanding of TTF.

CRediT authorship contribution statement

Givemore Muchenje. Conceptualization, Writing – original draft preparation, review and editing. **Marko Seppänen.** Supervision, Resources, Writing – original draft, review and editing.

Declarations of interest

none.

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