



# A Case Study of Inconsistency in Process Mining Use: Implications for the Theory of Effective Use

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**Abstract.** Responding to recent and repeated calls in literature, we sought to understand the effective use of business intelligence systems, specifically process mining. The intersection between effective use and business intelligence is pertinent to practice, as these systems do not automatically result in improved organizational outcomes, rather they must first be effectively used. Through a qualitative case study, we examined the effective use of process mining (analytical technique underpinning business intelligence), whereby inconsistency-in-use emerged as salient. We, therefore, shifted our focus to understanding the role of inconsistency-in-use in the effective use of process mining. We identified inconsistencies in: place, meaning, and content (i.e., entanglement of data and information). These types of inconsistency were interrelated and influenced informed action. Inconsistency in content also had implications for representational fidelity. Given, both informed action and representational fidelity are effective use dimensions, these inconsistencies need to be considered for process mining systems to be effectively used.

## 1 Introduction

Organizations continue to make substantial investments in business intelligence systems and technologies with the objective of improving decision making to yield a competitive advantage [1]. In line with Trieu [2], we view business intelligence as an umbrella term (encapsulating, for example, business analytics, big data, data mining, and process mining) that refers to “a set of concepts and methods based on fact-based support systems for improving decision making”. Process mining is a domain of business intelligence [3], consisting of techniques, algorithms, visualizations and methodologies for analyzing business process data, such that these processes can be improved using Business Process Management principles. For instance, process mining enables organizations to monitor performance indicators, discover process models, identify resource constraints and bottlenecks, and determine the extent of regulatory performance [4]. Recently, process mining is gaining traction with its uptake in multiple fields including: healthcare [5], financial services [6], and insurance [7]. Despite the increasing uptake of process mining as a form of business intelligence system, implementations of such systems do not automatically result in improved decisions or organizational enhancements [8].

Based on the theory of effective use, to attain the goals of a system, whether a business intelligence system or otherwise, it must be effectively used [9]. According to this theory, to make informed actions, which is the prime goal of business intelligence systems, users must be able to leverage data that provides an accurate account of the phenomenon of interest. There are repeated and recent calls in literature [2, 10] to understand the effective use of business intelligence systems. The importance of the intersection between these two areas is further compounded with Gartner predicting that self-service analytics (a capability of process mining) is a key future trend [11], which places more onus on business users effectively using these systems.

Due to the nascent state of research, we adopted a grounded theory approach [12] with the broad aim of understanding the effective use of business intelligence systems. We examined process mining as the analytic technique underpinning business intelligence. Process mining provides an evidenced-based foundation to improve an organization's processes by analyzing historical behavior of processes stored in event logs [4]. We investigated the effective use of process mining at a Dutch pension fund services provider. Following grounded theory, the salient theme of inconsistency-in-use (i.e., variations in meaning, content, and place) emerged as critical to the effective use of process mining. We then narrowed our aim to focus on inconsistency and aimed to provide insights into the following: What is the role of inconsistency-in-use in the effective use of process mining?

Although, we follow a grounded theory approach, we present our research sequentially. Next, we present related work followed by the case design. Then, we present our findings into types of inconsistency. We then integrate our findings with literature to show the role of inconsistency of use in the effective use of business intelligence.

## 2 Related Work

As we will unpack in this section, the notion of “use” in process mining literature is largely absent in the current discourse. Consequently, this section is structured as follows. First, we refer to seminal work grounded in the Information Systems domain investigating “use” and “effective use” of systems. We then examine how such terms have been investigated in conjunction with the umbrella concept of business intelligence narrowing to the specific domain of process mining.

### 2.1 Information Systems Use

For more than three decades, Information Systems literature has largely rebuked technology determinist assumptions through recognizing that systems must be used for benefits to be attained [13]. This has resulted in system use being a cornerstone of the field [14]. System use is defined as “an individual user’s employment of one or more features of a system to perform a task” [15] and has been conceptualized to consist of three components: the technological artifact, the user, and the task. Translating to the process mining domain, the process mining system is the technology artifact; the user is the individual who interacts with the process mining system; and the task centers on the informed decision the user is seeking to attain from their interactions with the process mining

system. Yet, while use is a precursor to benefits, it is an insufficient condition as not all use results in benefits [9].

