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Design Principles for Diffusion of Reports and Innovative Use of Business Intelligence Platforms

Martin Kretzer

Oliver Gass

Alexander Mädche

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Martin Kretzer[1,2], Oliver Gaß[1], and Alexander Mädche[1,2]

[1] University of Mannheim, Business School, Mannheim, Germany
[2] Institute for Enterprise Systems, Mannheim, Germany
{kretzer,gass,maedche}@es.uni-mannheim.de

Abstract. In order to innovate and respond quickly to new requirements, employees frequently supplement their information systems. This particularly applies to the context of business intelligence (BI) because many users supplement their BI platforms with individually tinkered spreadsheets. Unfortunately, these supplements bear numerous threats such as limited report reuse across all potential users.
To address this gap, we establish a design science project. First, we qualitatively explore impediments to diffusion of reports and impediments to innovative use. Second, upon our findings and extant literature, we derive meta-requirements for BI platforms that foster diffusion of reports and innovative use. Third, we develop and discuss principles for how to design a BI platform that would meet the identified meta-requirements. The resulting design principles emphasize (1) permanent user sandboxes to improve innovative use and (2) hybrid recommendation agents based on user interaction, collaborative-filtering, and users' social influence to improve diffusion of reports.

Keywords: business intelligence (BI), design science, innovative use, diffusion of reports, report reuse, post-acceptance use, generativity

1 Introduction

Organizations have made large investments into implementing standardized software products with the expectations that the resulting information systems (IS) integrate data and processes, allow control and reduce costs [1]. However, research indicates that many IS do not achieve these goals due to numerous reasons such as missing flexibility and long implementation times necessary to change them [2]. To mitigate this problem, end users tend to supplement their IS with additional artifacts. This phenomenon has recently gained momentum because individuals today may choose from, and are able to use, an unlimited pool of advices and services [3].

However, individually supplemented systems also constitute dangerous threats for organizations such as limited reuse of data and functionalities [4]. Therefore, literature embraces them only within defined boundaries [2]. Rather than continuously installing additional supplementary systems, organizations should target stable plat-

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forms that empower users and provide them with the flexibility to create new output [5].

As a consequence, exploring how IS may be used innovatively without seducing users to develop silo systems is highly interesting to industry and academia [6]. An according inquiry would be particularly interesting within the domain of business intelligence (BI) because (1) many users of BI platforms frequently develop supplementary, individually tinkered spreadsheets for reporting purposes [7] and (2) reuse of these spreadsheets across potential users is often limited [4].

Therefore, we aim to (1) explore the reasons why individuals do not use their BI platform in an innovative manner, (2) explore which factors impede diffusion of reports across users of a BI platform, (3) upon our findings and extant literature derive requirements for BI platforms that foster innovative use and diffusion of reports, and (4) propose design principles for BI platform vendors to develop according platforms.

To pursue these goals, we explore impediments to innovative use of a BI platform and reuse of reports within four organizations. In particular, section 2 presents our theoretical foundations and section 3 introduces our research approach. Section 4 first presents the impediments and then derives meta-requirements for a BI platform that supports innovative use and reuse of reports. Based on this, section 5 suggests according design principles and section 6 concludes our work.

2 Theoretical Foundation

In this paper, we investigate innovative use of BI platforms and diffusion of reports across users. Extant literature indicates tensions between the two that needed to be balanced by organizations [2], [4].

Following recent studies, we adapt the notion of generativity to the context of BI. Specifically, we use the notion of a generative BI platform to refer to a BI platform that targets both innovative use and diffusion of reports. This is consistent with recent studies that use the notion of generativity to describe platforms that are "simultaneously stable and flexible" [5, p. 753] and "enable and constraint activities" [8, p. 231].

On the one hand, generativity refers to the need of a BI platform to be flexible and empower users to quickly make use of this flexibility in an innovative manner [6], [9]. On the other hand, however, generativity also requires a BI platform to be stable because stability is a precondition for reuse of reports across users and a precondition for innovative use of the BI platform in the long run [5]. As a consequence, designers of a generative platform need to balance the tensions [10] between (1) usage of the BI platform in an innovative manner and (2) reuse of reports across users [11-12].

