APPLYING AND EXTENDING THE THEORY OF EFFECTIVE USE IN A BUSINESS INTELLIGENCE CONTEXT [1]

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The benefits that organizations accrue from information systems depend on how effectively the systems are used. Yet despite the importance of knowing what it takes to use information systems effectively, little theory on the topic exists. One recent and largely untested exception is the Theory of Effective Use (TEU). We report on a contextualization, extension, and test of TEU in the business intelligence (BI) context, a context of considerable importance in which researchers have called for such studies. We used a mixed-method, three-phase approach involving instrument development (n = 218), two-wave cross-sectional survey (n = 437), and three sets of follow-up interviews (n = 33). The paper contributes by: 1) showing how TEU can be contextualized, operationalized, and extended, 2) demonstrating that many of TEU's predictions hold in the BI context while also revealing ways to improve the theory; and 3) offering practical insights executives can draw on to improve use of BI in their organizations.

Keywords: Effective use, business intelligence, organizational resources, survey, interviews.

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[1] Viswanath Venkatesh was the accepting senior editor for this paper.

[2] Since 1-Jan-2021, Andrew Burton-Jones has served as Editor-in-Chief of MIS Quarterly. This paper was submitted on 13-Mar-2017 and underwent four rounds of review prior to his appointment.

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INTRODUCTION

This paper advances knowledge of what it takes to use information systems effectively in organizations. While researchers have studied system use for decades (Venkatesh et al. 2016b) a perennial challenge has been learning how to use systems to improve performance at work. One way to study this link has been to focus on system use *in general* and account for contextual specificities that shape how use affects performance, such as the system features used (Zhang and Venkatesh 2017), or various mediators (Ahearne et al. 2008; Venkatesh et al. 2011) or moderators (Ko and Dennis 2011; Tong et al. 2015; Zhang 2017) of the relationship. Another way to study this link has been to focus on specific *types* of use associated with performance, such as faithful use (Chin et al. 1997), infusion (Meister and Compeau 2002), exploitive use (Burton-Jones and Straub 2006), explorative use (Sun et al. 2019), extended use (Hsieh et al. 2011), and adaptation (Bala and Venkatesh 2016).

Motivated by this second stream of research, a new line of work on *effective use* has emerged (Burton-Jones et al. 2018; Pavlou et al. 2008). Its emerging nature is evident in the variety of terms used for the core idea, such as effective use (Burton-Jones and Grange 2013), enhanced use (Bagayogo et al. 2014), meaningful use (Blumenthal and Tavenner 2010), quality use (LeRouge et al. 2007), and proficient use (Veiga et al. 2014). Despite the variety of terms, the common theme is to search for how to use information systems to attain desired performance outcomes. While prior concepts such as faithful use, infusion, extended use, and adaptation have been used in this vein before, they were not designed to reflect effective use *itself*. For instance, faithful use refers to using a system as it was intended to be used, and extended use refers to using more of a system's features. The new line of work is motivated by developing concepts that focus squarely on *effective use*, its causes, and its consequences. Focusing squarely on effective use is important practically because it enables researchers to speak more directly to the goals of managers. It is also important theoretically because studying how systems are used effectively provides a path to understanding the nature of information systems (as objects constituted in use) (Burton-Jones and Volkoff 2017, p. 483).

Research on effective use is still developing its theoretical foundations. We are aware of only one general theory: Theory of Effective Use (TEU) (Burton-Jones and Grange 2013). Although TEU is well-cited, it has so far received only initial, partial testing (Adenuga and Kekwaletswe 2017; Campbell and Roberts 2019; Choi and Tulu 2017; Eden et al. 2019).[3] Recker et al. (2019) urged detailed testing. Just as Chin et al. (1997) advanced theory through measurement and testing, we advance research on effective use by creating detailed instruments and conducting TEU's first comprehensive, mixed-methods test and extension.

While our main goal is to test and extend TEU, any such study needs to account for context (Alvesson and Kärreman 2007 p. 1272; Johns 2006). Thus, our secondary goal is to contextualize TEU. Contextualizing a general theory for a specific context provides a top-down alternative to the recently-proposed bottom-up approach for studying effective use via grounded theory (Burton-Jones and Volkoff 2017). Top-down and bottom-up approaches are both necessary but a top-down approach has not yet been demonstrated. That is our aim.

We focus on the business intelligence (BI) context for three reasons, because: 1) learning how to leverage BI is of significant practical importance (Agarwal and Dhar 2014); 2) BI researchers continue to stress the mixed results in past work and the need to study effective use as a missing piece in this literature (Ain et al. 2019; Ramakrishnan et al. 2012; Trieu 2017); and 3) as we will explain (in the Background section), the assumptions of BI match the assumptions of TEU, so it makes an excellent setting in which to test TEU. Accordingly, our research questions are: 1) *What drives the effective use of BI systems?* (2) *What are the consequences of variation in the effective use of BI systems on the performance*

[3] We reviewed all 352 papers that cited TEU in Google Scholar up to 5/2020. Only eight measured and tested TEU, all of them very partially (see https://osf.io/tv6wh/?view_only=63b91a611b9a448f8df5ddb2fbfdcd79). There are no comprehensive mixed-methods tests. As Colquitt and Zapata-Phelan (2007) note, "Theory testing is particularly important…because some of the most intuitive theories … wind up being unsupported" (p. 1282).

outcomes of BI users? Consistent with TEU, we study these issues at the individual level of analysis. As we note later, this level has been relatively overlooked in past BI research.

Empirically, this work draws on a mixed-method, three-phase study: instrument development (n = 218), two-wave cross-sectional survey (n = 437), and three sets of follow-up qualitative interviews (n = 33). As we will show, our results support some aspects of TEU while challenging other aspects. While some of these challenges suggest a need for more contextualization, other challenges point back to TEU's specification in general.

Overall, our work contributes by 1) contextualizing, operationalizing, and extending TEU, 2) showing that many of TEU's predictions hold in a BI context while also revealing ways to improve it; and 3) helping executives see how they can improve use of BI in practice.

BACKGROUND

This study draws largely on three bodies of literature that we introduce in turn below.

Theory of Effective Use (TEU)

Burton-Jones and Grange (2013) explained how they derived TEU from representation theory. *Representation theory* states that the basic function of an IS is to provide users with a representation of a domain, such as when a sales system represents a region's sales activities for managers (Wand and Weber 1995). According to representation theory, an IS provides this representation via three structures: 1) deep structure, which conveys meaning about a domain to users (such as what the BI system can say about sales in a region); 2) surface structure, which provides facilities (such as a user interface) through which users can access the deep structure; and 3) physical structure, which is the machinery supporting the other structures (such as the servers on which the BI system runs). Data are viewed as tokens that populate the deep structure. For instance, numbers in a database inherit a specific meaning if input as a sales ID. Burton-Jones and Grange (2013 p. 4) defined *effective use* as "using a system in a way that helps attain the goals for using the system." They then proposed TEU by following the steps in Figure 1: (1) proposing a framework that fits the theory's assumptions and specifies the type of constructs and relationships; (2) taking a closer look at one link of the framework (Link 1 of the framework in Figure 1, i.e., the actions taken to improve effective use and its consequences on performance); and (3) developing a testable model.

Before explaining how we extended TEU, we outline three scoping decisions we made to keep this first test feasible while also focusing on the theory's core propositions rather than less-central aspects (per Colquitt and Zapata-Phelan 2007).

First, TEU considers two actions to improve effective use: learning and adaptation. In this study we consider learning actions alone (not adaptation). We did so to ensure a feasible test. Even though past studies have provided useful insights for studying adaptation (Bala and Venkatesh 2016; Sun 2012), Burton-Jones and Grange (2013) emphasize the complexity of both learning and adaptation activities in TEU. For instance, they describe how tests of TEU would need to account for the fact that adaptation in organizations often require change requests to be raised, authorized, and completed that can take substantial time and can involve additional levels of analysis (such as the team or organization) (Heales 2002). Given the complexity of these constructs in TEU, we considered it infeasible to conduct an adequate test of both learning and adaptation in the one study, and so focused on learning alone.

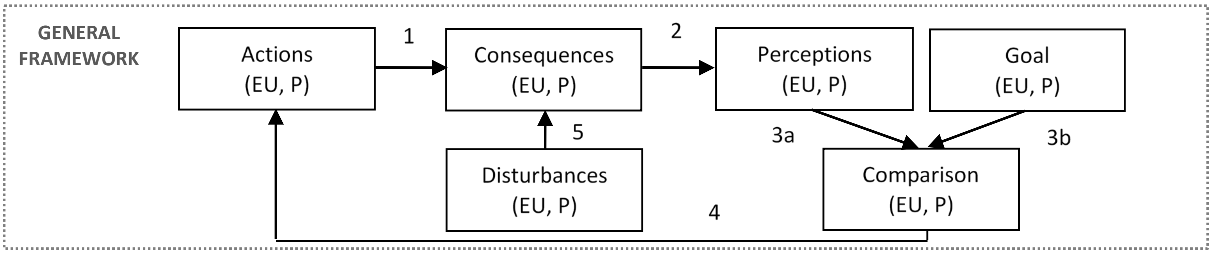
The second scoping decision was to focus on the primary learning actions in TEU, not ancillary ones. For instance, Burton-Jones and Grange (2013 p. 644 - 648) note how learning a system involves learning a system's representations, surface structure, and physical structure. We focus on the *overall* construct of learning the system and leave the learning of each component to future work. Likewise, we focus on learning fidelity (not its dimensions) as this matches our aim to study effective use and its direct antecedents and consequences.

Third, we focus on TEU's primary (i.e., stronger) rather than secondary relationships (per Colquitt and Zapata-Phelan 2007). Specifically, TEU proposes that its three dimensions of effective use can each affect both efficiency *and* effectiveness, but that some effects are primary ones, others are secondary (Burton-Jones and Grange 2013, p. 643). We focus on the primary effects. This ensures a more compelling test because if we fail to find such effects, it is more likely to reflect a substantive problem with the theory rather than an artifact of the setting.

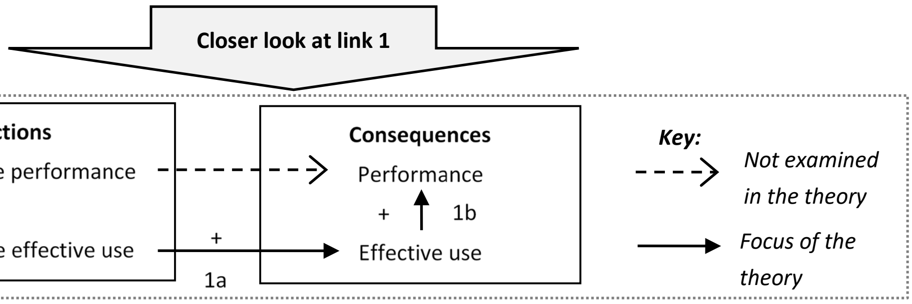
Given these scoping decisions, Figure 1 reflects the model of TEU we test. The figure also includes definitions of TEU's key constructs. As Burton-Jones and Grange (2013) explain, all of TEU's constructs stem from representation theory. In brief, TEU proposes that:

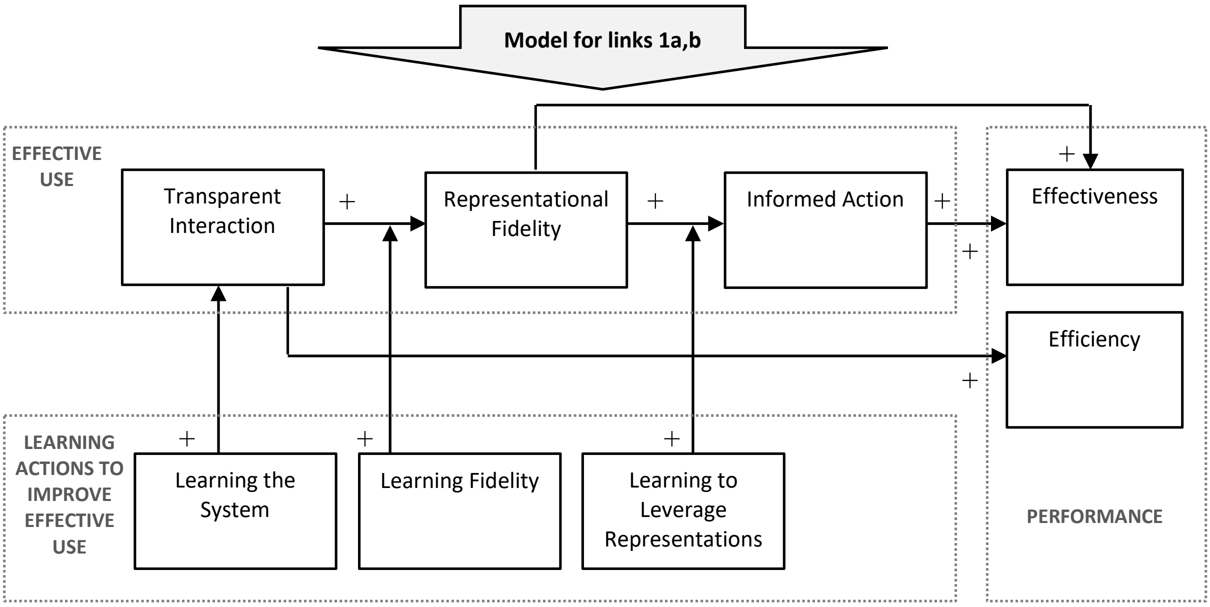
- more effective use involves seamlessly accessing the representations offered by a system (*transparent interaction*), obtaining more accurate representations (*representational fidelity*), and taking actions based on accurate representations (*informed action*).
- interacting with a system more transparently improves efficiency, while obtaining higher-fidelity representations and taking more informed actions improves a user's effectiveness.
- learning the system will directly improve transparent interaction because a user will be more able to access representations seamlessly if he or she has learned how to do so.
- learning fidelity and transparent interaction will jointly improve representational fidelity because representational fidelity requires knowing *what* to obtain (high fidelity data) and *how* to obtain it (transparent interaction) (Burton-Jones and Grange 2013 p. 647).
- *learning how to leverage representations* and *representational fidelity* should jointly improve *informed action* because *informed action* requires obtaining accurate data and knowing what to do with it (Burton-Jones and Grange 2013 p. 648-649).