Information Systems literature has started shifting to understanding effective use, defined as “using a system in such a way that helps attain the goals for using a system” [9]. The theory of effective use [9], based on representation theory [16], conceptualizes effective use to consist of three dimensions: 1) Transparent interaction: “The extent to which a user is accessing the system’s representations unimpeded by its surface and physical structures”; 2) Representational fidelity: “The extent to which a user is obtaining representations from the system that faithfully reflect the domain being represented”; and 3) Informed action: “The extent to which a user acts upon the faithful representations he or she obtains from the system to improve his or her state”.

Thus, for users to effectively use the system, they need to transparently interact with the hardware and software to access representations, determine the faithfulness of the representations they leverage to make informed actions based on these representations to attain their goal for using the system. When conceptualizing effective use, Burton-Jones and Grange [9] provided a generalizable account. As a result, there have been calls to examine effective use in different contexts [17, 18], where emerging insights are providing a more nuanced understanding. For instance, according to Burton-Jones and Volkoff [17] effectively using health information systems requires users using the system in consistent ways. Similar findings emerged in Eden and Burton-Jones [19] who highlighted that effective use involves balancing consistency and inconsistency-in-use. This notion of inconsistency-in-use proved critical to the effective use of the process mining tool within our case organization. While effective use research has begun to explore new contexts, revealing new concepts and insights for how organizations can improve how effectively their systems are used, these studies seldom reflect back on how their context can shed new light on the theory’s generalizable dimensions.

## 2.2 Business Intelligence Use

Business intelligence provides a contemporaneous context for studying system use and in particular, effective use [47]. This is because unlike traditional systems, which were primarily focused on repetitive data entry tasks, business intelligence system enable users to make informed decisions based on the outputted data. According to Ain, Vaia, DeLone and Waheed [20] business intelligence systems “supports decision processes by i) facilitating: more aggregation, systematic integration and management of unstructured data and structured data, ii) dealing with a huge amount of data (e.g., big data), iii) providing end users with increased processing capabilities to discover new knowledge, and iv) offering analysis solutions, ad hoc queries, reporting and forecasting”. In a systematic literature review, Ain, Vaia, DeLone and Waheed [20] identified studies have recognized organizational factors, system factors, and user factors influence the adoption, use, and success of business intelligence systems. However, studies investigating business intelligence use did so from the perspective of extent of use [21, 22] or beliefs and attitude towards use [23, 24] seldom were rich conceptualizations of use provided. Notable exceptions include Grublješič and Jaklič [25] who conceptualized that beliefs and attitudes regarding business intelligence, impact individuals intensity of use, extent of use, and embeddedness of use; Trieu [2] who proposed effective use

for business intelligence assets translate into impacts; and Surbakti, Wang, Indulska and Sadiq [10] who proposed realizing business value from big data is a function of effective use. However, these studies while highlighting the need for richer conceptualizations of use, particularly effective use, in the context of business intelligence systems are all conceptual in nature.

As previously highlighted, inconsistency-in-use plays a pivotal role in how effectively information systems are used, which per Sect. 4 is salient in our case study data. We therefore, further reflect on how the notion of inconsistency-in-use has been investigated in business intelligence literature. According to [26] “relational database assumes consistency in the way entities and their properties are defined”. This is further supported by [27], who highlights the difficulty in creating coherent and consistent data structures. Inconsistency in data [28] can ultimately hamper users ability to analyze data and result in erroneous reports. Despite, consensus over the importance of consistency in the data source, the interrelationships between inconsistent data with other forms of inconsistency (e.g., presentation format) has yet to be addressed nor has the implications of inconsistency for effective use been examined.