Toward this end, we draw on post-acceptance and diffusion theory [13] and posit that innovative use and diffusion are two key dimensions of generativity. First, innovative use is a necessary dimension because it allows the user to "create, generate, or produce a new output" [5, p. 750]. For instance, a generative BI platform would need to support the creation of new reports. Second, diffusion is a necessary dimension because diffusion enables reuse of innovations by additional users. Thus, for instance, a generative BI platform would also need to support reuse of reports across users.

2.1 Diffusion of Reports Across Users of the BI Platform

We determined diffusion [13] as one dimension of generative BI platforms. It emphasizes how new technologies, practices and ideas are adopted within a population of potential adopters [14]. The major underlying assumption is that diffusion starts slow but accelerates with each additional adopter until the innovation is adopted by the majority of the population. After this point, diffusion slows down, thus leading to an S-shaped curve as cumulative adoption function.

Early studies on diffusion identified available knowledge about a technology within an organization as a major driver of the technology's diffusion. Knowledge about a technology, which is available within an organization, decreases knowledge barriers and improves adoption of the technology. New adopters in turn generate and provide additional knowledge about the technology, which progressively lowers the knowledge barriers for others to adopt and use the same technology [15]. Furthermore, research noted the influence of socialization on diffusion. For instance, Dinev and Hu [16] draw on diffusion theory to explain socialization effects. They assume that individuals build up knowledge and become aware of new technologies through interacting with the society. This socialization effect then affects the individual's preferences and perceptions, for example, attitude formation, perceived behavioral control as well as social preferences, such as subjective norms. Similarly, Mustonen-Ollila and Lyytinen [17] determined organizational and environmental factors that cause a technology's diffusion within an organization and Siponen et al. [18] applied diffusion theory to investigate how the social context affects individuals' adoption decisions.

Within the context of generative BI platforms, we adopt the construct of diffusion of reports to refer to the number of users who request a certain report at a certain frequency. This construct has been used in IS previously as dependent variable to measure the diffusion and frequency of the information provided by a BI platform [19].

2.2 Innovative Use of the BI Platform

Broad IS literature views IS implementation as a multistage process divided into pre-acceptance (initiation, adoption, adaptation) and post-acceptance phases (acceptance, routinization, infusion; [20-21]) and argues that returns on IS investments are mainly gained within the routinization and infusion phases [22-24]. While IS literature has primarily examined IS use at the pre-acceptance phases, routinization and infusion have received limited attention (e.g., [23], [25]).

Commonly, the use concept associated with routinization is routine use and the use concept associated with infusion is innovative use [26]. Routine use and innovative use are widely acknowledged as two different behaviors that can coexist [27-29] and need to be balanced [30]. Routine use and innovative use can be contrasted based on (1) the distinction between standardization and innovation orientations of employees' IS usage behaviors [26] and (2) the distinction between exploitative and explorative organizational learning [29], [31].

Following extant literature we adopt the definition of innovative use as employee's usage of a BI platform in novel ways to support their work [26]. As explained above, we determined innovative use as one dimension of generativity.

To summarize, our research objective is to (1) explore which factors impede diffusion of reports across the users of a BI platform, (2) explore the reasons why individuals do not use their BI platform in an innovative manner, (3) upon our findings and extant literature derive requirements for BI platforms that foster innovative use and diffusion of reports, and (4) propose recommendations for BI platform vendors to design according BI platforms.

3 Research Method

We followed a design science research (DSR) approach to address our research questions, because DSR is particularly suited to theoretically prescribe how to design artifacts in order to improve a certain situation [32-33]. Researchers have recommended DSR to investigate complex, non-decomposable research and business problems [34-35], understand and change generative events [36], and highlight knowledge creation based on rigorous validations [37-38].

According to Hevner [39], researchers first need to become aware of the relevant business problem they intend to investigate. The results of this stage are typically formulated as impediments of the current system [40]. Second, researchers should rigorously make use of the extant scientific knowledge base and theorize attributes of the pursued future system [39]. These attributes are usually referred to as meta-requirements (MRs; [41]) because they reflect requirements that need to be met by an improved system. Finally, a system needs to be designed that fulfills the identified meta-requirements. Therefore, design principles (DPs) are proposed that describe how the new system should be implemented in order to meet the identified meta-requirements. Finally, these DPs should be implemented, evaluated and refined iteratively [34], [39].