Our study tests all these propositions. To test them faithfully, we initially took them as given rather than critiquing them. However, in later sections of the paper, we describe how we learned insights for respecifying some relationships and even reconsidering TEU as a whole.



Key: ***Meaning of links:*** 1. Peoples' actions have consequences; 2. People perceive the consequences of their actions; 3a,b: People compare their perceptions to their goals; 4. People conduct corrective actions if goals have not been achieved; 5. External disturbances can also affect consequences. ***EU, P:*** Performance and effective use are included inside each element to indicate that performance and effective use are relevant for each one, e.g., people can take actions to improve effective use, but they can also take other independent actions to improve performance.





Definitions of constructs in the model:

- **Transparent interaction**: During interaction with the system, the extent to which a user is accessing the system's representations unimpeded by the system's surface and physical structures
- **Representational fidelity**: During interaction with the system, the extent to which a user is obtaining representations that faithfully reflects the domain that the systems represent
- **Informed action**: The extent to which a user acts on faithful representations that he or she obtains from the system to improve his or her state in the domain
- **Learning the system**: Any action a user takes to learn the system (its representations, surface, or physical structure)
- **Learning fidelity**: Any action a user takes to learn the extent to which the system faithfully represents the domain
- **Learning to leverage representations**: Any action a user takes to learn how to leverage representations obtained from the system (i.e., how to engage in more informed actions)
- **Effectiveness**: A dimension of performance referring to the extent to which a user has attained the goals of the task for which the system was used
- **Efficiency**: A dimension of performance referring to the extent of goal attainment for a given level of input (e.g., time)

Figure 1. Theory of Effective Use (TEU), adapted from Burton-Jones and Grange (2013)

Theory Contextualization

Many researchers now stress the role of context in testing a theory (Bansal et al. 2016; Johns 2006; Te'eni 2016; Whetten et al. 2009). The contextualization literature suggests two broad ways to do so: a) *tailoring* a test to a context (e.g., testing TEU faithfully in a given context), or b) *varying* the context (e.g., testing TEU in different contexts to learn how results vary) (Hong et al. 2013; Johns 2006; Whetten et al. 2009). Arguably, a tailored test in one context should precede a test of a theory's generalizability across contexts. Given that TEU has not been comprehensively tested yet, we adopted the first strategy, focusing on the BI context.

BI is an over-arching term that refers to the use of information systems to bring together organizational data for analysis, reporting, and evidence-based decision making to improve performance (Fink et al. 2017; Seddon et al. 2012; Turban et al. 2008). A BI system, in turn, refers to the specific combination of technical and organizational elements through which BI is enacted in a given setting (Işık et al. 2013; Trieu 2017).

We chose the BI context partly due to its practical importance. Organizations invest heavily in BI (Agarwal and Dhar 2014; Chen et al. 2012; Shollo and Kautz 2010), but outcomes have been very mixed (Ramakrishnan et al. 2012). Two recent reviews have stressed that a key piece missing piece in this puzzle is understanding what it takes to use BI systems effectively (Ain et al. 2019; Trieu 2017). As Ain et al. (2019, pp. 8-11) write:

> "...effective use is one of the greatest challenges for BI systems. … Despite increasing investments in BI systems, many organizations are still unable to attain the desired success … due to underutilization and ineffective use."

While the fact that this piece is missing is alarming, it is unsurprising because learning how to use IS effectively has long been a missing piece in the IT-to-performance chain (Kettinger et al. 2013; Soh and Markus 1995). Understanding this link in the chain is practically important.

In addition to its practical importance, the BI context is an ideal context for testing TEU due to the inferences it affords. This situation is because TEU is derived from representation theory, which was designed for settings very similar to BI, i.e., managerial and operational settings where decision-makers benefit from using data for decision-making (Burton-Jones and Grange 2013, p. 652; Burton-Jones et al. 2017 p. 1323). That is, the assumptions of BI and TEU match: both assume users need to take informed actions using high quality data. Given the early stage of testing TEU, a finding in support of TEU in this setting can give confidence for tests in other settings where the theory's fit is less clear. Conversely, if the theory is refuted in a context in which it should fit, such a finding could signal serious weaknesses in TEU (Burton-Jones and Grange 2013 p. 652). Thus, this context allows for a critical test.

We applied and extended Hong et al.'s (2013) guidelines to contextualize, extend, and test TEU in a BI context. As Table 1 shows, this involved considering seven guidelines. As Hong et al. and others (e.g., Johns 2006) note, researchers can engage in contextualization by making changes to a model *a priori*, or *ex post* via a mixed-methods design. In the next section, we explain how we made *a priori* changes (Guidelines 1-4 in Table 1). We discuss the *ex post* changes (Guidelines 5-7 in Table 1) later when we discuss insights from our qualitative data.

Table 1: Applying and extending Hong et al.'s (2013) guidelines in this study of TEU	
1.Ground test in a general theory	TEU chosen as a general theory to study effective use.
Level 1 contextualization	
2. Contextualize and refine the general theory	Tailored TEU to the BI context by removing the effect of 'representational fidelity' on 'effectiveness.' This change was *a priori*, reflecting Level 1 contextualization (Hong et al. 2013)
Level 2 contextualization	
3. Evaluate the context to identify context-specific factors	Added 'organizational resources' as context-specific antecedents of core constructs. This change was *a priori*, reflecting Level 2a contextualization (Hong et al. 2013)
4. Model context-specific factors (decompose core constructs into context-specific versions)	Decomposed 'informed action' into 'informed decision' and 'effectiveness' and 'efficiency' into 'decision-making effectiveness' and 'decision-making efficiency'. This change was *a priori*, reflecting *Level 2c* contextualization (Hong et al. 2013)
5. Examine the interplay between the IT artifact and other factors	Used qualitative insights to identify interactions between TEU's core constructs and context-specific variables (users' roles and data cleaning). This change was *ex post*, reflecting *Level 2b* contextualization (Hong et al. 2013)
6. Examine alternative context-specific models	Used qualitative insights to enable testing of alternative models *ex post*, i.e., direct vs. moderating effects of learning on effective use.
Level 3 contextualization	
7. Identify how contextual insights can be made concrete in practice	Building on the results of Levels 1 and 2 contextualization, used qualitative insights to identify how the additional theoretical insights generated in this research can be made concrete in practice.

A Contextualized Model and the Role of Organizational BI Resources

As Table 1 shows, we derived the model by making two *a priori* changes. The first change included removing constructs or relationships of TEU to fit the BI context (per Guideline 2) and decomposing TEU's core constructs into context-specific versions (per Guideline 4). Specifically, we contextualized 'informed action' to the more specific concept of an 'informed decision' and narrowed the dependent variables accordingly to focus on decision-making outcomes (per Guideline 4). We did so because while BI users can engage in various actions (gathering, analyzing, and transforming data), the ultimate action of interest is to make evidence-based decisions (Cosic et al. 2012; Ranjan 2008; Sabherwal and Becerra-Fernandez 2011). This change also involved focusing on one type of BI user (decision makers) rather than multiple types (e.g., those who prepare or analyze data but who make no decisions). Bringing in such roles would require us to consider an additional level (the BI team) to understand how the various users and various roles generate value (Stodder 2016; Trieu 2017). As TEU is set at the individual level, we excluded the team level from this test.[4] This focus on decision-making and decision-makers led us to remove the link in Figure 1 between representational fidelity and effectiveness (per Table 1, Guideline 2). Burton-Jones and Grange (2013) included this link for contexts in which reaching a better understanding of a domain, in and of itself, is enough to perform effectively. In a BI decision-making context, this requirement is less relevant. While managers must understand the domains they manage, they ultimately need to incorporate such understanding into their decisions (Davenport 2006).

The second, and more significant step in contextualizing the model, was to add context-specific antecedents, to extend TEU not just apply it (per Guideline 3, Table 1). We focused on one class of antecedents – organizational resources – because while researchers have studied the link from BI to outcomes using various lenses, such as expenditures (e.g.

[4] Even though decision makers are the canonical type of BI user, as BI systems are designed to improve decision-making in organizations (Loshin 2013), we found in our *ex post* analysis that the variety of users within the 'decision maker' category was more relevant than we realized at the outset. We discuss this issue later.

Counihan et al. 2002), use (e.g. Deng and Chi 2012), and competition (e.g. Lau et al. 2012), one of the most consistent themes in the literature is that generating value from BI requires supporting organizational resources (e.g. Cosic et al. 2012; Cosic et al. 2015; Davenport 2006; Gillon et al. 2014; Krishnamoorthi and Mathew 2018; Sabherwal and Becerra-Fernandez 2011; Shanks and Sharma 2011; Trieu 2017). This is also a key theme in the broader literature on generating value from IT (Wade and Hulland 2004). Yet, while the BI literature notes the need for resources, recent reviews have called for such resources to be linked more closely to research on effective use to obtain clearer, more stable results (Trieu 2017). Thus, we sought to identify BI-relevant organizational resources as context-specific antecedents to TEU.

Resources refer to useful and available organizational assets and capabilities (Wade and Hulland 2004). While the importance of resources is well-accepted, the BI literature does not offer an accepted model of which resources are key. Our selection of resources was assisted by a systematic review guided by four criteria: 1) *literature salience*: BI resources shown in the literature to be critical; 2) *theoretical fit*: BI resources that relate conceptually to TEU dimensions; 3) *practitioner salience*: BI resources that practitioners believe are relevant; and 4) *parsimony*: a small set of resources to keep the model parsimonious. To check literature salience, we searched for papers on BI and resources in Scopus. The review yielded 67 papers that we reviewed in detail. To check practitioner salience, we interviewed 12 experienced BI practitioners, asking for their perceptions of key organizational resources for BI. Overall, based on our review, three resources – BI system quality, data integration, and evidence-based management culture – met all the criteria above (see Table 2 for a summary; Supplementary Appendix A for details, https://osf.io/tv6wh/?view_only=63b91a611b9a448f8df5ddb2fbfdcd79).

Table 2: Selecting Specific Resources to Integrate with TEU in the BI Context				
Business intelligence resources dimensions	**TEU Dimensions (individual level of analysis)**			**Level of support from the literature, from theory, and from practice**
	Transparent Interaction	Representational Fidelity	Informed decision	
BI system quality (For details, see Suppl. Appendix A2, sections 1.1-1.2)	Yes	No	No	**Salience of the dimension in the literature (# of reviewed papers):** 51/67 **Theoretical fit**: High. Relevant to transparent interaction because it affects the extent to which individual BI users can seamlessly access the content of the system. **Practitioner salience**: High. Example quotes: - *"OBI is is a web-based interface really. You can write some very low-level of SQL, but it's not very sophisticated. …So if I want to join table from different data domain [using] OBI's current interface, it's pretty hard to achieve what I want."* (Business analysis manager - Educational institution B) - *"The problem was for Business Objects, they didn't have consistent functionality [across machines]…. That makes it difficult if you're having to move between different machines depending on what you're using… So you end up with very strange behaviour."* (Business analysis manager - Educational institution A)
Data integration (For details, see Supp. Appendix A2, section 2.1)	No	Yes	No	**Salience of the dimension in the literature (# of reviewed papers):** 33/67 **Theoretical fit**: High. Relevant to representational fidelity because it affects the extent to which individual BI users can obtain faithful representations from the system. **Practitioner salience:** High. Example quotes: - *"When the data is not integrated you are signing off saying yeah, this is correct, but you've missed a digit or you've incorrectly assigned this to this department or what not."* (Data analyst manager - Organisation 1) - *"There was a very big effort from Karen and her team particularly to get the data into the system and to build links between the… data sets…it was very difficult for [BI users] to do their job until that was well underway. …. it was really a matter of the data… the data integration was sort of the key."* (Manager - Educational institution A)
Evidence based-management culture (For details, see Supp. Appendix A2, section 3.0)	No	No	Yes	**Salience of the dimension in the literature (# of reviewed papers):** 22/67 **Theoretical fit**: High. Relevant to BI users' informed decision-making because it affects the extent to which individual BI users feel willing and able to use data from BI systems to make their decisions. **Practitioner salience:** HIgh. Example quotes: - *"Every single decision they make [in banking] is driven by data…. W e need to apply those same principles in … mining…. We need to get more involved [with] data to drive our business."* (Data analysis manager 1 - Organisation A) - "*[At our bank]* our *management would … rely on those reports every single day and they're at their fingertips. They don't even have to request anyone."* (Senior data analysist - Organisation C) - *"It was entirely evidence based … Al (the top manager) would get Van (a BI user) to create a summary of all the codes (data report) every night."* (Professor and educational business analyst - Educational institution A)

As Table 2 shows, in terms of *literature salience*, these three resources have been shown to be salient in many studies (from 22 to 51). In terms of *theoretical fit*, each of these resources also links naturally with representation theory on which TEU is built. That is, as we explain in more detail in our hypothesis development, BI system quality relates to a system's surface and physical structure (and hence transparent interaction), data integration reflects aspects of the deep structure (and hence representational fidelity), and evidence-based management culture reflects the goal-oriented actions taken by users (and hence links with informed decisions) (Burton-Jones and Grange 2013). In terms of *practitioner salience*, the BI practitioners we interviewed judged each of these resources to be critical (see Table 2 for examples). In terms of *parsimony*, these three resources provide a parsimonious set to include in the model given that they were by far the most-studied resources in the literature (see Supp. Appendix A1), and together they cover all the dimensions of TEU.[5]

Despite being the three most widely-studied resources in the BI literature, prior research has not examined these three resources together. Our review found that only two of the 67 papers examined all three resources (Gillon et al. 2014, Seddon et al. 2012) and neither studied effective use. On the other hand, seminal practitioner sources (e.g.,Davenport 2006; Davenport and Harris 2017) have discussed all three resources, but implicitly and without theory or clear links to effective use. Thus, it is timely to bring all three resources into a common theoretical model together with effective use to explain BI performance outcomes.