The lack of robust investigation of how business intelligence systems are used is compounded in the process mining domain where the behavior and perceptions of individual users is often neglected. Process mining aims to gain insights into processes as run by organizations, by providing analysts with methods and systems to visualize behavior in these processes. Typically process mining literature has focused on the techniques and algorithms to perform analyses although some have examined the adoption of process mining at an organizational level across a variety of settings [5, 29]. Such studies provide details on the analysis performed [5], extent of process mining implementation [30], or techniques used across domains [31]. While process mining literature references notions of ‘use’ it generally does so from the perspective of ‘use cases’, which “represent the use of a concrete process mining functionality with the goal to obtain an independent and final result” [32]. This is in line with technology deterministic assumptions as use cases focus on the functionality provided to the user (e.g., discovery, conformance checking, and enhancement) [32]; rather than the actions of users to extract and interpret information to make informed decisions. It is counter-intuitive that process mining literature with its emphasis on unpacking representations of the behavior of individuals through event logs, has not yet explored how individuals adopt the process mining systems. Therefore, in this paper, we extend process mining literature by examining how users adopt these systems to make informed decisions.

### 3 Grounded Theory Case Study

To investigate effective use of process mining, we adopt a grounded theory approach [12] following the guidelines of Fernandez [33]. Grounded theory is recommended to explore revelatory phenomenon such as process mining and can be used to build novel theories [34, 35]. Algemene Pensioen Groep N.V. (APG) served as our case organization and is a large provider of services to pension funds in the Netherlands.

### 3.1 Case Organization

APG recognized process mining could provide them with the potential to improve its processes to benefit efficiency, effectiveness and quality of process outcomes. As such, APG formulated a strategy to trial, implement and embed process mining as a business intelligence system.

In 2016, APG commenced adopting Celonis, which is a commercial process mining system organizations adopt to enable business users to analyze business processes to identify inefficiencies and bottlenecks. Through performing process mining techniques on data derived from multiple sources, Celonis visualizes the output of the analysis to the users in the form of graphs and models via dashboards. Initially, Celonis was rolled out using what APG describes as a ‘launch and learn’ approach, with minimum governance. However, overtime they changed their approach establishing governance frameworks, providing data extraction expertise, and user guidance.

At APG, dashboard development typically involves several stakeholder groups. Dashboard development is done by an ‘Actionable Insights’ Data Intelligence (AI-DI) team of technical specialists, after which a ‘Self Service’ data intelligence team takes over user training, guidance, and provides assistance. The work of both teams is managed by the product owner of the ‘Actionable Insights’ team in APG. Each dashboard has an owner who asks for the dashboard in the first place and prioritizes features. The result is an interactive, custom-built dashboard where data is presented through charts and process graphs to business users. The users can be categorized as viewers or analysts. The viewers directly use the output provided by the system. Whereas, the expert analyst users, can also extend the dashboards to better meet the requirements of all users. Both types of business users are supported when necessary by the self-service data intelligence team where they receive additional training and advice.

Currently, several dashboards are used in APG. The following are referred to by our interview participants:

1. A customer journey analysis dashboard, which is a centralized dashboard that pension administrative teams use to analyze their administrative processes such as clients starting retirement, starting a new job, and other life events. The dashboard is also used to determine the fraction of cases that follow straight-through processing (STP, i.e., a fully automated process), and determine where STP fails. This dashboard has been developed by the AI-DI team and is now supported via the self-service team. This dashboard uses data prepared in a central data warehouse by AI-DI. The central data warehouses enables cross-process analysis, such as tracking process-chains for a customer. The dashboard also includes client satisfaction scores and number of contacts in order to analyze the customer journey in full.
2. A series of dashboards for specific pension-related processes, which were built by business users before the existence of the self-service team and without the help of the AI-DI team. The data used is taken directly from the pension administration system and therefore the dashboards have a process-specific scope.
3. An auditing dashboard to analyze the 4-eyes principle of a specific financial process. This dashboard was built by the AI-DI team as a one-time analysis on static as-is

data directly from the source system. Further development of the dashboard by the business analysts is supported via the self-service team.

In all cases Celonis is used as a self-service process analytics dashboard tool, allowing almost all employees of APG to make use of the dashboards. Furthermore, in all three cases, the dashboards are also maintained by a group of users, allowing them to adjust the dashboards to their changing needs. Therefore, Celonis is available company-wide, and not just of one department or legal entity. The same holds for the AI-DI availability, which performs projects for the whole of APG.