This paper suggests design principles that support innovative use to a BI platform and design principles which foster the diffusion of reports across the users of a BI platform. First, we reveal impediments of current BI platforms. Upon, we theorize meta-requirements of a BI platform which supports innovative use and diffusion of reports. Eventually, we introduce design principles for meeting these meta-requirements.

As the exploration of impediments requires flexibility for examining aspects of innovative use and report diffusion that may not be completely identifiable at the outset of the study, we conduct an exploratory interview study [42]. This is a common approach for establishing DSR projects because it generates a comprehensive understanding of a real world problem [40]. Four sites were selected on the basis of theoretical relevance –that is, to ensure an adequate foundation for comparison and to maximize variation [43]. Specifically, based on our personal experiences from working and collaborating with potential organizations, we selected two organizations that

focus on routine use and standardization [26] and two organizations that focus on innovative use. Furthermore, since literature indicates a beneficial effect on balancing routine use and innovative use by implementing additional specialized organizational units between end users and IT professionals [44], we assured that exactly one organization of each group had established a BI Competency Center (BICC). BICCs are specialized organizational units that perform cross-functional tasks regarding development, operation and support of BI platforms across a company [44].

Furthermore, we focused on vehicle manufacturing companies. Regarding collection of data, we conducted semi-structured in-depth interviews to gain detailed real-life data. We first interviewed managers from the IT department or BICC because they were able to provide us with rich information about their BI platforms. Additional respondents were recruited using snowball sampling and their suitability to provide additional insights [45]. Table 1 shows detailed descriptive information about all interviewees grouped by organization. An interview guide was developed. As needed, specific questions were asked to ensure completeness of data and comparability of cases. The interviews lasted 30-60 minutes and were transcribed and step-wise coded. Furthermore, codes were used to validate whether companies focused on routine use or innovative use. Finally, data collection was supplemented by review of internal documents, e-mail discussions and the companies' webpages.

Table 1. Descriptive case information

Firm	*Employees (HQ)*	*Respondents (total: 20)*
Alpha	300-500 (USA)	3 IT professionals [1 IT director, 2 BI experts], 3 power users [1 program manager, 1 lean manager, 1 financial analyst]
Beta	300-500 (UK)	2 IT professionals [1 IT director, 1 BI expert]
Gamma	20.000 (Germany)	1 IT professional, 2 BICC experts, 3 users [1 process owner (PO) marketing & sales, 1 PO cost accounting, 1 PO logistics]
Delta	10.000 (Germany)	1 IT professional, 3 BICC experts [1 BICC director, 2 BICC experts], 2 users [1 PO logistics, 1 supply chain m. director]

4 Findings

4.1 Diffusion of Reports

Impediments to diffusion of reports.

We conducted an interview study to explore which factors impede diffusion of reports across the users of a BI platform. Interestingly, a BICC expert at Gamma explains how he believes that the reason is not that existing reports are not adjusted to the needs of the users. Rather, the problem would be that users were not able to discover the reports they were looking for. This adversely affects diffusion, because being able to discover a report is a precondition for a user to reuse the report. Too many options create huge complexity and intransparency over existing reports.

> *„We have very detailed possibilities for analyses. […] I fear it is less a problem that a required report doesn't exist. Rather the user gets buried by the bulk of options for selecting the report."* (BICC expert 2, Gamma)

Not knowing where to get the needed information tempts users into creating new reports instead of reusing existing reports – which again reduces transparency and complicates source identification. This is a vicious circle for organizations: If existing reports are less often reused across individual teams and departments, scale effects cannot be achieved and operational efficiency decreases [11].

> *"The problem I see is this identification. [….] How do you identify 'Oh, this is so great that others need it too'. You somehow have to provide a possibility to make this public."* (BICC expert 2, Delta)

This lack of guidance toward the required information also impedes users from becoming aware of available knowledge.