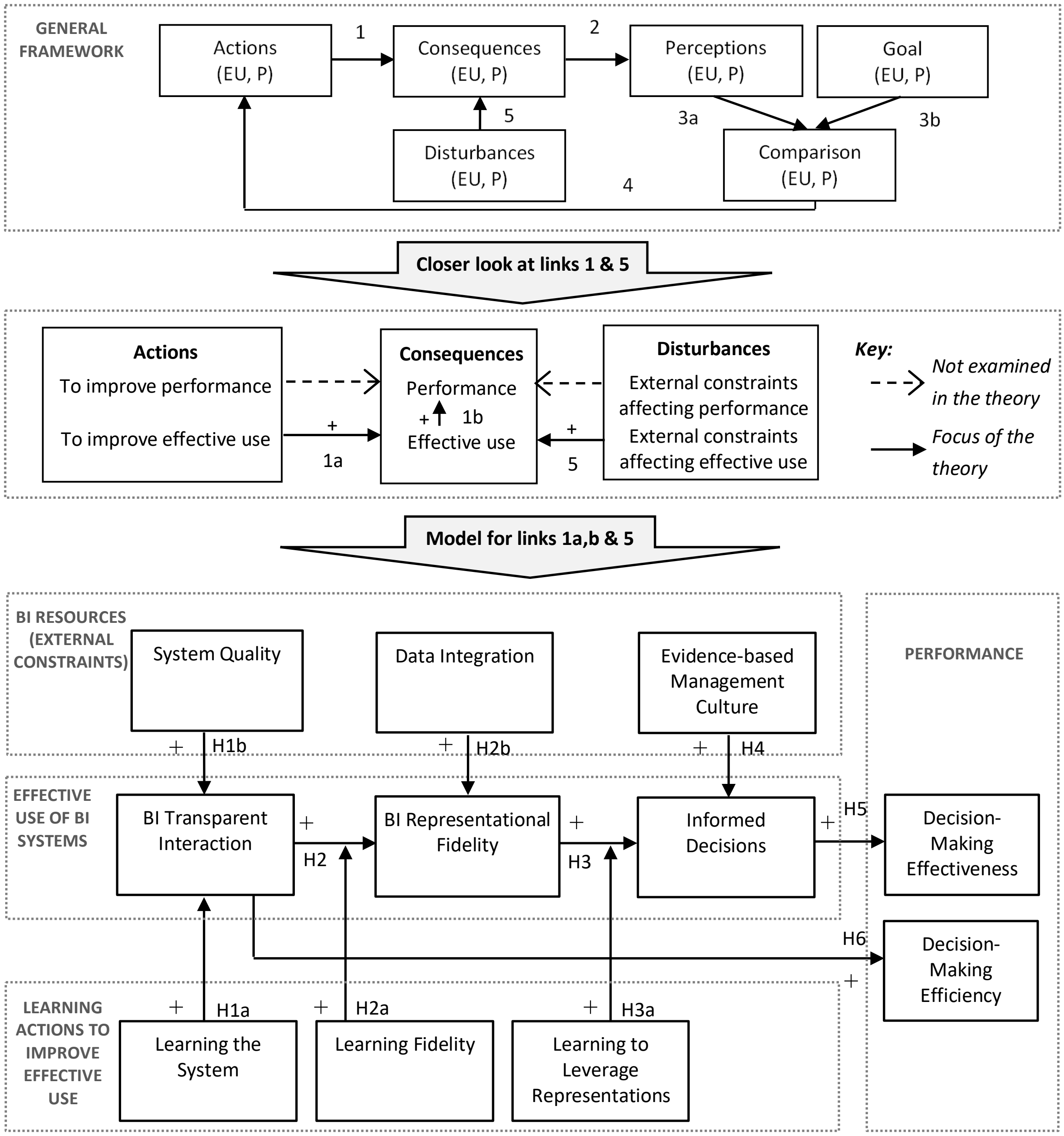
When considering the addition of resources as context-specific antecedents to TEU, it is

[5] Like Arnott and Pervan (2005), we view BI to be an evolution from earlier applications such as DSS and EIS. But does this mean that BI is just 'old wine in a new bottle'? To check, we repeated the review described above, but limited it to literature on DSS/EIS from 1985-1995, before the term 'BI' became popular (see Supp. Appendix A4). By comparing Supp. Appendices A3-A4, we can see that some aspects of the literature are similar across time, such as the lack of focus at the individual level. But there are also differences across time, such as *different resources*. Specifically, many papers in the earlier period (Supp. App. A4) considered system quality, but very few discussed data integration or evidence-based management culture. This is likely to be because DSS and EIS at that time were generally designed for simpler data environments and organizational contexts than today's BI. In other words, the new BI environments are different; they are not just 'old wine in a new bottle.'

relevant to ask why TEU does not already include them. Based on our reading of TEU, this omission did not stem from representation theory, the theory from which TEU was derived. Rather, it reflects the choices Burton-Jones and Grange (2013) made when they derived TEU from representation theory. Specifically, because Burton-Jones and Grange (2013) developed their model solely based on link 1 in their general framework (see Figure 1), the constructs in their model reflect *actions* and *consequences* alone; there is no construct to reflect *resources*.

This problem can be overcome by including resources within TEU's framework as disturbances. In TEU, disturbances are "the effects of uncontrollable or unpredictable factors in the environment" (Burton-Jones and Grange 2013 p. 10). For individual BI users, many resources that support BI use, including the three noted above (including those proposed by Davenport 2006; Davenport and Harris 2017) are characteristics of the environment over which users have little or no control. Their lack of controllability acts as an external constraint on performance (Baker et al. 2009). Thus, as Figure 2 shows, we elaborate both link 1 and 5 in TEU (not just link 1) to include access to BI resources as a disturbance or external constraint. Just as Burton-Jones and Grange (2013) focused on actions affecting effective use, not those having a separate effect on performance, we focus on actions and disturbances (external constraints) affecting effective use, not those separately affecting performance.

In sum, Figure 2 reflects the outcome of a set of *a priori* decisions to contextualize TEU to the BI context. As Table 1 showed, we drew additional contextualization insights *ex post*, from our qualitative data. We discuss them later because they were not hypothesized up front.



Definitions of *additional* constructs in the model (compared to Figure 1):

- **BI system quality**: The performance of the BI system from a technical and design perspective (DeLone and McLean 1992; Gable et al. 2008).
- **Data integration**: The extent to which data have the same meaning and use across time and across users, making the data in different systems or databases consistent or logically compatible (Goodhue et al. 1992)
- **Evidence-based management culture**: The extent to which it is the norm to use data and analysis to support decision-making (Pfeffer and Sutton, 2006)
- **Informed decisions**: The extent to which a user leverages high-fidelity information in the system to make a decision to improve his/her work performance (adapted from Burton-Jones and Grange, 2013)
- **Decision-making effectiveness**: The extent to which a user has attained the goals of the decision-making task for which the system was used (adapted from Burton-Jones and Grange, 2013)
- **Decision-making efficiency**: The extent to which decision-making goals are attained for a given level of input such as effort or time (adapted from Burton-Jones and Grange, 2013)

Figure 2. Application of TEU to the Effective Use of BI Systems

HYPOTHESES

We describe below the rationale for each hypothesis in Figure 2. In each subsection, we first describe TEU's existing hypotheses, then a new hypothesis that extends TEU. We keep the rationale for TEU's hypotheses brief, partly because those details are in Burton-Jones and Grange (2013), and partly because our aim is not to justify those hypotheses, but to test them.

Antecedents of BI Transparent Interaction (H1a, H1b)

Hypothesis in TEU. Transparent interaction refers to the extent to which a user of the BI system is accessing its representations seamlessly, unimpeded by the system's surface and physical structures. Burton-Jones and Grange (2013) suggest that a key driver of transparent interaction is learning the system (i.e., learning how an IS offers representations through its surface and physical structure). Their rationale was that such learning helps users understand the representations available in the system, and how to find and interact with them via the system's hardware (e.g., PC, tablet, mobile device) and software interfaces (e.g., menus, reports, visualizations). This argumentation leads to H1a:

> H1a: There is a positive relationship between *learning the BI system* and *BI transparent interaction.*

Context-Specific Extension of TEU. As noted above, we introduce system quality as a context-specific antecedent of transparent interaction. *System quality* is a measure of the performance of the IS from a technical and design perspective (DeLone and McLean 1992; Gable et al. 2008). As such, it relates mainly to a system's surface and physical structure rather than deep structure. We propose that system quality affects transparent interaction in much the same way as it affects ease-of-use in IS acceptance/success models (Burton-Jones and Grange 2013, p. 654). That is, a poorly designed, unfriendly system may still produce accurate and informative reports, but obtaining them may be hard. Users of high-quality systems can interact more seamlessly with their BI systems to create or customize reports and dashboards (Mathrani 2014), while users of poorly designed, unfriendly systems can be distracted and prevented from accessing and interacting with their data (Kulkarni and Robles-Flores 2013; Kulkarni et al. 2017) and from navigating through the systems to find functions they need. Thus, in line with the literature's accepted theorization of the link from system quality to ease of use (Nelson et al. 2005), we propose:

H1b: There is a positive relationship between *BI system quality* and *BI transparent interaction.*

Antecedents of BI Representational Fidelity (H2, H2a, H2b)

Hypotheses in TEU. TEU proposes that transparent interaction will facilitate representational fidelity. The rationale in TEU is that while getting desired output from an IS may sometimes be simple (e.g., running an automated report), it can often be more complex and require the user to access all the right pieces of data and manipulate them effectively (Zuboff 1988 p. 209). Thus, if the user can interact with a system more seamlessly (high transparent interaction), he/she is more likely to obtain the required output (high representational fidelity):

H2: There is a positive relationship between *BI transparent interaction* and *BI representational fidelity.*

TEU suggests that being able to interact with a BI system transparently should be especially useful for users who have spent time learning the fidelity (accuracy) of the data (Burton-Jones and Grange 2013). This situation is because they are more likely than other users to be able to work around the limitation in the data by accessing alternative data sources or using multiple data sources to triangulate to a truer picture of the domain. This gives rise to H2a:

H2a: *Learning fidelity* will amplify the positive effect of *BI transparent interaction* on *BI representational fidelity*

Context-Specific Extension of TEU. We examine data integration as a context-specific antecedent of representational fidelity. Data integration refers to "the use of common field definitions and codes across different parts of the organization" (Goodhue et al. 1992 p.294).

Data integration has long been viewed as a foundation for BI because it enables an organization to develop an organization-wide, rather than silo-based, data repository (Chen et al. 2012; Sabherwal and Becerra-Fernandez 2011; Turban et al. 2011). Organizational data repositories ideally integrate relevant data from operational databases, legacy databases, and external sources (Negash 2004; Ramamurthy et al. 2008; Sabherwal and Becerra-Fernandez 2011). Integrated data tend to be more consistent, trustworthy, and reliable (Gudfinnsson et al. 2015). Data integration should improve representational fidelity because if a user can query data from an integrated data repository, he or she is more likely to get a broader and truer picture of the domain than if the picture has to be pieced together from multiple partial and potentially conflicting data sources and organizational silos (Turban et al. 2011). Thus:

> H2b: There is a positive relationship between *data integration* and *BI representational fidelity*.

Antecedents of Informed Decisions (H3, H3a, H4)

Hypotheses in TEU. The link in TEU from representational fidelity to informed decisions is straightforward. If users can obtain information from the BI system with greater fidelity, they will have a more informed basis for action than if the information is problematic (e.g., inaccurate, incomplete, untimely) (Burton-Jones and Grange 2013). This leads to H3:

> H3: There is a positive relationship between *BI representational fidelity* and *informed decisions.*

However, representational fidelity alone will not always engender more informed decisions. Workers may fail to use the information or use it poorly (Ayres 2008; Berente and Yoo 2012; Cunha 2013; Dennis et al. 1996). Thus, in line with calls for BI users to perform more knowledgeably (Shollo and Galliers 2016), TEU argues that BI users must learn how to leverage representations. That is, BI users are likely to make more informed decisions if they not only have high-quality information, but also learn how to leverage it. This leads to H3a:

H3a: *Learning to leverage representations* will amplify the positive effect of *BI representational fidelity* on *informed decisions.*

Context-Specific Extension of TEU

The IS use literature has long noted the role of organizational culture (Wade and Hulland 2004 p. 126). Following this line, we examine evidence-based management culture as a context-specific antecedent of informed decisions. An *evidence-based management* (EBM) culture assumes that managers can improve performance if they know and apply the best evidence when making decisions (Pfeffer and Sutton 2006; Shanks and Bekmamedova 2012). This factor is particularly relevant for BI because BI's *raison d'etre* is to enhance evidence-based decision-making (Davenport and Harris 2017). In an EBM culture, managers are more likely to support the development and use of high-quality data and analytics (Davenport and Harris 2017; Reynolds et al. 2012; Watson 2014) and continually improve efforts to use data in decision-making (Carte et al. 2005; Cosic et al. 2012). An EBM culture helps people feel supported and encouraged to make data-driven decisions (Pfeffer and Sutton 2006). Thus:

H4: There is a positive relationship between the *evidence-based management culture* of an organization and *informed decisions*.