### 3.2 Data Analysis

Our objective was to understand the effective use of Celonis as a process mining system at APG. To collect data, we conducted semi-structured interviews and analyzed relevant archival data (e.g., presentations, training materials, and governance structures). We used purposeful sampling [36] and selected participants from each role, who had worked with one or more of the dashboards (excluding the product team owner). In total, 15 individuals participated across 14 interviews (see Table 1), which each lasted between 30 and 45 min on average.

The interviews were conducted in English. However, participants could switch to Dutch (native language) to explain key concepts. This was possible as two of the interviewers were fluent in Dutch. All interviews were recorded. The recordings were transcribed and uploaded into NVivo (v12), which was used as a data repository system, with coding and analysis manually performed [37].

**Table 1.** Overview of interview participants\*

Role	Participant count	Identifier
Actionable Insights Data Intelligence (AI-DI) member	5	P1–P5
Self-service Data Intelligence team member (SS-DI)	3	P6–P8
Dashboard owner	1	P9
Dashboard analyst (expert users)	4	P10–P13
Dashboard viewers (basic users)	2	P14–P15

\*The participant count is greater than the interview count as in an interview two individuals participated.

To analyze our data, we performed open coding [33] to enable key themes to emerge. As such, we did not have a preconceived framework for analyzing interviews. We used coder-corroboration to maintain reliability of the coding in which three researchers independently coded interviews followed by corroboration sessions to identify any differences and to attain consensus [38]. As a result of open coding, rather than effective use, the most salient themes pertained to ‘inconsistency of use’ emerged centering on the data within the system and the information extracted from the system. We then on-coded

the data comparing the quotes related to inconsistency to one another [37]. In doing so, we identified three types of inconsistency: 1) inconsistency in meaning, 2) inconsistency in content, and 3) inconsistency in place.

Next, we performed on-coding with constant comparison to literature. We discovered inconsistency in content was more complex than considered in past literature. Specifically, we identified it was important to consider inconsistency at the data layer and at the output layer (termed inconsistency in data and inconsistency in information respectively). We then progressed to theoretical coding, identifying the relationships between the types of inconsistency, as well as potential antecedents and consequences. We continued this process until theoretical saturation was reached [12], which was when no new themes nor relationships relating to inconsistency emerged.

## 4 Findings

In our case study, inconsistency related to meaning, content, and place were apparent in the use of Celonis. We identified that inconsistency in content is comprised of the entanglement of inconsistency in data and inconsistency in information. The types of inconsistency observed are defined with examples provided in Table 2.

**Table 2.** Examples of types of inconsistency

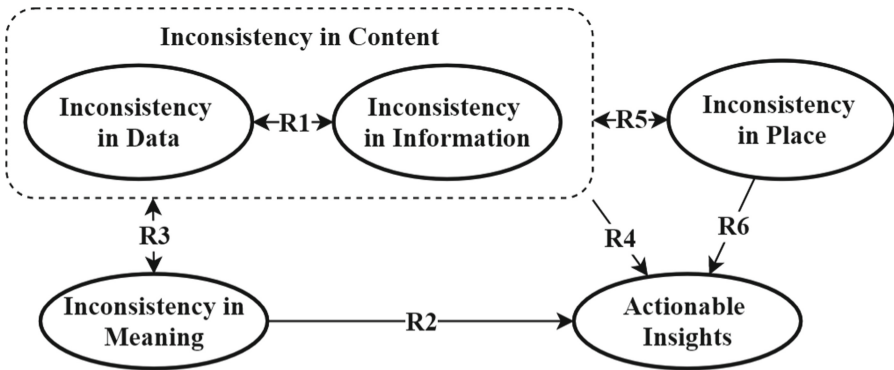
Inconsistency	Definition*	Example
Data	Variations in the completeness and accuracy of the data that is loaded into the process mining system	<i>“We find it very difficult to get the data we want. ...There are number of reasons for that sometimes its hard to get extractions from the systems, sometimes data is not available because it is not logged, sometimes the application managers dont know how to generate reports for data we are looking for. ...Another problem is that we want to have data from different systems because we want to have a look at the whole process in which more than one system is used ...making sure that the definitions from one application are [the] same in the other.” (P12)</i>
Information	Variations in the completeness and accuracy of output provided to the user by the system	<i>“If we know that if we selected one item or two cases ...then you have a more narrow item in your process flow and ...that gives a more [specific] overview...it’s not a whole spaghetti of things it was only one or two items. Which makes it easier to understand what we were looking for” (P13)</i>