> *"I believe an adaptive platform may really assist if it is very intelligent. […] For instance, I am looking at something and notice I made a mistake: I delivered late. Then I would like to know why and the system would need to say 'Okay, from here you can jump to this query or this query. Then you get additional information which your current query does not provide.' "* (User 1, Delta)

Meta-requirements addressing diffusion of reports.

Extant literature has shown that diffusion increases through social influence. In particular, Singh and Phelps [46] differentiate three types of social influence and show how they influence diffusion: infectiousness, social proximity and susceptibility. First, infectiousness refers to the influence of prior adopters. This includes factors such as the size, performance, status, success of prior adopters as well as the overall number of prior adopters. Second, social proximity refers to the social distance between two actors and determines how easily information is transmitted between them [47]. Marsden and Friedkin [48] distinguished social cohesion and role equivalence as two dimensions of social proximity. While social cohesion defines proximity in terms of the number, length, and strength of the paths that connect actors in a network, role equivalence defines proximity in terms of the similarity of two actors' profiles [46]. For instance, if a software designer and a requirements engineer would share an office and frequently work together, their social cohesion would be relatively high. However, role equivalence between them would rather be low because, e.g., the requirements engineer would gather and describe requirements while the designer would draw mockups. In other words, role equivalence would, probably, be much higher between two software designers – even if they were working on different projects and would be located in different offices. Finally, third, the impact of social influence on diffusion is shaped by susceptibility. Susceptibility of a new adopter to social influence describes the adopter's experience and skills. Building on the findings from our exploratory interview study and extant literature, we derive meta-requirements that a BI

platform would need to meet in order to improve diffusion of reports across all users of the BI platform.

> ***MR1:*** *In order to increase diffusion of a report, a BI platform needs to (a) make infectiousness of prior users of that report visible, (b) improve visibility of the role equivalence between a potential new user and previous users of that report, and (c) improve visibility of the social cohesion between a potential new user and previous users of that report.*

4.2 Innovative Use

Impediments to innovative use.

As a second dimension of generativity we identified innovative use. Thus, besides impediments to diffusion of reports, we also explored the reasons why users do not use their BI platforms in an innovative manner. Participants frequently mentioned the inflexible data model as an impediment for adjusting reports to the specific needs of the users and coping with bad data quality.

> "*The BI system takes away flexibility. […] And sometimes its data is wrong. […] And then you have to adjust something manually to reflect the reality again*." (User 3, Alpha)

In order to perform exploratory analyses in spite of limited flexibility, users tend to supplement their platform with individually tailored spreadsheets. While Beta and Delta configured their BI platforms to avoid any extraction of data, Alpha and Gamma do not forbid data extraction from the platform into spreadsheets. Interestingly, the IT department at Alpha even developed stored procedures within the BI platform for loading data from end user maintained spreadsheets.

> *"We take some spreadsheets that the users are maintaining and they save them to a folder which is mounted in way that the UNIX machine can read the same folder. […] And then I can use it in my BI platform."* (IT professional 3, Alpha)

In addition, Alpha also integrates data from external sources into the BI platform. This allows users to join internal and external data.

> *"We also have what's called the XXX. It's a database. […] This takes data from a company called XXX in the UK. […] It includes information related to our product. And we use it to […] derive our market share. […] Our database is extracted, and combined with the data that we have and that is used by our sales people and our executives to figure out where the market's going and how much market share we have."* (IT professional 2, Alpha)

Furthermore, end users at Alpha also explained that, as a consequence of their BI platform's openness, they sometimes would not be able to use the data anymore. For them, being able to assess the reliability of data is crucial. They needed to know the

source of the data. However, the BI platform's uncontrolled growth reduced transparency over data sources accessed by the BI platform and impedes users from evaluating the reliability of these sources: *"You have to ask: 'Where does this information come from?' […] If you don't know how you got the information, the report is worthless."* (User 3, Alpha)

A meta-requirement addressing innovative use.