Antecedents of Decision-Making Effectiveness and Efficiency (H5, H6)

Hypotheses adapted from TEU. TEU proposes that more informed actions will result in more effective outcomes. As noted earlier, we contextualized this relationship to the BI context by studying *decision-making effectiveness* – the extent to which the goals or intended outcomes of a decision are attained. It is widely argued that the goals of a decision are more likely to be attained if managers base their decision on data and analysis (Bean and Davenport 2019; Wang and Byrd 2017) and this is a core premise of BI and DSS research (Ayres 2008; Olszak and Batko 2012; Raghunathan 1999). For example, sales managers can make more effective product pricing decisions if they are informed by data from the BI on their customers' ability-to-pay rather than by relying on anecdote (Winig 2016). Accordingly, we hypothesize:

H5: There is a positive relationship between *informed decisions* and *decision-making effectiveness*.

The other outcome variable in TEU is efficiency, i.e., outputs over inputs (Beal et al. 2003). Efficiency is relevant for BI because BI systems are often implemented in business processes that require managers to make decisions quickly (Kulkarni and Robles-Flores 2013). In line with TEU, we propose that a key antecedent of decision-making efficiency is transparent interaction. Compared to users who can interact with BI output seamlessly, users who experience low levels of transparent interaction (who have difficulty accessing data, piecing it together, or interacting with output) will be hampered and thus delayed in using the BI for decision-making. This justification leads to H6:

H6: There is a positive relationship between *BI transparent interaction* and *decision-making efficiency*.

RESEARCH METHODS

The research involved three phases: instrument development, cross-sectional survey, and post-hoc interviews. We began with quantitative methods. Using a *sequential* design (Creswell and Clark 2007), or a *bridging* approach (Venkatesh et al. 2013), we then used qualitative methods to confirm and elaborate upon our findings, explore additional insights, and develop meta-inferences (Johns 2017; Venkatesh et al. 2013; Venkatesh et al. 2016a)

Phase 1: Instrument Development

While Burton-Jones and Grange (2013) gave broad indications of how scales for their constructs could be developed, they called for others to develop them in detail. In the absence of accepted scales, we conducted a rigorous scale development process (per MacKenzie et al. 2011). Specifically, we developed scales for 11 constructs for the model: *system quality, evidence-based management culture, transparent interaction, representational fidelity, data integration, learning system, learning fidelity, learning to leverage representations, informed* *decisions, decision-making effectiveness,* and *decision-making efficiency.* Appendix A shows the construct definitions and measures. We followed an 8-step process (see Supp. Appendix B, Figure B1). Stages 1-7 involved n = 218, while Stage 8 involved n = 437. For brevity, we explain Steps 1-7 in the Supp. Appendix B and discuss Stage 8 - item validation below.

Phase 2: Cross-sectional Survey

With the help of Qualtrics, we distributed the main survey to managers who described themselves as using a BI system and making decisions using data from the system. Respondents were asked to respond in the context of the BI system they used most.

Cross-sectional surveys have several limitations (Kozlowski 2009). To alleviate some of them, we conducted the survey in two waves, 7 to 10 days apart, with all Wave 1 respondents invited to respond in Wave 2, with the same questions in each wave. This afforded three samples (wave 1 responses, wave 2 responses, and a combination). Comparing Wave 1 and 2 responses enables us to assess the stability of the findings (Straub et al. 2004). Using a combined set provides a way to minimize some elements of common-method bias, through temporal separation between measures of the independent variables (IVs) and dependent variables (DVs) (Podsakoff et al. 2003). We analyzed the data from both waves and the results, for both measurement and structural models, were supportive in each case (for details, see Supplementary Appendix B). For parsimony, we present the combined data below.

In the combined data set, we introduced temporal separation between IVs and DVs by using the data for constructs in the first half of the model from wave 1 (*BI System Quality, BI Transparent Interaction, Learning the System, Learning Fidelity, Data Integration,* and *BI Representational Fidelity)*, and the data for constructs in the second half of the model from wave 2 (*Learning to Leverage Representations, Informed Decisions,* and *Evidence-based Management Culture)*. We used pre-screening questions at the start of the surveys to identify respondents who matched the target profile of managers who use BI in a hands-on manner for decision making. We also included bogus items to identify careless responders (Meade and

Craig 2012). Out of 2349 visitors to wave 1 of the survey, 1107 satisfied our sampling criteria (estimated response rate 47%). We conducted data-cleaning as per Tan et al. (2013): deleting responses based on incompletion, data runs, or responses to bogus questions. 307 participants were deleted, yielding n = 800 invited to do the second wave. Of these 800, 476 visited wave 2 (estimated response rate 59%). Again due to incomplete responses, data runs, or answers to bogus questions, 38 respondents were deleted, yielding a final sample of 437 (see Table 3 for descriptive statistics). Thus, we have two waves of data from the same 437 respondents, 7-10 days apart, and the combined sample for analysis uses Wave 1 data for the constructs in the first half of the model and Wave 2 data for the constructs in the second half of the model.

Table 3. Respondent Sample Demographic Data

Demographic characteristic		**No. of respondents**	**% of total**
Gender	Male	240	55%
	Female	197	45%
Age	18-30	47	11%
	31-40	243	55%
	41-50	104	24%
	>51	43	10%
Experience working in the current organization	<5 years	39	9%
	5-10 years	220	50%
	10.1 – 15 years	113	26%
	>15 years	65	15%
Number of employees	Less than 100	43	10%
	100-499	111	25%
	1000-4999	174	40%
	5000-9999	83	19%
	>10000	26	6%
Industry	Manufacturing	153	35%
	Banking/Finance	50	11%
	Insurance	10	2%
	Education	24	6%
	Wholesale & retail	40	9%
	Transportation	16	4%
	Utilities	21	5%
	Government	14	3%
	Others	109	25%
Experience using the current BI system	<2 years	22	5%
	2-5 years	176	40%
	5-10 years	179	41%
	>10 years	60	14%
Making decisions about what information to provide from the BI system to other decision makers	Yes	423	97%
	No	14	3%
Making business decisions made using information from the BI system	Yes	433	99%
	No	4	1%

In line with our theory-testing aims, we used covariance-based structural equation modelling for the data analysis (using AMOS v.22.0), following the two-step approach in Anderson and Gerbing (1988) and Gefen et al. (2000). We discuss each step in turn below.

Measurement Model

We first tested measurement models for each individual construct and analyzed their fit. For ill-fitting models, we assessed the loadings of the items on their intended constructs and we dropped items with low loadings (<0.50) (Gefen et al. 2000). We then set up an 11-factor measurement model under a confirmatory factor analysis (CFA) approach, with each item restricted to load only on its pre-specified factor, with the factors allowed to freely correlate. As Table 4 shows, the fit indices indicate a reasonable fit of the model to the data.

Table 4 Measurement Model Fit Statistics

FIT statistic	Statistic	Desired levels
$\chi 2$/df	1.74	≤3:1 (Gefen et al. 2000)
Standardized Root Mean Square Residual (SRMR)	0.03	≤ 0.08 (Gefen et al. 2000; Hu and Bentler 1999)
Root Mean Square Error of Approximation (RMSEA)	0.04	≤ 0.06 (Hu and Bentler 1999)
Comparative Fit Index (CFI)	0.95	≥ 0.90 (Bentler 1992; Hoyle 1995)
Goodness-of-Fit Index (GFI)	0.90	≥ 0.90 (Gefen et al. 2000)
Adjusted Goodness-of-Fit Index (AGFI)	0.87	≥ 0.80 (Gefen et al. 2000)

To test convergent validity, we first tested if each construct in the measurement model had an average variance extracted (AVE) ≥ 0.5 (Fornell and Larcker 1981). All constructs met this cut-off except for 'Informed Decisions' and 'System Quality' that were close (≥ 0.46) (see Table 5). Second, we conducted an exploratory factor analysis using principal components extraction to test if the factor loading of each item on its own construct was ≥ 0.60 (Chin et al. 1997). As Appendix B shows, our data met this cut-off except for two loadings between 0.58-0.60 (again, 'Informed Decisions' and 'System Quality'). We conducted tests of the structural model with and without the lesser-loading items for these two constructs, and the results did not change. Given the lack of change and given that the results were close to the recommended cut-offs, we kept these items in the final analysis.

We tested discriminant validity using a χ^2-difference test (Chin et al. 1997) to compare the original (unconstrained) measurement model with constrained models in which any two constructs in question were combined as one (Gefen et al. 2000). This test was conducted one pair of constructs at a time (as in Son and Kim 2008). For example, in testing *BI system quality* and *BI transparent interaction*, the χ^2-difference test between the two models $\chi^2(1) = 75.451$, $p<0.001$) affirmed the discriminant validity. All of the chi-square difference tests were significant ($p<0.001$), indicating that any pair of constructs could not be united as one, supporting discriminant validity (see Supplementary Appendix B, Table B1 for details). The clean pattern of loadings and cross-loadings from our exploratory factor analysis (see Appendix B) also supports discriminant validity.

As Table 5 shows, we also assessed composite reliability (CR). The composite reliability values for the constructs were well above the acceptable limit of 0.70, except for one construct (Decision-Making Efficiency), for which the value was very close (0.68). Given how close the value was to the cut-off, we chose to retain that construct in the model.

Finally, we examined the correlation matrix for high correlations. As Table 5 shows, some of the constructs were highly correlated, with higher correlations than the corresponding values on the diagonal (the square root of the AVE). These instances occurred for the correlations between '*Evidence-based Management Culture*' and '*Informed Decision'* (0.69>0.68), '*Learning to Leverage Representations*' and '*Informed Decisions'* (0.75>0.68), and '*Learning the System'* and '*Learning Fidelity'* (0.82 > both 0.78 and 0.80). These results raise two issues. The first is whether discriminant validity is threatened. As noted above, however, the χ^2-difference test affirmed discriminant validity. The second issue is whether multicollinearity could threaten tests of the structural model. CB-SEM is relatively robust to multicollinearity in the case of Type I errors (Goodhue et al. 2017) and for Type II errors when there are only moderate correlations among predictors, high R^2 values, and high reliability (Grewal et al. 2004). Each subset of our model met these criteria (per Grewal et al.

2004, p. 524). Thus Type II errors are unlikely. We also checked the variance inflation factor (VIF) for each set of relationships for each endogenous variable. All VIF scores were <1.6, well below the threshold of 3.33 (Diamantopoulos and Siguaw 2006). Overall, therefore, we conclude that the high correlations among some constructs (and the low AVE values for some other constructs) is not a major threat to the results. We return to this issue later, however, because it could reflect a theoretical issue, e.g., an over-specification within TEU.

Table 5. Descriptive Statistics, Reliabilities, AVE, and Constructs Correlation Matrix

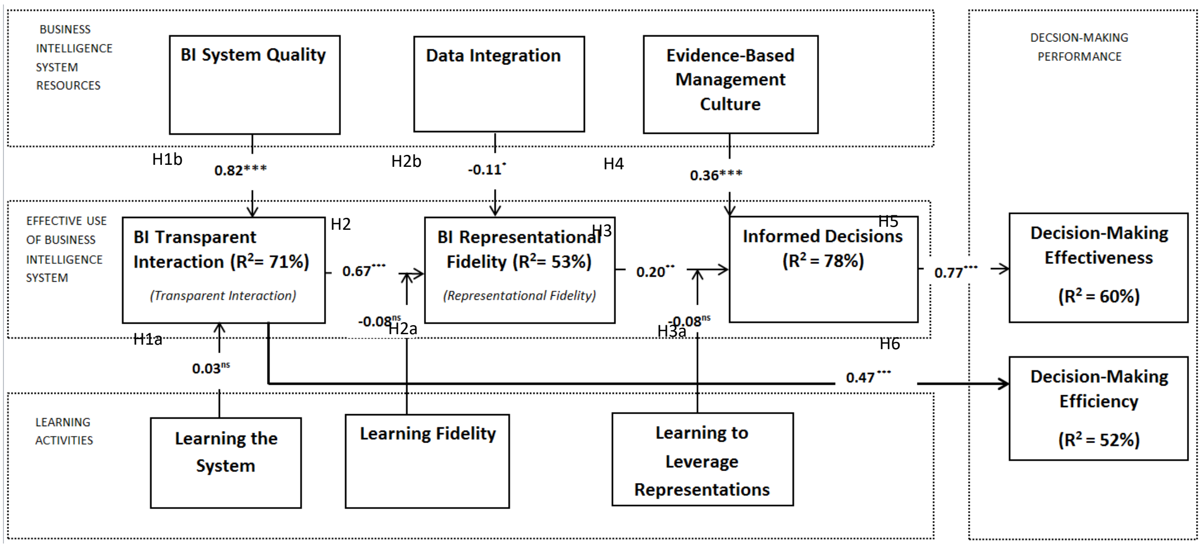
	ME	SD	CR	AVE	1	2	3	4	5	6	7	8	9	10	11
1. DI	5.55	1.25	0.82	0.61	0.78										
2. EBMC	5.97	1.02	0.78	0.54	0.38	0.73									
3. BITI	5.78	1.03	0.85	0.59	0.6	0.49	0.77								
4. BIRF	5.94	0.93	0.82	0.54	0.35	0.41	0.68	0.73							
5. ID	5.97	0.91	0.72	0.46	0.34	0.69	0.4	0.48	0.68						
6. LS	5.89	1.1	0.86	0.6	0.38	0.45	0.42	0.43	0.54	0.78					
7. LLR	5.84	1.12	0.86	0.61	0.32	0.67	0.43	0.32	0.75	0.67	0.78				
8. DMness	5.59	0.91	0.72	0.56	0.42	0.67	0.58	0.48	0.67	0.51	0.59	0.75			
9. LF	5.78	1.05	0.87	0.64	0.4	0.53	0.47	0.46	0.59	0.82	0.67	0.56	0.8		
10. DMency	6.05	0.87	0.68	0.51	0.43	0.61	0.68	0.58	0.58	0.39	0.46	0.61	0.51	0.71	
11. BISQ	5.93	0.99	0.73	0.47	0.6	0.55	0.75	0.6	0.56	0.49	0.5	0.62	0.46	0.62	0.69

Notes:
ME = Mean, SD = standard deviations, CR = composite reliability, AVE = average variance extracted
Diagonal elements display the square root of AVE
DI = Data Integration, EBMC = Evidence-Based Management Culture, BITI = Business Intelligence Transparent Interaction, BIRF = Business Intelligence Representational Fidelity, ID = Informed Decisions, LS = Learning the System, LLR = Learning to Leverage Representations, LF = Learning Fidelity, DMness = Decision Making Effectiveness, DMency = Decision Making Efficiency, BISQ = Business Intelligence System Quality.