(continued)

**Table 2.** (continued)

Inconsistency	Definition*	Example
Meaning	Variations in how individuals interpret the content present in either the data structure or output provided	<i>“The definition of straight-through processing (STP) only applies to processes in which no manual interference comes in. ...At assets management, they use straight processing for processes with a high automation degree. That’s already a difference in definition, because ...an STP process is 100% automatic. If a process has 10 steps, and 9 are automatic, that isn’t STP..., it is a process with a 90% degree of automation.” (P10)</i>
Place	Variations in where individuals perform their process mining analysis (i.e., Celonis or other software)	<i>“Celonis can provide a lot, it’s just due to a lack of understanding of what Celonis can be and the fact that we constantly have to ask...can you build this. ...That’s the reason why we chose to extract to Excel and we can do it ourselves in the timeframe that is working for us.” (P13)</i>

Definitions formed through constant comparison with literature. Adapted from [26].



**Fig. 1.** Conceptual model of the interrelationships between the types of inconsistency-in-use and influence on actionable insights

These types of inconsistencies had implications for the goal of using the process mining system, Celonis, which was to form actionable insights. The participants described actionable insights as *“insights actionable for the business...where the business can translate those insights into actions”* (P7). We also identified interrelationships between the types of inconsistency. Below we describe the relationships between the types of



inconsistency and actionable insights and the interrelationships between the types of inconsistency (Fig. 1).

#### 4.1 Interrelationship Between Inconsistency in Data and Inconsistency in Information (R1)

We define inconsistency in content as variations in the completeness and accuracy of the data/information in a process mining system. Through constant comparison, we identified the entanglement between inconsistency in data and inconsistency in information. Inconsistency in data refers to variation of the completeness and accuracy of the data that is loaded into a process mining system, whereas inconsistency in information refers to the variations in the completeness and accuracy of output provided to the user by the system. As the participants describe:

*“The corporate actions audit is [based on] predefined audit criteria ...The difficulty for us is ...we are telling somebody please build it for us [but] he doesn’t understand or ...know what we would really like to see. So he just builds something that he thinks is the best of course. Every outcome is also checked by us. ...We first check ...is it the right analysis that we intended ... or is it something completely different built that we didn’t really want.” (P13)*

*“Because we want to make the data as good as possible...we have to change something so the data becomes better then we have a straight through processing figure that’s accurate and we can all rely on it.” (P1)*

#### 4.2 Relationships Between Inconsistency in Meaning and Actionable Insights (R2)

Based on our data and constant comparison with literature, we defined inconsistency in meaning as variations in how individuals interpret the content present in either the data structure or output provided by process mining system. For instance, there are multiple ways a process can start, yet all of these starting points were collapsed under the one field in the data structure. Yet these starting points mean different things to different users. Therefore, users can ultimately attribute different meanings to the output and misinterpretations can result. As one participant describes:

*“And of course, you can interpret yourself what you think is the real name for a data element. ...I have already seen 4 or 5 process with the same name. ...For instance the first letter people get, startbrief (initial letter), three processes startbrief exactly the same name, [...] startbrief 1, and there are a lot of other data elements that sound ...like startbrief, so a lot of risk for misinterpretation when people combine those things. I even don’t think DI [data intelligence] has all the knowledge what people made in 25 years which startbrief is the real one.” (P9)*

Concerns regarding the terminology used to denote the phenomenon being represented in the dashboard was highlighted as a core impediment to actionable insights.

This was evident as different departments had different definitions for the term ‘straight through processing’ and it was feared users would act on their interpretation of STP rather than the dashboards fundamental meaning, as a participant highlights:

*User’s definitions of straight through processes will differ from AI-DI’s definition of straight through processes and then we implement AI-DI’s definition of straight through process and you will look at our dashboards you will think this is straight through processes but it doesn’t necessary mean its your definition of straight through processes. More like the definitions and the terminologies and the way we implement them in the dashboards that could make the users misinterpret. (P8)*

### **4.3 Interrelationships Between Inconsistency in Meaning and Inconsistency in Content (R3)**

Inconsistency in meaning also has important implications on inconsistency in content. Participants regularly highlighted the difficulties of inconsistent terminology between stakeholder groups (i.e., inconsistency in meaning). For instance, auditors were initially challenged in communicating to the data intelligence team. It was difficult for auditors to communicate what data they required and what analyses needed to be performed. This resulted in inconsistent data being loaded into the system, which could result in data inaccuracy in some cases.