Our observations regarding innovative use are consistent with extant literature. For instance, Faraj et al. [49] indicate how experimentation offers a response to organizing issues if outcomes are not known in advance. This uncertainty over potential outcomes constraints BI platforms to only encourage experimentation within defined boundaries and to avoid it outside [2]. Organizations should establish BI platforms in which users can perform new analyses and go beyond their standard uses and techniques [50]. Thus, we derive the following meta-requirement:

> ***MR2:*** *In order to increase innovative use, a BI platform needs to allow experimentation within predefined boundaries while avoiding experimentation outside these boundaries.*

5 Design Principles

While the previous section identified impediments of generative BI platforms and derived meta-requirements that a generative BI platform should meet, this section builds on extant literature to explain how these meta-requirements may be accomplished. Therefore, we develop according design principles (DPs) that aim at increasing innovative use of the BI platform and diffusion of reports.

5.1 How can a BI Platform foster Diffusion of Reports?

To improve diffusion of a specific report, we found that a BI platform needs to improve visibility of infectiousness of prior report users (MR1a) and social proximity (role equivalence and social cohesion) between new users and prior users of that report (MR1b, MR1c). Building on literature, a key factor for improving visibility is user guidance, because it allows focusing the user's attention on desired information and functionalities. In the 1990s, Silver [51] started examining possibilities for decisional guidance and their potential impacts. Briefly after that, Dhaliwal and Benbasat [52] developed a framework for knowledge-based system explanations. Ever since, guidance studies have examined manifold application areas and have been conducted on individuals as well as groups [53]. More recently, guidance studies highlighted the need for recommendation agents. Especially within the field of e-commerce, recommendation agents who provide additional information and explanations have been found to focus customers' attention and affect their shopping behavior [54-57]. The goal of affecting online customers' shopping behaviors is conceptually similar to our goal of improving diffusion of reports. In both situations a user's attention is being focused on a particular information (e.g., a shopping item or the infectiousness of a report's prior users) in order to lead the user into performing a certain action (e.g.,

buying the item or executing the report). Therefore, we suggest adoption of recommendation agents in order to address MR1a-MR1c.

Extant research within the Human-Computer Interaction (HCI) discipline distinguishes two design approaches for recommendation agents: collaborative filtering and content-based filtering. Collaborative filtering algorithms analyze and compare users' profiles to predict users' preferences [58]. One example for these algorithms is Amazon's patent on "Collaborative recommendations using item-to-item similarity mappings" [59] which provides the basis for the well-known "people who buy A also buy B" recommendations. However, collaborative filtering also has some fundamental downsides: users cannot influence the recommendation process [60], users do not understand why certain things are suggested and thus do not trust the recommendations [57], and user profiles are required beforehand [61].

In contrast to collaborative filtering, content-based filtering does not compare users with each other [62]. Instead recommendations are solely based on a single user's profile – especially on the user's preferences and history. While historical data about a user can be collected automatically over time, data about a user's preferences is typically gained through user interaction (e.g., inviting users to rate items which are managed by the recommendation agent). Therefore, a key challenge of content-based filtering algorithms are their ability to continuously learn and adapt and users' willingness to enter their preferences [61].

Not surprisingly, researchers recently started to develop concepts for combining collaborative filtering with content-based filtering in order to realize the advantages of both algorithms [63]. To our knowledge, only Loepp et al. [61] tested a hybrid approach against alternative algorithms yet. Their results indicate advantages regarding (1) fit of recommendations to users' interests, (2) automatic learning and adaptation to users' preferences, (3) required user effort. Furthermore, their algorithm performed best in situations where (4) users do not have any search directions in mind and (5) second best in situations where users have vague directions in mind.

Following recent research findings, we propose recommendations based on hybrid algorithms. That is, in addition to considering users' infectiousness, role equivalence between users and social cohesion between users [42], the algorithms underlying the recommendations should also consider user preferences that might be gained through additional user interactions.