Structural Model

We used SEM (in AMOS) to test the model, with a mean-centering, unconstrained product indicator approach to test interaction effects (Marsh et al. 2004; Marsh et al. 2006). Table 6 shows the fit statistics. The GFI values were slightly below the 0.90 cutoff of, but acceptable given the number of constructs in the model (Cenfetelli et al. 2008). All other fit indices in Table 6 indicated that the model fit reasonably well. In particular, the measurement model and the structural model both pass Hu and Bentler's (1999) recommendation of SRMR ≤ 0.08 and (RMSEA ≤ 0.06 or CFI ≥ 0.95). Figure 3 shows the results of testing the model and Table 7 summarizes the results of our hypothesis tests. As Table 7 shows, five hypotheses were supported, three were insignificant, and one was refuted (opposite to the prediction).

Table 6. Structural Model Fit Statistics		
FIT statistic	**Statistic**	**Desired levels**
$\chi 2/df$	2.01	≤3:1 (Gefen et al. 2000)
Standardized Root Mean Square Residual (SRMR)	0.05	≤ 0.08 (Gefen et al. 2000; Hu and Bentler 1999)
Root Mean Square Error of Approximation (RMSEA)	0.04	≤ 0.06 (Hu and Bentler 1999)
Comparative Fit Index (CFI)	0.90	≥ 0.90 (Bentler 1992; Hoyle 1995)
Goodness-of-Fit Index (GFI)	0.84	≥ 0.90 (Gefen et al. 2000)
Adjusted Goodness-of-Fit Index (AGFI)	0.82	≥ 0.80 (Gefen et al. 2000)



Note: *p<0.5; **p<0.01; ***p<0.001; ns: not significant (two-tailed)

Figure 3. Results of Structural Model Analysis

Table 7. Results of Hypotheses Tests	
Research Hypothesis	**Supported?**
H1a: There is a positive relationship between learning the system and BI transparent interaction	Insignificant
H1b: There is a positive relationship between BI system quality and BI transparent interaction	Yes
H2: There is a positive relationship between BI transparent interaction and BI representational fidelity	Yes
H2a: Learning fidelity will amplify the positive effect of BI transparent interaction on BI representational fidelity	Insignificant
H2b: There is a positive relationship between data integration and BI representational fidelity	No (refuted)
H3: There is a positive relationship between BI representational fidelity and informed decisions	Yes
H3a: Learning to leverage representations will amplify the positive effect of BI representational fidelity on informed decisions	Insignificant
H4: There is a positive relationship between the evidence-based management culture of an organization and informed decisions	Yes
H5: There is a positive relationship between informed decisions and decision-making effectiveness	Yes
H6: There is a positive relationship between BI interaction transparency and decision-making efficiency	Yes

We conducted a post-hoc test to learn if our results were sensitive to control variables. We controlled for the effects of organizational experience (measured per Table 3) on decision-making effectiveness and efficiency because experienced employees might perform differently. As users might be expected to overcome usability issues over time, we controlled for users' experience with their BI systems (measured per Table 3) on transparent interaction. We also controlled for the effects of job autonomy (Ahuja and Thatcher 2005) and organizational size on decision-making efficiency (because staff with fewer resources or less work autonomy may have less ability to improve their work efficiency) and for the effects of organizational size and task interdependence (Goodhue 1995) on decision-making effectiveness (because staff with fewer resources or whose work depends on others have less control over their performance).

We found these control variables varied in their effects. Nonetheless, adding the control variables did not change any of the relationships in the model except for H2b (data integration → BI representational fidelity) which changed from negative to insignificant. Other than that, adding control variables produced only a maximum of 0.07 change in path coefficient values. That is, they had little practical effect. We therefore kept the model without these variables (Figure 3) as our final model.

Phase 3: Interviews: Exploratory, Confirmatory, and Further Contextualization

In this phase, we conducted three sets of interviews (n=33). The first set of 10 was *exploratory* and focused on the unexpected survey results, i.e., the unsupported hypotheses for learning (H1a, H2a, and H3a) and from data integration to BI representational fidelity (H2b). We sought to learn if these results were due to contextual effects not hypothesized *a priori* (per Guidelines 5-6 in Table 1) or if they related to general issues with TEU's specification. Our goal was to use these findings to generate meta-inferences from all the results to this point (Venkatesh et al. 2013). The second set of 10 interviews was *confirmatory* and focused on checking if the insights from the exploratory interviews held in a second set. If they did, we could be fairly confident in our conclusions (per Lee and Hubona 2009). With this confidence in hand, the third and final set of 13 interviews was designed to show how the contextual insights generated in the study could be made even more concrete in practice.

The interviews were held one-on-one with 33 managers from a range of industries who had used BI for decision-making for at least five years (see Supplementary Appendix C - https://osf.io/tv6wh/?view_only=63b91a611b9a448f8df5ddb2fbfdcd79 for interview questions). In the exploratory (formative) interviews, we asked directly about relationships in the model as well as open-ended questions to learn of other relationships, e.g., interactions between TEU's core constructs and context-specific variables or other alternative models (per Guideline 5-6, Table 1). In the confirmatory (summative) interviews, we asked participants for their views on the insights we inferred from the first set of interviews, to test their credibility and generalizability. In the final interviews, we focused on the contextual factors added to the model to extend TEU (the three organizational resources) and focused on learning how these factors could be made concrete in practice.

The interviews ranged from 40-60 minutes, were audio-recorded, and were coded and analyzed using NVivo. To analyze the data, we used a flexible pattern-matching logic (Sinkovics 2018; Yin 2003) that involved preparing a coding template based on our theory while allowing for new codes to arise from the data, applying theses codes to the interview data, and identifying and analyzing themes (Silverman 2011).

As Table 8 shows, we used meta-inferences (Venkatesh et al. 2013) to formalize our insights. We describe these findings and meta-inferences in the next sections. We begin by describing the results of our first two sets of interviews and the meta-inferences that we drew and confirmed. We focus, in particular, on explaining our unexpected findings, namely the effects of the three learning constructs (H1a, H2a, H3) and data integration (H2b). We then describe the insights from our third set of interviews.

Table 8. Meta-Inferences and Explanations					
Relationship	**Hypothesis**	**Quantitative inference**	**Qualitative inference from exploratory interviews**	**Meta-Inference**	**Explanation for Discrepant Results from the Post-Hoc Interviews**
The relationship between BI transparent interaction and its antecedents	H1a: There is a positive relationship between learning the system and BI transparent interaction.	Learning the system does not appear to affect BI transparent interaction	The effect of learning the system on BI transparent interaction is positive for power users but not salient for regular users.	**Need to account for context:** The predicted benefit of learning the system on BI transparent interaction holds for power uses but not regular users	Power users need to engage in progressive learning of the system; regular BI users may interact with simple system options that do not require more intensive learning. **Support in confirmatory interviews:** Yes; 8/10 interviews **Implication:** The boundary conditions of TEU are only partially specified. More contextual conditions should be identified.
	H1b: There is a positive relationship between BI system quality and BI transparent interaction.	Data consistent with the theory.	Data consistent with the theory.	The theory appears to hold.	
The relationship between BI representational fidelity and its antecedents	H2: There is a positive relationship between BI transparent interaction and BI representational fidelity	Data consistent with the theory.	Data consistent with the theory.	The theory appears to hold.	
	H2a: Learning fidelity will amplify the positive effect of BI transparent interaction on BI representational fidelity.	Learning fidelity does not appear to influence the benefit of BI transparent interaction on representational fidelity.	Learning fidelity can lead to greater representational fidelity even when BI transparent interaction is low.	**Need to respecify the theory**: In contrast to TEU's prediction, learning fidelity has a direct effect on representational fidelity rather than an interaction effect. This result was confirmed in a post-hoc test of the quantitative data.	Learning fidelity can provide benefits even when transparent interaction is low by enabling adaptations and workarounds and by allowing users to mentally fill-in-the blanks and make inferences from partial outputs. **Support in confirmatory interviews:** Yes; 9/10 interviews **Implication:** Revise TEU to account for the direct effects of learning.
	H2b: There is a positive relationship between data integration and BI representational fidelity.	Data Integration has a small but significant negative effect on	Without appropriately cleaned data, data integration can impede	**Need to account for context:** Data integration can have negative effects on representational fidelity if data is not appropriately cleaned.	The data needs to be cleaned to eliminate redundant data and to consolidate different data representations otherwise integrated data will not improve, and can even reduce, representational fidelity.

		representational fidelity	representational fidelity.		**Support in confirmatory interviews:** Yes; 8/10 interviews **Implication:** The boundary condictions of TEU are only partially specified. More contextual conditions should be identified.
The relationship between informed decision and its antecedents	H3: There is a positive relationship between BI representational fidelity and informed decisions.	Data consistent with the theory.	Data consistent with the theory	The theory appears to hold.	
	H3a: Learning to leverage representations will amplify the positive effect of BI representational fidelity on informed decisions.	Learning to leverage representations does not appear to influence the benefit of BI representational fidelity on informed decisions	Learning to leverage can lead to greater informed decisions even when representational fidelity is low.	**Need to respecify the theory**: In contrast to TEU's prediction, learning to leverage representations has a direct effect on informed decisions rather than an interaction effect. This was confirmed in a post-hoc test of the quantitative data.	Irrespective of the level of representational fidelity, learning to leverage representations can help decision makers to make informed decisions by enabling them to know how best to identify and articulate the assumptions and caveats that need to be understood and documented. **Support in confirmatory interviews:** Yes; 8/10 interviews **Implication:** Revise TEU to account for the direct effects of learning.
	H4: There is a positive relationship between the evidence-based management culture of an organisation and informed decisions.	Data consistent with the theory.	Data consistent with the theory	The theory appears to hold.	
The relationship between decision-making effectiveness and its antecedents	H5: There is a positive relationship between informed decision and decision-making effectiveness.	Data consistent with the theory.	Data consistent with the theory	The theory appears to hold.	
The relationship between decision-making efficiency and its antecedents	H6: There is a positive relationship between BI transparent interaction and decision-making efficiency	Data consistent with the theory.	Data consistent with the theory	The theory appears to hold.	

The Effects of the Three Learning Constructs (H1a, H2a, H3a)

We discuss the effects of the three learning constructs in turn below.

Learning the BI System (H1a). TEU proposes that learning the system will enhance BI transparent interaction, but we found no support for this in our survey. Our interviewees offered an explanation: a user's role. As Table 8 shows, this insight emerged inductively from the first set of interviews; it was then confirmed in 8 of the 10 confirmatory interviews.

The following quote illustrates the feedback we received, indicating that learning is important for some users (power users) but not for most (regular users). While power BI users need progressive learning, regular BI users may interact with simple drill-down options pre-built into BI systems, and thus may not need to engage in intensive learning:

> *Users of BI systems are a very diverse group…So you have people [who] are… power users who have very high technical skill level, and you have majority of users who are actually unskilled IT workers so they just get 'canned' reports…[They] just download reports [or] receive reports from emails and the emails contain data tables and graphs so there is nothing to learn in their mind…[Just click on a web link and they download the reports] that's what most people would understand BI to be…Learning the BI system would have impacts when you actually have to use specialized tools, say something like SAS or SAP or SPSS…"* (Organization C-BI director 1).

For example, a regular BI user, who is a manager of a large education institution using the built-in capabilities of a BI system to inform decision making, felt that learning the system she used was very simple because she only used reports generated from it. All she needed was one presentation about the system and she could use it easily (Organisation D-Director of operations department). On the other hand, a power BI user from the same organization (Organization D-Data analysis manager 5) working on the same project conveyed to us a very different view:

> *"…it takes some hours of training and a lot of the training is actually yourself, experience. You make mistakes, you don't know how to use all the little tricks and I must say, in 2010 [when I first learned the system], I must have written…500 emails asking …questions…[to learn] what you need to do."*

In other words, regular users appear to experience rapidly diminishing marginal returns to learning, whereas power users' need for learning does not diminish or only diminishes slowly. Instead, power users benefit from progressive learning to continually improve (Barki et al. 2007). Sharing the same view as the power BI user above, a power BI user at a bank noted "even after five years …I was still learning new things" *(Data analysis manager 6).* We did not control for users' roles in the survey but, based on the post-hoc interview results, it appears the non-significant effects of Learning the BI System on BI Transparent Interaction in the survey may have stemmed from having a dominance of regular users in the sample.