Inconsistency in meaning is further compounded when a dashboard is created for a centralized goal rather than a team-specific goal. For instance, APG developed a dashboard to measure ‘straight through processing’ (STP) to be used across many departments to improve their processes. However, different teams have different perspectives of how STP should be measured. If a team views the term differently, they could ultimately reach different, and potentially, inappropriate conclusions. Resolving inconsistent terminology is imperative when you have data coming from multiple systems and multiple stakeholder groups, as an auditor states:

*“...We need data also from an external provider; their definition of its corporate action ...they use as an external provider of data are different from definitions we use internally. So, if you want to connect data that’s one thing, we have to get rid of because we have to use same definitions.” (P12).*

Recognizing the implications that inconsistency in meaning can have on data, the data intelligence (AI-DI) team have been actively establishing consistent data definitions. As one participant notes:

*“But, in the DI department we are already working since I think two or three years trying to get the same names for the same data elements.” (P9)*

### **4.4 Relationships Between Inconsistency in Content and Actionable Insights (R4)**

It was often described that it is not possible to have data in the system that is entirely complete and correct, with challenges associated with extracting data and required data

not always being logged. Responding to this challenge, the data intelligence team tries to provide insights in the accuracy and completeness of the data, terming this golden data. This inconsistency makes it difficult for people to trust the data and the output. This can make business users reluctant to use the system, potentially impeding decision making. To resolve the inconsistency in the data, the DI team has been working on establishing a data core as a single source of truth. As one participant notes:

*“But [the AI-DI] team says, “hey its golden data”, but golden data doesn’t necessarily mean its correct. It means, there is data and you know what’s wrong with the data. Where do you draw the line, when is the data correct enough, who says it correct enough, who tests the data. That’s why I say the dashboard is great, but people are still like hmmm can I honestly trust what I am seeing. That’s what people are still wondering about.” (P8)*

Asides from inconsistency in meaning and inconsistency in data, inconsistency in information can also result from different visualization approaches being adopted. While these differing visualization approaches may result in interesting actionable insights. If the users filter down to such a small level, the misinterpretations can result or the insight may not be feasible to address. As one participant notes,

*“It’s one of the most difficult things to compare processes because what I saw once was people filter so much on that particular group, the group becomes so small that you can ask if they are still representative enough for the whole group. ...Sometimes you see activities which appear less frequently and are focusing on exceptions or are you focusing on the major things that go wrong. And if you try to compare and you can filter everything you want of course you get a difference is it still making sense to invest in this difference.” (P5).*

#### **4.5 Interrelationships Between Inconsistency in Content and Inconsistency in Place (R5)**

When challenges arise with respect to inconsistency in data, workarounds occur, which ultimately results in people using different systems to perform their analysis (i.e., inconsistency in place). These workarounds can result in actionable insights being formulated but can result in inefficiencies in deriving the insights, as one participant notes:

*“We had 46,000 payments and we should change in some cases, ...you need to use the bank account number and in some cases you need to use the bank account name. And those should be switched. ...We thought it was already done in Celonis but we find out that it wasn’t already done. So we thought ok let’s extract in to excel and we will do it by ourselves, but filtering in excel with 46000 payments it just didn’t work out. And in the end we thought we might just check if [AI-DI] can do this in Celonis. And he could do it in just five minutes. But we just maybe three days we spent over Excel changing all these things” (P13)*

#### 4.6 Relationship Between Inconsistency in Place and Actionable Insights (R6)

Inconsistency in place does not solely originate from inconsistency in data, but it was also a direct effect of participants having previous expertise in other systems, in some cases Excel. In other cases, they have extracted their own data sources to be used in the analysis and created bespoke analysis for themselves and their teams. This creates the need for data governance practices to be put into place as it can lead to inappropriate actionable insights.