> ***DP1:*** *In order to increase diffusion of a certain report, the BI platform should recommend that report to a potential new user based on (a) the potential user's preferences, (b) the infectiousness of prior users of that report, (c) the role equivalence between the potential user and previous users of that report, and (d) the social cohesion between the potential user and previous users of that report.*

5.2 How can a BI Platform foster Innovative Use?

Experimentation refers to the use of technology to encourage participants to try out novel ideas [49]. One way to allow this while also defining boundaries is to provide

an environment to the user in which the user can access only a subset of the data and/or a limited set of the BI platform's functionalities [64]. Such an environment is typically referred to as a sandbox (e.g., [50], [65]). Sandboxes provide a way to avoid adverse effects from one user's experimentation on other users of the same platform. Sandboxes can either be permanent where resource changes persist after the programs finish running, or ephemeral where changes are discarded after the sandbox is no longer in use [66-67]. Importantly, isolation-based sandboxes where the effect of what happens inside a sandbox is entirely isolated from resources outside the sandbox, are usually configured in ways to circumvent this isolation because for users to intervene with each other they need to copy data into and out of their sandboxes [64], [66].

The roots of sandboxes as a way to protect resources of an IS date back to the early 1970's when computer scientists showed that virtual machines can be used to improve overall system security by providing an additional layer of controls [68]. Ever since, researchers have proposed and adopted sandboxes for manifold usage scenarios. For instance, sandboxes for emulation of entire devices [69], sandboxes as an environment in which plugins may compile and interpret program code [70-74], sandboxes for running single-application lightweight operating systems as embedded systems [72], sandboxes as so-called "powerboxes" to virtualize full commodity operating systems [73], sandboxes for multimedia composition on mobile devices [74] and sandboxes for flexible data analytics [75]. However, only recently IS and organizational management researchers have suggested innovation sandboxes [76] for experimentation in order to allow piloting of software ideas [65], afford generative responses to new requirements [49] and deal with pressures to change and innovate [77].

Following these recommendations, we conclude that BI platforms should provide their users with sandboxes in order to allow them experimentation in a controlled environment. In contrast to the standardized core of the BI platform, such sandboxes should allow users to load data from additional organization-internal as well as organization-external sources. Thus, as our second design principle, we propose:

> ***DP2:*** *In order to increase a user's innovative use of a BI platform, the BI platform should provide a permanent sandbox to the user in which the user can load the data from the BI platform, modify it, and enrich it with data from external data sources.*

6 Discussion and Conclusion

In this paper, we built on generativity research to design BI platforms that simultaneously foster flexibility and stability [5]. In particular, we defined innovative use and diffusion of reports as two dimensions of generativity. While innovative use refers to employees' post-acceptance use of a BI platform in novel ways [26], diffusion of reports refers to the number of users who request a certain report at a certain frequency [19]. Upon this understanding we established a DSR project. We first conducted an exploratory interview study to identify impediments of current BI platforms to these two dimensions. Subsequently, we studied extant literature and theorized meta-requirements for a BI platform that would mitigate these impediments. Finally, we

suggested design principles that provide guidance on how to meet these meta-requirements.

Our design principles can be classified as an exaptation to existing knowledge if positioning them within Gregor and Hevner's [32] "DSR Knowledge Contribution Framework". In particular, our design principles extend the existing state of knowledge within the BI domain for the following reasons. First, we draw on virtualization research from the Computer Science discipline to explain how and why sandboxes could increase users' post-adoptive, innovative use of their BI platforms while still enabling administrators to set boundaries. Second, we draw on personalization research from the Human-Computer-Interaction discipline to explain how a recommendation agent could support factors for diffusion (i.e., infectiousness, role equivalence, and social cohesion). Third, we used logical reasoning to determine the class of algorithms that should be used by a recommendation agent within the BI domain. Fourth, in combination with the impediments identified through our interview study and the meta-requirements derived from literature to solve the identified impediments, the proposed design principles form a sequence consisting of (a) impediment, (b) solution, and (c) action to be taken [40]. Each of these sequences represents a theoretical proposition that could be subjected to empirical testing and confirmation. Hence, each combination of impediment, MR and DP represents a contribution to theory [40], [78].