As Table 8 shows, the meta-inference we draw is that tests of TEU should account for a user's role as a contextual factor. We suggest accounting for roles as a contextual factor (rather than respecifying TEU in general) because it will only be a salient issue in some contexts. That is, it reflects an interaction between TEU's core constructs and a context-specific variable (Guideline 5 in Table 1). Moreover, while TEU does not have a construct to represent a user's role, it does consider how the effect of learning might depend on users' pre-existing knowledge; it just assumes this effect is uniform, i.e., more knowledgeable users engage in more learning and benefit more from it (Burton-Jones and Grange 2013, p. 651). Our interviews suggest that this outcome might reflect the reality for power users, but not regular users. Some BI studies have shown the salience of users' roles (Deng and Chi 2012; Tamm et al. 2013). This meta-inference, therefore, can help researchers to build on such work by accounting for user's role when testing TEU in BI settings.

Learning Fidelity (H2a). TEU proposes that learning fidelity will strengthen the benefit of transparent interaction on representational fidelity, but we found no evidence for this link in our survey. The rationale for the interaction is that learning fidelity and transparent interaction work together: if you know what good data looks like (due to high learning) and if you can access it (due to high transparent interaction), then you are more likely to get the output you need (high representational fidelity). What we learned through our first set of interviews, however, is that learning fidelity can sometimes have benefits even when transparent interaction is low, an insight confirmed in 9 of the 10 confirmatory interviews. One way this outcome can occur is by enabling adaptations and other workarounds, allowing users to bypass problems with low transparent interaction. An interviewee noted:

> *"So we wouldn't be able to necessarily get the system to correct, we would then correct in …the output. [Alternatively,] we can raise change requests, but those can take three months at the quickest turnaround. So for those three months we still have to do business. We still have to report. So we need to change that and account for it based on the business rules that we've got from the subject matter experts"* (Organisation A-Data analysis manager 1)

Another way that learning fidelity can have benefits when transparent interaction is low is by allowing users' to mentally fill-in-the blanks and make inferences based on partial output they obtain. We were told in one organization, for instance, that because the finance director had spent years learning the fidelity of data in his systems, he knew how to get an accurate picture even if it was difficult to access and piece together (Organisation C-BI Director 1).

As Table 8 shows, the meta-inference we draw is that TEU should be respecified to enable researchers to account for the direct effect of learning rather than just moderating effects (per Guideline 6, Table 1). That is, if learning fidelity can lead to greater representational fidelity irrespective of whether transparent interaction is high or low, then it implies that learning fidelity has a direct rather than a moderating effect. We tested this idea in our survey data and found that direct effect of learning fidelity on representational fidelity was positive and significant ($p<.05$), supporting these insights from the interviews, and challenging TEU.

Learning to Leverage (H3a). TEU proposes that learning to leverage will strengthen the benefit of representational fidelity on informed decisions, but we found no support for this in the survey. In fact, in our detailed analysis from each wave (see Supp. Appendix B for details), we found that the moderating effect was insignificant in the combined data set (Waves 1 and 2), also insignificant in Wave 1, but significant and negative in Wave 2. This runs counter to TEU, as TEU suggests that the moderating effect should be positive, as learning to leverage representations and representational fidelity should work together: if you know how to leverage good data (due to high learning) and if you obtain such data (high representational fidelity), then you are more likely to make informed decisions.

Our interviews helped us understand why TEU's proposition was not supported. Specifically, we were told that learning could still be useful even when representational fidelity was low (much as we learned for H2a above, that learning could still be useful when transparent interaction was low). As Table 8 shows, this result was confirmed in 8 of the 10 confirmatory interviews. From this perspective, even the negative interaction in Wave 2 becomes understandable because it implies that the more the BI user learns, the less effect that representational fidelity has on informed decisions. This situation is reminiscent of the power of pragmatics over semantics in a prior test of representation theory (Bera et al. 2014).

The underlying reason for this effect, according to our interview data, is that managers are often under pressure to make decisions even with bad data. TEU and representation theory both appear to implicitly assume that decision-makers will seek out good data upon which to make decisions; they do not speak directly to the reality of managers having to proceed to make decisions regardless of the quality of the data. Our interviews suggested that data quality is often poor, but learning to leverage representations can still be helpful by enabling them to know how best to identify and articulate the relevant assumptions and caveats that need to be understood and documented.

> *"We had to find an option for a cloud-based solution and we couldn't get any accurate data but we still had to proceed with a decision because that is a business decision we are under a lot of pressure to make. So even with low quality data we still made the decision because the business driver for the decision forces us to make a decision. So in that scenario we just took whatever we could get as some kind of defensible justification for making that decision. That put lots of assumptions and caveats around what we don't know…. That is an example of what people do around low quality information."* (Organisation C-BI director 1)

As noted above, we could use this line of argument regarding the power of learning to suggest a negative rather than a positive interaction effect. However, at this stage of theory refinement, we believe it is more conservative to suggest a direct effect. That is, as with H2a, the meta-inference we draw in Table 8 is that TEU should be respecified to account for the direct effects of learning (per Guideline 6, Table 1). This is because if learning to leverage representations can lead to more informed decisions irrespective of whether representational fidelity is high or low, then learning has a direct effect. As with H2a, we tested this idea in our survey data and found the direct effect was positive and significant ($p<.05$). Moreover, when we compared our model to an alternative model in which *all three* learning constructs were modeled with direct rather than moderating effects (learning the system → transparent interaction, learning fidelity → representational fidelity, and learning to leverage → informed decisions), model fit improved (i.e., the fit indices for the revised model were all equal or stronger than those shown earlier in Table 5, i.e., $\chi^2/df = 1.88$, CFI 0.94, GFI: 0.88, RMSEA: 0.045, SRMR 0.05). Thus, it is possible that the lack of support for the learning constructs in our survey results may reflect a more global need to respecify TEU to allow for direct effects.

The Relationship between Data Integration and Representational Fidelity (H2b)

The quantitative results showed that rather than data integration having a positive effect on representational fidelity, it had a small but significant negative effect. This result was unexpected and we looked, but did not find, strong potential explanations in the literature. Goodhue et al. (1992) indicated that data integration may not always be useful (e.g., if a manager needs to make local decisions on local data, and so does not require integrated data), but even in such cases we did not expect a negative relationship. The interviews were useful, therefore, in identifying a reason. According to interviewees, data integration projects *should* be accompanied by data cleaning projects but this step often does not occur – a problem noted in 8 of the 10 confirmatory interviews. When the integration proceeds without appropriately cleaned data, representational inadequacies are exacerbated, leading to the observed negative effect. One interviewee highlighted the necessity of data cleaning:

> *"So …this was the case at [our organization]: bad data, great execution, poor end result…So the ERP system and everything was put in place. … So we still were able to produce … reports, [but that] doesn't help management because those numbers – we have no idea. We can't verify…There's no confidence in the reports …So like we can generate reports but then we go, "we don't know how accurate that really is" The data is actually incorrect. …The data's not cleaned. Integrated, it's pretty good. But in terms of cleansing, there is no cleansing process."* (Organisation C-Data analysis manager 3)

Upon seeking clarification of the importance of having data cleaned before producing integrated BI outputs, one of interviewees asserted:

> *"You can't have one (BI system) without the other (data warehousing team), … Without that, I couldn't do my job properly, because I've been hired to provide insights, not to try and clean up the data and merge 12 million data sets together.* (Organization B-Data analysis manager 2)

These perspectives are consistent with Raham and Do's (2000 p.1) argument that:

> *"…when multiple data sources need to be integrated, e.g., in data warehouses, federated database system, or global web-based information systems the need for data cleaning increases significantly. This is because the sources often contain redundant data in different representations. In order to provide access to accurate and consistent data, consolidation of different data representations and elimination of duplicate information become necessary".*

As Table 8 shows, the meta-inference we draw is that researchers should account for data cleaning as a contextual factor. That is, it reflects an interaction between TEU's core constructs and a context-specific variable (per Guideline 5 in Table 1). Interestingly, when we reviewed the prior literature, *data cleaning* was rarely noted. While some papers considered the related concept of data quality, they still paled in comparison to the number that studied data integration (6 of 67 papers vs. 33 of 67 papers; see Supp. Appendix A1). Practitioner papers such as Davenport (2006) also failed to discuss data cleaning. Overall, our results suggest that more attention needs to be placed on data cleaning in addition to data integration. Practically, this is important because data cleaning limitations constrain the value users can generate from BI (Rahm and Do 2000; Wade and Hulland 2004). Theoretically, this finding is important because the presence of data cleaning needs to be accounted for if researchers are to understand the possibilities of achieving representational fidelity in BI contexts.

Further Contextualization: Insights on Enacting Resources in Practice

The final set of interviews aimed to explore how the insights from Table 8 could be enacted in practice, reflecting an extra level of contextualization (Table 1, Level 3) beyond those conducted to this point. The goal was to identify how the theoretical extensions made in this research could be made concrete. That is, we have extended TEU theoretically by identifying the salience of three organizational resources (*BI system quality, data integration and data cleaning,* and *evidence-based management culture*).

We interviewed 13 BI users from two universities that use BI extensively. Focusing on one sector (universities) enabled us to identify common themes more easily. In addition to traditional coding (Miles and Huberman 1994), we used approaches for coding contextual factors (Venkatesh et al. 2016b; Zhang and Venkatesh 2017), focusing on elements of the discrete BI context related to the antecedents, i.e., features of the BI system (for system quality), features of the data (for data integration and data cleaning), and the organization (for evidence-based management culture). We asked interviewees how they saw and interacted with these elements and why they were important (see Supp. Appendix C for our questions). Table 9 shows the results. For BI system quality, the key contextual elements were report functions, dashboards with drilldown, analysis functions, and query facilities. For data integration and data cleaning, the key elements were the data dictionary, business rules/logics, and the staging environment for data checking and validation. For evidence-based management culture, the key elements were a dedicated organizational BI unit, organizational buy-in regarding the value of data and analysis, and an assumption in the organization that data-driven decision-making is the norm. In sum, interviewees based their assessments of the three antecedents on the quality of these contextual elements. Likewise, improvements to the three antecedents in practice involved making improvements to these contextual elements.

Table 9. Further Contextualizing the Antecedents to TEU (BI system quality, Data integration and data cleaning, and Evidence-based management culture)				
BI Context dimensions	**BI Contextual elements**	**Support**		
		Interviewees identifying the element	*How the contextual elements relate to the BI resource antecedents*	*Representative quotes*
BI system features *Technology class* *(Venkatesh et al. 2016b)*	- **Reports:** Revealing what has happened in the past and what is happening now	13 of 13	**BI System quality:** - Various types of reports, dashboards, queries, and analysis capabilities are available in the systems for users when they need to use them for their tasks - The system facilitates users' interaction so that the user can quickly access, customize, design, and develop reports, dashboards and run queries and analyses	*Interview 6:* Query studio [lets] you drag and drop any field. With the Cognos package you get all the fields in there. [But] with the Query studio you just …extract whatever field that you want to extract, you know how you can design the report and drill down and all this sort of stuff. *Interview 8*: There are [several] functions in any BI system. One is … reporting and dashboarding. That's basically pre-built analysis. … But [it's] not the most valuable … The most valuable is ad hoc analysis and exploratory analysis where people are trying to find where the business should be going, rather than just looking at the historical data…. you mostly use …query studio or analysis studio to do that sort of analysis. *Interview 13:* [SAP Business Objects] is not very intuitive [and] it's tough to get exactly what you want from SAP BO… It's great at producing anything tabular and it's great at crunching large data sets. But it doesn't make nice looking reports or visualizations, it doesn't have a lot of choice …and it is extremely hard to change things in and develop in. [So] if a user contacts us to ask for a column to be added, it sounds like a very simple task but in BO that's actually extremely complex. Whereas, in something like Power BI it's drag and drop, it only takes two seconds to implement and you can send that out to the user.
	- **Dashboard with drilldown:** Enabling quick, flexible access to data that give a broad perspective yet specific insights	12 of 13		
	- **Analysis:** Converting data into information for decision-making	13 of 13		
	- **Ad-hoc query:** Obtaining and retrieving information from large dataset when the need arises	10 of 13		
Features of data underlying BI system *Technology class* (Venkatesh et al. 2016b)	- **Data dictionary/Data glossary:** standard and agreed data definitions, and data structure	10 of 13	**Data integration:** - Data is integrated from different source systems for reporting, dashboard development, queries, and analysis. - Data is standardized from different source systems for reporting,	*Interview 3:* Many of the variables [in our warehouse] are defined by the Commonwealth. So there's a good data glossary from the Commonwealth and there's a very good data glossary from the system as well. So we've got very clear definitions around variables, very clear business rules about how to derive variables. And…[so] when we've got different packages, [such as] one for student enrolments and another for course completions, they can just use the same variables across the packages [and] … you're getting consistency across all the packages and tools…. [If you need to transform the data, you also have to manage those business rules]. The rule for [data] transformation will be discussed and agreed by all parties. *Interview 7*: When the data comes into…the initial area, it is duplicated and inconsistent. What we do when we curate the data [is to] put it in the staging area where it gets presented for Business
	- **Business rules** and **logics applied** to identify, map, and integrate data, and deduplicate data columns and rows.	10 of 13		