*“Someone [is] making new stuff on the views ...on the base tables. ...It is a person who can do very good SQL. ...But then you have two, you have this one, and the Celonis one. ...In this new world, we want to have data governance. ...We are eager to have a metadata agreement.... If someone is going to make his own connections, joins, calculations, then you don’t know whether it is the same calculation as we do in Celonis, which represents the definition of how we want to use it in this company. ...We are fading away from the goal.” (P6)*

In other cases, they extracted their own data sources to be used in the analysis and created bespoke analysis for themselves and their teams. This creates the need for data governance practices as it can lead to inappropriate actionable insights.

*The second risk I see is that they are used to their own dashboards, they worked on it for months to make their own dashboards. ...but when they are combining them in their own dashboards, we are not sure they will get all the data. I’m not sure that managers’ [personal dashboards] has all the data in it. In this new world, we want to have data governance about our stuff. (P6)*

#### 4.7 Summary of Findings

In summary, inconsistency was present in terms of meaning, data, information, and place. However, this inconsistency was not always detrimental. For instance, inconsistent presentation of information allowed for more specific conclusions to be drawn, inconsistency in place allowed for limitations associated with the data structure to be overcome. Moreover, inconsistency in data is an inevitability. Some actions have been put into place by the organization to minimize the detrimental effects that result from inconsistency. Including iterative development of dashboards to optimize data correctness; visualization training to minimize poor data visualization practices; establishment of a self-service team to quickly respond to issues minimizing the need for workarounds; and active collaboration to form an agreed upon data dictionary.

### 5 Discussion

In examining the effective use of process mining, we identified the importance of the interdependent nature of inconsistency in meaning, content, and place in attaining actionable insights. This notion of actionable insights mirrors the definition of informed action a key dimension of effective use. As such, our findings highlight that inconsistency

in meaning, content, and place all influence the “extent to which a user acts upon the faithful representations he or she obtains from the system to improve his or her state” [9]. However, while our findings largely pointed towards the challenge of inconsistency, inconsistency was not always detrimental and positive outcomes can still be obtained. Our findings extend current literature pertaining to inconsistency-in-use and business intelligence. We discuss these contributions in turn. We then reflect on how our findings contribute to the theory of effective use.

### 5.1 Importance of Inconsistency-In-Use for Process Mining

The importance of inconsistency-in-use has been identified in previous literature. For example, Burton-Jones and Volkoff [17] found to effectively use health systems, users need to attribute consistent meanings to form fields and input data in a consistent manner. Eden, Akhlaghpour, Spee, Staib, Sullivan and Burton-Jones [26] also identified the importance of inconsistency of use, however unlike Burton-Jones and Volkoff [17], they found effective use requires balancing consistency and inconsistency of use, where perfect consistency was deemed improbable and undesirable. Specifically, Eden, Akhlaghpour, Spee, Staib, Sullivan and Burton-Jones [26] identified five types of inconsistency (process, form, place, meaning, and content) of which the latter three were identified in this research. Our research also identified that in the context of process mining a more nuanced understanding of inconsistency in content is required by decomposing it into inconsistency of data and inconsistency of information.

Separation of data and information is well recognized in information systems and business intelligence literature. Data is often considered as the raw, structured collection of facts, whereas information is the “outcome of extraction and processes activities carried out on data, and it appears meaningful for those who receive it in a specific domain” [39]. Information can also be considered data in context [40]. While recognizing the distinction between data and information, the business intelligence domain does not specifically examine inconsistency in the two, rather it is often implied. For instance, variation in context can result in meaningless output and result in misinterpretation, even in the presence of highly accurate data [41]. The risk of misinterpretation is a key barrier to the adoption and continued use of business intelligence systems [42, 43]. Our findings reinforce the notion of inconsistency present in business intelligence literature, but provides a more nuance view including: 1) defining the specific elements of inconsistency-in-use: data, information, content, and place; 2) demonstrating the inter-related nature of these types of inconsistency and 3) identifying relationships between inconsistency-in-use and effective use.