Furthermore, the two suggested design principles improve generativity of a BI platform, because (1) DP1 increases diffusion of reports across users without limiting innovative use and (2) DP2 enables innovative use of the BI platform while maintaining a stable platform base that supports innovative use and diffusion of reports in the long run [5]. Consequently, the design principles can reduce users' tendencies to supplement their BI platforms with individually tinkered spreadsheets [7] and, thus, limited reuse of reports and information [4]. This facilitates the work of both power user as well as infrequent users. For instance, power users can access and manage all reports from within the BI platform and infrequent users are assisted with suggestions when searching for reports. Also, both user groups can extend existing reports and experiment with external data without having to care about data integration losses

Toward this end, we constantly reviewed extant literature to support our decisions. For instance, we proposed a combination of collaborative filtering and content-based filtering algorithms for the implementation of a recommendation agent because recent studies showed that such a combination performs particularly well in domains in which user effort needs to be minimized and users only have a vague knowledge about all available data. To our knowledge, suggestions for BI sandboxes and recommendation agents in previous literature were either less specific (mostly IS literature) or focused on improvements of algorithms without a strong theoretical backing (mostly HCI literature). Thus, our design principles based on case studies and extant research are valuable for BI managers as well as BI researchers. However, we acknowledge that our design principles are subjective and other researchers may propose different principles for improving BI platform generativity.

Furthermore, an empirical evaluation of the suggested design principles is still outstanding. Thus, the design principles are tentative in nature. However, by reviewing

the existing literature and conducting an interview study, we already provide some theoretical and empirical backing for our design principles. This view of design principles is consistent with extant design science literature stating that empirically backed design principles represent a theoretical contribution if they clearly suggest a cause-effect relationship [40], [80].

In order to empirically evaluate our suggested design principles, we are currently testing possible implementations within a laboratory BI platform. In particular, we are using a data warehouse provided by SAP and implement and configure BI sandboxes for end users. Furthermore, we are developing a recommendation agent which accesses metadata about previous usage of the data warehouse and BI sandboxes directly from the underlying database. The recommendation agent combines this information with information collected from the user's BI client (e.g., currently filtered dimensions). Thus, the agent is able to provide recommendations about, e.g., commonly used reports from colleagues who are frequently performing similar tasks (DP1c).

Our BI platform will be evaluated as follows. Over a term of twelve weeks, 100 Management and Information Systems graduate students who are specializing in "Business Intelligence and Management Support Systems" are exploring a BI test data set. They are divided into ten teams with ten participants each. Five teams are equipped with BI sandboxes while the remaining five teams are not equipped with BI sandboxes. Importantly, participants are assigned to a team with or without a BI sandbox based on their individual preference. Furthermore, they are equipped with and trained and supported in a wide range of BI clients from which they may freely choose their preferred client(s): Microsoft Excel Pivot, Tableau Desktop, SAP BusinessObjects Analysis, SAP Design Studio, SAP Crystal Reports. Additional web links to further BI clients are also provided, e.g., IBM Contoso and QlikView. The outcome, that is (re-)usage, is measured in terms of (1) actual data warehouse usage and (2) experiment participants' self-reported usage (via bi-weekly questionnaires). We deem triangulation of usage measures to be appropriate for our study because we intend to measure both usage of the central data warehouse as well as usage of potential supplements (e.g., local spreadsheets). Finally, each team's performance is evaluated by the course instructors and students receive credit based on their team's performance.

Regarding further research, an exploratory investigation of additional organizations may indicate additional impediments that our design principles do not address yet. In particular, we focused on improving visibility of a report's social influence in order to increase diffusion of reports. This is consistent with extant literature which determined social influence as main predictor of diffusion [26]. Nevertheless, researchers may adopt different concepts to improve diffusion and, consequently, arrive at different meta-requirements. Similarly, we determined recommendation agents and sandboxes as suited measures for meeting the identified meta-requirements because extant literature has adopted these concepts in conceptually similarly situations (e.g., [49], [54-56]). However, other researchers may alternatively adopt different concepts and arrive at different design principles. Finally, we acknowledge that the suggested design principles are still tentative since they are still subject to evaluation and refinement [34], [39]. The actual value of our design principles can only be determined

after their implementation and examination within a real world scenario. Therefore, future work may compare and assess alternative theory bases and focus on implementation and evaluation of the proposed design principles in practice.

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