	- **Staging environment for data checking and validation,** backed up by data governance oversight	13 of 13	dashboard development, queries, and analysis **Data Cleaning** - Incomplete, irrelevant, and inaccurate data is corrected for reporting, dashboard development, queries, and analysis - Duplicated data are removed for reporting, dashboard development, queries, and analysis	Objects and the reporting tools … [We then] clean, present, and structure the data so that it's meaningful and we don't have duplication in it. *Interview 8*: [To] integrate two data sets … you need to know the different data elements and make sure [they] are consistent across systems before you are trying to integrate them. [For example, we once tried to integrate data from two regions but due to an upgrade], all the keys for the region would change in one system, which was not replicated in our system. Nothing was matching…. So if you want trusted and accurate data, it needs to be clean, integrated, and validated, before it is used with the BI system. *Interview 9:* We need that [data dictionary] so [that] if I look up …student attrition, I know how that's defined. …To assist that, we've put data and analytics governance in place…So, if we don't agree on how we define a term, we … get that resolved.
Organizational culture *Organization class* (Johns 2006)	**- Organizational Business Intelligence Unit** included in organizational structure	12 of 13	**Evidence-based management culture:** - Business Intelligence Unit is included in organizational structure to support organizational decision-making - BI outputs are regularly produced, updated, and made available for organization or public access - Senior buy-in: executive team commits to fact-based decision making: often request for or present evidence and data insights - Collective buy-in: employees often communicate analytics outputs	*Interview 1*: So there are lots of decisions that based on data [at the university. For example], every time we put up a request to recruit staff, you have to demonstrate staff to student ratio and workload capacity [and] demonstrate that … there is no way we could shift or reallocate resources and do a better job. So we demonstrate those things through data, not words…So it is set as a policy matters for the university …I'm [now] working with the director of student analytics…, and Associate dean of teaching and learning so…we talk about [data analytics] …all the time, in terms of trends and … expectations…[and] weekly meetings. *Interview 8:* Because we are… a strategic intelligence unit, we need to make sure that we are ahead of most of the analysis, but we also leverage some of the analysis done by other teams and extend it to make it more compelling than what they've done... In terms of…BI artefact delivery, we have lot of reports and dashboard refreshed every day. So people directly go to the system and use it. But in terms of the…new analysis…we work in an agile environment … where we take the…new analysis project and then we complete whatever we are able to complete in two weeks. We showcase it within our team and then we refine it to – if we think it is good enough to go and share with the users, then we put it in our production system to gain further input from the users or if we think it needs to be further refined, then we continue to the next sprint and see how we can get it to the users in a form where they can use it easily. *Interview 8:* Well, you see data used in pretty much all presentations. I'd be sceptical if someone said to me, "I went to a presentation the other day where there wasn't a graph, or some piece of analytical insight in there." Especially recently around the Covid work. There's been a lot of graphs and analysis done, I guess to support decision making [and] get a current state view. …There's appetite in senior management, as well, and that's the positive thing about where we are at the moment, that there is so much enthusiasm for data analytics in the university. There always has been.
	- Organizational value of using data and analysis for decision making (Senior buy-in, and collective buy-in)	12 of 13		
	- Data-driven decision making is the **underlying assumption of the organization**	11 of 13		

DISCUSSION

In this section, we discuss the paper's contributions, limitations, and research implications.

Contributions to Research and Practice

This paper contributes by: 1) showing how TEU can be contextualized, operationalized, and extended, 2) demonstrating that many of TEU's predictions hold in the BI context while also revealing ways to improve the theory; and 3) offering practical insights executives can draw on to improve use of BI in their organizations.

The first contribution stems from TEU's high-level nature. Burton-Jones and Grange (2013, p. 651) developed the theory to apply to information systems in general, but they called for context-specific insights. Drawing on and extending Hong et al.'s (2013) guidelines, we showed how TEU can be tailored to the BI context *a priori*, by identifying context-specific antecedents and modeling context-specific versions of core constructs. As Figure 4 shows (in the movement right to left in the figure), this approach reflects a theory-driven trajectory. That is, just as Burton-Jones and Grange (2013) derived TEU from representation theory, we derived a contextualized version of TEU and generated results from our test of this BI-specific model. By demonstrating this approach, future researchers will now be in a better position to apply and test TEU in the same or other contexts.

In addition to contextualizing TEU, we responded to the call of Burton-Jones and Grange (2013) and Recker et al. (2019) to develop detailed scales for its constructs. Workable instruments are needed to test and progress IS theories (Chin et al. 1997). Because of the abstract nature of TEU (and representation theory in general), it is not obvious a priori how to construct its scales. By following a detailed, multi-round process with a large sample of users and academics (incl. 21 faculty experts), researchers can have confidence in the rigor with which the scales were constructed. By writing the scales to apply to BI systems in general (not one type of BI, or one vendor's BI), the scales should also be useable in many studies.

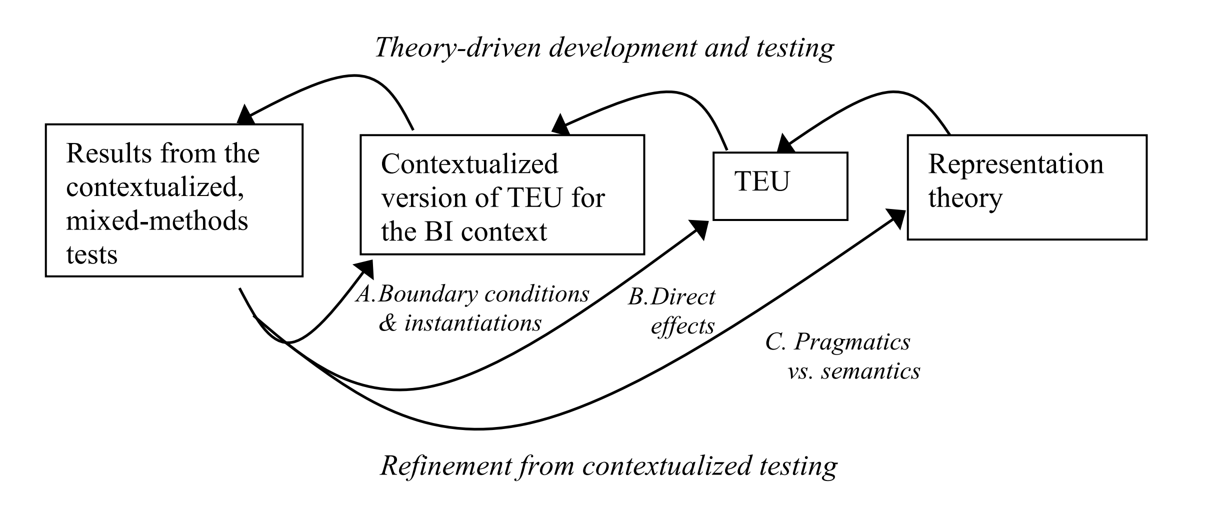


Figure 4. Trajectories of Theory Development and Refinement

The second contribution stems from the insights from our mixed-method, multi-phase test. On one hand, we gained insights for improving and rethinking TEU from the interviews and the re-analyses of survey data prompted by them. As Figure 4 shows (in the movement left to right in the figure), three insights were gained – boundary conditions and instantiations, direct effects, and pragmatics vs. semantics – that reflect successively more general implications:

- *Link A*: Our results suggest that future applications of TEU in a BI context should account for additional *boundary conditions* such as user's role (regular user vs. power user) and the presence of joint resources (e.g., data integration and data cleaning, not just data integration alone). New instruments will be needed to measure these additional boundary conditions. Our work also identified how the antecedents to TEU can be instantiated in practice. This makes the theory more actionable and testable because researchers can manipulate these concrete factors and test the effects of doing so in a field experiment or action research.
- *Link B*: Our results also revealed the need to consider the direct effects of learning. While these direct effects were not expected *a priori*, our interviews offered good reasons for why they may occur. While the best solution for TEU awaits future research, the lack of support for its expectations suggests a need to revisit its specification. Given that the potential for

such effects was not mentioned in TEU (Burton-Jones and Grange 2013), this insight is relevant for TEU's specification in general, not just in a BI context.

- *Link C*: Our results also reveal insights for representation theory in general – to consider the power of pragmatics. In particular, our interviews suggested that one of the reasons for the unexpected results for learning could be due to overly-idealistic assumptions of organizational life (such as an ability to obtain and use high-quality data) in representation theory and thus TEU. These assumptions stem from representation theory's focus on the power of semantics in information systems rather than the pragmatic contexts in which they are designed and used (Burton-Jones et al. 2017, p. 1325). The interviews suggest a more complex reality in which managers routinely cope with poor-quality data by drawing on their experiences, making inferences, and explicating assumptions. In such contexts, it may be naïve for a theory to focus on semantics alone. Even though TEU was created with an appreciation of this issue (see Burton-Jones and Grange 2013, p. 638), the results of this study together with others (e.g., Bera et al. 2014) suggest that the relative weight of semantics and pragmatics in representation theory needs careful reconsideration.

On the other hand, despite revealing opportunities for improving and rethinking TEU, the paper also demonstrated that most of TEU's hypotheses held in the BI context. Likewise, the results confirmed some of our context-specific extensions to TEU, such as the value of resources such as system quality and evidence-based management culture. We chose the BI context partly because it was a context well-suited to the assumptions of representation theory (the theory from which TEU is derived). Given that TEU was largely supported in this context, future researchers should feel motivated to move beyond 'safe' contexts for testing TEU and conduct tests in contexts for which it might be less suited – that is, to seek its failure (Gray and Cooper 2010). Such contexts may include those that are contested, equivocal, or chaotic (Burton-Jones and Grange 2013, p. 652, Burton-Jones et al. 2017, p. 1323).

Finally, the study contributes by providing executives with insights for improving BI use in practice. This is critical because researchers (Ain et al. 2019) and practitioners (McShea et al. 2016; NVP 2019) both stress that organizations are failing to reap benefits from BI. One way the paper helps practitioners is by integrating multiple sets of relevant factors normally discussed separately. For instance, while the benefits of strong resources, learning, and effective use are not surprising, practitioners do not have models that explicate their dimensions and how they jointly affect performance. Instead, practitioner sources often emphasize BI resources in general without identifying specific resources explicitly or identifying the role of effective use (e.g., Davenport and Harris 2017). Our paper provides a more explicit and integrative guide. In addition, we also showed how the antecedents to TEU can be instantiated in practice so that executives can act on our findings more directly. For instance, our findings go beyond general advice to ensure a data-driven culture (Bean and Davenport 2019; White 2020) to describe what this involves in practice (per Table 9).

Another way our paper helps practitioners is by revealing the complexity of achieving effective use. In particular, some of the learning effects we found were complex, such as the need for power users to engage in progressive learning and the need for BI users to learn how to make inferences from partial output, and articulate relevant assumptions and caveats when making decisions with suboptimal data. While such actions may not be entirely unexpected, they are not the type typically covered in organizational training. It is likely they are learned through individual trial-and-error or social interactions with peers (Gallivan et al. 2005). The weakness with this approach is that the knowledge can depend on particular staff members. This knowledge can leave the organization when the staff members do. More structured learning activities would be a useful complement. A key lesson from our study is the need for training on how to use BI in the most effective manner in *non-ideal* settings (e.g., when system limitations need to be worked around or when decisions must be made with poor data).

Limitations and Future Research

We acknowledge several limitations. First, great care was taken to develop high-quality scales, but greater discrimination among our constructs could be gained by refining the scales and seeking greater parsimony in TEU's specification of learning (e.g, via a higher-order model). Second, while online survey panels can provide reliable data (Park et al. 2014; Steelman et al. 2014), such panels inevitably tell us little about the survey participants. Research can address this by collecting data from known organizations. Third, cross-sectional surveys suffer from common method bias (Sharma et al. 2009). Although we reduced the risk by having temporal separation between measures (Podsakoff et al. 2003), the risk cannot be eliminated completely or reliably controlled (Richardson et al. 2009). Multi-source, matched-pair designs can help address this issue. Longitudinal designs are also needed to tease out the effects of learning. Fourth, this study excluded adaptation actions from its scope. Researchers could test when adaptation actions are needed in concert with learning to improve effective use. Fifth, although the post-hoc interviews gave clues for why some hypotheses were not supported, which we confirmed in later interviews, quantitative tests are still needed. Finally, while we began this paper stressing differences among various ways to study the use→performance relationship, future research is needed to examine complementarities amongst them (Sun et al. 2019).

CONCLUSION

Motivated by the need to understand what it takes to use BI systems effectively, this paper tailored a recently-developed theory of effective use (TEU) and extended it to fit the BI context, created instrumentation for its constructs, and tested it using a two-wave survey with follow-up qualitative interviews. The results advance our understanding of TEU's efficacy and they can help practitioners charged with improving the effective use of BI in organizations. Despite its limitations, we trust the work in this paper can stimulate further context-specific applications and extensions of TEU, and further studies of how to use BI systems effectively.