In the process mining domain, Baier, Mendling and Weske [44] highlight the meaning of different events in a process may have different interpretations at different points in time. While the use of process mining has been advocated [45], how users use process mining systems is seldom explored, with most studies performed from a technical process mining expert’s perspective [46]. Our findings highlight the importance of not taking a technology deterministic perspective when examining process mining systems. This is reflected by a participant who stated: “*if you cannot translate what you see into actionable insights then it became something that is gimmick*”. As such, rich and robust theorizing from the broader information systems literature could shine light on the relationship

between process mining systems and its resultant impacts. We call for researchers to further explore the intersection of information systems and process mining.

## 5.2 Extending the Theory of Effective Use

As previously discussed, we set out with the objective of understanding the effective use of business intelligence through the examination of process mining. In doing so, the notion of inconsistency arose. Yet, how does this notion of inconsistency contribute to the ‘theory of effective use’? In Sect. 2 we mentioned effective use with its foundations in representation theory consist of three dimensions: 1) transparent interaction, 2) representational fidelity; and 3) informed action: As described below, we believe inconsistency in content and meaning has implications for representational fidelity.

Information systems are designed to represent real-world phenomenon. In this case, the process mining system should provide an accurate reflection of the pension fund processes. We observed that in some instances data was required to be extracted from multiple systems and thus each system only provided a partial account of the overarching phenomenon of interest. Integrating the data sources into a centralized data warehouse (APG referred to this as the data core) to be analyzed in an analytical process mining system, such as Celonis, provides a more complete representation. However, while necessary, this can result in inconsistencies in content and meaning. As our interview participants highlighted, data from different sources can have different underlying meanings. Moreover, the data used in the analysis is ‘golden data’, which means that the data is usable, its limitations are known, but it is not a completely accurate representation of the phenomenon of interest.

Adding complexity to attaining representational fidelity is the data sources used in the analysis are dependent on what the data intelligence team perceives the dashboard owner/users require. This influences the extent the representations contained in the analysis are meaningful. This is due to each team possessing knowledge and skills that are at opposing ends of a spectrum. In the case of APG, the data intelligence team has technical expertise, and the dashboard owner/user has requisite domain knowledge. These differences in knowledge can be expressed as tensions. As Pike, Bateman and Butler [47] notes “tensions represent poles of perspective that frequently work against one another, creating oppositional pulls, or tensions, that vary in degree”. Tensions do not have to result in direct conflicts, rather they can be considered as the “push-pull between different poles” [48]. In this case, the data intelligence team and dashboard owners/users need to collaborate regularly in these pull-push activities to derive a shared understanding [49].

Overall, our findings demonstrate the implications that inconsistency in content and meaning have on representational fidelity, in terms of the completeness, accuracy, and meaningfulness of the representations in the system. Our findings also demonstrated that inconsistency in content and meaning (i.e., representational fidelity) can result in misinterpretations hindering actionable insights (i.e., informed action), and therefore provides initial support for the relationship between representational fidelity and informed action proposed by the theory of effective use.

## 6 Conclusion

In conclusion, this study sought to investigate the effective use of process mining systems. Through conducting a qualitative case study, we identified that inconsistency-in-use (i.e., inconsistency in content, data, information, meaning, and place) plays an important role in the effective use of process mining systems. In analyzing these types of inconsistencies we reveal important implications for the theory of effective use. This research contributes both to the information systems and process mining domains and is one of the first attempts to bridge these two areas together.

Our study is limited as we only investigate a single case in the early stages of process mining adoption. Further, the case design was scoped to the process mining tool, Celonis. As such, broad canvassing statements related to generalizability cannot be made. Nevertheless, the case study provides indicators of how organizations may adopt process mining in effective ways. We encourage others to perform case studies of the adoption of other process mining tools within different settings. In addition, future research should also seek to compare how the effective use of process mining differs to other types of business intelligence systems. We also encourage future research efforts to employ different methodological approaches, for instance experimental and longitudinal survey designs could provide insights into causality of the relationships.

With process mining and other business intelligence systems shifting to self-service modes, the potential for ineffective use and misinterpretations is heightened. Failure to understand this intersection could therefore have detrimental effects on practice hampering the proliferation of process mining at the coalface. Future examination of the effective use of process mining system will, therefore, prove highly desirable to practice.

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