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APPENDICES

Appendix A. Research Constructs and Survey Instruments (See Supplementary Appendix B for details*)

Constructs	Construct Definition	Survey Instruments (Responses to each items are recorded on a 7-point Likert scale)	Source
BI System Quality	*BI system quality is a measure of the performance of the BI system from a technical and design perspective (DeLone and McLean 1992; Gable et al. 2008)*	**The items in this question focus on the quality of the BI system in your organization.** *Please indicate the extent that you agree or disagree with each of the following items.*	
		• SQ1.The system is designed in a reliable way, always being available when I need it.	(Petter and Fruhling 2011)
		• SQ2. The design of the system facilitates user interaction, always responding to my commands quickly.	(DeLone and McLean 2003)
		• SQ3. I would rate the quality of the system highly from a design/technical perspective.	Developed
		• SQ4. The system makes available all the features and functionality that are needed**	(Kulkarni and Robles-Flores 2013)
Data Integration	*Data integration ensures that data have the same meaning and use across time and across users, making the data in different systems or databases consistent or logically compatible (Goodhue et al. 1992)*	**The items in this question focus on the extent to which the data held in information systems of your organization is integrated.** *Please indicate the extent to which you agree or disagree with each of the following items.*	
		• DI1. The data available in the BI system is integrated from different source systems of the organization**	(Wixom and Todd 2005)
		• DI2. The data available in the BI system is pulled together from different places in the organization addressing local business unit or functional needs**	
		• DI3. The data available in the BI system is standardized across the organization.	Developed
		• DI4. The data available in the BI system has the same meaning across different departments of the organization.	
		• DI5. The data available in the BI system is defined the same way across different departments of the organization.	
Transparent Interaction***	*The extent to which a user is accessing the system's representations unimpeded by its surface and physical structures (Burton-Jones and Grange 2013)****	**The items in this question focus on the ease of accessing content through the BI system in your organization.** *Please indicate the extent to which you agree or disagree with each of the following items.* ***In the questions below, the 'system interface' refers to the means by which users can interact with a system and obtain information from it (e.g., via its screens, menus, and layouts).***	
		• TI1. When using the BI system I find it easy to get to the data/information I need through the system's interface.	Developed based on Burton-Jones and Grange (2013)
		• TI2. When using the BI system I find it easy to use the system's reporting and/or presentation functionalities to access information I require.	
		• TI3. When using the BI system I am not troubled by the interface in obtaining content I need.	
		• TI4. When using the BI system I find that the system's interface provides me with a user-friendly way to get the data/information I need.	
		• TI5. When using the BI system I have no difficulty interacting with the system to get the data/information I need**	

Constructs	Construct Definition	Survey Instruments (Responses to each items are recorded on a 7-point Likert scale)	Source
Learning Fidelity	*Any action a user takes to learn the extent to which the output from the system faithfully represents the relevant real-world domain (Burton-Jones and Grange 2013)*	**The items in this question focus on actions you take to *learn* about the quality of the information/output you obtain from the BI system.** *Please indicate the extent to which you agree or disagree with each of the following items.*	
		• LF1. I invest much effort (in time and energy) to better understand if the information/output I get from the system is of sufficiently high quality for my needs.	Developed based on Burton-Jones and Grange (2013)
		• LF2. I invest much effort (in time and energy) to increase my ability to judge if the information/output I get from the system is accurate enough for my needs.	
		• LF3. I invest much effort (in time and energy) to better understand if the information/output I get from the system is of sufficiently high quality for me.	
		• LF4. I invest much effort (in time and energy) to better understand if the information/output I get from the system is accurate given my needs.	
Learning The System	*Any action a user takes to learn the system (its representations, or its surface or physical structure) (Burton-Jones and Grange 2013)*	**The items in this question focus on actions that you take to *learn* how to get content from the BI system.** *Please indicate the extent to which you agree or disagree with each of the following items.*	
		• LS1. I invest much effort (in time and energy) to better understand how to use the system interface to access the information/data.	Developed based on Burton-Jones and Grange (2013)
		• LS2. I invest much effort (in time and energy) to learn how to use the system's reporting and/or presentation facilities.	
		• LS3. I invest much effort (in time and energy) to learn how to access the system's offerings through the system interface.	
		• LS4. I invest much effort (in time and energy) to better understand how to access information/data through the system interface.	
Learning How To Leverage Output	*Any action a user takes to learn how to leverage the output obtained from the system in his/her work (Burton-Jones and Grange 2013)*	**The items in this question focus on actions you take to *learn* how to leverage the BI output in your job.** *Please indicate the extent to which you agree or disagree with each of the following items.* ***In your work, you may have taken many actions to learn to do your work. For this question, please consider the actions you take to learn how to leverage the BI output in your job only.***	
		• LL1. I invest much effort (in time and energy) to increase my ability to leverage the information/output I get from the system to do my work.	Developed based on Burton-Jones and Grange (2013)
		• LL2. I invest much effort (in time and energy) to learn how to leverage the information/output I get from the system to do my job.	
		• LL3. I invest much effort (in time and energy) to better understand how to leverage the information/output I get from this system to do my job.	
		• LL4. I invest much effort (in time and energy) to gain a better understanding of how to leverage the information/output I get from this system to do my job.	
Representational Fidelity ***	*During interaction with the system, the extent to which a user is obtaining representations that faithfully reflects the domain that the systems represent (Burton-Jones and Grange 2013)*	**The items in this question focus on the quality of the output you obtain from the BI system.** *Please indicate the extent to which you agree or disagree with each of the following items. In the questions below, the* ***'real world domain'*** *refers to the* ***real-world processes***, ***transactions***, ***things***, *or* ***events*** *that the BI system provides information about.*	
		• RF1. When using the BI system, the information/output I obtain from it about the relevant real-world domain is sufficiently accurate.	Developed based on Burton-Jones
		• RF2. When using the BI system, the information/output I obtain from it about the relevant real-world domain is sufficiently timely.	

Constructs	Construct Definition	Survey Instruments (Responses to each items are recorded on a 7-point Likert scale)	Source
		• RF3. When using the BI system, the information/output I obtain from it about the relevant real-world domain is sufficiently clear.	and Grange (2013)
		• RF4. When using the BI system, the information/output I obtain from it about the relevant real-world domain is a sufficiently faithful reflection of that domain.	
Evidence-Based Management Culture	*An evidence-based management culture involves the use of data and analysis to support decision-making (Pfeffer and Sutton 2006)*	**The items in this question focus on the extent to which your organization has a culture of collecting and analyzing data to support decision-making.** *Please indicate the extent to which you agree or disagree with each of the following items*	
		• EBM1. The organization encourages me to look for data/information to support decision-making.	(Kulkarni and Robles-Flores 2013)
		• EBM2. The organization respects the measurement and evaluation of data to make decisions**	Developed
		• EBM3. The organization encourages me to conduct quantitative/numeric analyses to make decisions informed by data.	(Kulkarni and Robles-Flores 2013)
		• EBM4. The organization encourages me to make decisions informed by data.	
Informed Decisions	*The extent to which a user acts on the information/output that he or she obtains from the system to improve his or her work performance (Burton-Jones and Grange 2013)*	**The items in this question focus on the extent to which you leverage the BI output in your job.** *Please indicate the extent to which you agree or disagree with each of the following items.*	
		• IF1. When I obtain data/information from the system, I leverage good pieces of it to create focused recommendations and/or decisions.	Developed based on Burton-Jones and Grange (2013)
		• IF2. When I obtain information/output from the system, I leverage good pieces of it to create focused recommendations and/or decisions.**	
		• IF3. When I obtain data/information from the system, I leverage good pieces of it to improve my reports/ recommendations and/or decisions.	
		• IF4. When I obtain data/information from the system, I use key parts of it to identify problems, find solutions and/or take correction action in my work.	
Decision-Making Efficiency	*Decision-making efficiency refers to the extent to which decision-making goals are attained for a given level of input such as effort or time (Burton-Jones and Grange 2013)*	**BI systems are typically implemented to support decision-making. The items in this question focus on the decisions for which you have used the BI system.** *Please indicate the extent to which you agree or disagree with each of the following items.*	
		• DMEcy1. I make decisions without taking up too much time. **	Developed
		• DMEcy2. My process for making decisions is efficient.	
		• DMEcy3. I find that I make decisions very efficiently.	
		• DMEcy4. I make decisions speedily when I need to. **	
Decision-Making Effectiveness	*The extent to which a user has attained the goals of the decision-making task for which the system was used (Burton-Jones and Grange 2013)*	**BI systems are typically implemented to support decision-making. The items in this question focus on the decisions for which you have used the BI system.** *Please indicate the extent to which you agree or disagree with each of the following items.*	
		• DMEes1. My decisions have been effective in helping to achieve Key Performance Indicators expected by my division/department/organisation.**	Developed
		• DMEes1. My decisions have been effective in helping to achieve Key Performance Indicators expected by my division/department/organisation.**	
		• DMEes3. My decisions have been effective in helping to achieve the objectives desired by my organization/division/department.	

Constructs	Construct Definition	Survey Instruments (Responses to each items are recorded on a 7-point Likert scale)	Source
		• DMEes4. My decisions have been effective in helping to achieve outcomes desired by my division/department/organization.	
Task Interdependence	*The extent to which a BI user engages in tasks that are interdependent with other organizational units (Goodhue, 1995)*	**The items in this question focus on the extent to which you engage in tasks that are interdependent with others in your organization.** *Please indicate the extent to which you agree or disagree with each of the following items.*	
		• TIce1. The business problems I deal with frequently involve more than one business function.	Goodhue (1995)
		• TIce2. The problems I deal with frequently involve more than one business function.	
		• TIce3. The tasks I engage in frequently involve more than one business function.	
Job Autonomy	*Autonomy refers to "the degree to which the job provides substantial freedom, independence and discretion in scheduling the work and in deter mining the procedures to be used in carrying it out" (Oldham and Hackman 2010 p. 464)*	**The items in this question focus on the extent to which your job provides substantial freedom, independence and discretion in scheduling the work and in determining the procedures to be used in carrying it out.** *Please indicate the extent to which you agree or disagree with each of the following items.*	
		• JA1. I have a lot of freedom to choose how I make my decisions.	Ahuja and Thatcher (2005)
		• JA2. I control how I make my decisions.	
		• JA3. I have the authority to make decisions in my job.	
		• JA4. I set my own schedule for making my decisions at work.	

*Supplementary Appendix B is available at: https://osf.io/tv6wh/?view_only=63b91a611b9a448f8df5ddb2fbfdcd79

** Item dropped from final analysis due to low reliability.

*** We briefly note how TEU's constructs differ from other constructs. In particular, 'transparent interaction' differs from 'perceived ease of use' because the focus is not just ease *per se*, but ease of accessing representations without being impeded by the system's surface and physical structures. Likewise, 'representational fidelity' differs from information quality because information quality is a property of a system whereas representational fidelity is a property of use. Two users might use a system with a given level of information quality, but obtain different levels of representational fidelity because one user uses it more effectively than the other. For more on these distinctions, see Burton-Jones and Grange (2013).

Appendix B. Exploratory Factor Analysis

	Learning System	Learning to Leverage the representations	Representational Fidelity	Learning fidelity	Transparent Interaction	Data Integration	Evidence-Based Management Culture	System Quality	Informed Decisions	Decision-making Effectiveness	Decision-Making Efficiency
LS1	**.735**	.174	.107	.262	.091	.069	.105	.131	.081	.041	-.011
LS2	**.724**	.165	.101	.288	.155	.049	.159	.126	.173	-.011	-.084
LS3	**.718**	.209	.131	.260	.028	.176	.020	.015	.121	.113	.098
LS4	**.688**	.248	.102	.306	.066	.106	.009	.041	-.098	.165	.111
LL1	.129	**.779**	.073	.201	.105	.094	.241	.010	.147	.018	.034
LL3	.272	**.704**	.017	.180	.052	.074	.084	.068	.243	.013	.168
LL4	.291	**.660**	.009	.154	.114	.032	.197	.174	.218	.089	.004
LL2	.209	**.730**	.088	.194	.135	.021	.175	.151	.042	.250	-.004
RF1	.066	.052	**.776**	.078	.128	.081	.062	.203	-.028	.143	-.079
RF2	.118	.034	**.753**	.096	.187	.064	.134	.116	.003	.179	.171
RF3	.197	-.047	**.687**	.056	.274	.015	.107	.140	.196	-.065	.149
RF4	.051	.130	**.741**	.176	.178	.095	.002	.011	.188	-.032	.096
LF1	.303	.136	.137	**.690**	.098	.221	.188	.066	.097	.167	.069
LF2	.311	.226	.157	**.711**	.139	.055	.065	.062	.081	.027	.068
LF3	.306	.267	.100	**.661**	.124	.039	.043	.088	.124	.147	.118
LF4	.354	.168	.107	**.723**	.016	.111	.155	.042	.079	.086	.113
IT1	.081	.084	.182	.085	**.730**	.175	.098	.210	.003	.102	.173
IT2	.039	.030	.230	.149	**.750**	.191	.189	.031	.169	.090	.118
IT4	.134	.183	.234	-.015	**.610**	.200	.051	.172	-.145	.213	.164
TI5	.117	.149	.275	.125	**.703**	.235	.042	.252	.060	.072	.035
DI3	.084	.109	.031	.094	.166	**.702**	.149	.164	-.064	.101	.202
DI4	.119	.055	.061	.053	.222	**.825**	.081	.151	.076	.071	-.036
DI5	.096	.016	.129	.138	.173	**.830**	.032	.087	.127	.010	.030
EBM1	.037	.296	.118	.151	.113	.113	**.712**	.007	.242	.011	.078
EBM3	.033	.253	.037	.109	.083	.141	**.735**	.143	.117	.162	.073
EBM4	.207	.081	.134	.092	.132	.039	**.737**	.137	.015	.219	.158
SQ1	.012	.093	.182	.131	.253	.088	.067	**.770**	.175	.062	-.038
SQ2	.196	.144	.141	-.016	.108	.253	.126	**.668**	.104	.055	.199
SQ3	.135	.111	.199	.093	.220	.222	.139	**.578**	-.067	.228	.133
IF2	.042	.345	.211	.149	-.038	.157	.042	.090	**.608**	.120	.202
IF3	.311	.217	.087	-.094	-.034	.083	.215	.138	**.595**	.270	.212
IF4	.075	.225	.102	.259	.136	-.005	.206	.078	**.695**	.106	-.039
DMEes3	.200	.099	.069	.123	.201	.060	.205	.090	.139	**.747**	.095
DMEes4	.033	.176	.153	.219	.160	.137	.178	.169	.214	**.684**	.055
DMEcy2	.024	.030	.109	.220	.193	.072	.188	.281	.217	-.053	**.689**
DMEcy3	.060	.143	.201	.107	.280	.127	.143	-.010	.042	.236	**.730**

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. a. Rotation converged in 9 iterations.